Exploring Urban Expansion using the Global Human Settlement Layer (GHSL) in the Yangtze River Delta (YRD) metropolitan region, China

SHUO CHENG
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SUPERVISORS:
Dr. N. Schwarz
Dr. M. Kuffer

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SHUO CHENG
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SUPERVISORS:
Dr. N. Schwarz
Dr. M. Kuffer

ABSTRACT

China has experienced a rapid urban expansion. As one of the largest metropolitan regions in the world, the Yangtze River Delta (YRD) region is the most populous area with the highest city density and urbanization level in China. Thus, the thesis aims at exploring urban expansion patterns in the YRD. The spatiotemporal characteristics of the urban expansion process in the YRD are investigated by using the global human settlement layer (GHSL) with time-series thematic data. The development of built-up area and landscape metrics describing urban expansion are analyzed from 1975 to 2014. The analysis uses a multi-scale approach on the level of the metropolitan region as well as for 17 cities in the YRD metropolitan region. For these cities, results are presented for the whole city as well as for six buffer zones which provide detailed zonal-based analysis from the cities' centers. In addition, land planning policies are analyzed to relate urban expansion and policy targets. Overall, the results of this work will be valuable for a deeper understanding of urban expansion processes and can contribute to improvements for monitoring and managing urban expansion in the YRD region.

Keywords:
Spatial metrics, GHSL, YRD, Urban expansion, Land policy

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TABLE OF CONTENTS

Contents

LIST OF FIGURES

LIST OF TABLES

INTRODUCTION

The world is experiencing a rapid expansion of urban areas. There is a rapid and large-scale process of urban expansion in China as well. As one of the most populous area in China, the Yangtze River Delta (YRD) has the highest city density and urbanization level (Liu, 2012). The metropolitan region of the YRD has the largest space coverage (across three provinces) and the most diverse city levels compared to other metropolitan regions in China. In the meanwhile, urban expansion has resulted in a series of significant consequences related to resource and environment. Therefore, this research explores the spatial and temporal trajectory of urban expansion in the YRD metropolitan region using the Global Human Settlement Layer (GHSL), which provides global built-up information (European Commission, 2017). In this context, the results of this analysis will be valuable for a deeper understanding of urban expansion processes and can contribute to control and manage urban expansion.

1.1. Background and Justification

The 21st century is an epoch of rapid urbanization. Urbanization is a term that conveys an image that radius of one city expands into its rural surroundings (Carlson & Traci Arthur, 2000). The process of urbanization is accompanied by changes in terms of society, economy and technology from urban to rural areas. It has an impact on a wide range of issues such as social, demographic, economic and environmental concerns (George, 2008). Extensive land use change has resulted from the rapid urbanization especially in developing countries. Urbanization can be recognized as one of the most anthropogenic causes of arable land loss (Lopez, Bocco, Mendoza, & Duhau, 2001). Arable land is decreasing dramatically in due to urbanization, which threats the food security for human being (Wu, Zhang, & Shen, 2011). Despite the positive impacts such as lower capita costs of infrastructure and services because of higher population densities, a series of environment problems come along with rapid urbanization, e.g., threats to city health and safety coming from water and air pollution, traffic congestions and water pollution, serious health consequences because of uncontrolled and improperly handled solid waste, pressure on ecological sensitive areas due to conversion from agricultural land, forest and wetlands to urban uses and infrastructure, as well as destruction of sensitive ecosystem in coastal land (Ichimura, 2003). Thus, it is necessary to understand urbanization processes to avoid negative impacts of urban growth.

The land expansion has been regarded as an important part of urbanization, additionally, it can be seen as the main indicator to reflect the urbanization of land in some regions and the most easily identifiable characteristic of urban growth processes in a spatial dimension (Yang, Li, & Hou, 2016). Land use changes and urban expansion have been brought by rapid urbanization, changing landscape patterns. Analyzing the process of urban expansion is essential for understanding and assessing the pace and pattern of urban expansion and providing basic information for planning and decision making. Urban expansion mainly refers to the conversion of built-up area from rural to urban. Thus, the analysis of built-up area changes is a significant part of exploring the urban expansion process.

China has experienced accelerated and large-scale urban expansion since its reform and opening during the last two decades. The built-up area increased from 7,438 km2 in 1981 to 32,520.7 km2 in 2005, thus an increase of 3.37 times (Liu, He, Zhang, Huang, & Yang, 2012). The provinces in central and eastern China with high population and economic growth, especially those coastal areas such as the Yangtze River Delta, have experienced the most accelerated urban expansion. The rapid expansion of urban land area has resulted in land resource degradation as well as a variety of environmental and ecological issues. And urban development is likely to be by relevant policies (Wu et al., 2011). Thus, an optimal allocation of land resource, particularly for urban uses, is urgently needed in order to achieve sustainable development. This can be supported by an analysis of the process of urban expansion using a large-scale urban data set.

A core element for sustainable development of urban and rural settlements is a deep understanding of the global spatial distribution and evolution of human settlements (Squires, 2002). Some basic questions such as where urban land use expands, how (extend and rate), why settlement growth, how urban land use changes and environment changes affect each other are necessary to answer for a better understanding of global urbanization processes in a complex urban environment (Montgomery, 2008). Recently, several data sets with promising information can be used to identify the global urban area. For instance, the Global Urban Footprint is a worldwide mapping product of settlements with an unprecedented spatial resolution of approximate 12 m but restricted to 2010 and 2013 (Esch et al., 2012). The GHSL (Pesaresi et al., 2013), a project supported by the Joint Research Centre (JRC), developed an approach for mapping and monitoring the urbanization process over time. The GHSL uses Landsat imagery organized in four temporal collections which are 1975, 1990, 2000 and 2014. It involves built up environment and its dynamic changes and is globally available. Therefore, it can be used to analyze the dynamics of urban expansion processes at a large-scale region.

1.2. Research Problem

Since the economic reform in the late 1970s, the YRD has experienced rapid urbanization and expansion of urban areas. With the expansion of urban areas, a number of environmental issues emerged. Urban expansion directly influences land use and land cover pattern, affect the surrounding atmosphere, water quality, local climate, and biodiversity as well. During last few decades, there also exists sharp decrease of farmland, decrease of plants, increase of heat island effect, and air pollution, which are consequences of urban expansion. Although urban expansion brings some negative impacts on ecological environment in the YRD, we can also see that the economic development is accelerated by urbanization. Thus, it is necessary to analyze the process of urban expansion in the YRD.

There are a few researches analyzing the urban expansion process in the YRD using spatial metrics. These previous researches selected several big cities (e.g. 4 and 7 cities) in the YRD region to explore their spatiotemporal expansion (Tian, Jiang, Yang, & Zhang, 2010; Yue, Zhang, & Liu, 2016). The YRD megalopolitan region covers three provinces, which have different geographical and socioeconomic characteristics. Thus, an analysis of the cities selected form all the three provinces is helpful for a deeper understanding of urban expansion dynamics of the YRD. Furthermore, 'One core city and five metropolitan circles' are defined in the Development Planning of Yangtze River Delta Urban Agglomeration (China National Development and Reform Conmmision, 2016). They cover 17 cities of the three provinces in the YRD megalopolitan region. Thus, the research will explore the process of the YRD covering the 17 cities included in the development planning. In this research, spatiotemporal characteristics of urban expansion in the YRD metropolitan region was identified by a multi-scale analysis. Spatial metrics were used to characterize urban patterns at city level, following with the comparison across different provinces and different city scales. The research also analyzed land policies related to urban expansion as well as derived associations between policy and urban expansion process.

Collecting evidence and understanding the urban expansion process is beneficial to balance the relationship between urban development and environment protection. Thus, the research aims to explore the process of urban expansion in the YRD using GHSL and to analyze the different expansion pattern of different regions and cities for sustainable development. As the GHSL has not yet been validated for the YRD, validating the data set is an intermediate step to be taken.

1.3. Research Objectives and Questions

1.3.1. General Objective

The main objective of the research is to explore spatiotemporal patterns of urban expansion in in the Yangtze River Delta using the GHSL.

1.3.2. Sub-Objectives

1) To assess the quality of the GHSL for the purpose of urban expansion analysis.
2) To analyze the pattern and pace of urban expansion for the YRD from 1975 to 2014 using GHSL.
3) To provide suggestion for the improvement of urban expansion management and control in terms of land policies.

1.4. Research Questions

1) Sub-objective 1: To assess the quality of the GHSL for the purpose of further urban expansion analysis

- What are suitable accuracy measurement methods to assess the quality of the GHSL?
- What are suitable reference data to assess the quality of the GHSL?
- What is the quality of the GHSL for the study area?

2) Sub-objective 2: To analyze the pattern and pace of urban expansion from 1975 to 2014.

- Which indicators and metrics are suitable to quantify the spatial and temporal urban growth?
- What are spatial and temporal characteristics of urban expansion in the case study?
- What are the differences and similarities of spatiotemporal urban expansion in different regions and different scales?

3) Sub-objective 3: To provide suggestion for the improvement of urban expansion management and control in terms of land policies.

- Were policy targets met during the process of urban expansion?
- How to monitor urban growth to inform future land policies related to urban expansion?

1.5. Thesis structure and framework

The structure of the thesis is as follows: the chapter 1 is the introduction part which describes the general information of research background and problem, research objectives and questions as well as research frame work. In chapter 2, the literatures related to research concepts and methods are discussed. Chapter 3 is the specific description on study area, data source required and methodology of the GHSL assessment and urban expansion analysis. Chapter 4 are the results and discussion which cover the results with sections on validation of the GHSL, urban expansion process analysis. Furthermore, review the policies during the urban expansion process in study area, exploring whether the policy targets were met or not and provide suggestions on how to inform future urban policies by monitoring urban expansion. Chapter 5 is conclusion that includes the conclusion of the research. At last it concludes the achievements of this study and describe the outlook.

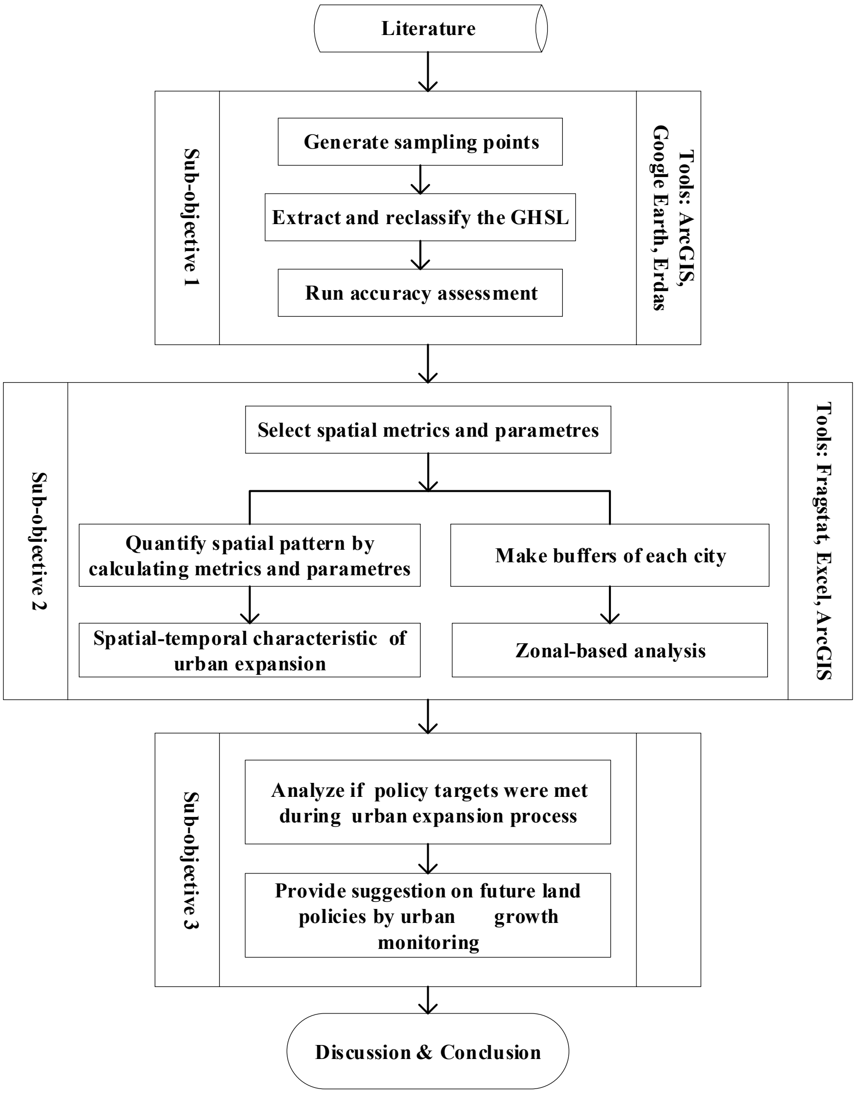


Figure 1. Research framework

Figure 1 illustrated the conceptual framework of this thesis. Accuracy assessment is the essential foundation for further analysis of urban expansion and relevant land policies. Then spatial metrics are used to characterize urban expansion dynamics quantitatively. Later on, based on the urban expansion analysis, correspondence analysis will be conducted to explore the relationship between land policies and urban expansion.

2. LITERATURE REVIEW

2.1. Review on Conceptual Thoughts and Ideas

2.1.1. Urban Expansion

Globally, urban areas expand rapidly. The urban population is 54% of world's population in 2014 and it is expected the world will be two-thirds urban (66 percent) by 2050 (United Nations, 2012). Presently, urban areas are expanding on average twice as fast compared to their population around the world (Angel, Parent, Civco, Blei, & Potere, 2011; Seto, Fragkias, Guneralp, Reilly, & Pidgeon, 2011). It is apparent that there is a rapid process of urban expansion around the world.

In general, the expansion of cities is ongoing and the cover of cities is almost 0.5% of the planet's land area (Angel et al., 2011). Despite urban areas just cover a small fraction of the world's surface, a variety of consequences relate to natural land scape, environment and ecosystem at all geographical scales (Lambin & Geist, 2001). The urban expansion requires more land and promotes the conversion of urban land use and land cover (LULC) from rural to urban land (Manju et al., 2011). Urban expansion and associated changes of land cover drives the loss of habitat (Mcdonald, Kareiva, & Forman, 2008; McKinney, 2008) and the decrease of biodiversity (McKinney, 2002). In addition, ecosystem productivity can be affected by urban expansion through the loss of habitat, biomass and carbon storage (Seto, Guneralp, & Hutyra, 2012). In the context of global climate change, the influence of urban expansion has resulted in a significant environment issue on transportation in growing megacities, which is because increasingly motorized mobility is one of the major sources of greenhouse gas emission (Zhao, 2010). Thus, it is essential analysis urban expansion for relating it to the mentioned consequences.

The expansion of urban land has been regarded as an important part of the urbanization (Yang et al., 2016). The built-up area in cities, the actually constructed area with basic facilities, can reflect the expansion of urban land (Yang et al., 2016). Hence, analyzing the pace of built-up area expansion is a significant way for deepen the understanding and assessment of urban expansion. Because of the impacts of urban expansion, exploring dynamics of urban expansion and balancing the relationship between urban expansion and environment are important for sustainable development of our society.

2.1.2. Urban Expansion in the Yangtze River Delta (YRD), China

As a developing country, China has experienced a rapid urbanization over the last decades. Since the reform and opening up in 1978, initial reforms in early 1980s happened primarily in rural areas followed by rapid urbanization beginning in late 1980s (Gu & Pang, 2009). At the beginning of the

21st century, China's urbanization gained an unprecedented speed, the fastest in human history (Li et al., 2017). Furthermore, with rapid expansion of urban areas, resource consumption and a variety of environmental and ecological problems and disasters have emerged in China (Li et al., 2017). To alleviate the negative impacts of urban expansion, policy makers, urban planners, and stakeholders should consider appropriate adaptation options, based on dynamics of urban expansion over time. For sustainable development, they should also work together to conduct appropriate policy, planning and management choices effectively before such problems become irreversible (Li et al., 2017).

The YRD metropolitan region is one of the most developed and populated coastal area of China. Much urban expansion has been seen from the late 1970s in the YRD region. From 1979 to 2005, the increase in urban area was 37.66 km^2, 112.43 km^2, 174.86 km^2 and 421.73 km^2, respectively, in the four periods (1979-1990, 1990-1995, 1995-2000 and 2000-2005) (Wang et al., 2017). In 2009, the GDP of the YRD region reached 59,711.25 million RMB which was approximate 6,217.91 million Euros (Zhang, Li, & Zhang, 2007). By 2012, the built-up area of the YRD region was 4269.75 km2 for and 44,998,000 urban residents (Zhou, Huang, Xu, & Li, 2013). The growth rate of built-up area and population were 7.85% and 3.7%, respectively, in 2010 (Zhou et al., 2013). Thus, the growth speed the YRD urbanization was accelerating obviously.

In early researches, statistical data on population number, urban area and Gross Domestic Product were commonly used of urban expansion for YRD region. There are researches which analyze the relationship between population increase and the urban expansion in the YRD region (Fang, 2009). (Zhang et al., 2007)Recently, remote sensing data were applied, mainly for small-scale analysis, for example for application of remote sensing for monitoring and analysis of urban expansion in Dongguan (Li, 1997), urban expansion and its driving forces based on remote sensed data and GIS in Hangzhou from 1991 to 2008 (Wang, Jin, Xiao, & Shi, 2009) and exploring the spatial factors of urban expansion in Nanjing during 1988-2007 (Zhang et al., 2007). The spatial structure of urban environments and urban morphology structure are quantitatively described using remote sensing images. Landscape metrics were used for describing, analyzing, and modelling form and changes of urban development (section 2.2.2). The urban growth of the YRD metropolitan region was characterized by spatial metrics as a diffusion-coalescence process over time (Tian et al., 2010).

2.1.3. Policies on Urban Expansion

Being a developing country, China started urbanization late and its urbanization developed slowly between the founding of the nation in 1949 and the launch of reforms and opening-up in 1979. After 1979, China has experienced a booming urban development. Between 1995 and 2000, cultivated land protection policies have been published to slow down the urban area development and the loss of cultivated land in some regions such as northern and western China (Liu, Zhan, & Deng, 2005). Nevertheless, urban land expansion was revitalized in west China because of implementation of the Western Development Policy which aimed at improving economic and social development in the western region of China.

In addition, the implementation of China's plan for increased urbanization has given its rapid growth of urban population and dynamic changes in land use. Obviously, the policy changes in land protection or urban development have effects on urban land expansions. In view of China's limited usable land resources resulted from rapid urbanization, therefore, it is obvious that policy is a vital guide for urban development. Conversely, analyzing the process of urban expansion can help to improve the formulation of future urbanization policies for an optimization of land resource allocation.

2.2. Review on Approaches

2.2.1. The Global Human Settlement Layer (GHSL)

The GHSL, developed by the Joint Research Centre (JRC), produces global spatial information about the presence of human settlements on the earth over time. The dataset contains three major information products: built up maps, population density maps and settlement maps. The GHSL is an open and free dataset with open input, open method and open output. It can be downloaded for free and without registration. There are researches assessing the quality of the GHSL products (Pesaresi et al., 2016; Sliuzas, Kuffer, & Kemper, 2017). We can use reference data to assess the quality of the GHSL by statistical and visual comparison of built-up land cover (Pesaresi et al., 2016; Sliuzas et al., 2017).

The GHSL is created by automatic classification using information collected from Landsat data records in the past 40 years (Johannes, Leyk, Florczyk, Aneta, Pesaresi, & Balk, 2016). Because the GHSL is the most spatially detailed data and can show the greatest temporal depth globally, Spatial and temporal characteristics of human settlements can be analyzed by the GHSL. The GHSL project can be used to assess human presence on the planet over time by a combination of built-up area information and census data. At high resolution, the Landsat GHSL dataset can be set as seamless global mosaic at high resolution (approx. 38m) and for different points for a long time (Johannes et al., 2016).

The GHSL can provide support for disaster risk management, territorial modelling as well as for international scientific and decision-maker communities to address regional policies, urbanization or crisis/disaster management. It provides us a new view on global urbanization process and demonstrates how a new open and innovative data processing technologies may support novel global awareness on trends and dynamics of urbanization practically.

The core methodology to extract the GHSL is Symbolic Machine Learning (SML) which is based on the concept of the empirical multidimensional histogram (Sliuzas et al., 2017). The GHSL offers a systematic discrimination of built-up (BU) and not-built-up (NBU) areas which are computed in an unsupervised and fully auto-mated manner (Ouzounis, Syrris, & Pesaresi, 2013). It is capable to map a large-scale and complex human settlement patterns with unprecedented spatial resolution and global scales of it are becoming available as well (Klotz, Kemper, Geib, Esch, & Taubenbock, 2016). Additionally, the GHSL covers a long time-series of the epochs 1975, 1990, 2000, and 2014. The full resolution set has a spatial resolution of approximate 38.2 m (Sliuzas et al., 2017). The

GHSL, capturing the detail not only of the large cities but also of smaller settlements (e.g. towns and villages). It is thus an ideal dataset for urbanization analysis (Pesaresi et al., 2016).

2.2.2. Methods for Urban Expansion Analysis

The researches on urban expansion in the YRD mainly obtain information from socio-economic statistical data and medium-to-high resolution remote sensing data, for instance Landsat images (). Qualitative analysis and statistical analysis such as analysis of urban growth rates, expansion extent and visual analysis of expansion can be used to analyze urban expansion dynamics (Fang, 2009; Liu et al., 2005). It is convenient to analyze urban expansion in this way, however, a clear insight into a spatial description of urban expansion process cannot be provided. There are a variety of approaches using urban models to analyze spatial processes of urban expansion, such as cellular automata (Xu & Min, 2013), Markov chains (Lopez et al., 2001) and spatial logistic regression (Cheng & Masser, 2003). Urban models can trace urban development in the past and predict future growth. They have to make use of knowledge and understanding of the physical processes of urban expansion and it are limited by data quality and scope for parameterization, calibration and validation. Recently, landscape metrics have been used to quantitatively describe and analyze the spatiotemporal changes of urban expansion (Herold, Goldstein, & Clarke, 2003; Taubenbock, Wegmann, Roth, Mehl, & Dech, 2009; Tian et al., 2010).

Spatial metrics can be defined as measures for the analysis of thematic maps which exhibit spatial heterogeneity at a particular scale and resolution (Tian et al., 2010). Spatial metrics were developed in the late 1980s and can be computed as patch-based, class-based and landscape-based metrics with indices such as size, shape, edge length, patch density and fractal dimension (Gustafson, 1998). When applied to multi-scale or multi-temporal datasets, spatial metrics are widely used to analyze dynamic patterns and structure changes (Seto & Fragkias, 2005).

Recently, spatial metrics have been widely used to also study urbanization and its underlying social, economic and political processes (Yue et al., 2016). For instance, a study quantified spatiotemporal patters of 15 cities in the different provinces in China using spatial metrics such as edge density, number of patches and landscape shape index (Xu & Min, 2013). Also, an analysis of urban land use changes in 4 cities of Pearl River Delta was conducted in 2005 with spatial metrics such as total area index, edge density and mean urban patch index (Seto & Fragkias, 2005). There are also studies for the urban expansion process in the YRD metropolitan region. A study analyzed the spatial-temporal characteristics of the YRD metropolitan region using five metrics: landscape shape index, number of patches and largest patch index: number of patches, largest patch index, landscape shape index, patch COHESION index and aggregation index (Chang & Wu, 2014). Finally, another study provided a comparison of spatial and temporal dynamic patterns of urban expansion for five cities in the YRD metropolitan region, using spatial metrics such as total urban area, mean urban patch size and edge density (Tian et al., 2010). However, none of the previous studies has compared the development of the region on different spatial scales across time 1975, 1990, 2000 and 2014. Thus, the thesis will mainly use landscape metrics to analyze the pattern and trajectories of urban expansion in the 17 cities with different spatial scales, across the three provinces of the YRD metropolitan region, from 1975 to 2014.

3. METHODOLOGY

In this section, the study area, the data, the method of accuracy assessment, the measurement of the indicators and the method of urban expansion analysis is discussed, following with policy analysis. In this research, GHSL data of the study area was extracted to study the urban dynamics of the YRD metropolitan region. Table 1 provided an overview of research methodology for three sub-objectives in three main steps which were explained specifically in this section.

Table 1. Overview of the research methodology

Main steps	**Methodologies**	**Research objectives**
Quality validation of the GHSL	Accuracy assessment using reference data by visual interpretation.	Sub-objective 1
Urban expansion analysis	Spatial analysis using spatial metrics.	Sub-objective 2
Policy analysis	Literature review on land policies related to urban expansion and connect policy targets to urban expansion analysis.	Sub-objective 3

3.1. Study Area

The YRD is the area in China with the most accelerated urban expansion. As the most developed metropolitan region in China, the YRD has rapid economic development, continuous optimization of industrial structure and strong population attraction ability (Tian et al., 2010). Recently, the analysis of the YRD urban expansion has been a hot research fields, e.g., on cultivated land protection and land administration (Xu, He, Liu, & Dou, 2016). In the Development Planning of Yangtze River Delta Metropolitan region (China National Development and Reform Conmmision, 2016), YRD is described as one of the most dynamic, open and innovative regions in China as well as an important intersection of 'The Belt and Road' and Yangtze river economic belt and the YRD metropolitan region is in the key stage of transformation and development at present. As one of the six megalopolitan regions in the world, the YRD has the highest density of cities and urbanization level in China (Du, Xie, Zeng, Shi, & Wu, 2007). With the area of 118,000 km2, the Gross Domestic Product (GDP) of the YRD is about 17.5% of the total Chinese GDP in 2008 (Liu, 2012). Demographic changes have effects on urbanization and urban sprawl directly. Obviously, the migration of population goes along with the expansion of urban areas. The built-up area of the YRD increased from 844 km2 to 3,695 km2 during the period from 1990 to 2010 with average annual growth 17% (Zhang, Liu, 2013). Rapid urbanization has been accompanied by large scale urban land expansion and the loss of arable land (Seto, Kaufmann, & Woodcock, 2000; Tan, Li, & Lu, 2005).

The YRD metropolitan region includes Shanghai city, Jiangsu, Zhejiang and Anhui provinces. In total, there are 26 cities in the YRD metropolitan region which covers 21.17 million square kilometers area accounting for about 2.2 percent of China (China National Development and Reform Conmmision, 2016). In 2014, the Gross Domestic Product (GDP) of the YRD metropolitan region is 12.67 trillion yuan (RMB) and the total population is of 150 million respectively accounting for 18.5% and 11.0% of the whole country (China National Development and Reform Conmmision, 2016). In the YRD metropolitan region, 17 cities are selected as leader cities for the development of the whole YRD metropolitan region, which were classified into one core city and 5 different metropolitan circles (Table 2) (China National Development and Reform Conmmision, 2016). Except for the provincial city Shanghai, other 16 cities belong to the three different provinces and these cities can be classified into three classes based on administrative level. Shanghai is a provincial-level city which is directly controlled by Central Government. Shanghai, located near the edge of the Yangtze River, is the largest core city with highest economic level in China and most of its area is plain (Tian et al., 2010). Nanjing, Zhenjiang, Yangzhou, Suzhou, Wuxi, Changzhou metropolitan areas belong to Jiangsu province. Hangzhou, Jiaxing, Huzhou, Shaoxing, Ningbo, Zhoushan, Taizhou are distributed in Zhejiang province. Anhui province is a new member of YRD metropolitan region, which joined in 2014. Three cities in Anhui province are selected forming the Hefei metropolitan circle (China National Development and Reform Conmmision, 2016).

Table 2. Description of selected cities

Cities	**Administrative level**	**Metropolitan circle**
Shanghai	Provincial city	One core city
Nanjing	Sub-provincial city	Nanjing Metropolitan Circle
Zhenjiang	Prefectural city	
Yangzhou	Prefectural city	
Suzhou	Prefectural city	Suxichang Metropolitan Circle
Wuxi	Prefectural city	
Changzhou	Prefectural city	
Hangzhou	Sub-provincial city	Hangzhou metropolitan circle
Jiaxing	Prefectural city	
Huzhou	Prefectural city	
Shaoxing	Prefectural city	
Ningbo	Sub-provincial city	Ningbo Metropolitan Circle
Zhoushan	Prefectural city	
Taizhou	Prefectural city	
Hefei	Sub-provincial city	Hefei Metropolitan Circle
Wuhu	Prefectural city	
Ma'anshan	Prefectural city	

Table3. Description of selected cities

City	Area (km²)	Population (2016)	GDP(RMB) (2016)
Shanghai	6,340	24,197,000	27,466 billion
Nanjing	6,587	8,270,000	10,503 billion
Zhenjiang	3,843	3,181,300	3,834 billion
Yangzhou	6,634	4,991,000	4,449 billion
Suzhou	8,488	10,625,700	15,475 billion
Wuxi	4,628	6,529,000	9,210 billion
Changzhou	4,385	4,708,000	5,773 billion
Hangzhou	16,596	9,188,000	11,050 billion
Jiaxing	3,915	4,614,000	3,760 billion
Huzhou	5,818	2,688,400	2,243 billion
Shaoxing	8,279	4,988,000	4,710 billion
Ningbo	9,816	7,875,000	8,541billion
Zhoushan	1,440	1,158,000	1,094 billion
Taizhou	9,411	6,001,700	3,843 billion
Hefei	11,445	7,869,000	6,274 billion
Wuhu	6,062	3,670,000	2,699 billion
Maanshan	4,049	2,229,000	1,494 billion

Note: The exchange rate of the Euro to the RMB is: 1 euro equals to approximate 7.3 RMB at the end of 2016.

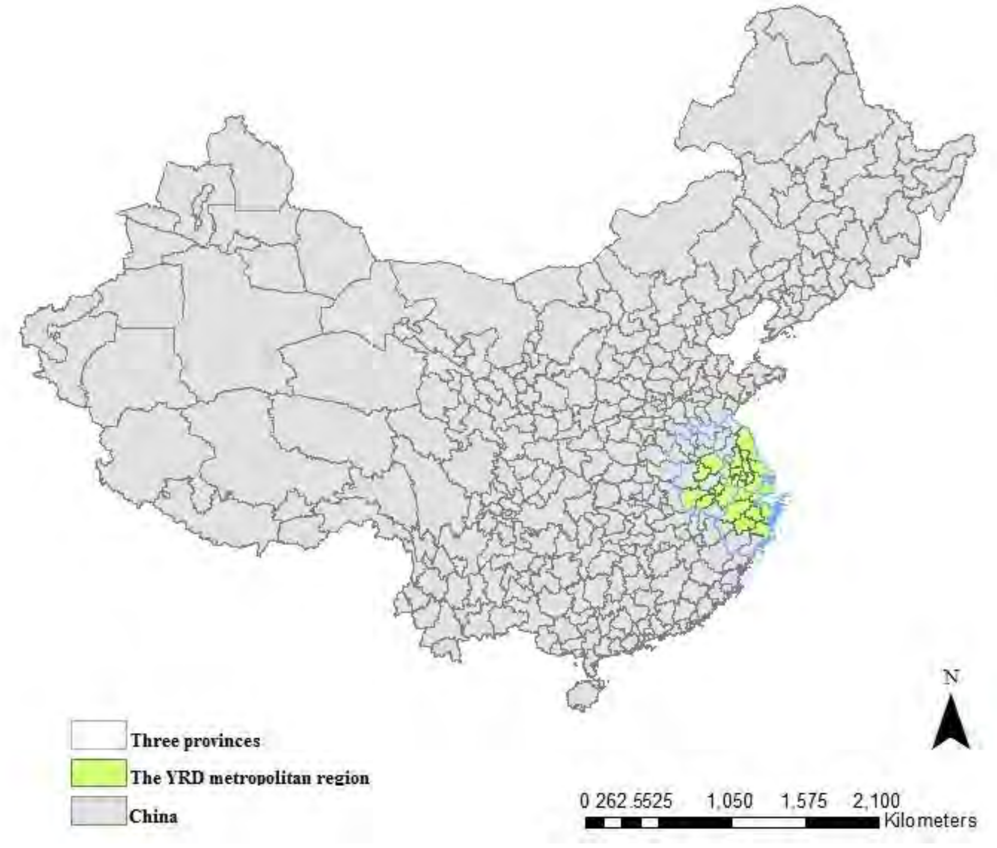


Figure 2. The YRD metropolitan region in China

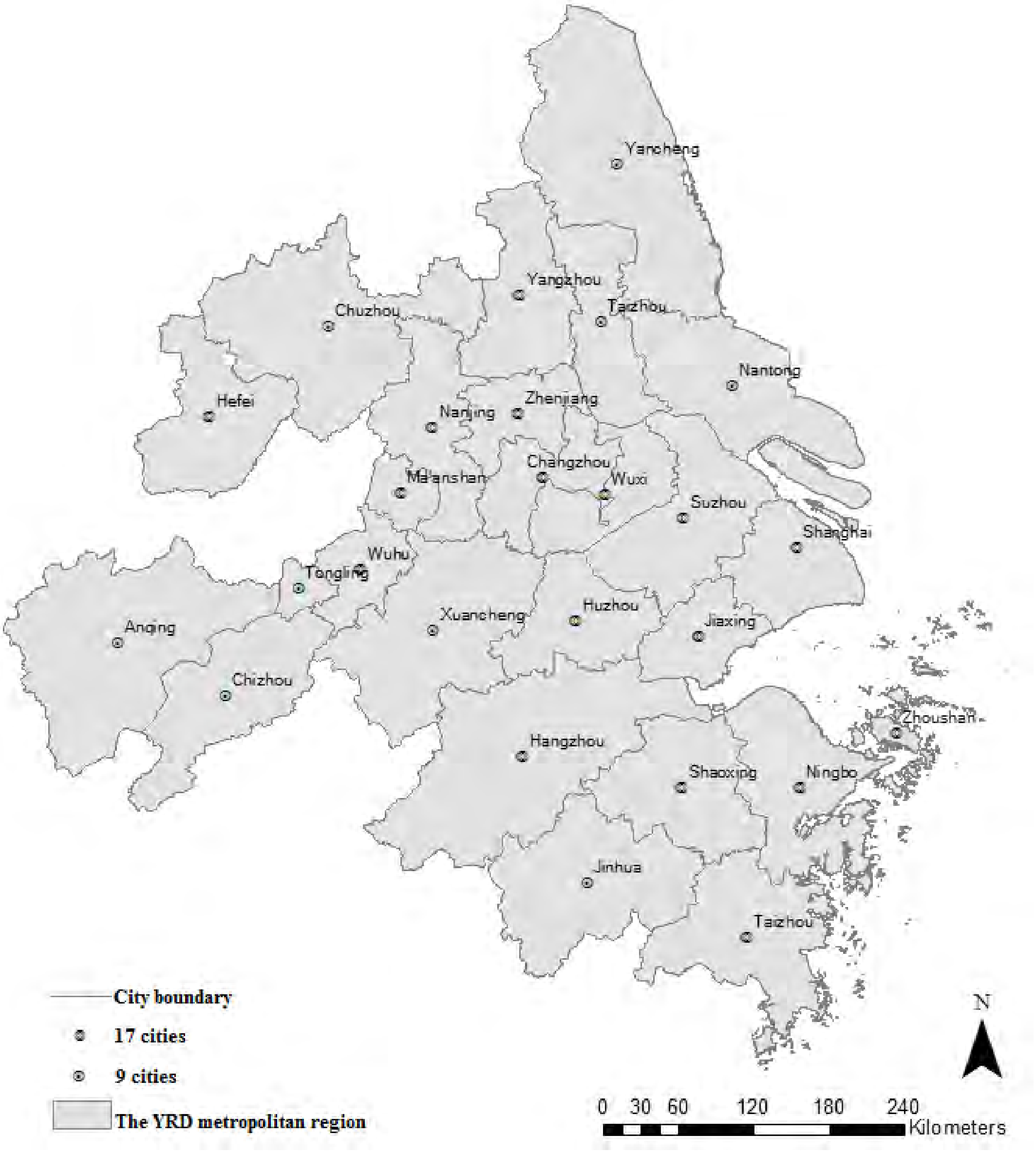


Figure 3. The 17 cities of the YRD metropolitan region.

3.2. Data Description

In this research, all the data needed are secondary data. The data source is summarized in table 4. China administrative boundary provided boundary for study area. Wudapt samples, Google Earth image and random sampling points were used for accuracy assessment of the GHSL. And land polices was used for policy analysis related to urban expansion.

Table 4. Data description of the research.

Data type required	Purpose	Origin
China Administrative Boundary	Provide boundary for validation	GADM database
Wudapt Sample	Reference data used as ground truth for accuracy assessment	The Chinese University of Hongkong
Google Earth Image	For visual interpretation in order to verify sampling points' property	Google Earth
GHS built-up grid (LDS)	Spatial analysis: Validate the quality and for further urban expansion analysis.	Global Human Settlement Layer (GHSL)
Land Policies related to urban expansion	Policy suggestion	The Internet

The GHSL built-up grid (LDS) is the main data set used for this thesis. Thus, Landsat images (GLS1975, GLS1990, GLS2000, and ad-hoc Landsat 8 collection 2013/2014) were collected for the multi-temporal information layer with 38m resolution. There are three aggregated classes of land use within the LDS: water, land no built up and built-up. The built-up class is further divided into 4 sub-classes (different years), which were used in this study (Table 5) (European Commission, 2017).

Table 5. Multi-temporal classification of the GHS built-up grid (LDS).

Value	Name
1	water surface
2	land no built-up in any epoch
3	built-up from 2000 to 2014 epochs
4	built-up from 1990 to 2000 epochs
5	built-up from 1975 to 1990 epochs
6	built-up up to 1975 epoch

For this study, Wudapt samples could be acquired. The samples cover the YRD region and have been provided by Chinese University of Hong Kong. These samples will be used for the accuracy assessment of the GHSL. The Wudapt samples are in total 1886 polygons, each classified according to Local Climate Zone (LCZ) classification. There are 17 LCZ defined for Wudapt data in total.

There are three different administrative levels of cities in the research: provincial city, sub-provincial city and prefectural city. China Administrative Boundary includes four levels of Chinese boundary system: country boundary, province boundary, city boundary and county boundary

(Robert & Sun, 2009). Thus, the boundaries for the 17 cities and 3 provinces in this research were provided by China Administrative Boundary.

To use the training polygons for validating the GHSL, they were reclassified into three classes, matching the GHSL data (Table 4). In order to improve the reliability of assessment result, the research also created 300 randomly distributed sampling points because there are 3 classes of the specific year GHSL layer (water, land no built and built-up,) (Table 7). Because there were sampling points of each class to conduct accuracy assessment for all the four time stages. The value of these sampling points is matching the GHSL layer as well. These 300 random sampling points were created in a stratified way. According to the classification of the LDS, 300 points were divided into 6 groups and each group has 50 points theoretically. In 2014, the pixel counts of the GHS built layer are showing in Figure 4. The count of water is less than 10%. Therefore, 50 random points were created for water. The percentage of the built-up area is also less than 10%, however, the research focus on built-up expansion. Thus, 50 points were created for non-built up and 50 points for each of the four built-up classes (Table 7).

Table 6. Reclassification of Wudapt samples.

Before reclassification	**After reclassification**
LCZ 1: Compact high-rise **LCZ 2: Compact mid-rise** **LCZ 3: Compact low-rise** **LCZ 4: Open high-rise** **LCZ 5: Open mid-rise** **LCZ 6: Open low-rise** **LCZ 7: Lightweight low-rise** **LCZ 8: Large low-rise** **LCZ 9: Sparsely built** **LCZ 10: Heavy industry**	Built-up (Value = 3)
LCZ A: Dense trees **LCZ B: Scattered trees** **LCZ C: Bush, scrub** **LCZ D: Low plants** **LCZ E: Bare rock or paved** **LCZ F: Bare soil or sand**	Land no built-up (Value = 2)
LCZ G: Water	Water (Value = 1)

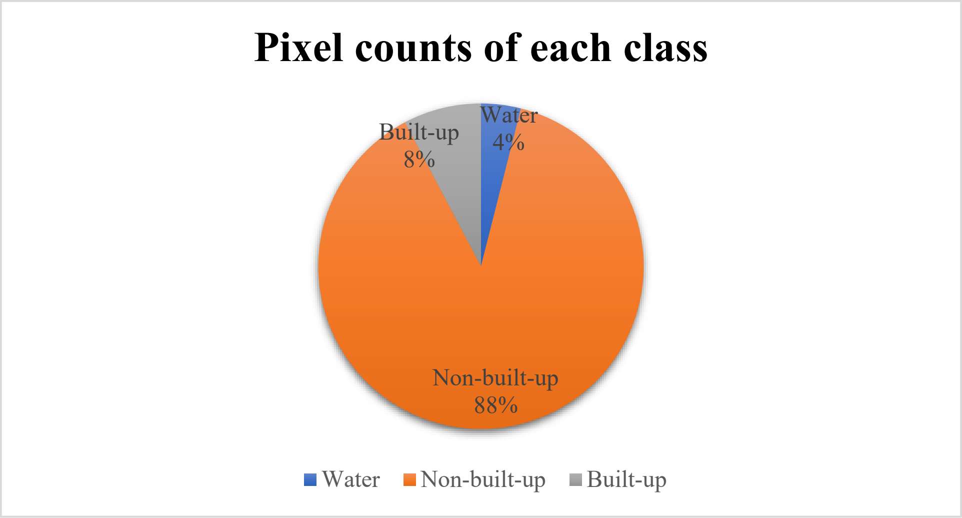


Figure 4. Pixel count of each class in 2014 layer.

Table 7. Number of random sampling points

Value of the GHS built-up grid (LDS)	Number of points
1	50
2	100
3	50
4	50
5	50
6	-

The historical imagery function of Google Earth can provide not only current imagery but also past versions of a map on a timeline. Because Wudapt samples can only provide reference data for the accuracy assessment of a specific year 2014. Random sampling points were needed as reference points for the past three periods. Thus, the classification of each Wudapt samples and sampling points can be verified and corrected by Google Earth historical imagery visually. There was no historical image provided for 1970s by Google Earth. Therefore, accuracy assessment in this research was for 1990, 2000 and 2014.

3.3. Accuracy assessment of the GHSL

The quality of the GHSL will be validated for the YRD metropolitan region. There are many methods of classification accuracy assessment in the remote sensing literature, however, the most widely promoted and used method may be derived from a confusion or error matrix (Foody, 2002). The most common methods of accuracy assessment are Error Matrix and Kappa Statistics. Error Matrix reflected correct number for classification on the diagonals. And Kappa Statistics, considering commission and omission errors out of the diagonals, can overcome some disadvantages of overall accuracy. Many measures of classification accuracy can be derived from the confusion matrix such as the percentage of cases correctly allocated. Through the calculation based on a confusion matrix, error of commission and omission, user's and producer's accuracy as well as the over accuracy can be calculated. In this thesis, overall classification accuracy, users' accuracy and kappa coefficient were used for quality validation of the GHSL. There are researches about accuracy assessment of a large-scale dataset using the reference data (Li et al., 2017). In the research, the Wudapt sample and random sampling points will be used to assess the classification accuracy of the GHSL layer in the YRD metropolitan region.

As mentioned in 3.2, Wudapt samples are training areas collected in 2016. The GHSL covers from 1975 to 2014. Initially, the polygons were converted to points using centroid by ArcGIS, and these points were reclassified using value 1 to 3 (1 = water, 2 = land no built-up, 3 = built up in 2014). After that, the values of these points were compared with the 2014 imagery in Google Earth, unmatched value were corrected by visual interpretation. Then, randomly distributed sampling points were created within the boundary of the YRD metropolitan region. Next, values were added using Google Earth by visual interpretation. For each period, value 1 represented water, value 2 represented no built-up area and value 3 represented built-up area in this specific period.

The whole study area of the YRD metropolitan region is extracted from the GHS built-up grid (LDS) using China Administrative Boundary in ArcGIS. After the extraction of the study area, the new layer need to be reclassified for accuracy assessment. Because the Wudapt sampling points were used only for the accuracy assessment in 2014, and random sampling points were used for 1990, 2000 and 2014. Thus, the YRD GHS built-up layer and Wudapt sampling points can be reclassified as follow:

Table 8. Reclassification of the YRD GHS built-up layer and corresponding validation data.

Assessment year	Reclassification value of The YRD GHS built-up layer	Validation data
1975	1 = 1 2, 3, 4, 5 = 2 6 = 3	(no validation planned)
1990	1 = 1 2, 3, 4 = 2 5, 6 = 3	300 random sampling points, Google Earth
2000	1 = 1 2, 3 = 2 4, 5, 6 = 3	300 random sampling points, Google Earth
2014	1 = 1 2 = 2 3, 4, 5, 6 = 3	300 random sampling points, Google Earth
	1 = 1 2 = 2 3, 4, 5, 6 = 3	Wudapt sampling points (Table 6) and 308 random sampling points, Google Earth

Finally, after reclassification of the YRD GHS built-up layer and reference points, the accuracy assessment can be run in Erdas Imagine software for 1990, 2000 and 2014.

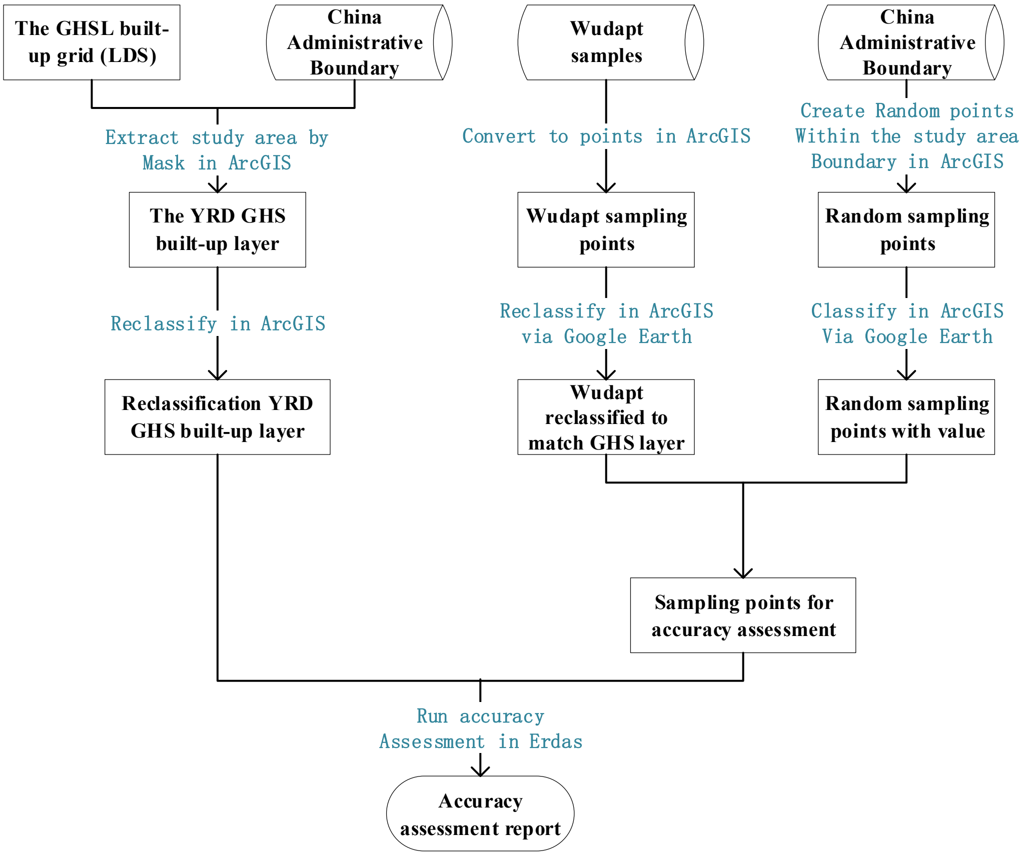


Figure 5. Flowchart of the GHSL accuracy assessment

3.4. Urban expansion analysis

The research will use landscape metrics to explore the process of urban expansion. Firstly, in section 3.4.1 the characteristics of dynamics urban expansion can be described by spatial metrics and parameters for the 17 cities. Based on the urban information extracting from the GHSL, absolute parameters such as area growth and built-up density as well as spatial metrics such as SHAPE index are used to quantify the characteristics of spatial pattern of cities (Xu & Min, 2013). Then, spider charts, with each axis representing the values of one parameter, are used to describe urban expansion as a relative diagram (Yue et al., 2016). Each spider chart characterizes the spatiotemporal urban expansion for one city using different metrics. The spatiotemporal characteristics of urban expansion for individual cities and comparison with other cities is analyzed by the spider chart in a spatial visualized way.

Furthermore, detailed spatial ingredients are provided through zonal-based analysis. The landscape metrics are calculated for different buffer zones in different cities. The zone 1 is defined as a circle around the center which is generated from the largest urban patches (Tian et al., 2010). The density and shape parameters is used to carry out zonal-based analysis across cities in detail (Taubenbock et al., 2009). Landscape metrics are calculated for each year across buffer zones drawn at a certain radius from the city centers. Three criterions are essential zonal-based analysis (Seto & Fragkias, 2005) as following, standard buffer size by which cities are compared through time, variation are captured within and among cities by the buffers and the measure of change for edge (Seto &

Fragkias, 2005; Tian et al., 2010). The similarities and differences of urban expansion trend is analyzed by spatial parameters such as built-up density in different cities and SHAPE index is used to describe the complexity of each individual patch and extract the average value for the particular zone (Taubenbock et al., 2009). Different landscape metric across the buffers are employed for the detailed measure of the spatial pattern of urban expansion (Tian et al., 2010).

3.4.1. Resampling

Fragstats 4.2 was used in the research for urban expansion analysis. It is a spatial analysis program, which can quantify the spatial heterogeneity of thematic map. There is a memory constraint of Fragstats. Therefore, the GHS dataset of the whole YRD metropolitan region could not be processed in Fragstat and needed to be resampled to a coarser resolution to reduce the grid size effectively (Mcgarigal, 2015). The original cell size of the YRD metropolitan GHS layer is about 38*38m. The output cell size after resampling is 50*50m, which is close to the original cell size. There are four optional resampling techniques available in ArcGIS: Nearest, Bilinear, Cubic and Majority. Because the GHS built-up grid layer is discrete data, Nearest neighbor and Majority techniques, suitable for discrete data, can be used for resampling. These two techniques were both used to resample the GHS grid of the 2014 YRD metropolitan region and output maps were compared. The resampling results show that the result of technique Nearest is more faithful to original data with a minimum geometric distortion, while the result of technique Majority is smoother (Figure 6 c). The areas of three classes and ratio of pixel counts among water, non-built-up and built up in each layer are shown in Table 9. The pixel counts ratio of Nearest resampling is closer to original data. And compared to resampling by technique Majority, it is apparent that class areas of resampling by technique Nearest are much closer to class areas before resampling (Table 9). Therefore, the Nearest technique was used in the research for all raster data resampling.

Table 9. The pixel counts of water, non-built-up and built up a) Before resampling b) Resampling by technique Nearest c) Resampling by technique Majority

a) Before resampling

Value	Pixel counts	Ratio of pixel counts	Class area (km²)
1 (Water)	7,410,242	1	10,823.8
2 (No built-up)	165,533,994	22.35	241,934
3 (Built-up)	14,500,425	1.96	21,180.1

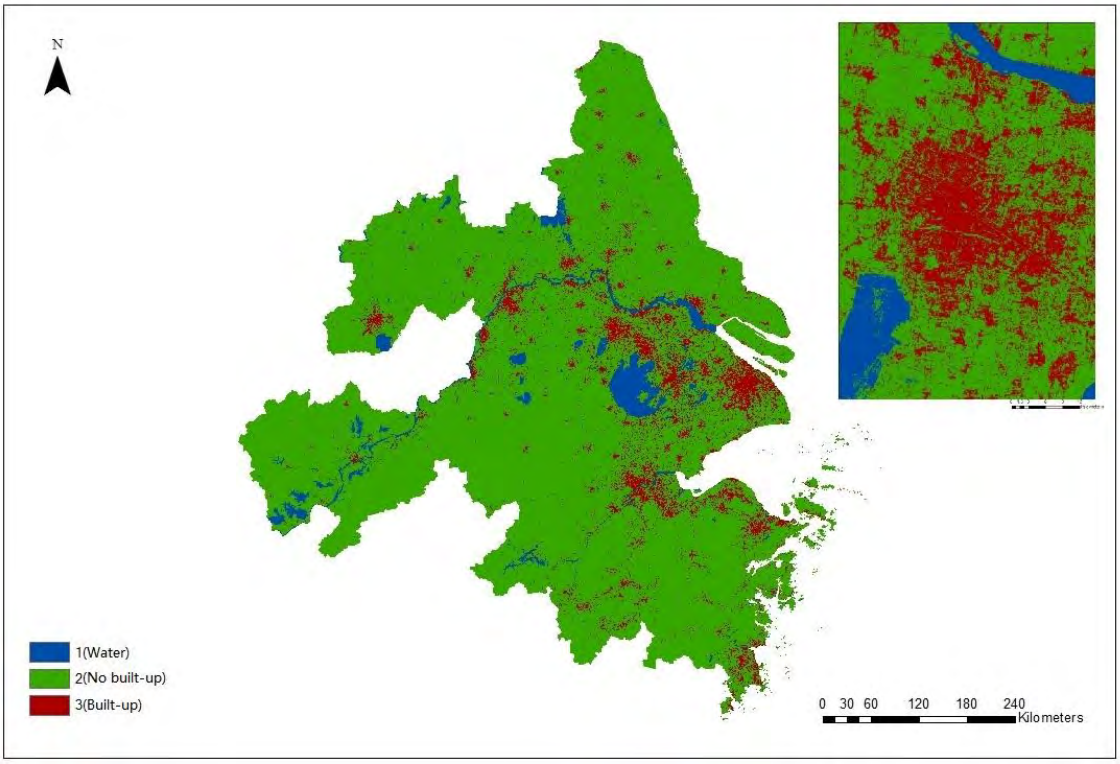
b) Resampling by technique Nearest

Value	Pixel counts	Ratio of pixel counts	Class area (km²)
1 (Water)	4,329,267	1	10,823.2
2 (No built-up)	96,771,834	22.35	241,932
3 (Built-up)	8,474,190	1.96	21,185.5

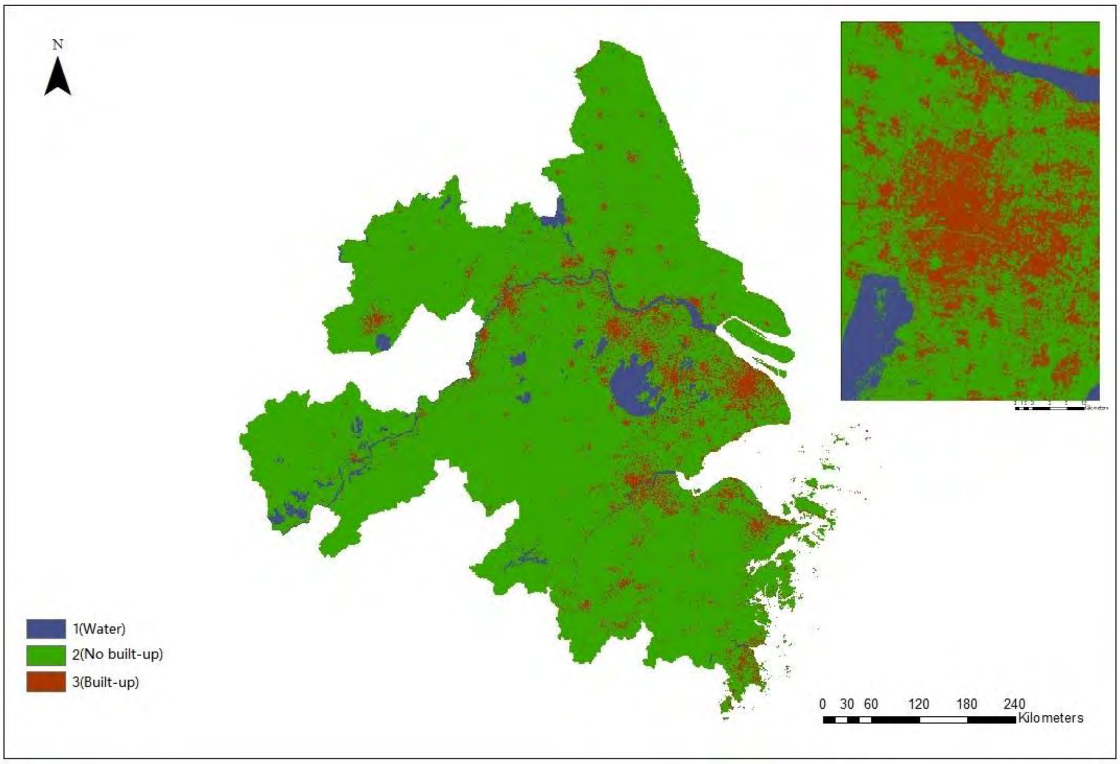
c) Resampling by technique Majority

Value	Pixel counts	Ratio of pixel counts	Class area (km²)
1 (Water)	4,462,419	1	11,156
2 (No built-up)	97,916,321	21.94	244,791
3 (Built-up)	7,305,472	1.64	18,263.7

a)



b)



c)

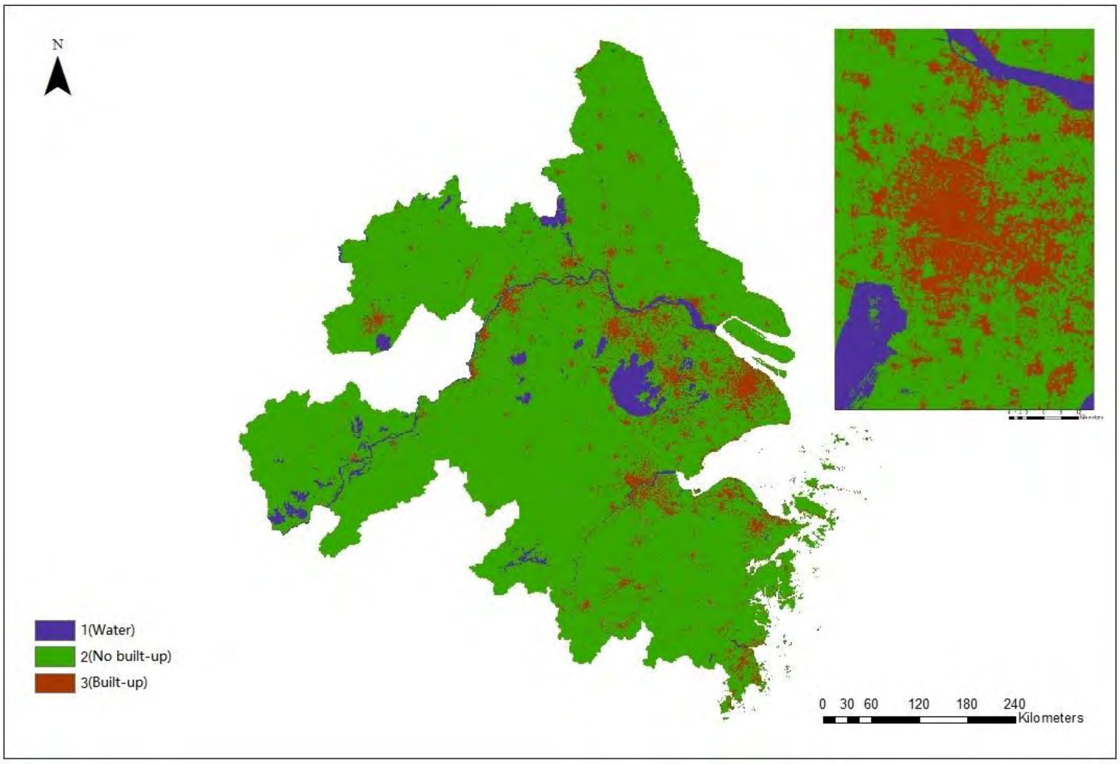


Figure 6. Reclassification of the 2014 YRD GHS built-up layer a) Before resampling b) Resampling by technique Nearest c) Resampling by technique Majority

3.4.2. Spatial metrics

The research is exploring the urban expansion of the YRD metropolitan region using the GHSL. There are three classes of land use in the GHSL: water, no built up, and built-up. The research focus on built-up class analysis. Thus, the indicators are selected from class metrics in Fragstats. Many spatial metrics have strong correlation and cannot represent complicated changes of urban spatial pattern (Riitters et al., 1995). Only a few landscape metrics are uncorrelated and can be used to analyze patch compactness and fragments, grain size shape complex and so on (Riitters et al., 1995). However, it is impossible to describe the complex patterns of urban dynamics with only one indicator, thus the consideration of using various spatial metrics across space and time is taken in the research. In the Development Planning of the YRD metropolitan region (European Commission, 2017), there are three urban expansion areas: the optimized development area, key development area, limited development area and we should improve the intensified use of urban land. The optimized development area is the area with saturated bearing-capacity of resource and environment. Key development area has great potential of resource and environmental bearing-capacity. Limited development area is area with ecological sensitivity.

Thus, spatial metrics describing the complex dynamics of urban expansion are chosen. Absolute size of landscape is described by total area (CA) and number of patches (NP). Due to urban expansion, total area of built-up and number of built-up patches are expected to increase. They can generally describe the growth of urban area of the YRD metropolitan region.

Largest patch index (LPI) refers to the proportion of the largest patch which can represents the primate urban area of study area. Thus, an initial understanding of urban development can be provided by LPI. If the entire landscape only consists of a single patch the LPI will reach 100 and the largest patch will become increasingly small when LPI is closed to zero (Taubenbock et al., 2009). Landscape shape index (LSI) can describe the extend of urban area expansion. The larger the proportion of total area occupied, the larger the LSI is.

Aggregation Index (AI) and Patch cohesion index (COHESION) characterize the integration degree of the metropolitan area. The value of AI and COHESION indicates the agglomeration level of built -up patches. The increase of AI and COHESION value indicates aggregation of the built -up area and increase of complexity.

Built-up edge density (ED), related to the total landscape, measures the total edge of built-up area. It increases when new urban nuclei occur and decrease when urban areas dissolve. Patch density (PD) represents the total built-up area divided by landscape. ED and PD are expected to increase during urban expansion period, however, to decrease during the coalescence phase.

The research used the area-weighted mean patch fractal dimension (AWMPFD) to measure the spatial and temporal dynamics of urban expansion process. AWMPFD is the metric which describes the degree to irregular or complex of built-up area shape. The higher the value of AWMPFD, the more irregular the shape of built-up area. It is a normalized metric which values range between 1 and 2 (Seto & Fragkias, 2005). Complex and irregular shape can be represented by values which are closed to 2 (Seto & Fragkias, 2005).

Following is the Table 10 which is the description of selected spatial metrics for urban expansion analysis in the research.

Table 10. Selected spatial metrics for the YRD metropolitan region

Metrics types	**Spatial metrics**	**Abbreviation**	**Description**	**Source**	**Metrics applied for**		
					The YRD metropolitan region	**Each city**	**Zonal-based analysis**
Area and edge metrics	Total area	CA	Total urban area	(Tian et al., 2010)	✓	✓	✓
	Largest patch index	LPI	The percentage of the largest patches in the total landscape	(Taubenbock et al., 2009)		✓	
	Edge density	ED	The total length of all edge segments per hectare urban patches	(Seto & Fragkias, 2005)	✓	✓	
	Total edge	TE	Total edge of built-up area.		✓		
Shape metrics	Area weighted mean patch fractal dimension	AWMPFD	The higher the value of fractal dimension, the more irregular the shape of built-up land.	(Seto & Fragkias, 2005)	✓	✓	
	Mean SHAPE Index	SHAPE_MN	Describe the complexity of each patch.	(Seto & Fragkias, 2005)			✓
Aggregation metrics	Number of patches	NP	The total number of built-up patches in the landscape	(Taubenbock et al.,	✓	✓	

				2009)			
	Patch Density	PD	Total number of patches divided by the area	(Taubenbock et al., 2009)	✓	✓	
	Landscape shape index	LSI	The extend of urban expansion	(Taubenbock et al., 2009)	✓	✓	
	Aggregation Index	AI	Compactness and integration level of metropolitan area		✓	✓	
	Patch cohesion index	COHESION	Compactness and integration level of metropolitan area		✓	✓	

3.4.3. Buffer zones

In order to provide a detailed analysis of urban expansion in terms of distance to city centre, landscape metrics were calculated for six buffer zones.

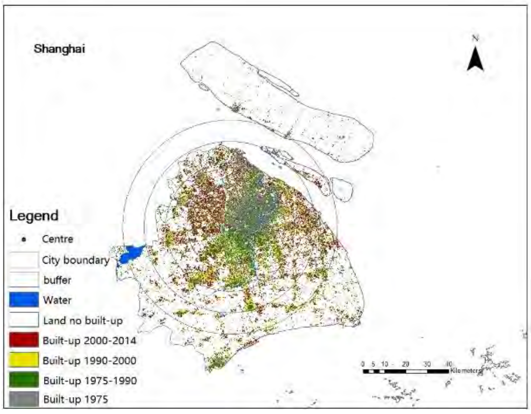
- City Centre

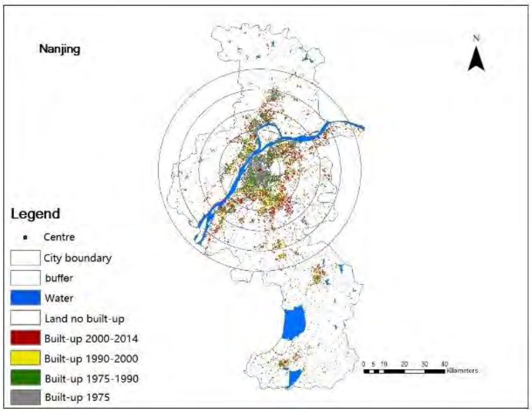
There is not a clear definition of city centre by local information. For example, there are 7 Central Business District (CBD) in Shanghai which can be recognized as different city centres. And People's Square of Shanghai can be also recognized as one city centre because of its historic significance. It is difficult to select a city centre for one city according to local information. However, there is research that extracted the centroid of built-up area in the initial year as CBD or city centre for each period (Xu et al., 2007). Thus, the geometric centre (centroid) of built-up area in 1975 was used to define the city centre in this research. Around this centre, buffers were created.

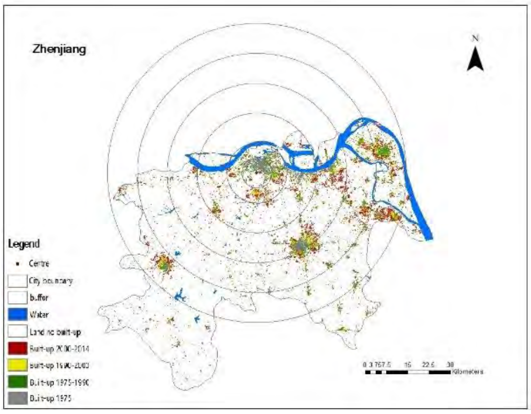
- Create buffers

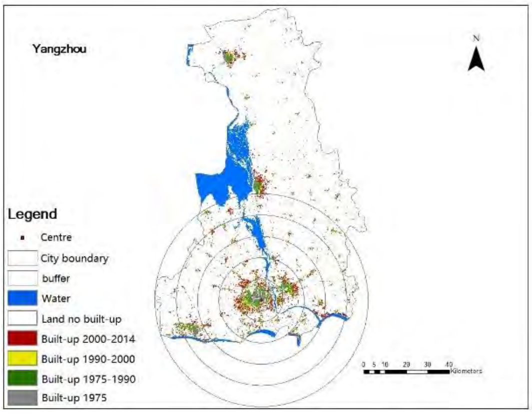
I calculated nine spatial metrics for six different buffer zones for four periods. The six buffer zones were drawn at 0-5km, 5-10km, 10-20km, 20-30km, 30-40km, 40-50km from each city centres. The choice of number and size of multiple buffer rings is based on the experience of author and the questions the research planned to explore. In this study, the rationale for buffer zones is based on the following three criteria (Xu & Min, 2013): Firstly, we need a standard size by which the cities could be compared through time. Secondly, the buffer zones should cover variation with and among cities. The third criterion is that the boundaries of built-up centres tend to extend through time. In this research, Shanghai has the largest aggregation of built-up area. Buffer zones should contain it as much as possible. Thus, the cover range of the buffer is 50km. In addition, the buffer zones should not be too distant from city centre in case that they will capture a too large area. The interest of the study is the expansion of built-up area. The fringe of built-up and no-built-up area – that is, the boundary between built up and no built-up tend to shift during study periods. During the early years of the research period, the metrics of the 0-5km buffer and 5-10km buffer are expected to be more representative of the process taking place around the boundary of built-up and no built-up area. It was for these reasons these six buffer zones were created in the research.

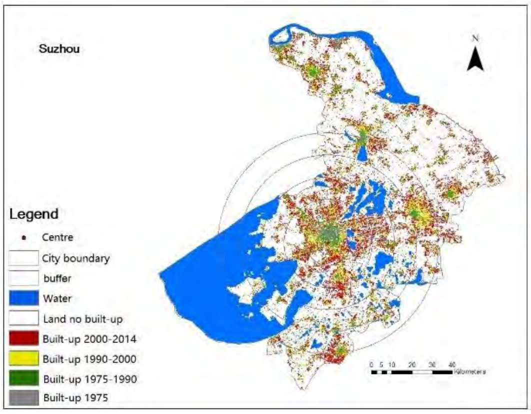
At the fist, the geographic centres of 1975 built-up area in these 17 cities were generated as city centres for the study. However, as the Figure 7 shows, the geographic centres of 1975 did not apply to every city as the city centre for all the four periods. The Figure 7 below is the GHSL data with 1975 city centers for 17 cities. For example, only the 1975 city centres of Wuxi and Changzhou is at the edge of the built-up area and also not within the large built-up patches. It is because there are a few built-up areas of Wuxi and Changzhou in 1975. And the distribution of these built-up areas is scattered. Thus, the 1975 geographic center of Wuxi and Changzhou cannot be recognized as a center of urban agglomeration area for other three years in Wuxi and Changzhou. Because there is not enough built-up area for zonal-based analysis within buffers around these two centres. Thus, the research created the 1990 geographic centres for Wuxi and Changzhou (Figure 8). There is obvious aggregation of built-up area in 1990. Therefore, the city centres of 1990 were used as city centers for Wuxi and Changzhou in the study. Additionally, the buffer zones of Changzhou and Wuxi were overlapped (Figure 9). Thus, the research will analyze the urban expansion of each city within the administrative boundary. The parts which extend administrative boundary and buffer zones of each city were clipped in this research for zonal-based analysis.

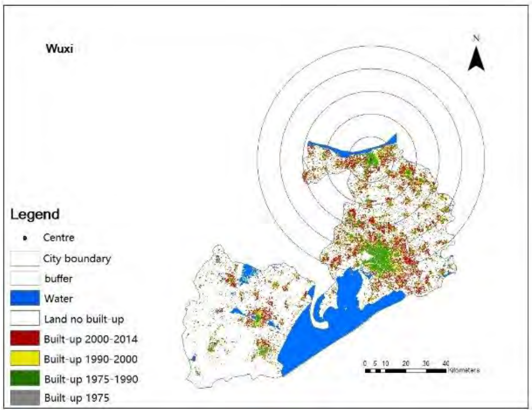


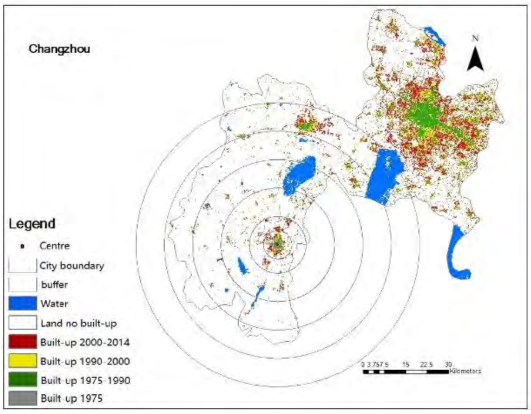











Changzhou
N
Legend
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City boundary
buffer
Water
Land no built-up
Built-up 2000-2014
Built-up 1990-2000
Built-up 1975-1990
Built-up 1975
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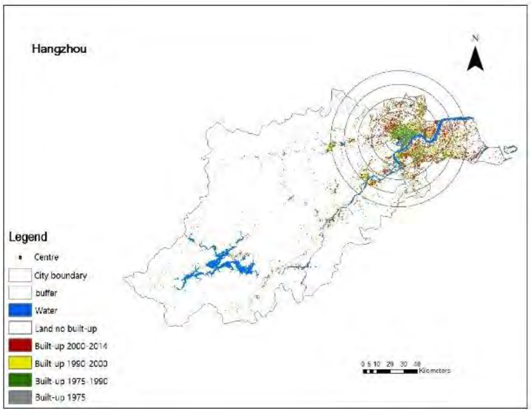
Kilometers


Hangzhou
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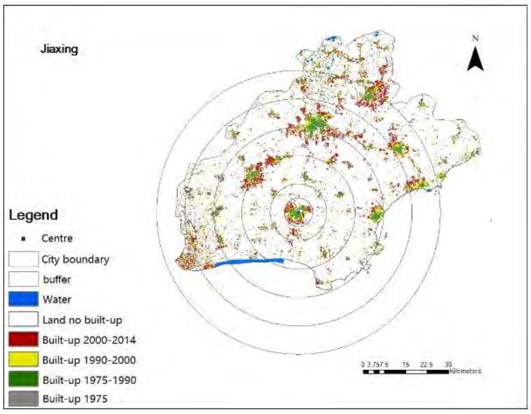
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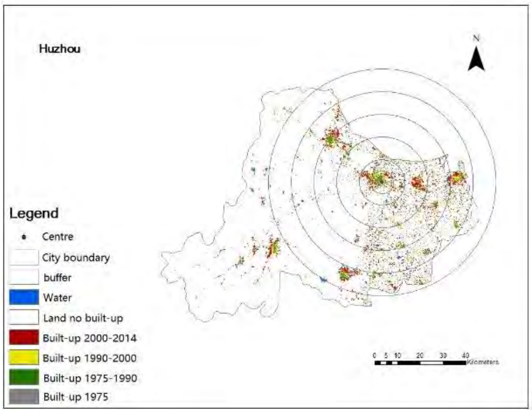
Kilometers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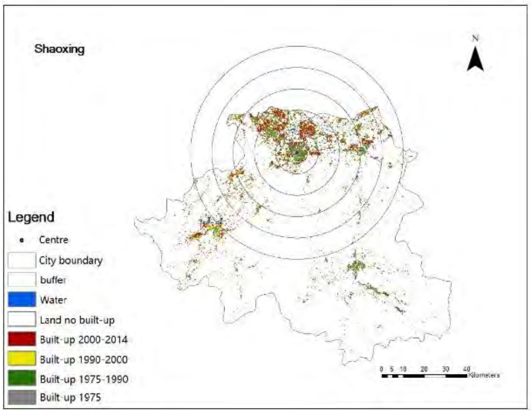
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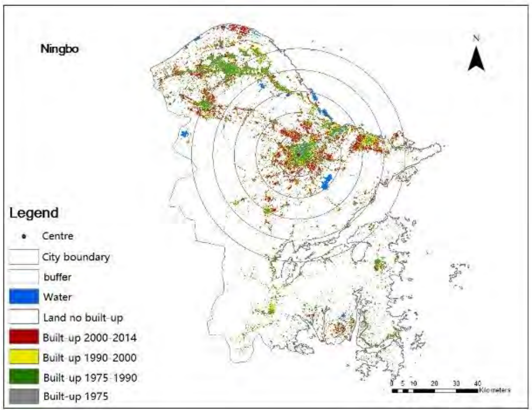
Ningbo
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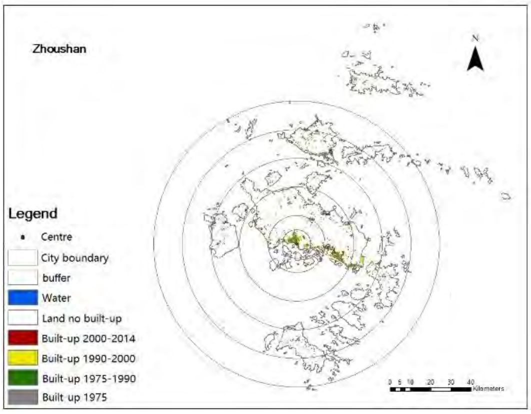
Kilometers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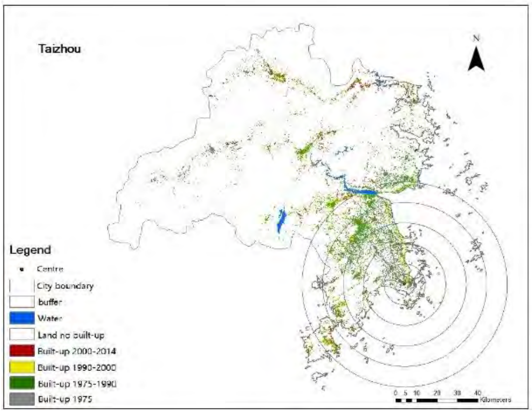
Taizhou
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Built-up 2000-2014
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Kilometers

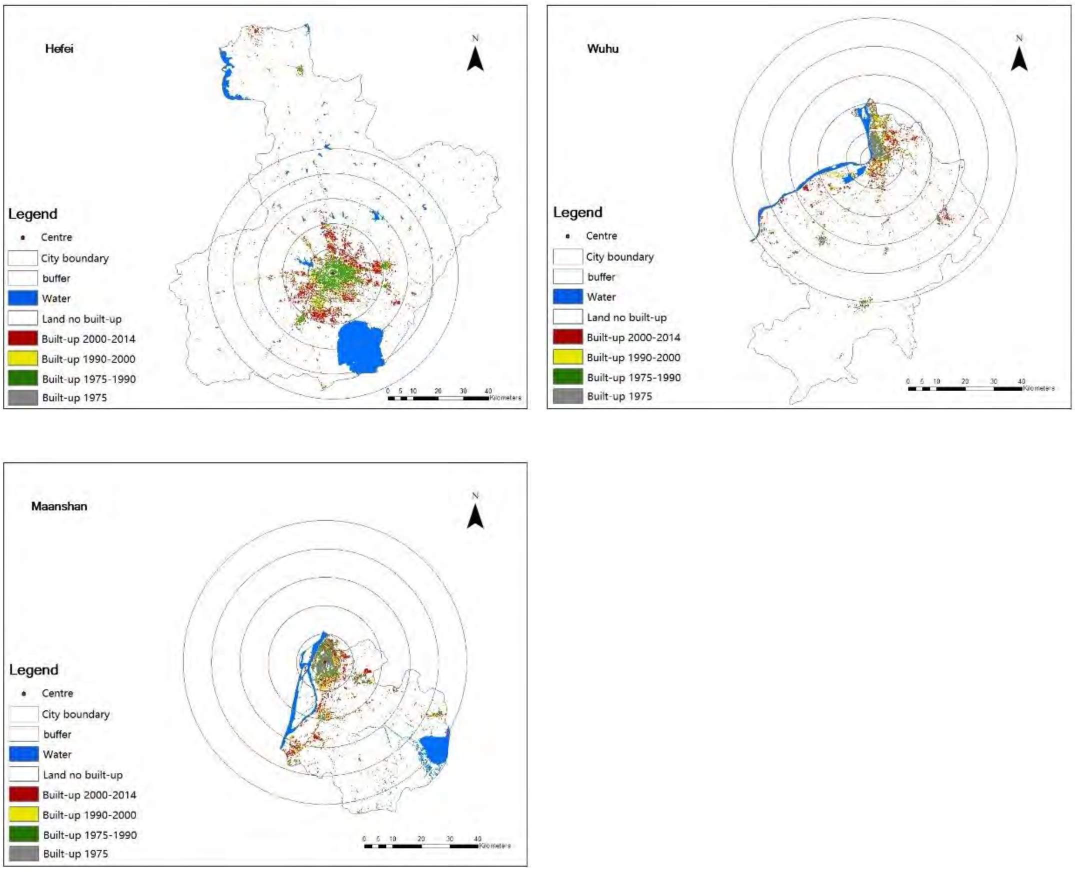
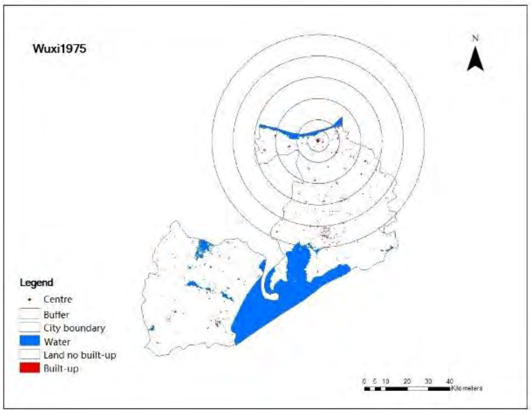
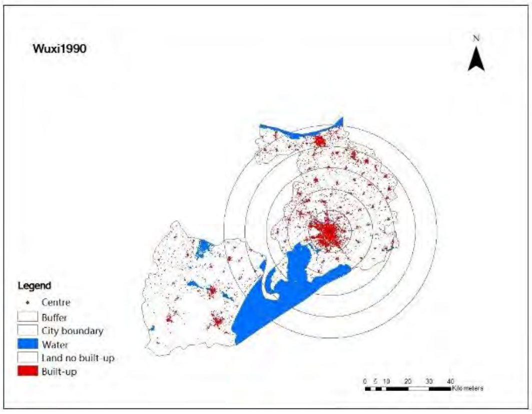


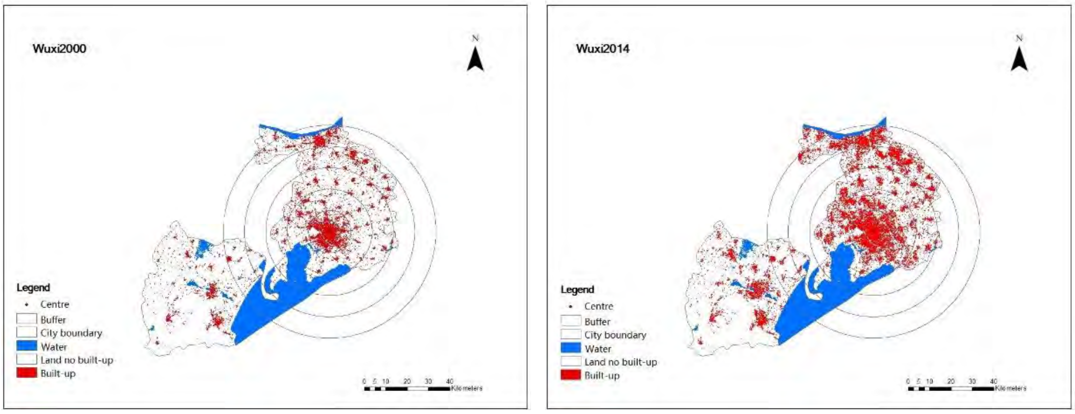
Figure 7. The buffer zones (around 1975 centres) of the 17cities in the YRD metropolitan region



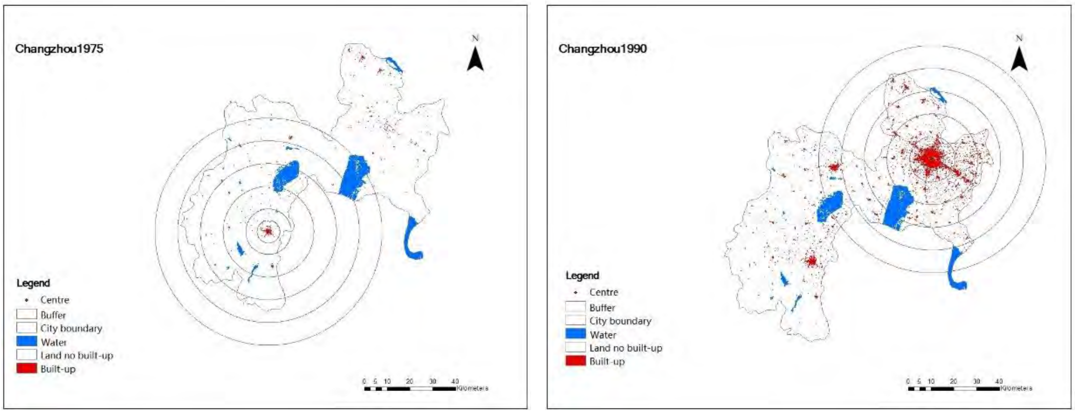
a) Around 1975 centre in 1975



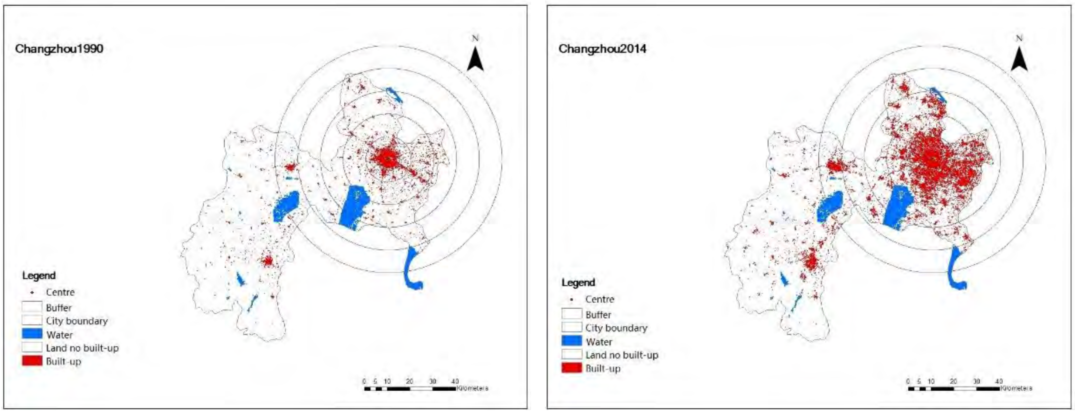
b) Around 1990 centre in 1990



c) Around 1990 centre in 2000 *d) Around 1990 centre in 2014*



a) Around 1975 centre in 1975 *b) Around 1990 centre in 1990*



c) Around 1990 centre in 2000 *d) Around 1990 centre in 2014*

Figure 8. The buffer zones (around 1975 centre and 1990 centre) of Wuxi and Changzhou

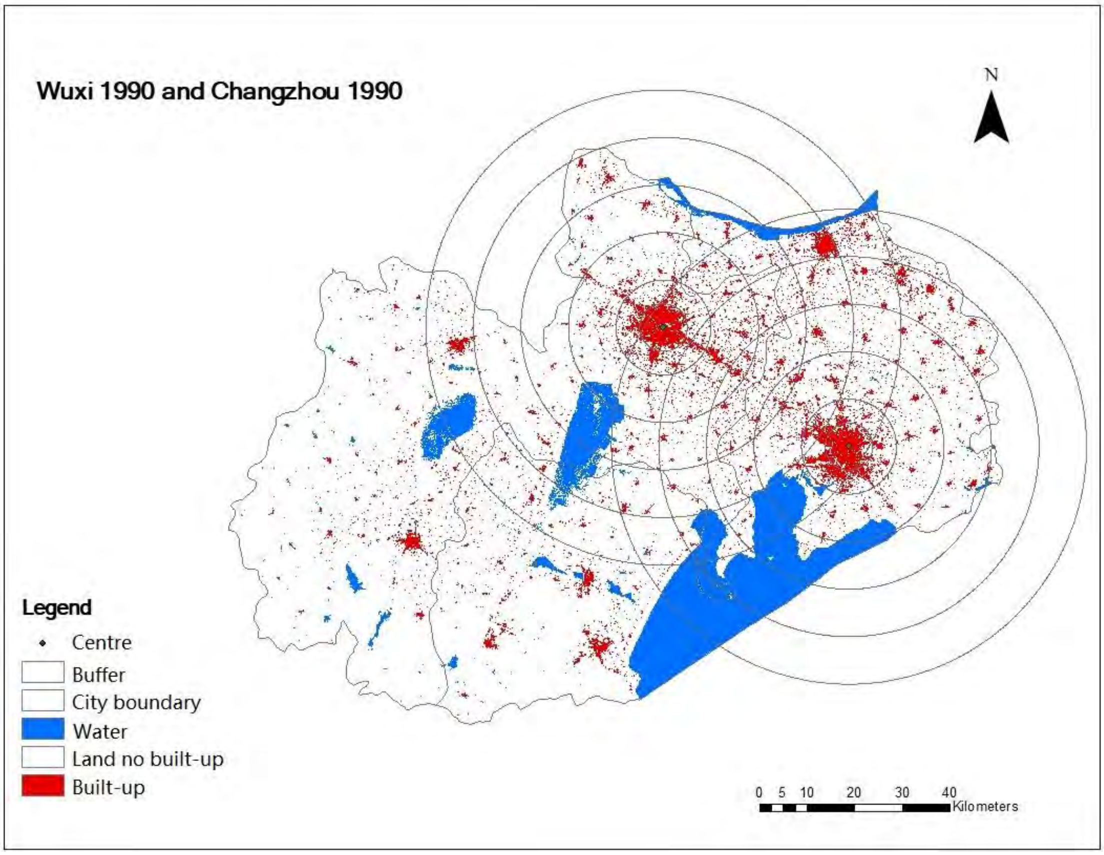


Figure 9. The buffer zones (around 1990 centres) of Wuxi and Changzhou in 1990

4. RESULTS AND DISCUSSION

4.1. Accuracy assessment result

The accuracy assessment is an essential part for remote sensing image classification, because almost all the further analyses are based on an accurate classification. As mentioned in section 3.3, overall classification accuracy, users' accuracy and Kappa statistics were used for the accuracy assessment of the GHSL in 1990, 2000 and 2014. The research used the combination of Wudapt sampling points and computer random points and assess the accuracy of the GHS built-up grid (LDS) with 308, 308 and 2182 points in 1990, 2000 and 2014 respectively. Because there was not historic image of the YRD region provided in 1975. As the accuracy assessment result showed in Table 11, we can see the overall classification accuracy are higher than 80% in all the three years and they are 95.13% (1990), 90.58% (2000), and 90.91% (2014) when only used 300 random sampling points. Furthermore, Overall Kappa Statistics in these three years are 0.8990 (1990), 0.8436 (2000) and 0.8536 (2014) which are higher than 0.7. And when both random sampling points and Wudapt samples were used for accuracy assessment in 2014, overall classification accuracy is 83.92% and Kappa coefficient is 0.7094 which are also higher than 0.7. According to the agreement criteria for Kappa statistic defined by (Landis & Koch, 1977), the classification was good for further analysis.

The results show that the method used in the research for accuracy assessment of the GHS built-up grid (LDS) has got the result which can provide a foundation for further analyses.

Table 11. Classification accuracy assessment results of the GHS built-up grid (LDS)

Year	**Overall classification accuracy**	**Kappa statistics**	**Users accuracy**
1990	95.13%	0.8990	100.00% (Class1)
			94.01% (Class2)
			97.67%(Class3)
2000	90.58%	0.8436	95.83%(Class1)
			87.06%(Class2)
			95.51%(Class3)
2014 (300 Random sampling points)	90.91%	0.8536	97.92% (Class1)
			84.17% (Class2)
			94.96%(Class3)
2014 (300 random sampling points and Wudapt samples)	83.92%	0.7094	97.54%(Class1)
			69.38%(Class2)
			95.18%(Class3)
Class 1= water, Class 2= No Built-up Area, Class 3= Built-up Area			

Table 12. Classification quality associated to a Kappa statistics value (Landis & Koch, 1977)

Kappa Statistics Value	Classification Quality
<0.00	Very Poor
0.00-0.20	Poor
0.20-0.40	Normal
0.40-0.60	Good
0.60-0.80	Very Good
0.80-1.00	Excellent

4.2. Urban expansion analysis

4.2.1. Urban footprint

The Figure 9 shows the urban footprint of the YRD metropolitan region. The result of the change detection of urban expansion in the YRD metropolitan region reflected the built-up areas and their development over the study time. In the following, quantifiable metrics were used to describe and analyze the urban development in the YRD metropolitan region.

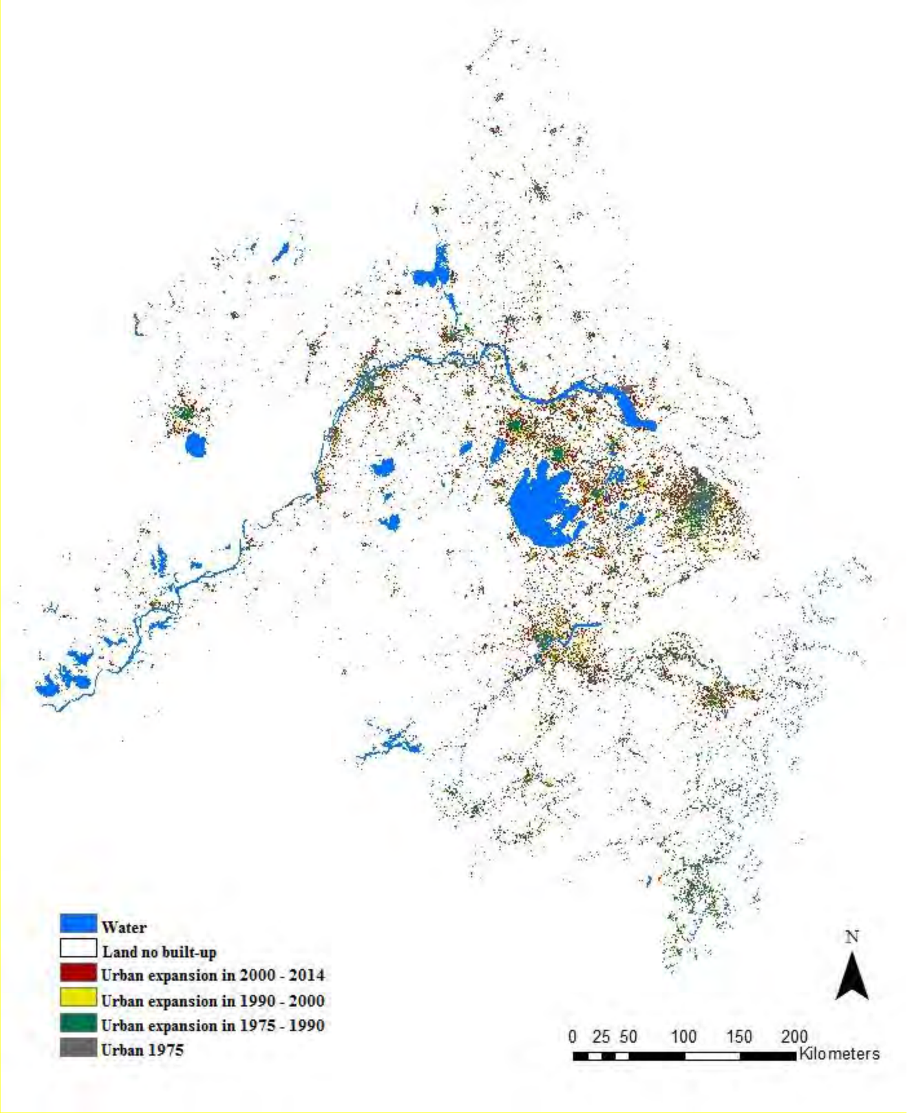
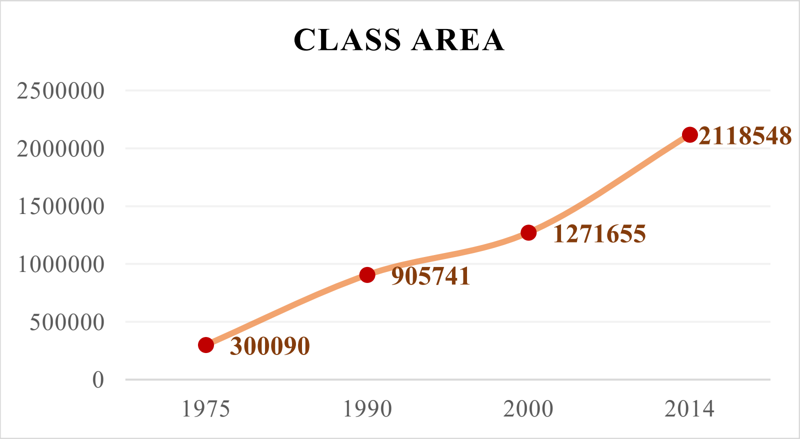


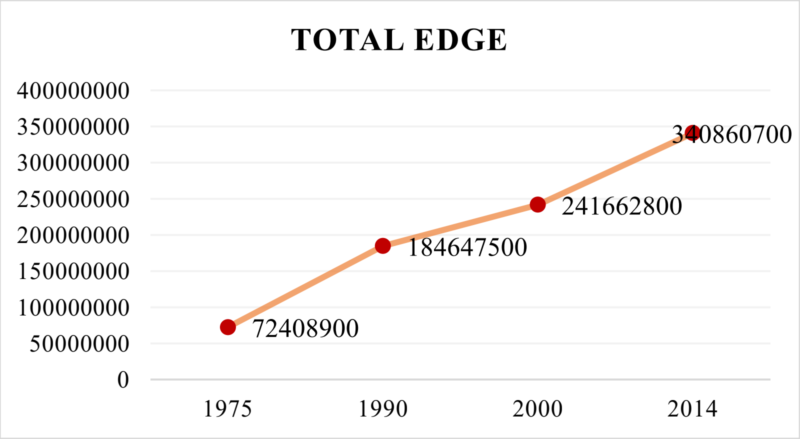
Figure 10. Spatial-temporal urban footprints of the YRD metropolitan region

Quantifiable analysis of urban expansion on the metropolitan level were derived by spatial metrics. In the research, Class level metrics were adopted in Fragrats software to analyze spatial pattern. In total, 9 parameters were determined in 3 dimensions to analyze the result. Namely, area and edge, shape and aggregation.

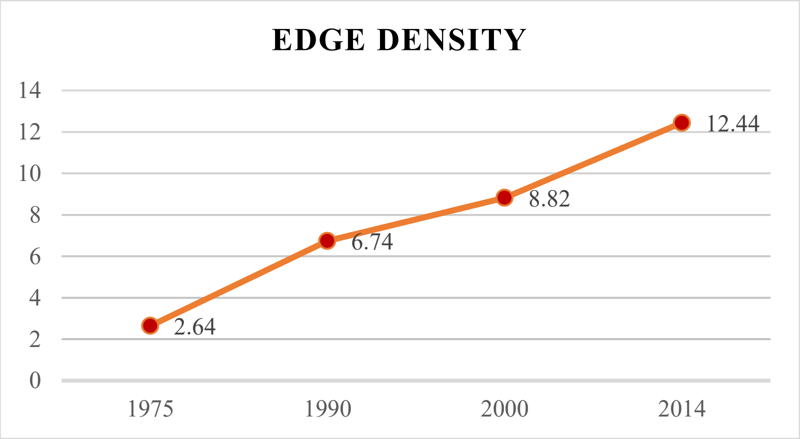
- Area and edge



a) Statistic of built-up area growth



b) Total edge (TE) for built-up area in the YRD metropolitan region



c) Edge density (ED) for built-up area in the YRD metropolitan region

Figure 11. Area and edge metrics for built-up area in the YRD metropolitan region

The urban growth of the YRD metropolitan region was obtained from the total built-up areas. As visualized in Figure 11, the total built-up area of the YRD metropolitan region increased during the periods and increased over time. Both total edge and edge density increased from 1975 to 2014. We can easily see that with the increase of total built-up area, more separated built-up patches occurred.

- Shape

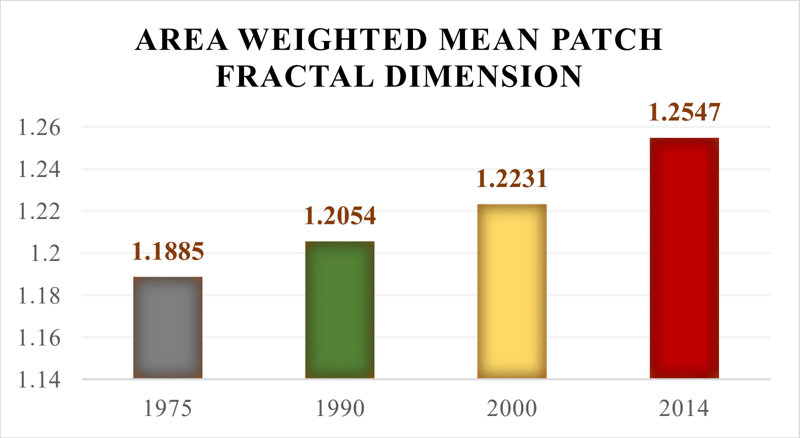


Figure 12. Area weighted mean patch fractal dimension (AWMPFD) for built-up area in the YRD metropolitan region

The AWMPFD of the YRD metropolitan region has increased from 1975 to 2014 which means the shape of urban area became more irregular and complex over time. From the urban footprint (Figure 12), we can see new urban nuclei occurred and existing built-up areas expanded which created irregularly shaped landscape patterns. However, the AWMPFD of all these 4 years were lower than 1.5 which were closer to value 1 than to value 2. Thus, the urban areas were rather simple shapes such as circles and squares from 1975 to 2014 in the YRD metropolitan region.

- Aggregation

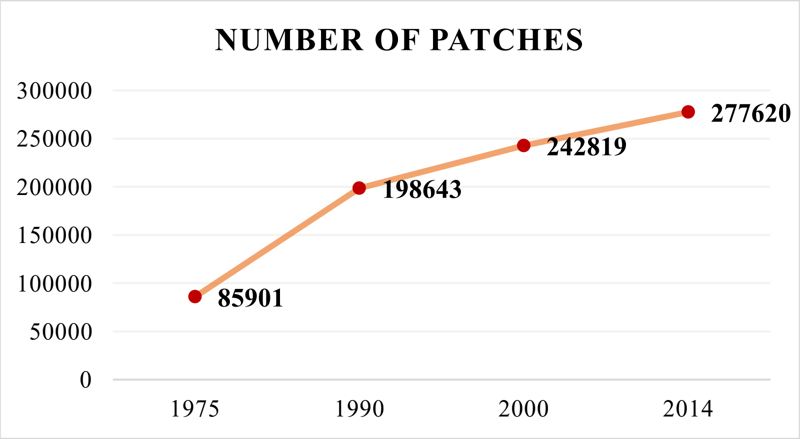


Figure 13. Number of patches (NP) for built-up area in the YRD metropolitan region

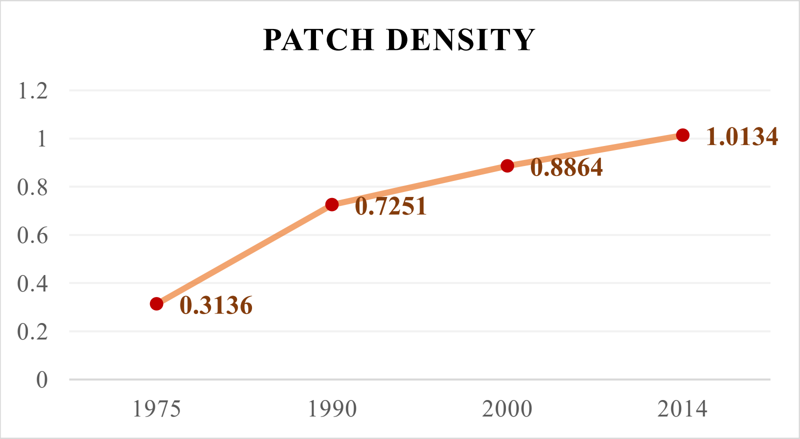


Figure 14. Patch density (PD) for built-up area in the YRD metropolitan region

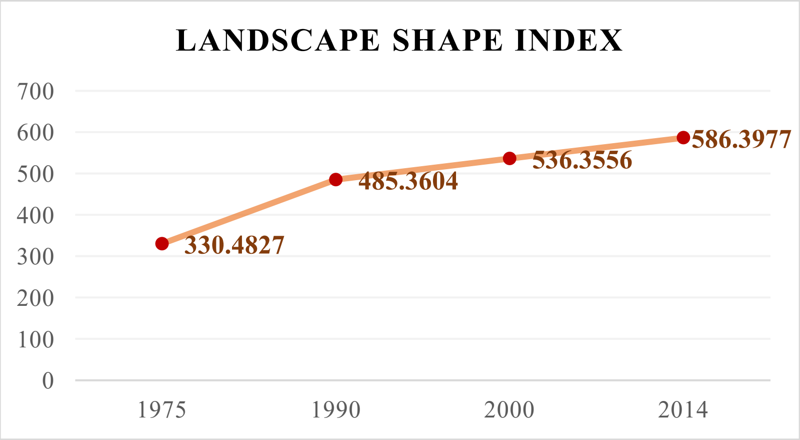


Figure 15. Landscape shape index (LSI) for built-up area in the YRD metropolitan region

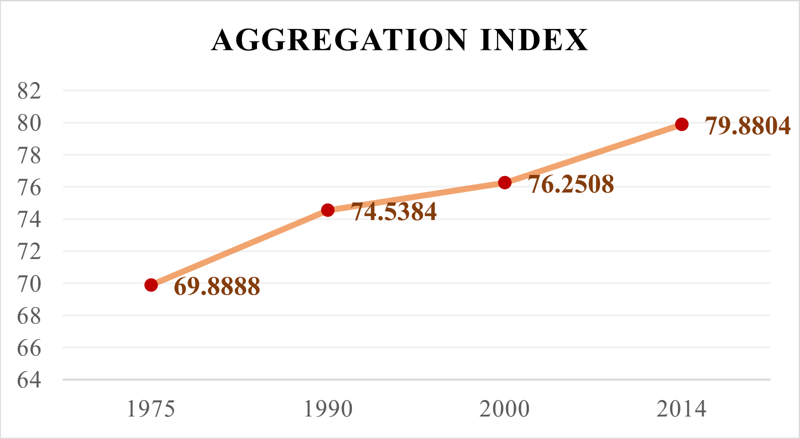


Figure 16. Aggregation index (AI) for built-up area in the YRD metropolitan region

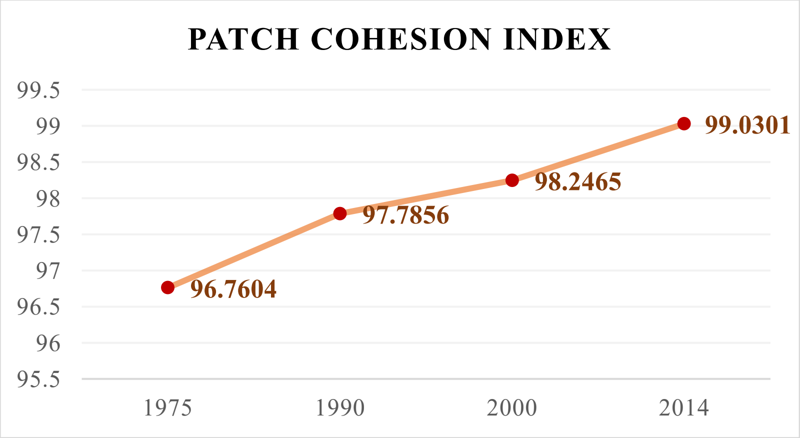


Figure 17. Patch COHESION index (COHESION) for built-up area in the YRD metropolitan region

The YRD metropolitan region showed a consistent increase of number of patches and patch density. Based on Figure 14, the patch density increased by 1.31, 0.22, 0.24 for the three time periods. The landscape shape index is measured the shape complexity. From Figure 15, for all the 4 time steps, the LSI increased. The increase of NP and PD shows that built-up patches became more numerous during the urban expansion process. The rise of NP means built-up area has been increasing constantly; and with the expansion of built-up area, the shape of built-up patches was more complex which means that built-up patches were mostly highly fragmented.

COHESION and aggregation index reflected the extent of integration for the YRD metropolitan region. Both the COHESION and aggregation index have been increased during the four periods and they reached the highest value 79.88 and 99.03 respectively in 2014. The trend of these two metrics indicated the aggregation of built-up patches and more complexity of landscape shape as well topography. Furthermore, it also reflected that built-up landscape connectivity with other landscape was better and distribution of built-up area was more concentrated. They were inseparable from the built-up area expansion.

By the analysis of the YRD metropolitan region with landscape metrics, built-up area was growing continuously. The expansion of urban area, built-up patches tended to connect together and is more complex.

4.2.2. Spatiotemporal urban patterns at city level

- Analysis of urban expansion pattern

The fractal dimensions of all built-up patches are quantified by AWMPFD. The higher value closed to 2 reflect more complex and fragmented patches, and lower values closed to 1 represent relatively simple and compact shapes. There are two types of urban area growth described in 2002, the urban region is based on infilling expansion type if the irregular portion of urban area becomes larger, and most of the growth is dependent on edge expansion type with filling areas at the fringe of urban area on the contrary (Wang, 2002). It means that as the decrease of AWMPFD value, fragmented patches surrounded by urban land connected and became a lager urban area. And urban area expansion is based on the internal filling within built-up area. Otherwise, newly urban land will develop on the edge of existing built-up patches with increasing AWMPFD values

Average AWMPFD values of 17 cities are 1.17, 1.20, 1.22 and 1.25 respectively in 1975, 1990, 2000 and 2014. These average values show that the morphology of built-up area got increasingly complex and its borders became increasingly irregular from 1975 to 2014. Figure 18 shows the AWMPFD values change over time. From 1975 to 1990, Suzhou, Wuhu and Maanshan posted dramatically decreased AWMPFD values, compared with significant increase of AWMPFD values for Wuxi, Ningbo, Zhoushan, Taizhou and Hefei. Other 9 cities provided stable values in this period. There were no obvious urban expansion patterns during this period. From 1990 to 2000, an obvious increase of AWMPFD values was found in 14 cities and no changes occurred of Zhoushan and Hefei. Only AWMPFD value of Yangzhou decreased. It indicates that there was more complexity of urban form in most cities with patch margin extension as dominant urban expansion pattern from 1990 to 2000. From 2000 to 2014, 14 cities have increasing AWMPFD values; only Maanshan showed decreasing AWMPFD; and no changes were found in Taizhou and Hefei. As mentioned before, AWMPFD value represents complexity and the fragmentation. These results indicate that urban complexity increased in most cities, with edge expansion type as predominant expansion pattern between 2000 and 2014

In general, there was no obvious regularity of the urban expansion pattern in YRD metropolitan region from 1975 to 1990. However, after 1990, the rapid urban expansion of the YRD metropolitan region brought incremental changes in built-up area, driven mainly by patch margin extension, which resulted in more irregular urban shapes as indicated by increasing AWMPFD values. Of all 17 cities, only Suzhou, Wuhu and Maanshan showed declining AWMPFD values during three periods; and Hefei has no changes of AWMPFD value after 1990. Notably, Hefei, Wuhu and Maanshan all belong to Anhui, an inland province, which is a new member of the YRD metropolitan region.

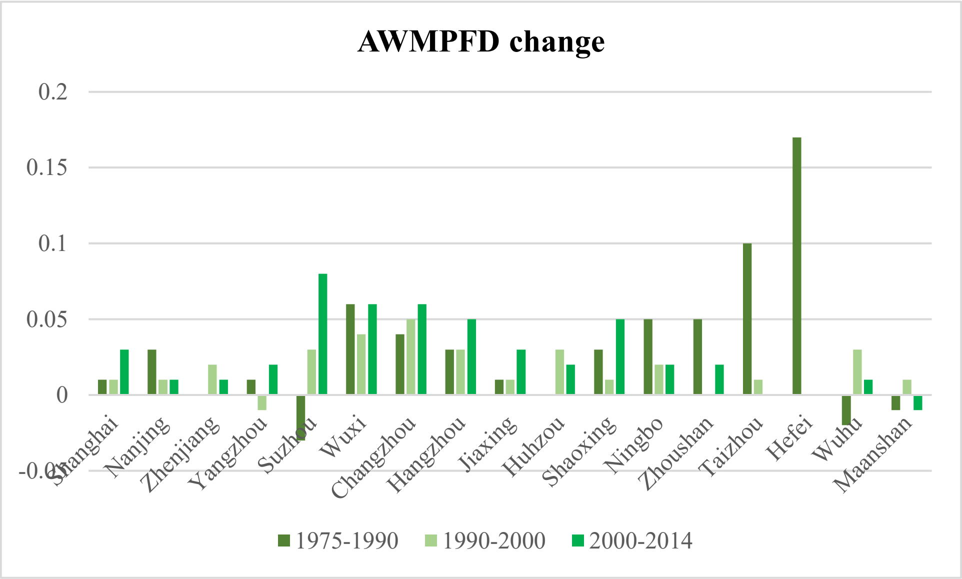


Figure 18. AWMPFD change of 17 cities at four-time stages

- Characteristics of urban expansion development

The spider charts (Figure 19) were calculated as relative diagrams, the maximum and minimum value of one particular metric was used for one axis as 1 and 0 for the 17 cities. The values of other remaining cities were calculated relative to the maximum value so that a comparison would be made among 17 study cities. The spatial and temporal characteristics of urban expansion in the study areas can be descried and visualized spatially by spider charts. The 17 study cities of the YRD metropolitan region of China are displayed at four different time stages from 1970 to 2014. Therefore, the dynamics of urban expansion and comparison across different regions and city sizes can be analyzed. The increase of these metrics indicated the extent of urban expansion.

Spider charts were provided to characterize spatiotemporal urban expansion qualitatively and quantitatively with seven spatial metrics (ED, NP, PD, LSI, AI and COHESION). The axes of spider charts were interpreted by grouping the axes into three aspects: the NP-PD axis indicates fragmentation of built-up patches, the AI-COHESION represents the aggregation of built-up patches and LSI-ED axis represents the shape complexity of built-up patches.

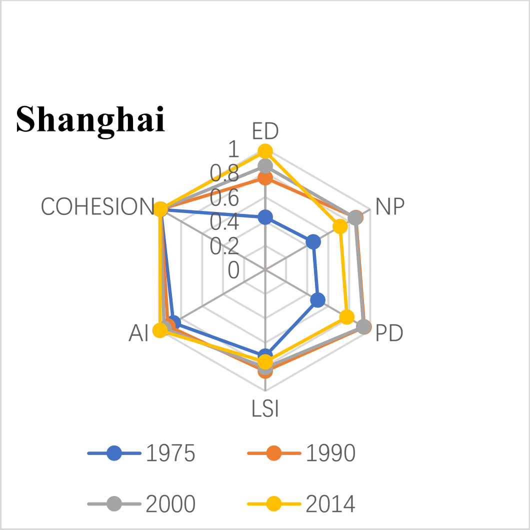
The 17 cities can be divided into five groups according to spider charts. The first group consisted of Suzhou, Wuxi, Changzhou, which have high levels of aggregation, complexity and fragmentation. The second group comprised Nanjing, Zhenjiang, Hangzhou, Jiaxing, Ningbo and Taizhou with high levels of aggregation, but lower complexity and fragmentation. The third group included Yangzhou, Shaoxing, Hefei, Wuhu and Maanshan, characterized by high aggregation, low complexity and low fragmentation. Huzhou and Zhoushan belonged to the fourth group, which have lower aggregation, high complexity and fragmentation. The fifth group is Shanghai which almost has the highest value of all axes. The second group showed in spider charts have stable shapes relatively.

During the initial period of urban expansion, urban development is marked by urban footprint and it is less significant and less aggregation (Dietzel, Herold, Hemphill, & Clarke, 2005). As the process of urban expansion goes on, built-up patches tend to be augmented and more aggregated. These general trends and spatiotemporal characteristics of urban expansion of the study areas can be seen in the spider charts. Analyzing the total built-up area of 17 cities over time (Figure 20), we see that built-up area increased from 1975 to 2014. From Table 2, there are three administrative levels of these 17 cities. Characteristics of urban form and structure changes were almost not related to administrative level in the YRD metropolitan region. City size can be divided by population for urban expansion analysis (Taubenbock et al., 2009). In Development Planning of Yangtze River Delta Metropolitan region as table 12 showed (China National Development and Reform Conmmision, 2016), the 17 cities in the YRD metropolitan region were divided by urban resident population as 4 types. However, the characteristics of urban expansion are not similar based on city size divided by urban resident population. However, through the analysis above, cities in the same province have similar expansion characteristics, especially when they are in the same metropolitan circle such as Suxichang metropolitan circle and Hefei metropolitan Circle. Surprisingly, cities in Hangzhou metropolitan circle seem to have little in common. And compared with cities (Hefei, Wuhu, Maanshan) in the inland province Anhui, the other two provinces have a higher degree of urban expansion activity.

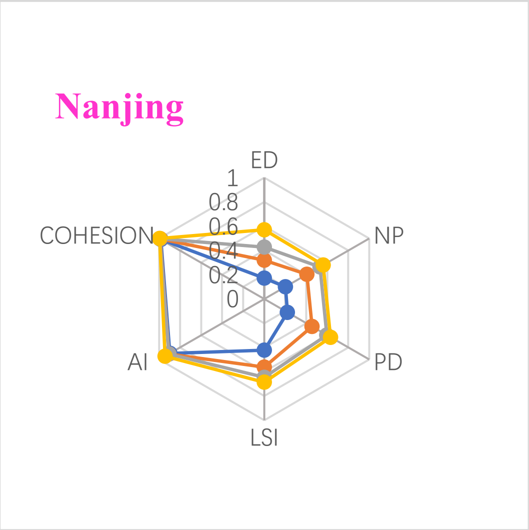
Legend:

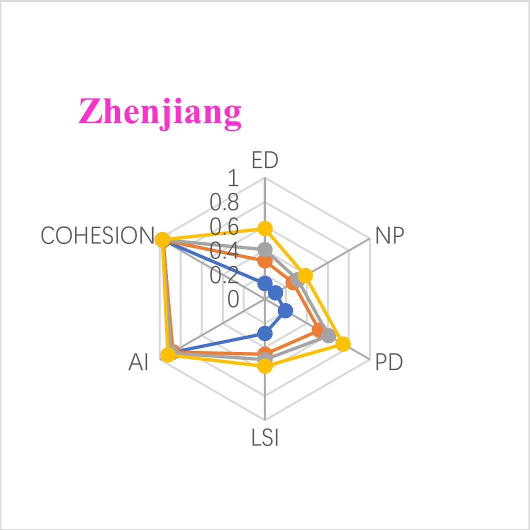
ED=Edge density; NP=Number of Patches; PD=Patch Density; LSI=Landscape shape index; AI=Aggregation index; Cohesion=Patch COHESION index;

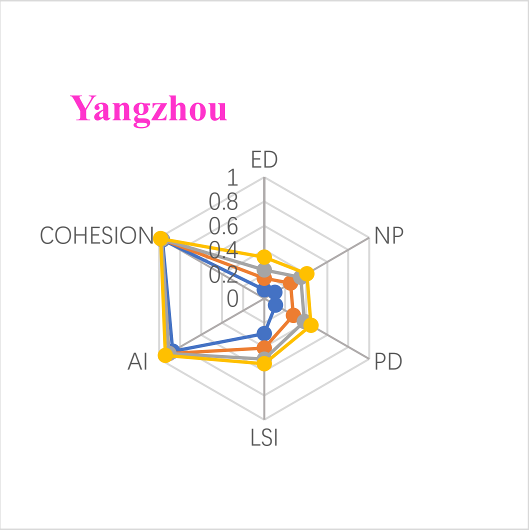
Provincial city (One core city)

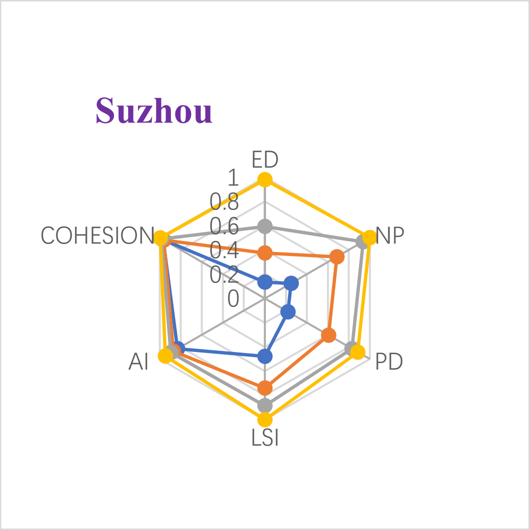


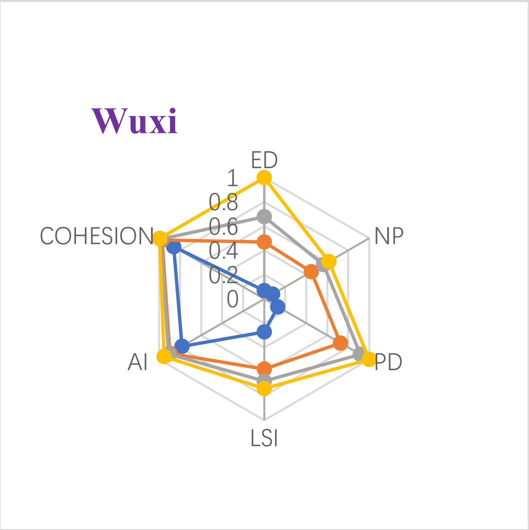
Jiangsu province (Nanjing Metropolitan Circle, Suxichang Metropolitan Circle)

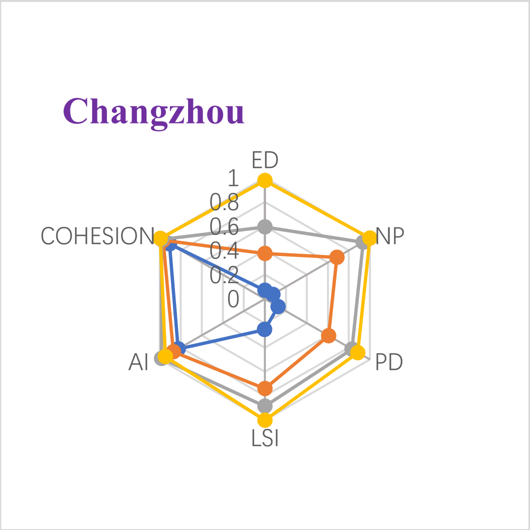




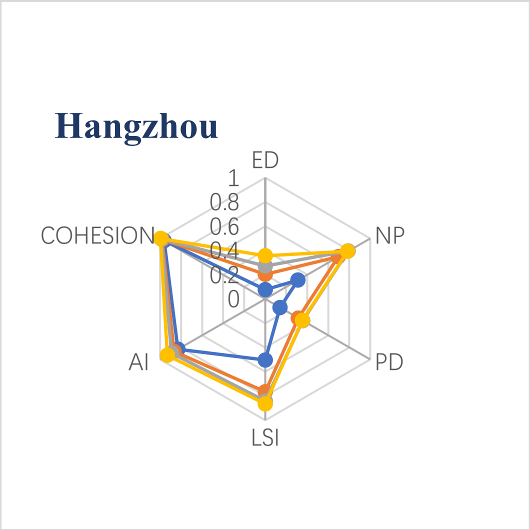


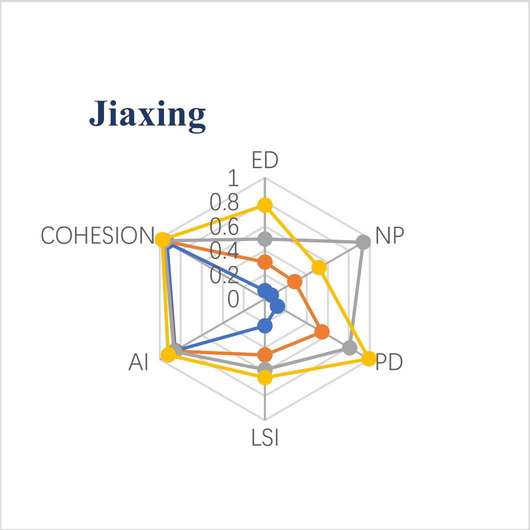


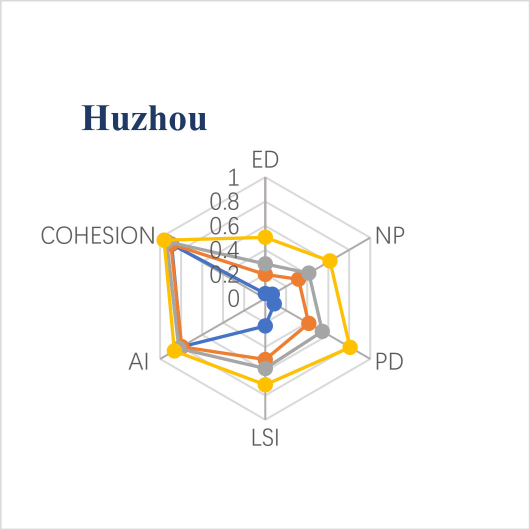


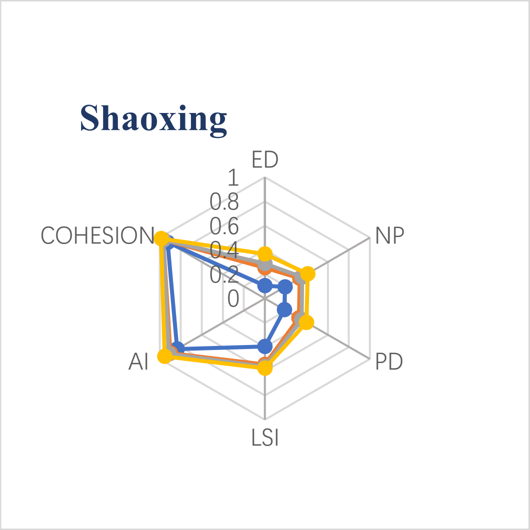


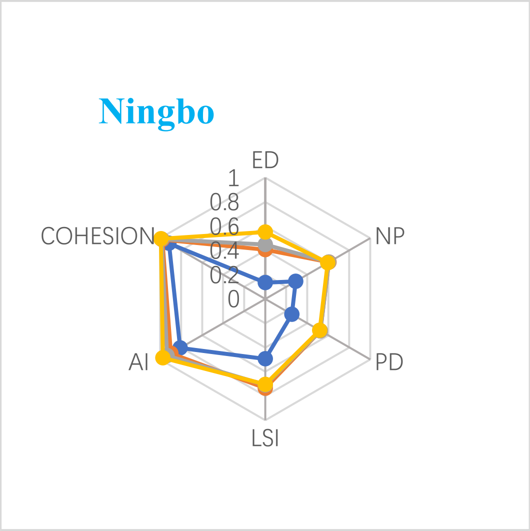
Zhejiang province (Hangzhou metropolitan circle, Ningbo metropolitan circle)

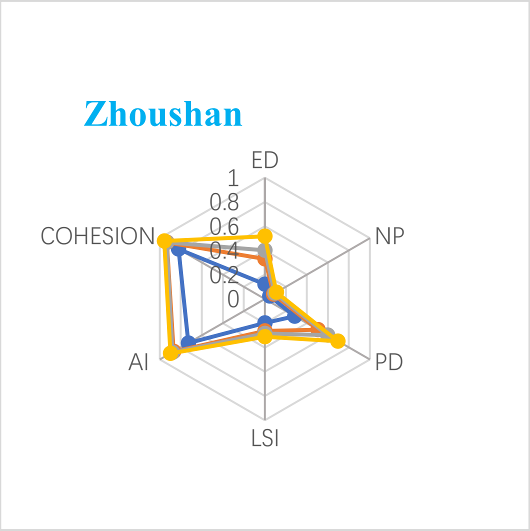

Hangzhou

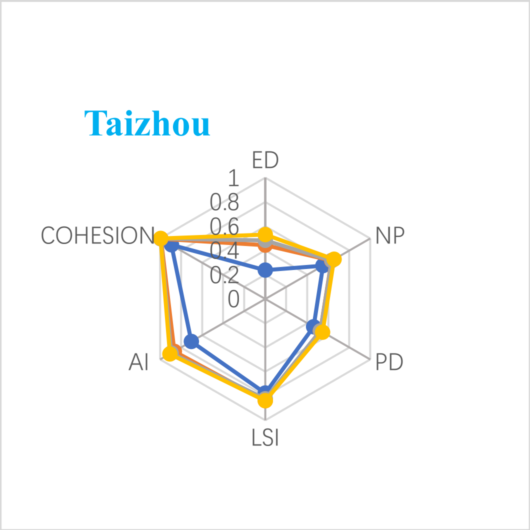

Jiaxing


Huzhou

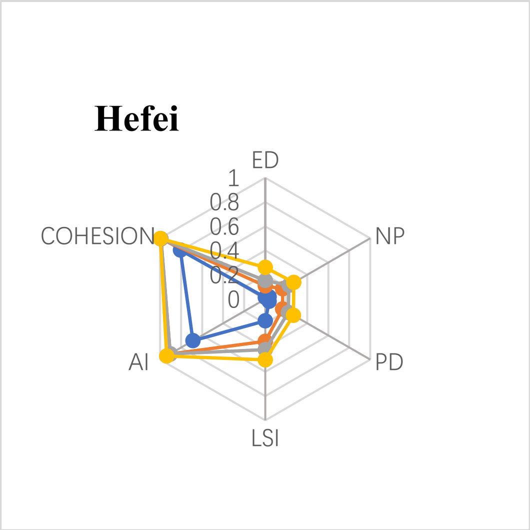

Shaoxing

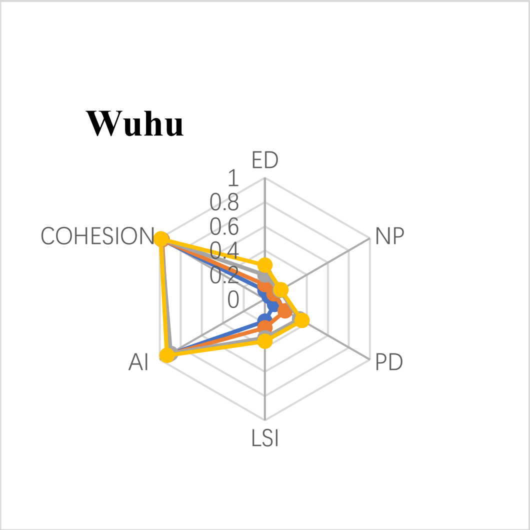

Ningbo


Zhoushan



Anhui province (Hefei metropolitan circle)





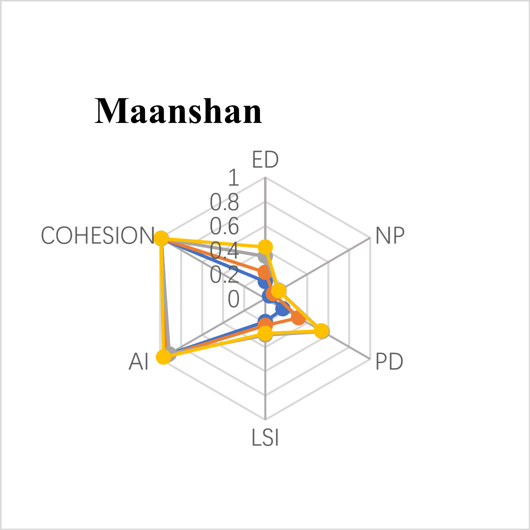


Figure 19. Spider charts characterizing spatiotemporal urban development.

Note: The minimum and maximum values were normalized as 0 and 1.

Table 13. City hierarchical structure division by urban resident population

City hierarchical structure (Divided by Urban resident population)	City
Megacity: > 10 million	Shanghai
Megalopolis:5 million – 10 million	Nanjing
Big cities: 1 million – 5 million	Hangzhou, Hefei, Suzhou Wuxi, Ningbo, Changzhou, Shaoxing, Wuhu, Yangzhou, Taizhou
Middle cities: 500,000 – 1 million	Zhenjiang, Huzhou, Jiaxing, Maanshan, Zhoushan

Source: The Development Planning of Yangtze River Delta Urban Agglomeration

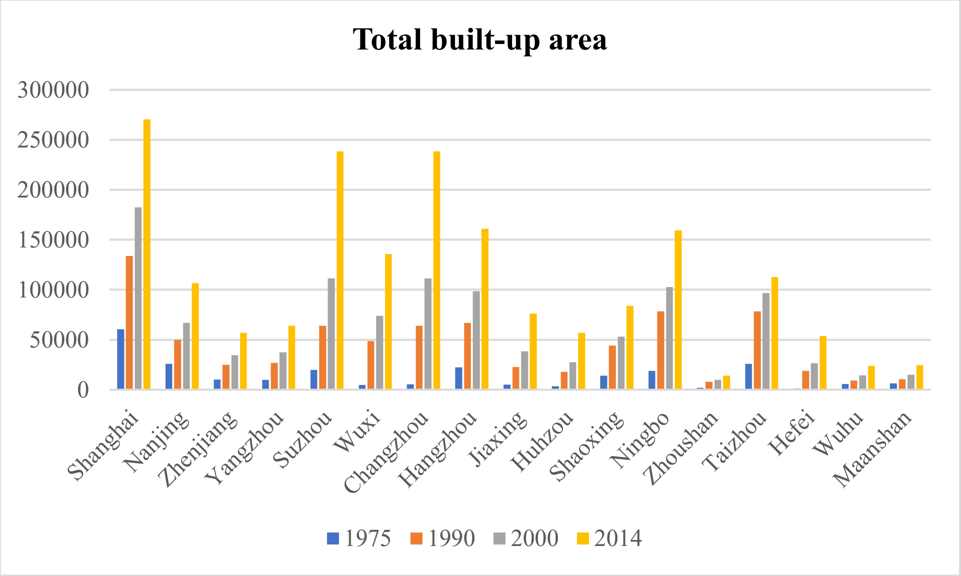
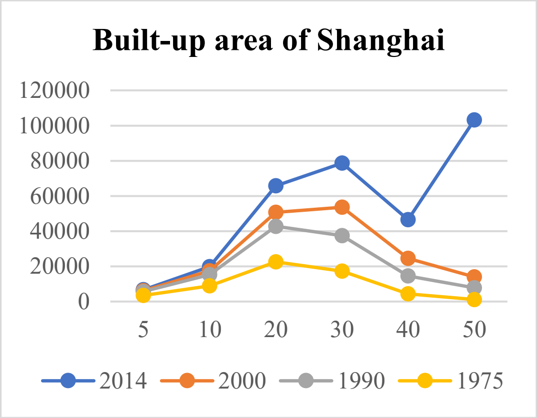
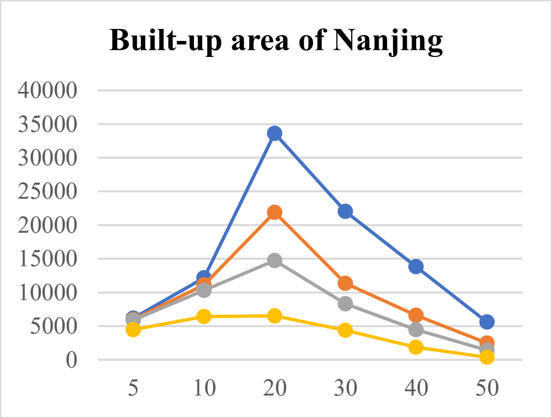


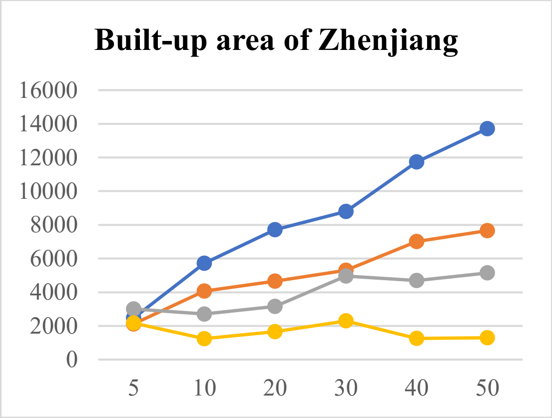
Figure 20. Total built-up area of 17 cities at four-time stages

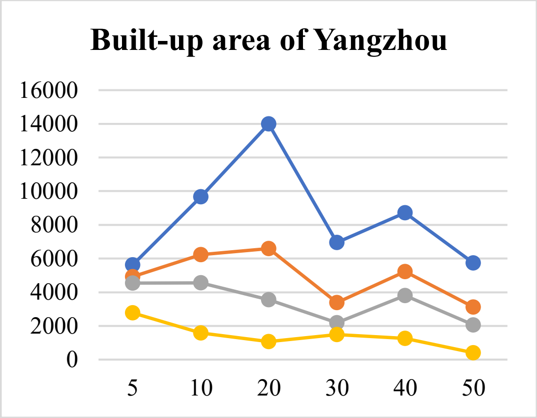
4.2.3. Zonal-based analysis

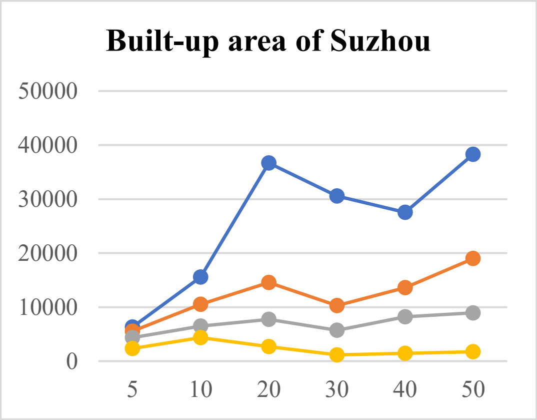
In addition to the urban patterns analysis at the extent of cities, spatial metrics were used to analyze in detail the spatiotemporal characteristics of urban expansion across buffers. In the thesis, total built-up area and SHAPE metric were employed to conduct the zonal-based urban structure analysis.

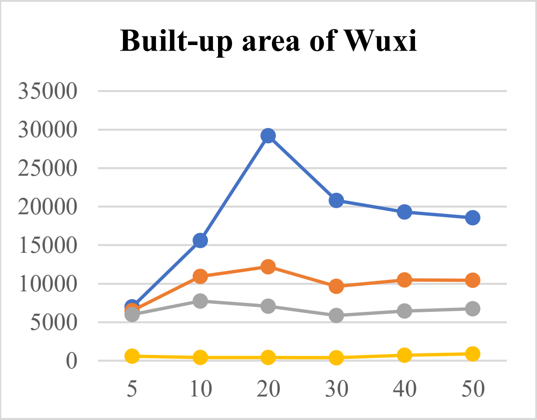

Built-up area of Shanghai
120000
100000
80000
60000
40000
20000
0
5
10
20
30
40
50
2014
2000
1990
1975

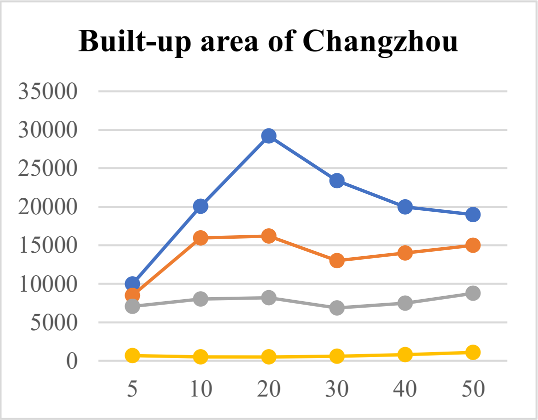

Built-up area of Nanjing
40000
35000
30000
25000
20000
15000
10000
5000
0
5
10
20
30
40
50

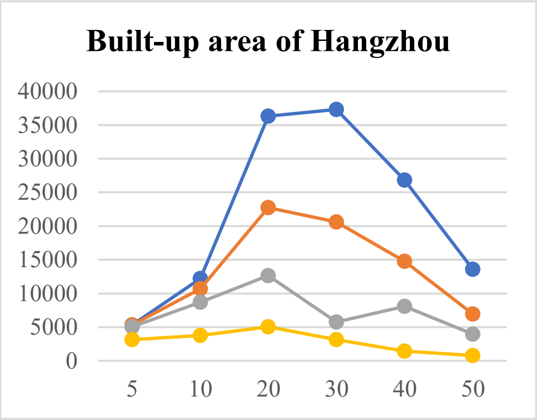

Built-up area of Zhenjiang
16000
14000
12000
10000
8000
6000
4000
2000
0
5
10
20
30
40
50

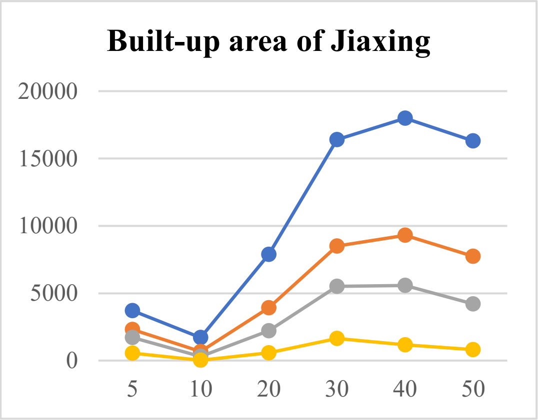

Built-up area of Yangzhou
16000
14000
12000
10000
8000
6000
4000
2000
0
5
10
20
30
40
50


Built-up area of Suzhou
50000
40000
30000
20000
10000
0
5
10
20
30
40
50


Built-up area of Wuxi
35000
30000
25000
20000
15000
10000
5000
0
5
10
20
30
40
50


Built-up area of Changzhou
35000
30000
25000
20000
15000
10000
5000
0
5
10
20
30
40
50


Built-up area of Hangzhou
40000
35000
30000
25000
20000
15000
10000
5000
0
5
10
20
30
40
50


Built-up area of Jiaxing
20000
15000
10000
5000
0
5
10
20
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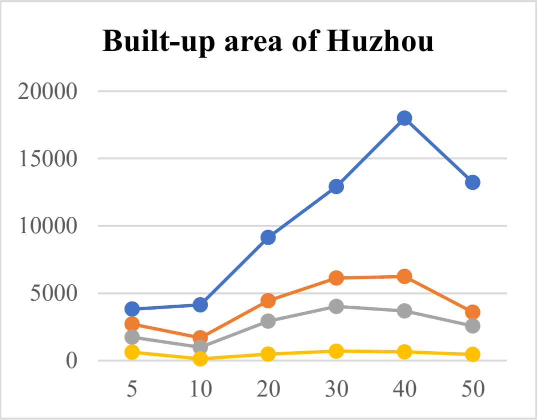
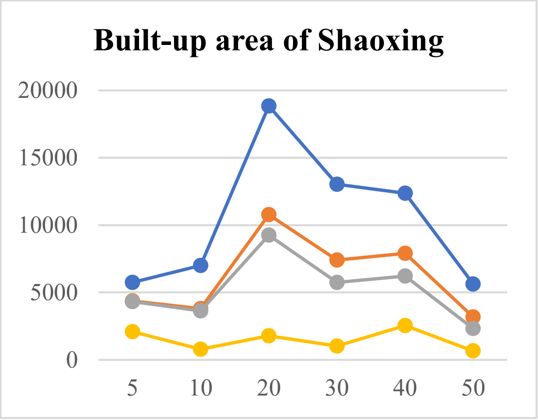
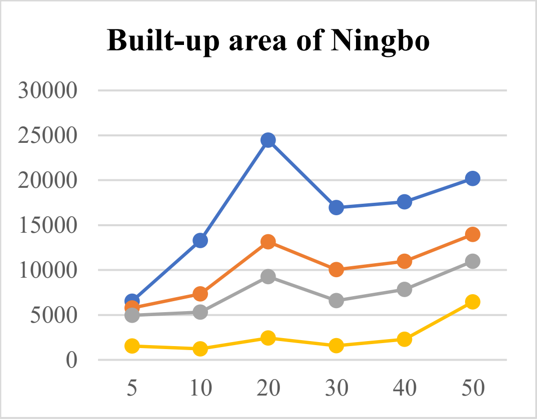

Built-up area of Huzhou
20000
15000
10000
5000
0
5
10
20
30
40
50


Built-up area of Shaoxing
20000
15000
10000
5000
0
5
10
20
30
40
50


Built-up area of Ningbo
30000
25000
20000
15000
10000
5000
0
5
10
20
30
40
50

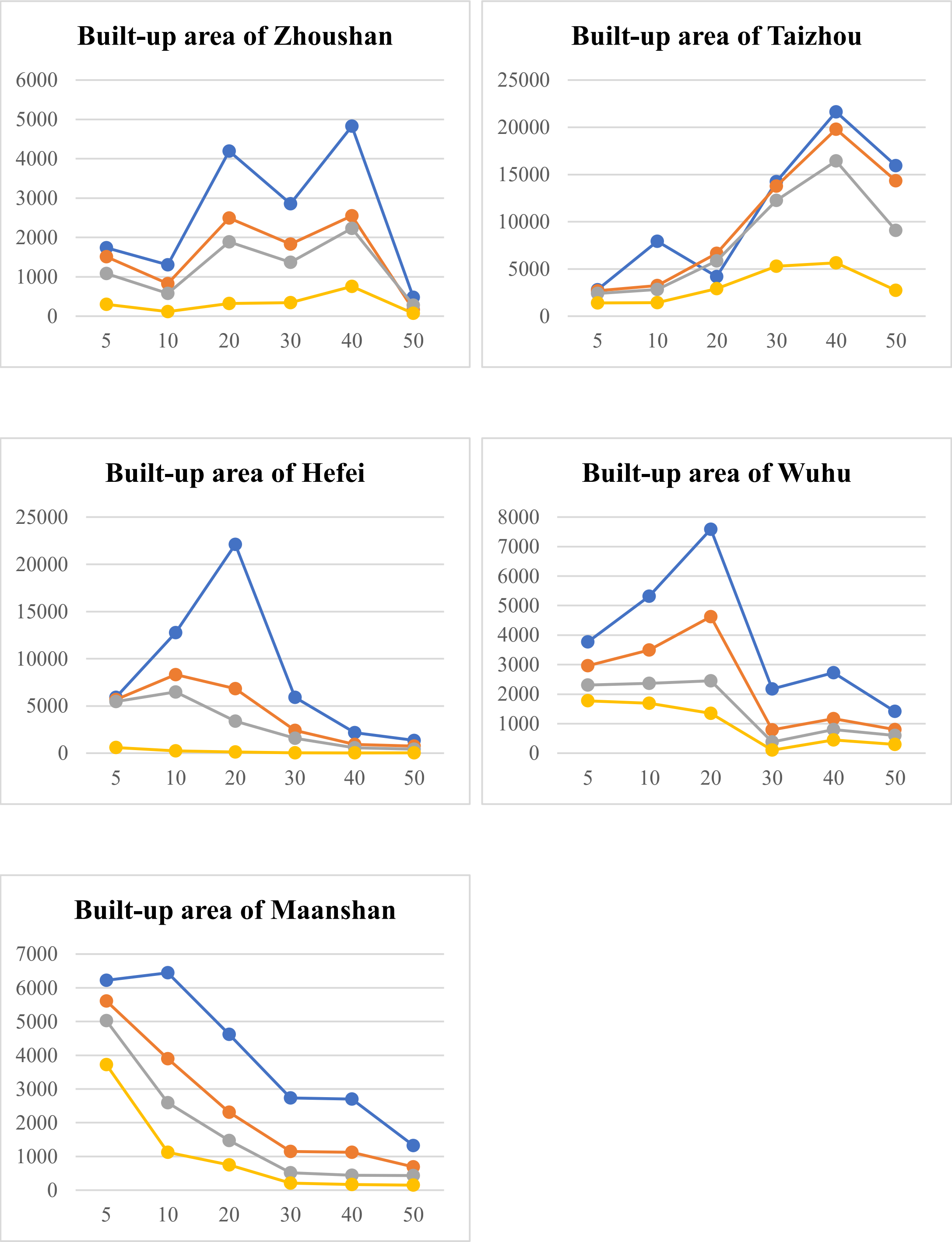
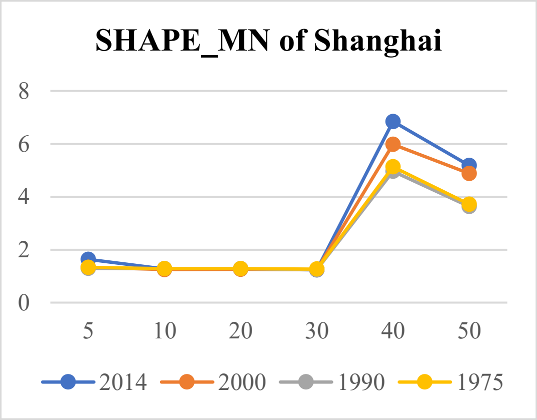
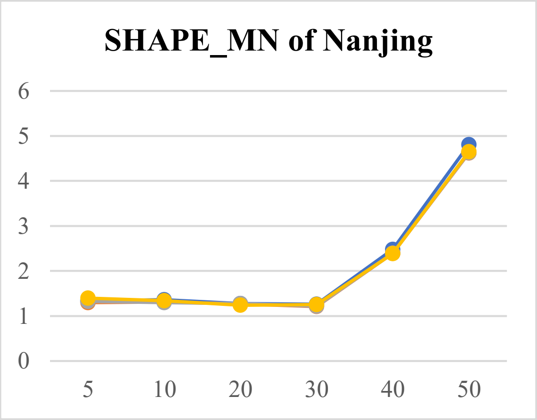
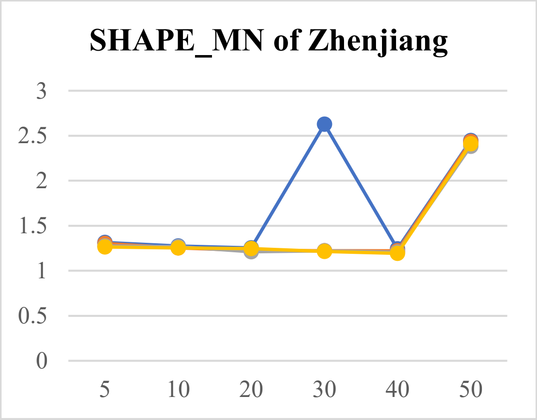


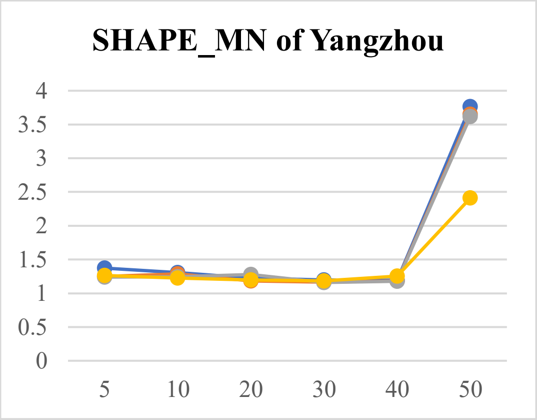
Figure 21. Built-up area of the YRD metropolitan region in different buffer zones

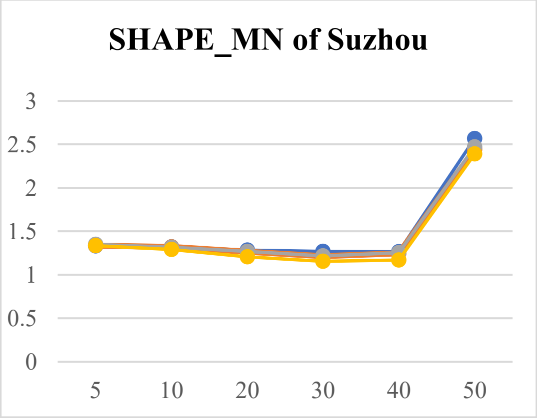
Figure 21 presents the changes in total built-up area in the buffers around the respective city centers of the 17 cities. In general, the built-up area of all 17cities increased for all 6 buffer zones over time. It is apparent that the built-up area of all the cities increased in the first buffer zone (5 km). Also, almost all cities show similar trends in built-up area across the six buffer zones in 1975, 1990, 2000 and 2014. It means that these cities had the similar increased or decreased trends in same buffer zone of all the 4 years. in the However, Shanghai and Taizhou showed remarkable other trends in 2000 to 2014 compared with the previous time periods. The built-up area of Shanghai increases when moving away from the city center until a buffer distance of 30 km. Buffers further than 30km away showed again smaller built-up area between 1975 and 2000. But in 2014, Shanghai's built-up area rose significantly at 50 km from city center. The built-up area of Taizhou increased from the city center to buffer 5 (40 km) and decreased above 40km between 1975 and 2000. In 2014, however, the built-up area shrank below the level of 1990 at the distance of 20 km from the city center. In general, the built-up area of 16 cities was increased in each buffer zone over time. Only in Taizhou, the built-up area at 20 km from the centre decreased in 2014

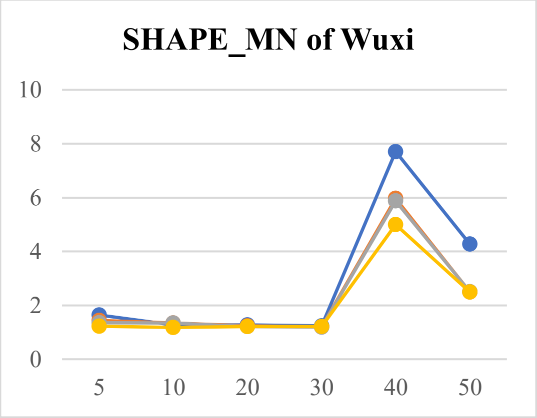


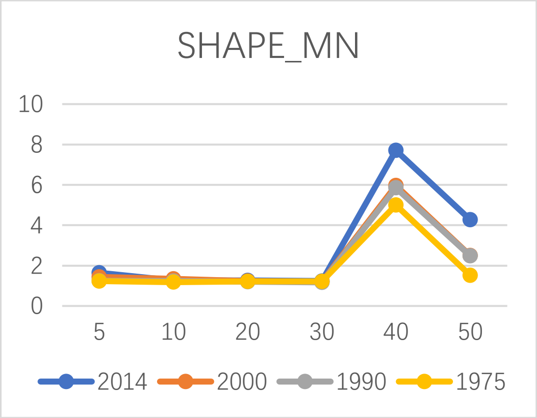


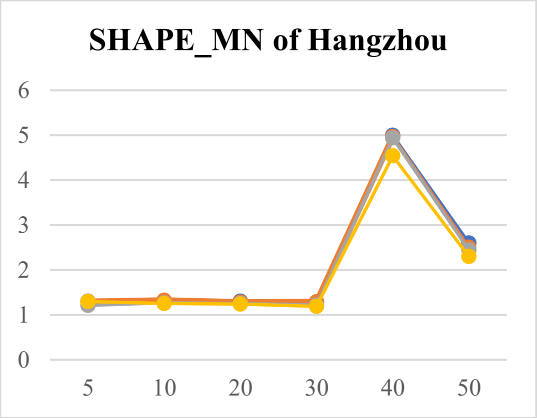


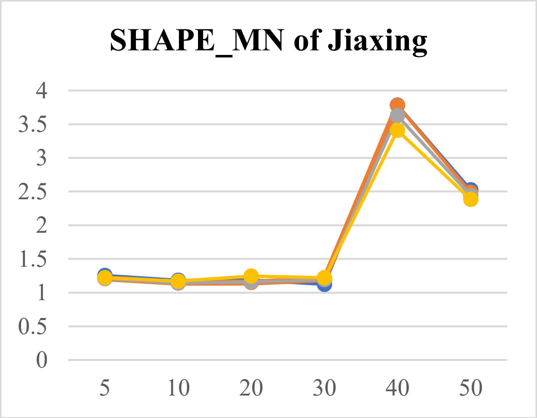


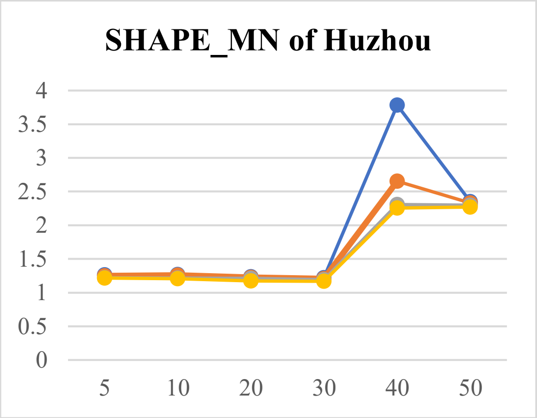





SHAPE_MN
10
8
6
4
2
0
5
10
20
30
40
50
2014
2000
1990
1975


SHAPE_MN of Hangzhou
6
5
4
3
2
1
0
5
10
20
30
40
50


SHAPE_MN of Jiaxing
4
3.5
3
2.5
2
1.5
1
0.5
0
5
10
20
30
40
50


SHAPE_MN of Huzhou
4
3.5
3
2.5
2
1.5
1
0.5
0
5
10
20
30
40
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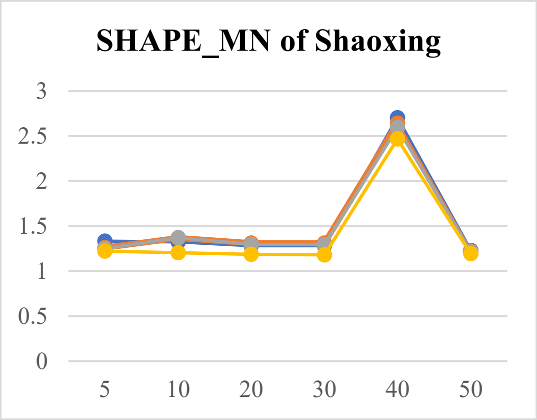
SHAPE_MN of Shaoxing
3
2.5
2
1.5
1
0.5
0
5
10
20
30
40
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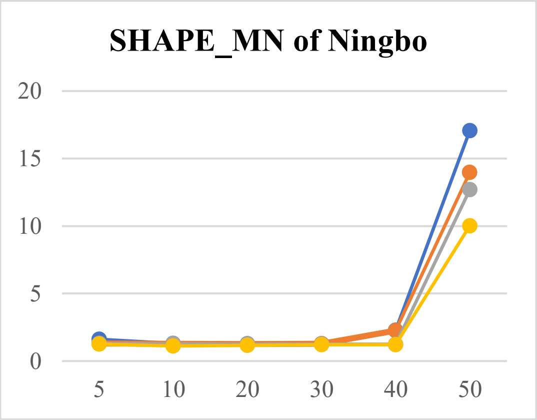
SHAPE_MN of Ningbo
20
15
10
5
0
5
10
20
30
40
50

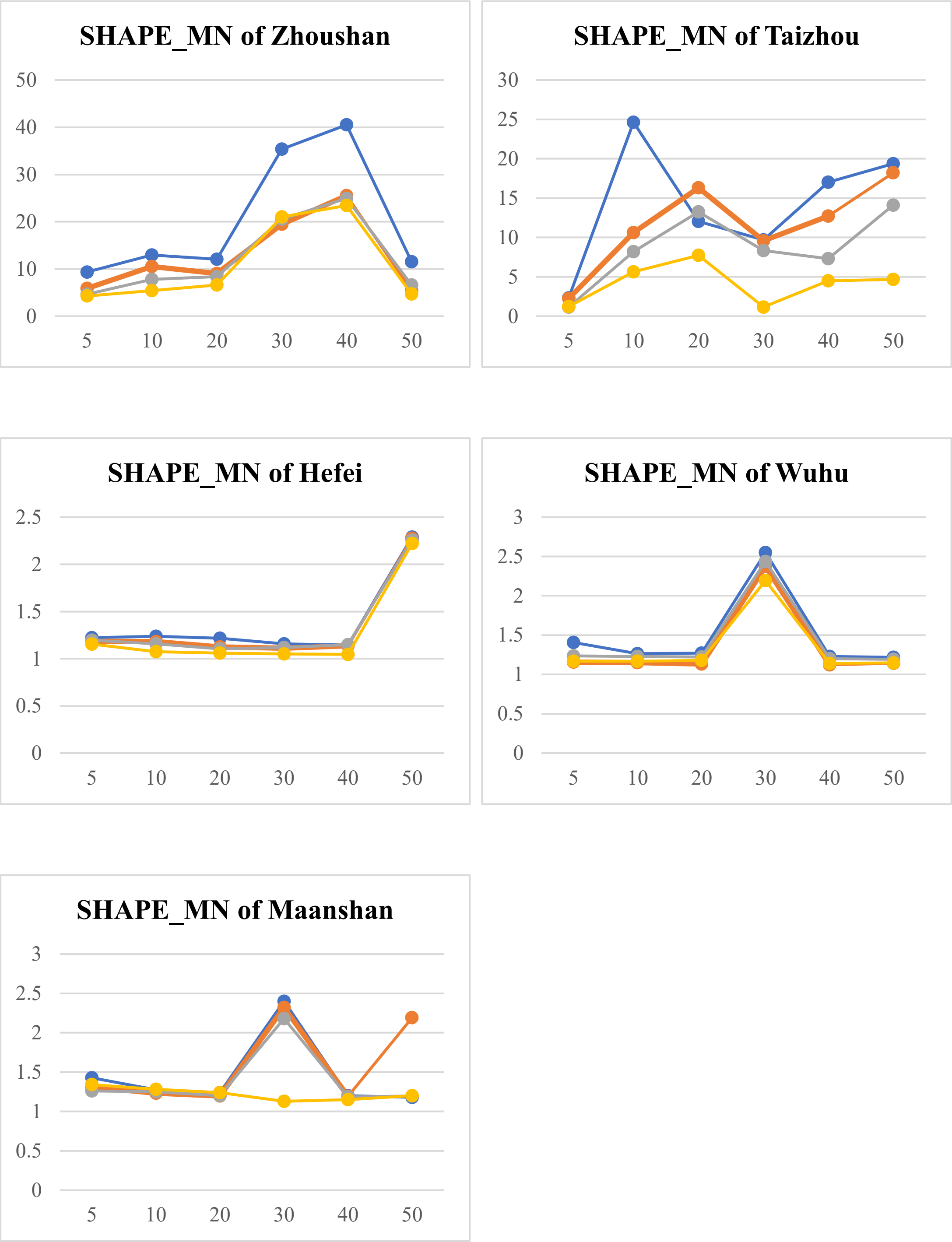

Figure 22. SHAPE metric of the YRD metropolitan region in different buffer zones

The SHAPE metric is the second parameter for the zonal-based analysis. In Figure 22, the development of the SHAPE metric is shown for the buffers with increasing distance from the city centres at four-time stages. The spatial characteristics according to SHAPE index were divided into two categories, the pattern is rather that built up areas are first rather compact and then complexity rises, either until the last buffer, or a decrease in complexity can be seen again. Figure 22 shows one notable exception, as Taizhou shows fluctuant changes of the SHAPE index from the urban centre to the periphery and over time, with high complexity near the urban centre in 2014. A similar

SHAPE index trend is shared by Shanghai, Wuxi, Changzhou, Hangzhou, Jiaxing, Huzhou, Shaoxing and Zhoushan. They have the most complex built-up area at 40 km from the urban core and their SHAPE index declines again beyond 40 km. Nanjing, Zhenjiang, Yangzhou, Suzhou, Ningbo and Hefei also show constant low values of SHAPE index from the city centre to the fifth buffer zone; only the last buffer zones have high SHAPE index values. This means only the city margin has high complexity. Assuming one or two more buffers would be added for Zhenjiang, Yangzhou, Suzhou, Ningbo and Hefei, probably also a decrease in built-up area could be expected, which is likely to result in lower value of SHAPE index. For Wuhu and Maanshan, the fourth buffer zone is the most complex area. It became apparent that cities in the same provinces tend to share the similar development trend of SHAPE Index. In general, the built-up area is compact around the city centre and complex at their peripheries of all these 17 cities. Furthermore, most cities had stable values of SHAPE index over time which means they barely become more complex between 1975 and 2014. In addition, Ningbo, Zhoushan and Taizhou had higher values of SHAPE index compared other 14 cities. And they are coastal cities with many small islands.

4.3. Policy analysis

4.3.1. Land policies related to urban expansion

Table 14 summarizes the land use plans found on the national, metropolitan, and city level. Several points are remarkable here. First, explicit land use planning policies for the city level only exists from 2006 onwards, no earlier planning documents were found. Only for the national scale, also an earlier policy, covering the period from 1997 to 2010, exists. Thus, only the urban expansion characteristics of last time period were matched with existing policies in the research. For the YRD, there was a new planning policy called Development Planning of Yangtze River Delta Metropolitan region related to urban development from 2014 to 2020. Secondly, land use planning aiming at each province and city were created based on all the national land policies and current situation of urban development. Thus, the actual content of the land use plans is very similar.

These documents, third, do not specify quantified target values, such as number of built-up area, the content of planning policies related to urban expansion can be summarized as follows: to control the total and incremental area of urban land, and to optimally and intensively utilize urban land resource. The first item means that the amount of total urban area and increased urban area should be limited. And the second one means the urban expansion should be aggregated for integrative and balanced urban development. Therefore, it was not straightforward to compare the policies' outcomes with the results of the time series analysis using spatial metrics. In order to compare the actual expansion of urban area and the intensive use of urban areas with policies, the following indicators were depicted for the 17 cities in Figure 20 and Figures 23 to 27. Figure 20 shows significant increases of built-up area in 13 cities between 2000 and 2014, the increase of built-up area is more rapid than previous two time stages (from 1975 to 1990 and from 1990 to 2000) While Zhoushan, Wuhu and Maanshan have relatively stable trends of built-up area changes. Finally, the increase in built-up area slowed down for Taizhou from 2000 to 2014.

Largest patch index indicates the proportion of the largest built-up patch and was selected here to reflect on optimally and intensively utilize urban area. However, in general the values are very low for the largest patch index. And it cannot be large for coastal cities as well. The largest patch index of Shanghai, Nanjing, Suzhou, Wuxi, Changzhou, Hangzhou, Shaoxing, Ningbo and Hefei dramatically increased from 2000 to 2014. Only Zhoushan had decreased large patch index after 2000. Other 7 cities have stable increasing trend of large patch index during last time period compared to previous time. It means that these 7 cities a had balance development of urban areas. As mentioned in section 4.2.2, aggregation index and COHESION described the aggregation of built-up area. Figures 24 to 25 show that built-up patches became more aggregated generally over time. Most cities had stable increasing trends of aggregation index and COHESION index. From Figure 24, values of aggregation index increased from 2000 to 2014 for all the 17 cities. Wuhu and Maanshan have fluctuant trends for aggregation index between 1975 to 2014. Figure 25 represents that all 17 cities had increasing values of COHESION during all the time stages. And from 1975 to 1990, Wuxi, Changzhou, Taizhou and Hefei had the most significant increase of COHESION index compared to other time stages. The value of COHESION index of other 13 cities increase stably from 1990 to 2014.

Figure 26 reflected that patches number increased significantly for Huzhou after 2000. And Shanghai, Hangzhou, Jiaxing, Ningbo had decreased number of built-up patches between 2000 to 2014. Other 14 cities had steady growth of built-up patches. It indicated in Shanghai, Hangzhou and Jiaxing, their built-up patches tended to connect during urban expansion. The values of landscape shape index represent complexity of built -up area. Shanghai, Ningbo and Maanshan had decreased values of landscape shape index from 1990 to 2014 which indicated their built-up area of these three cities became compact at this time stage.

To sum up, built-up areas have still increased considerably during the last time period and has become more integrated. Thus, the policies targets to control total and incremental were not met effectively. However, the aggregation values of built-up area increased in all the 17 cities and Shanghai, Ningbo had both less patches and lower values of landscape shape index between 2000 and 2014. It reflected a more intensive and optimal use of urban area. Because most cites required integrated and cluster development of urban area for intensive and saving urban land use.

Table 14. Overview of land planning policies on urban expansion

National		
Policy	**Content**	**Target time**
National plan on the general use of land	• The total amount of construction land is effectively controlled. • Strictly control the scale of urban construction area at all levels. • Strictly delimit urban construction areas and restrict blind urban expansion. • If the urban per capita land exceeds the prescribed standard and the unused land	1997-2010

	is not fully utilized, the urban built-up area should not be extended.	
National plan on the general use of land	• Curb excessive extension of construction land, effectively control the total amount of construction land. • Reduce construction land increment in the YRD region. • Optimally and intensively utilize construction land resource.	2006-2020
YRD metropolitan region		
Development Planning of Yangtze River Delta Metropolitan region	• Strictly control the scale of built-up area in mega-cities and large cities.	2014-2020
Shanghai		
*General land use planning of **Shanghai***	• Control construction land increment. • To suppress the spread of central urban area. • Improve dispersed distribution of construction land, optimally and intensively utilize construction land resource.	2006-2020
Jiangsu province		
General land use planning of **Nanjing**	• Control the total amount of construction land. • Enhance urban agglomeration and radiation capacity. • Improve the function of central city, promote construction land cluster development and their spatial integration, optimally and intensively utilize construction land resource.	2006-2020
General land use planning of **Zhenjiang**	• Control construction land increment • Implement agglomeration development strategy, optimally and intensively utilize construction land resource. • Rationally delineate the boundary of urban construction land for the central urban area.	2006-2020
General land use planning of **Yangzhou**	• Control the total area of construction land. • Optimally and intensively utilize construction land resource.	2006-2020
General land use planning of **Suzhou**	• Strictly control total and incremental amount of construction land.	2006-2020

	• Improve the function of central city, promote construction land cluster development and their spatial integration, optimally and intensively utilize construction land resource.	
General land use planning of **Wuxi**	• Control total and incremental amount of construction land. • Gradually convert land use from extension type to intension and intensive type, optimally and intensively utilize construction land resource.	2006-2020
General land use planning of **Changzhou**	• Strictly control total and incremental amount of construction land. • Strictly delimit the boundary of construction land and its expansion boundary, avoiding construction land sprawl around, optimally and intensively utilize construction land resource.	2006-2020
Zhejiang province		
General land use planning of **Hangzhou**	• Strictly control the total amount of construction land. • Strengthen integration of urban land use, optimally and intensively utilize construction land resource.	2006-2020
General land use planning of **Jiaxing**	• Control total and incremental amount of construction land. • Gradually convert land use from extension type to intension and intensive type, optimally and intensively utilize construction land resource.	2006-2020
General land use planning of **Huzhou**	• Control total and incremental amount of construction land. • Gradually convert land use from extension type to intension and intensive type, optimally and intensively utilize construction land resource.	2006-2020
General land use planning of **Shaoxing**	• Control total and incremental amount of construction land. • Adjust construction land use structure, optimally and intensively utilize construction land resource.	2006-2020
General land use planning of **Ningbo**	• Control total and incremental amount of construction land.	2006-2020

	• Adjust construction land use structure, optimally and intensively utilize construction land resource.	
General land use planning of **Zhoushan**	• Strictly control the total amount of construction land. • Implement the boundary control of urban and rural construction land, optimally and intensively utilize construction land resource.	2006-2020
General land use planning of **Taizhou**	• Control total and incremental amount of construction land. • Optimally and intensively utilize construction land resource.	2006-2020
Anhui province		
General land use planning of **Hefei**	• Control total and incremental amount of construction land. • Optimally and intensively utilize construction land resource.	2006-2020
General land use planning of **Wuhu**	• Control total and incremental amount of construction land. • Optimally and intensively utilize construction land resource.	2006-2020
General land use planning of **Maanshan**	• Control total and incremental amount of construction land. • Optimally and intensively utilize construction land resource.	2006-2020

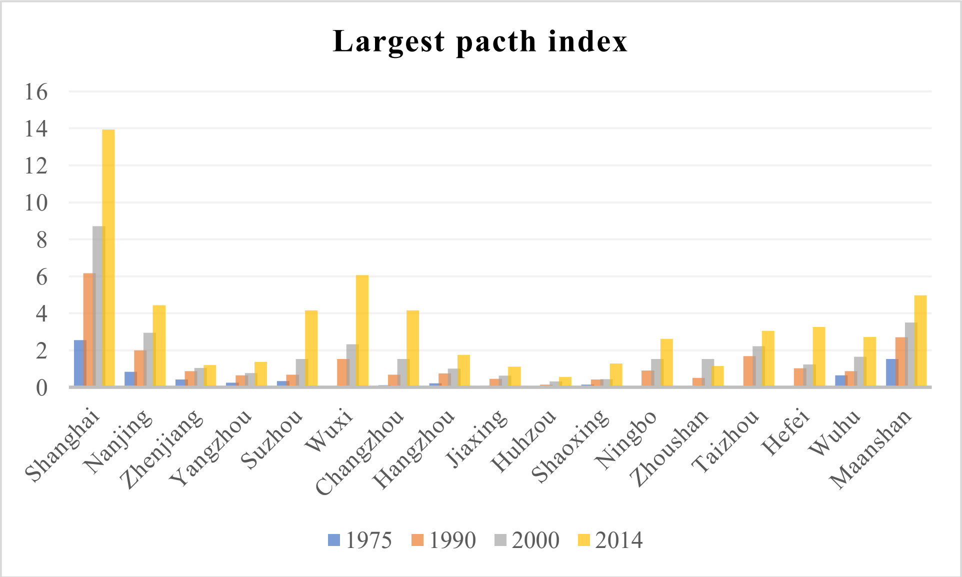

Figure 23. Largest patch index of 17 cities at four-time stages (Unit: %)

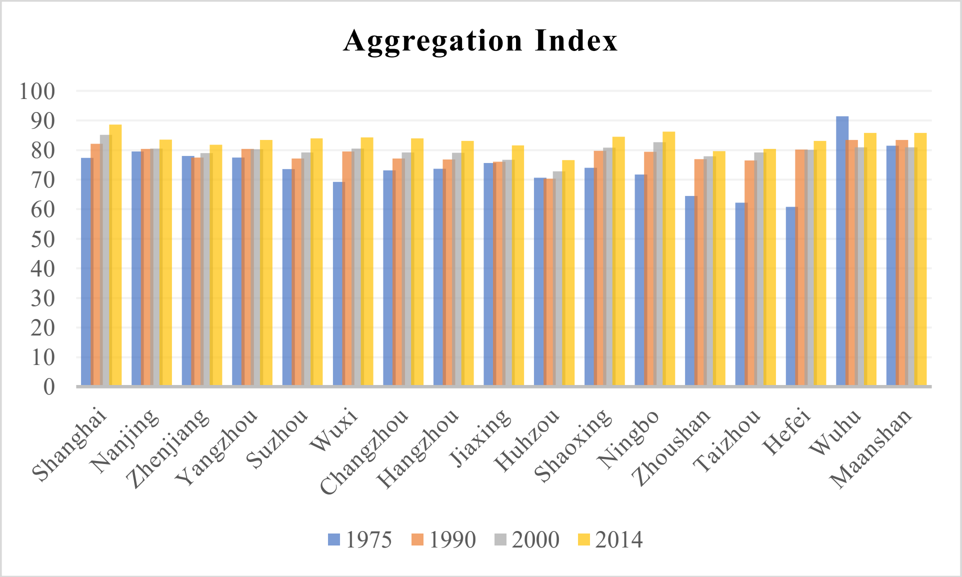

Figure 24. Aggregation index of 17 cities at four-time stages

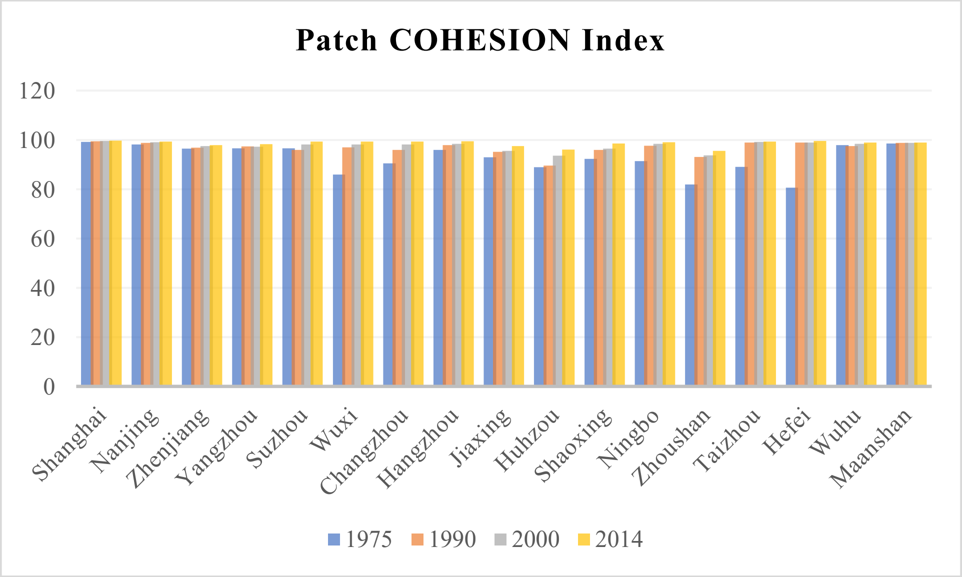

Figure 25. Patch COHESION index of 17 cities at four-time stages

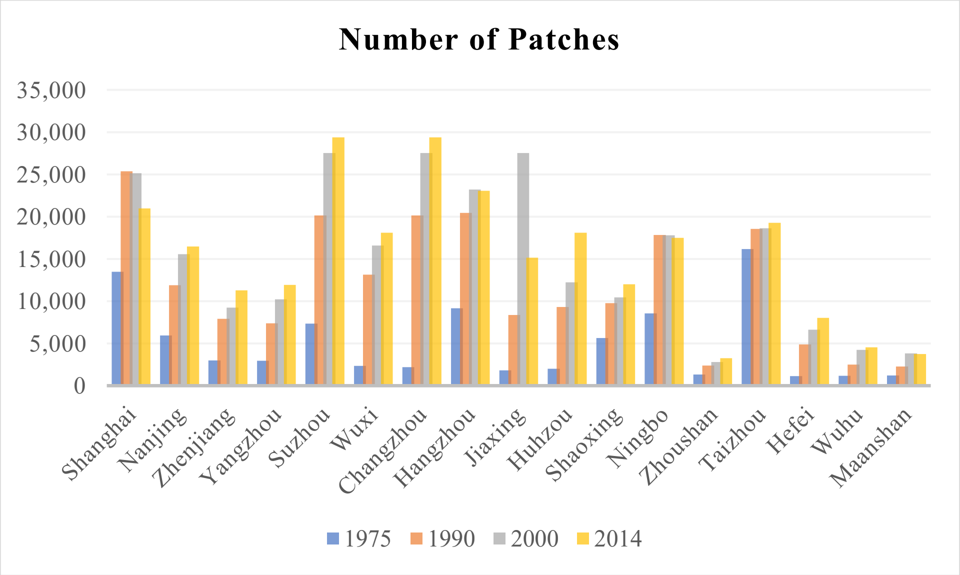

Figure 26. Patches number of 17 cities at four-time stages

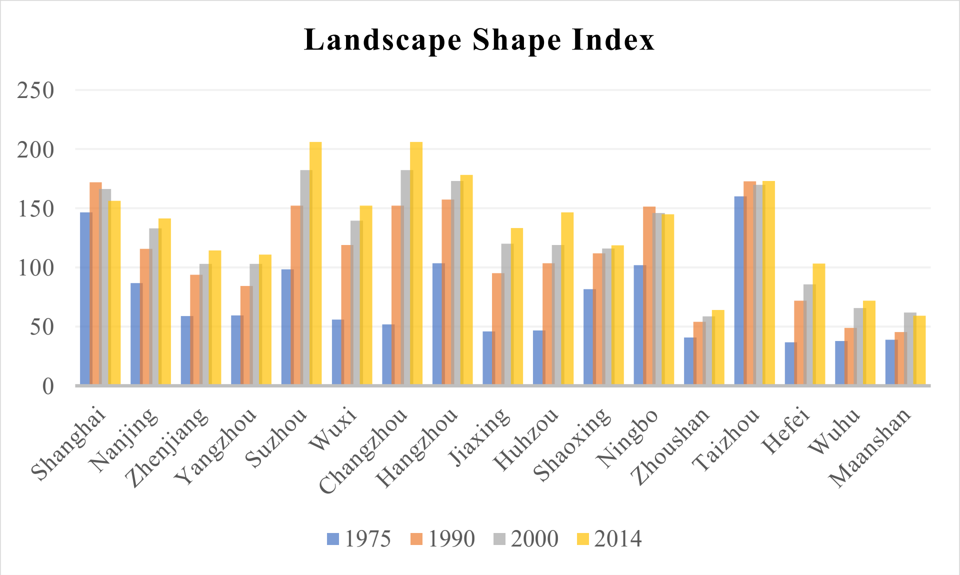

Figure 27. Landscape shape index of 17 cities at four-time stages

4.3.2. Suggestions on land policies

The spatial metrics reflect land-use decision-making that occurred at all administrative levels and different time stages. From urban expansion analysis in section 4.2, there was not a uniform expansion pattern which could be applied for all the 17 cities. However, the cities in the same province especially in the same metropolitan circle seems had the similar characteristics of spatiotemporal urban development. Specific measures referred to total and incremental amount of built-up area, the level of built-up area aggregation, complexity and fragmentation should be created for ‘fit-for-purpose' land policies. At least one type of urban expansion pattern should have a target policy.

The general principles of planning policies related to urban expansion are limit total and incremental urban area and promote saving and intensive use of urban land. Total built-up area index can be analyzed for urban land amount in policies. Large patch index, aggregation index and patch COHESION index reflect integration level of built-up area. Number pf patches and Landscape index represent spread degree of built-up patches. High value of aggregated metric and spread degree metric indicates compact and interpreted urban expansion. Thus, these metrics can be used for monitoring urban expansion for future policies making. Furthermore, if existing policies of these 17 cities were met effectively which can be worth learning for other cities with similar cultural area in the same provinces.

4.4. Discussion and limitation

- Synthesis of findings

To study the spatiotemporal pattern dynamics of urbanization process in the YRD metropolitan region, the GHSL was used to provide thematic information for urban expansion. As mentiond in section 4.1, overall classification, users' accuracy and kappa statistics of the GHSL are all higher than 0.7 to provide foundation for further analysis. There was a researche validated the quality of the GHSL for 12 urban sites, the mean accuracy measures were overall classification 82.28% and Kappa statistic were 0.623 respectively (Esch et al., 2017). And the overall accuracy and Kappa statistic of Beijing were 84.02% and 0.613 (Esch et al., 2017).

The extent of AWMPFD was used to analyze urban expansion pattern for the 17 cities in the YRD metropolitan region. Table 15 provides a synthesis of findings on the urban expansion patterns which was identified by AWMPFD mentioned in section 4.2.2. Urban expansion pattern is classified into five types by two studies, infilling, edge extension spontaneous, isolated development, linear development and spontaneous devotement (Berling-Wolff & Wu, 2004). And The spatial evolution of cities can be described as diffusion process and coalescence process (Dietzel et al., 2005). Both infilling and edge extension are considered as a compact expansion which is a coalescence process (Tian et al., 2010). From Table 15, there were two urban expansion patterns of the 17 cities in the YRD metropolitan region, infilling and edge extension. And after 1975, the edge extension was the dominant urban expansion pattern. It means no additional urban patches occurred as the total built-up area increases. Thus, coalescence process is the dominant expansion process for the 17 cities as well as the YRD metropolitan region after 1975. A previous study also described the coalescence process occurred during 1990 to 2005 in the YRD region (Tian et al., 2010). Spatial metrics were comprised by spider charts to interpret characteristics of urban development. The 17 cities were divided into five groups as Table 16 showed. The cities in Jiangsu and Zhejiang provinces had a higher degree of active urban expansion than the cities in Hefei. Furthermore, based on the analysis in section 4.2 and information shoed in Table 15 and Table 16, similarities of urban expansion processes existed in cities which belong to the same province. And city with same size (classified by urban population) and same administrative level did not show obviously similar characteristics during urban expansion process in the YRD region from 1975 to 2014.

Table 15. Urban expansion pattern AWMPFD of 17 cities

Cities	1975-1990	1990-2000	2000-2014	Administrative level
Shanghai	Edge extension	Edge extension	Edge extension	Provincial city
Nanjing	Edge extension	Edge extension	Edge extension	Sub-provincial city
Zhenjiang	Edge extension	Edge extension	Edge extension	Prefectural city
Yangzhou	Edge extension	Infilling	Edge extension	Prefectural city
Suzhou	Infilling	Edge extension	Edge extension	Prefectural city
Wuxi	Edge extension	Edge extension	Edge extension	Prefectural city
Changzhou	Edge extension	Edge extension	Edge extension	Prefectural city
Hangzhou	Edge extension	Edge extension	Edge extension	Sub-provincial city
Jiaxing	Edge extension	Edge extension	Edge extension	Prefectural city
Huzhou	Edge extension	Edge extension	Edge extension	Prefectural city
Shaoxing	Edge extension	Edge extension	Edge extension	Prefectural city
Ningbo	Edge extension	Edge extension	Edge extension	Sub-provincial city
Zhoushan	Edge extension	-	Edge extension	Prefectural city
Taizhou	Edge extension	Edge extension	-	Prefectural city
Hefei	Edge extension	-	-	Sub-provincial city
Wuhu	Infilling	Edge extension	Edge extension	Prefectural city
Maanshan	Infilling	Edge extension	Infilling	Prefectural city

Table 16. Characteristics of urban form and structure changes for 17 cities

City	Province
Group 1 High aggregation, complexity and fragmentation	
Suzhou	Jiangsu province
Wuxi	Jiangsu province
Changzhou	Jiangsu province
Group 2 High aggregation, lower complexity and fragmentation	
Nanjing	Jiangsu province
Zhenjiang	Jiangsu province
Hangzhou	Zhejiang province
Jiaxing	Zhejiang province
Ningbo	Zhejiang province
Taizhou	Zhejiang province
Group 3 High aggregation, low complexity and fragmentation	
Yangzhou	Jiangsu province

Shaoxing	Zhejiang province
Hefei	Anhui province
Wuhu	Anhui province
Maanshan	Anhui province
Group 4 **Lower aggregation, high complexity and fragmentation**	
Huzhou	Zhejiang province
Zhoushan	Zhejiang province
Group 5 **Highest aggregation, high complexity and fragmentation**	
Shanghai	Provincial city

A series buffers and total built-up area and SHAPE index were used for zonal-based analysis in the YRD metropolitan region. As mentioned in section 4.2.3, the built-up area increased in all buffers over time for 15 cities. Only the built-up area of Taizhou decreased in one buffer zone in 2014. The spatial characteristics of urban expansion were divided into two categories by SHAPE index: built up areas are first rather compact and then complexity rises, either until the last buffer, or a decrease in complexity can be seen again. Only Taizhou had fluctuant trend of SHAPE index across buffer zones. Wuhu and Maanshan belonged to the second group and other 14 cities belonged to the first group. As mentioned before, coalescence process was the main expansion process for all the 17 cities. However, Shanghai had less complexity of built-up patches after 1990, Maanshan has less complexity after 2000 according to the value changes of landscape shape index. Zhoushan, Ningbo and Taizhou had high values of SHAPE index compared to other 14 cities. This is likely because they are coastal cities with many small islands around city centre.

There are two main goals in land planning policies, limit urban area increase and make built-up area more aggregated for intensive use during urban expansion. Dramatic increase of built-up area was seen for the 17 cities in the YRD region. Only Shanghai, Ningbo and Maanshan has less complexity of built-up area. Therefore, policies still need to be strengthened for these two targets. Monitoring the amount of total built-up area and increased built-up area can be used to identify whether urban area is expansion excessively fast. And monitoring the expansion outside the city centers, margin area development can be investigated. The establishment of urban area development for margin area can make contribution to balanced urban expansion. The combination of decreasing numbers of urban patches, and increasing values of landscape shape index, aggregation index, COHESION index is an indicator that urban expansion become more compact. Finally, the decrease of largest patch index indicates a more balanced urban expansion pattern. Thus, specific policies can be created based on these analyses.

- Limitations of the study

To some extent, the results of accuracy assessment are limited by the limited experience of visual interpretation and the numbers selection for random sampling points. From the section 4.1, different selection of random sampling points amount resulted in different values of indicators.

However, the accuracy assessment with enough Wudapt points produced satisfying results regarding the accuracy of the GHSL for urban expansion analysis.

In this thesis, the selection of city centres was a challenge. First, it was not possible to locate city centres for 17 cities by local knowledge. Therefore, city centers were chosen based on land cover by built-up area in 1975. However, second, the geographic centre of 1975 is also not appropriate for all the cities as Wuxi and Changzhou. Because centres of 1975 were out of aggregated built-up patches in 1990, 2000 and 2014 for Wuxi and Changzhou. Therefore, centres of 1990 were used for these two cities. The size and number of buffer zones is also difficult to decide. The buffer zone should represent the urban core at each time stage and also cover the built-up area of each city as much as possible. Some metrics do not work for coastal cities with islands such as largest patch index. There are many small islands in coastal cities such as Ningbo, Zhoushan and Taizhou. In addition, due to the data unavailability, only land planning policies about urban expansion were used in the policy analysis. Other relevant policies such as urban planning policies were not analyzed for urban expansion.

5. CONCLUSIONS

Understanding the changes of urban pattern and form will be important for quantifying and hopefully mitigating the impact of urban expansion for a sustainable urban development. Therefore, the overall objective of this thesis was to explore spatiotemporal patterns of urban expansion in in the Yangtze River Delta using the global human settlement layer (GHSL) as main data source. More precisely, dynamic characteristics of urban expansion were presented for the 17 cities in the YRD metropolitan region. A multi-scale approach was used in this thesis on the level of the metropolitan region and for 17 cities in the YRD metropolitan region as well. For each city, results are presented for the whole city as well as for six buffer zones which provide zonal-based analysis from the cities' centers in detail. Three sub-objectives were addressed: (1) To assess the quality of the GHSL for the purpose of urban expansion analysis.; (2) To analyze the pattern and pace of urban expansion for the YRD from 1975 to 2014 using GHSL; (3) To provide suggestion for the improvement of urban expansion management and control in terms of land policies.

First, reference data were used for accuracy assessment of the GHSL in the YRD metropolitan region. Three indicators, namely overall classification, users' accuracy and kappa statistic, were used for classification quality assessment of the built-up area. All values were satisfactory (i.e. higher than 0.7). Therefore, the GHSL was considered appropriate for further urban expansion analysis.

Second, the results showed that the built-up area of the whole YRD metropolitan region became larger and more complex. Between 1975 to 2014, patch margin extension was the expansion pattern for 14 of the 17 cities within the YRD metropolitan region. From 1975 to 1990, the expansion pattern of Suzhou, Wuhu and Maanshan can rather be described as infilling type. And between 1990 and 2000, urban expansion pattern of Yangzhou was infilling; while Hefei and Zhoushan had no obvious expansion pattern at this stage. After 2000, patch infilling became the predominant urban expansion pattern only for Maanshan. Hefei and Taizhou had stable values of AWMPFD. Both edge expansion and infilling patterns belong to coalescence process. Thus, it indicated that coalescence process was the major expansion model after 1990 in the YRD metropolitan region. Based on spatial metrics comprised by spider charts, the 17 cities were divided into five groups. Cities of coastal province Jiangsu and Zhejiang had higher degree of active urban expansion than cities of new member in the YRD metropolitan region, Anhui province. In most cities, built-up area increased in all six buffers over time. And coastal cities were likely to have higher values of SHAPE index. Furthermore, as mentioned in section 4.4, it was apparent that cities in the same province had similar urban expansion characteristics according to analysis of spatial metrics. Finally, the analysis showed that urban expansion characteristics is not scale-dependent among these 17 cities.

Third, land planning policies were analyzed for urban expansion. Metrics were divided into two categories for the two policy targets related to urban expansion. Total built-up index was used to check if the total and incremental urban area were limited effectively. Large patch index, aggregation index, COHESION index, number of patches and landscape index represent aggregation and complexity level of urban land which reflect intensive use for urban area. All the cities had obviously increasing value of built-up area index; and only a few cities became more compact after 2000. Thus, more specific policies should be created aiming at different expansion pattern to meet two main targets for mitigating wasteful urban expansion. As mentioned in 4.4, monitoring urban expansion by built-up area index, number of patches, landscape shape index, aggregation index, COHESION index and largest patch index is necessary for future policy making. And it will also help to alleviate negative influence of urban expansion and coordinating the relationship between human and land resource.

Urban expansion processes in the YRD will be further promoted by population increase. And population is unevenly distributed in each city. For example, a city can have more than one urban core with different functions like tourism center, commercial and shopping centre as well as leisure and entertainment centre. In such a case, multiple city centres can be considered for urban expansion analysis across buffers. Furthermore, future studies should investigate more policies which have indirect influence on urban expansion to analyze the relationship between policy and urban pattern. Finally, predicting the future trend of urban expansion by modeling which can also provide suggestion on future policies for sustainable urban development.

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LIST OF APPENDIX

Table 1. Spatial metrics for the 17 cities from 1975 to 2014

Shanghai	1975	1990	2000	2014
CA	60,552.11	133,679.75	182,266.31	270,353
LPI	2.55	6.17	8.71	13.94
ED	15.28	26.66	30.07	34.32
AWMPFD	1.28	1.29	1.30	1.33
NP	13,488	25,373	25,146	20,981
PD	1.43	2.69	2.67	2.22
LSI	146.49	172.05	166.30	156.23
AI	77.36	82.09	85.18	88.58
COHESION	99.17	99.41	99.58	99.76
TE	14,414,372.3	25,148,216.7	28,364,536.6	32,379,099

Nanjing	1975	1990	2000	2014
CA	25,711.39	49,954.93	66,938.11	106,366.6
LPI	0.83	2.00	2.94	4.43
ED	6.06	11.27	14.99	20.09
AWMPFD	1.23	1.26	1.27	1.28
NP	5,941	11,894	15,567	16,485
PD	0.65	1.30	1.70	1.80
LSI	86.68	115.73	133.00	141.46
AI	79.51	80.34	80.47	83.52
COHESION	98.12	98.82	99.11	99.33
TE	5,561,476	10,340,914.8	13,749,208.8	18,424,004

Zhenjiang	1975	1990	2000	2014
CA	10,202.06	24,967.32	34,459.33	56,834.36
LPI	0.42	0.87	1.05	1.19
ED	4.46	11.09	14.31	20.38
AWMPFD	1.19	1.19	1.21	1.22
NP	3,001	7,922	9,250	11,296
PD	0.56	1.48	1.73	2.11
LSI	58.97	93.80	103.01	114.34
AI	77.96	77.50	78.94	81.79
COHESION	96.50	96.81	97.44	97.93
TE	2,383,145.75	5,922,683.77	7,640,666.04	10,881,599

Yangzhou	1975	1990	2000	2014
CA	9,698.12	26,716.20	37,299.65	64,038.63
LPI	0.24	0.64	0.77	1.37
ED	2.51	5.89	8.26	11.96
AWMPFD	1.20	1.21	1.20	1.22
NP	2,943	7,371	10,238	11,932
PD	0.317	0.79	1.09	1.27
LSI	59.58	84.45	103.01	110.90
AI	77.14	80.43	80.29	83.37
COHESION	96.58	97.32	97.26	98.28
TE	2,349,780.56	5,522,569.06	7,749,972.38	11,221,672

Suzhou	1975	1990	2000	2014
CA	19,914.05	63,892.27	111,377.47	238,277.6
LPI	0.33	0.68	1.52	4.16
ED	4.77	13.21	20.87	34.46
AWMPFD	1.20	1.17	1.20	1.28
NP	7343	20,141	27,513	29,384
PD	0.63	1.73	2.36	2.52
LSI	98.32	152.29	182.26	205.95
AI	73.55	77.09	79.21	83.94
COHESION	96.57	95.95	98.09	99.27
TE	5,552,074.13	15,385,287.8	24,302,659.5	40,127,198

Wuxi	1975	1990	2000	2014
CA	4,705.62	48,590.65	73,782.62	135,665.13
LPI	0.02	1.52	2.32	6.07
ED	2.41	16.49	23.83	35.18
AWMPFD	1.12	1.18	1.22	1.28
NP	2,356	13,153	16,593	18,093
PD	0.37	2.07	2.61	2.85
LSI	55.87	119.00	139.51	152.14
AI	69.25	79.50	80.48	84.30
COHESION	85.93	97.00	98.17	99.30
TE	1,532,734.78	10,480,490.60	15,140,265.80	22,356,051.00

Changzhou	1975	1990	2000	2014
CA	5,337.66	63,892.27	111,377.47	238,277.60
LPI	0.10	0.68	1.52	4.16
ED	2.51	13.21	20.87	34.46
AWMPFD	1.13	1.17	1.22	1.28
NP	2,201	20,141	27,513	29,384
PD	0.36	1.73	2.36	2.52

LSI	51.98	152.29	182.26	205.95
AI	73.14	77.09	79.21	83.94
COHESION	90.53	95.95	98.09	99.27
TE	1,521,001.54	15,385,287.80	24,302,659.50	40,127,198.00

Hangzhou	1975	1990	2000	2014
CA	22284.61	66947.46	98614.82	160816.05
LPI	0.25	0.76	1.01	1.84
ED	0.44	1.20	1.64	2.33
AWMPFD	1.17	1.20	1.23	1.28
NP	263	617	705	677
PD	0.01	0.03	0.03	0.03
LSI	16.70	26.74	29.79	33.59
AI	27.29	33.15	39.44	46.55
COHESION	62.99	76.75	81.09	92.63
TE	1,005,509.38	2,726,205.02	3,713,689.91	5,286,971.00

Jiaxing	1975	1990	2000	2014
CA	5,026.83	22,747.21	38,425.84	76,039.24
LPI	0.08	0.46	0.63	1.11
ED	2.42	10.64	17.41	27.22
AWMPFD	1.16	1.17	1.18	1.21
NP	1,811	8,350	27,513	15,155
PD	0.34	1.55	2.36	2.81
LSI	45.91	95.23	119.99	133.45
AI	75.59	76.03	76.75	81.60
COHESION	92.93	95.153	95.57	97.44
TE	1,303,726.53	5,738,735.73	9,387,924.07	14,677,395.00

Huzhou	1975	1990	2000	2014
CA	3,597.10	17,694.24	27,502.78	56,902.28
LPI	0.06	0.15	0.32	0.55
ED	1.43	7.00	10.00	17.72
AWMPFD	1.13	1.13	1.16	1.18
NP	2,005	9,324	12,240	18,114
PD	0.25	1.18	1.55	2.30
LSI	46.82	103.69	118.88	146.58
AI	70.60	70.37	72.77	76.62
COHESION	88.89	89.53	93.55	96.02
TE	1,123,600.38	5,518,097.44	7,872,196.74	13,963,235.00

Shaoxing	1975	1990	2000	2014
CA	14,142.71	43,988.30	53,026.04	83,891.19
LPI	0.15	0.42	0.43	1.29
ED	3.68	8.87	10.08	12.94
AWMPFD	1.14	1.17	1.18	1.23
NP	5,635	97,80	10,432	11,986
PD	0.53	0.92	0.99	1.13
LSI	81.71	112.06	116.03	118.60
AI	73.95	79.72	80.86	84.46
COHESION	92.34	95.94	96.39	98.55
TE	3,888,630.37	9,382,573.41	10,666,617.1	13,688,364.00

Ningbo	1975	1990	2000	2014
CA	18,688.68	78,217.868	102,797.078	159,502.90
LPI	0.05	0.90	1.53	2.62
ED	4.70	14.28	15.76	19.42
AWMPFD	1.15	1.20	1.22	1.24
NP	8,538	17,830	17,799	17,482
PD	0.72	1.50	1.50	1.48
LSI	101.85	151.44	146.01	144.92
AI	71.70	79.41	82.69	86.21
COHESION	91.34	97.63	98.34	99.05
TE	5,572,330.20	16,919,589.50	18,670,478.30	23,015,788.00

Zhoushan	1975	1990	2000	2014
CA	1,871.73	7,828.72	9,983.98	14,140.67
LPI	0.04	0.51	1.53	1.14
ED	4.28	11.58	14.10	18.17
AWMPFD	1.10	1.15	1.15	1.17
NP	1,339	2,383	2,803	3,259
PD	0.81	1.45	1.70	1.98
LSI	40.76	54.12	58.62	64.07
AI	64.47	76.90	77.87	79.64
COHESION	81.92	93.03	93.75	95.51
TE	704,452.61	1,908,236.45	2,323,524.11	2,993,350.00

Taizhou	1975	1990	2000	2014
CA	25,998.71	78,318.07	96,713.73	112,695.70
LPI	0.04	1.69	2.22	3.05
ED	8.35	15.62	17.01	18.67
AWMPFD	1.16	1.26	1.27	1.27
NP	16,184	18,558	18,612	19,254
PD	1.31	1.50	1.51	1.56

LSI	160.00	172.68	169.75	172.96
AI	62.21	76.51	79.23	80.40
COHESION	89.04	98.95	99.18	99.34
TE	10,320,467.70	19,296,238.00	21,021,596.60	23,066,504.00

Hefei	1975	1990	2000	2014
CA	1,255.90	18,850.52	26,496.37	53,551.30
LPI	0.01	1.03	1.24	3.26
ED	0.50	3.78	5.34	9.15
AWMPFD	1.10	1.27	1.27	1.27
NP	1,115	4,901	6,626	8,007
PD	0.11	0.47	0.637	0.77
LSI	36.81	71.88	85.70	103.22
AI	60.84	80.20	80.06	83.09
COHESION	80.58	98.96	98.88	99.54
TE	522,797.70	3,948,252.01	5,578,368.8	9,549,514.00

Wuhu	1975	1990	2000	2014
CA	5,747.82	9,282.26	14,305.14	23,982.08
LPI	0.64	0.87	1.64	2.73
ED	2.54	4.19	6.95	9.87
AWMPFD	1.23	1.21	1.24	1.25
NP	1,164	2,480	4,240	4,525
PD	0.26	0.55	0.94	1.01
LSI	37.76	48.98	65.58	71.848
AI	81.368	80.868	79.298	82.46
COHESION	97.918	97.47	98.40	98.86
TE	1,143,627.14	1,886,604.50	3,130,900.48	4,442,615.00

Maanshan	1975	1990	2000	2014
CA	6,196.84	10,619.52	14,995.46	24,428.90
LPI	1.53	2.71	3.50	4.98
ED	4.96	7.58	12.24	14.90
AWMPFD	1.26	1.25	1.26	1.25
NP	1,196	2,251	3,816	3,757
PD	0.48	0.91	1.55	1.52
LSI	39	45.52	61.90	59.15
AI	81.46	83.40	80.93	85.74
COHESION	98.57	98.73	98.75	98.87
TE	1,224,918.95	1,872,310.59	3,021,517.70	3,678,502.00