Analysis of Urban Form Parameters with a Focus on Energy Consumption

By

Jie Zhao

A doctorate dissertation submitted to the Faculty of Spatial Planning at TU Dortmund University in partial fulfillment of the requirements for the degree of Doctor of Engineering

Dissertation Committee:

Chairman: Univ.- Prof. Dr. Dietwald Gruehn

Supervisor: Univ.-Prof. Dr. habil. Nguyen Xuan Thinh

Supervisor: Univ.-Prof. Dr.-Ing. Ralf Bill

Disputation Date： 15.07.2016

July 2016, Dortmund

Acknowledgements

I would like to take this opportunity to express my heart-felt gratitude to a great many people who have contributed to the production of this dissertation.

My deepest gratitude is to my supervisor, Prof. Dr. Nguyen Xuan Thinh for his enthusiasm, encouragement, and faith in me throughout. He inspired me to create new ideas and to validate that further. He has been always there to give me the guidance when I felt confused on the study road. His patience and support helped me overcome many crisis situations both in my life and study. I have been extremely fortunate to be a student of my dear supervisor.

I wish to express my warmest gratitude to my co-supervisor Prof. Dr. Ralf Bill for his immediate review and feedback. His insightful comments enriched my ideas and grammar correction improved the readability. I am so thankful to him for carefully reading and commenting of this dissertation. I am grateful to Prof. Dr. Dietwald Gruehn, the chairman of my disputation, for his considerable advice and support as well.

My sincere gratitude is expressed to Dr. Jan W. Owsiński from Systems Research Institute, Polish Academy of Sciences. He gave me positive answer and effective solutions to the questions confused me in the part of panel data analysis. I am also indebted to the former or current members of the Department of Spatial Information Management and Modeling with whom I have interacted during these years, Szilvia Kollár, Kathrin Schulte-braucks, Florian Spieß, Jakob Kopec, Mu Yang, Jie Zhang, Yan Chen, Yong Xu. I am grateful to them for their various forms of support during my study.

Many friends helped me adjust to a new country. I did not feel loneliness through their care and attention and because of them my study experience has been more colorful. I greatly value their friendship and I deeply appreciate their belief in me.

Most importantly, I wish to express my warmest gratitude to my parents and young sisters. They give me a family with constant love and strength. It is the source of my power to overcome difficulties all these years. I have to give a special mention for the support given by my husband, Dr. Cheng Li, who has helped me stay sane and supported me to overcome setbacks through these difficult years. I would like to express my deepest gratitude and love to him for his company and concern.

Finally, I appreciate the financial support from China Scholarship Council (Grant number: 201206420002) that funded the research.

Abstract

As the center of human activities and socioeconomic development, urban area is the greatest contributor to energy consumption. The significant increase in energy consumption has profound social, economic, and environmental consequences. Suppressing energy consumption while maintaining rapid economic development in urban areas constitute a key challenge for the sustainable development. With the consideration of the importance of energy saving and the key challenge, it is becoming increasingly urgent to formulate and implement effective measures to promote energy efficiency in order to mitigate climate change.

However, previous related studies presented us with some major challenges. The studies are limited in exploring the quantitative relationship between energy consumption and urban form from the perspective of spatial patterns. Furthermore, the studies were conducted only at global or national level. Consequently, the analysis of the relationship suffers from a lack of knowledge and understanding of the relationships at urban scales. Although most of the developed countries are well equipped with detailed and consistent energy consumption data, the absence of urban energy consumption data still occurs in China and other developing countries, which makes the analysis of energy consumption more difficult. In addition, the previous studies ignored the prediction and comparison of future energy consumption. Considering these challenges and limitations in previous studies, it is important to develop and apply modified methods for better understanding the effect of urban form on energy consumption in order to design viable and scientific energy saving policies. 20 province capital cities in China were selected as the study area.

In order to derive urban land use information for the study area, Maximum Likelihood Classification (MLC) was used to classify multi-temporal Landsat images in 2000, 2003, 2006, and 2010. Moreover, a set of spatial metrics were adopted to quantify the urban spatial pattern. The result confirms the effectiveness of the combination of remote sensing and spatial metrics in better understanding the urban spatial pattern and its regional differences. The results indicate the significant differences in the urban form among the cities.

The study developed a new method for estimating urban energy consumption based on nighttime light (NTL) data and statistical province energy consumption. The validation result suggests that the relationship between the province energy consumption and cumulative digital number (DN) value of NTL data can be effectively quantified by power law regression model. Focusing on each study area, the study proposed linear regression model with variable coefficients by modifying the identified regression models within the specific province. The finding proves the effectiveness of the proposed method in building a systematic energy consumption data set for developing countries.

Panel data analysis was employed to estimate whether and to what extent the spatial patterns of urban form are correlated with energy consumptions. In order to address the concern whether the impact of urban form on energy consumption differs across regions in China, the panel data analysis was conducted at two different levels: national level and regional level. At national level, the result demonstrates a positive correlation between the increasing energy consumption and the growth of urban areas. Moreover, it is found that the increase in number of urban patches could result in rising energy consumption. The dominance of the largest urban patch is positively correlated with urban energy consumption. The finding also indicates the positive relationship between irregularity of urban land use pattern and energy consumption. The energy consumption will increase when the spatial connection between relatively smaller patches and city core is strong. At regional level, the impact of the urban form on energy consumption varies across regions. Therefore, the planning and land use management should consider the disparities of regions in order to lessen regional disparities and realize balanced development.

The method that integrates panel data model and cellular automata (CA) was proposed to simulate the future urban form and to predict the corresponding energy consumption. The CA model is developed and further applied to simulate various urban forms under three different development scenarios (business as usual, compact development, and dispersed development) in 2020 for four representative cities. Based on these metrics values of different scenarios, the panel data model was adopted to calculate the future energy consumption for each scenario. The combination of scenario simulation and the panel data model has proved to be capable of predicting the future energy consumption with focus on the historical development trend and various strategies. The finding suggests that a compact urban development is highly beneficial for fast growing cities in China in order to achieve high efficiency of energy use and sustainable development. Moreover, the result can form a basis for urban development policy recommendations towards sustainable urban development.

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List of Abbreviations

AI	Aggregation Index
BAU	Business As Usual
CA	Cellular Automata
CD	Compact Development
CLUE	Conversion of Land Use and its Effects
CO_2	Carbon dioxide
COHESION	Patch Cohesion Index
CR	Central Region
DD	Dispersed Development
DEM	Digital Elevation Model
DIVISION	Landscape Division Index
DMSP/OLS	Defense Meteorological Satellite Program/Operational Linescan System
DN	Digital Number
ED	Edge Density
ENN	Euclidean Nearest Neighbor Distance
ENN_AM	Area Weighted Mean Euclidean Nearest Neighbor Distance
ER	Eastern Region
FRAC	Fractal Dimension Index
GDP	Gross Domestic Product
GHG	Greenhouse Gas
GIS	Geographic Information System
GLS	Generalized Least Squares
GRP	Gross Regional Product
IPCC	Intergovernmental Panel on Climate Change
LPI	Largest Patch Index
LSI	Landscape Shape Index
MLC	Maximum Likelihood Classification
NGDC	National Geophysical Data Center

NP	Number of Patches
NR	Northeast Region
NTL	Nighttime Light
PARA	Perimeter Area Ratio
RMSE	Root Mean Square Error
rRMSE	relative Root Mean Square Error
RS	Remote Sensing
RSS	Residual Sum of Squares
SCE	Standard Coal Equivalent
SHAPE	Shape Index
SHAPE_AM	Area Weighted Mean Shape Index
TCT	Tasseled Cap Transformation
U.S.	United States
UTM	Universal Transverse Mercator
WMO	World Meteorological Organization
WR	Western Region

1. Introduction

The motivation of the present study is the awareness of a number of environmental and socioeconomic problems caused by the energy consumption and climate change. The first chapter briefly states the problems related to the energy consumption and indicates the significance of using modified methods to better understand the relationship between energy consumption and urban form. Moreover, the research objectives and questions are presented as well as the structure of the dissertation.

1.1 Background

During the recent decades, significant climate change has been observed globally as a universal and important phenomenon (Zhou et al., 2013a), of which global warming was the most obvious. According to the report of the Intergovernmental Panel on Climate Change (IPCC) and the World Meteorological Organization (WMO), the world is warming because of the increase in greenhouse gas (GHG) emissions (IPCC, 2007). Carbon dioxide (CO_2) emission, which accounts for more than 60 % of GHG emissions, was proved to be the dominant driving factor of global warming (IPCC, 2007). During the past three decades, the CO_2 emission generated from energy usage has grown several-fold.

As the center of human activities and socioeconomic development, urban area cover only 3 % of the Earth's land surface (Dewan & Yamaguchi, 2009), it is, however, the greatest contributor to energy consumption and GHG emissions (Kennedy et al., 2010). Urbanization has been accelerating with the significant increase in urban population. Currently, over half of the world population live in urban areas, and the figure is expected to reach 67.1 % (6.25 billion) by 2050 (United Nations, 2012). Urbanization promotes socioeconomic development and improves living standards, but it has been accompanied by an increase in demand for energy in urban areas and associated CO_2 emission (Al-mulali et al., 2012).

As the largest developing country in the world, China has witnessed dramatic economic growth and fast-paced urban development since the Chinese economic reform in 1978. The level of urbanization rises from 17.9 % in 1978 to 54.8 % in 2014 (China National Bureau of Statistics, 2015). Rapid urbanization has posed some tremendous challenges related to environmental pressures, including energy consumption and CO_2 emission (Zhang & Lin, 2012; Wang et al., 2016). These challenges have attracted great attention around the world. China consumed less than half of the energy consumed by the United States (U.S.) in 2001. In 2010, however, total energy consumption in China was 3606.5 million tons of Standard Coal Equivalent (SCE), exceeding that of the U.S. as the global leader for the first time, and is expected to surpass the U.S. energy consumption by 68 % in 2035. The rapid increase of energy consumption resulted in many environmental and social problems. Regarding to CO_2 emission, China is one of the top three nations for coal-related emissions, and its emissions surpassed that of the U.S. in 2006 (Auffhammer & Carson, 2008). The fossil fuel-related emissions increased dramatically from 671.1 million metric tons of carbon in 1990 to 2459.6 million metric tons of carbon in 2011 in China. Urban areas play a significant role in energy consumption and CO_2 emission in China. Focusing on the urban areas in China, it contributed to 75.2 % of China's total energy consumption and the energy use for each person in urban areas was 6.8 times as that in rural areas in 2009 (Dhakal, 2009). The CO_2 emission produced from urban areas was 73 % of the total emissions in 2011 (Liu et al., 2011). The significant increase in energy consumption has profound social, economic, and environmental consequence. At the same time city administrations also promoted urban development. In China especially urban areas, therefore, have to face increasing pressure in energy saving and emission reducing.

However, suppressing energy consumption and emissions in urban areas while maintaining rapid economic development constitute a key challenge for the local governments (Wang et al., 2014a). With the consideration of the importance of energy saving and the key challenge, it is becoming increasingly urgent to formulate and implement effective measures to promote energy efficiency in order to mitigate climate change. Continual, historical and precise information about energy consumption is prerequisite to the further analysis. In order to better understand the factors of the increasing energy consumption, recent issues related to analyzing its driving factors have attracted increasing attention, ranging from population, Gross Domestic Product (GDP), architectural design and industrial structure to energy efficient production technologies (Ma, 2014; Saidi & Hammami, 2015). In addition to the previous traditional study that focused on traditional consumption saving measures relying on technology and policy solution, urban form is recognized as the main factor that has significant impact on energy consumption (Thomas & Cousins, 1996; Wang et al., 2014b). This highlights the need to study the relationship between urban form and energy consumption to support decision making on sustainable development and climate change.

However, previous related studies presented us with some major challenges. Many studies have addressed a number of parameters related to urban form which can be used to explain the increase of energy consumption, such as the size, shape and function of new urban development, the mixing of land uses, travel patterns (Owens, 1986). The impact of urban form on energy consumption from the perspective of spatial patterns has not been widely analyzed. Furthermore, comprehensive studies on the relationship between urban spatiotemporal patterns and energy consumption are relatively scarce in developing countries, where urbanization process is more significant than those in developed countries. Additionally, the studies only focused on larger regions, such as global or national. Consequently, the analysis of the relationship suffers from a lack of knowledge and understanding the relationships at urban scales. As centers of human activities, urban areas play a significant role in improving energy efficiency. Estimating energy consumption at the urban scale is therefore the first step for decision adaptation and mitigation of climate change (Li et al., 2012a). In addition, because of the imbalances in the socioeconomic development level, the characteristics of energy consumption in different regions display different patterns. Therefore, the regional disparities on the energy consumption need to be carefully considered.

The study of urban energy consumption is strongly limited by the quality of the energy consumption data. Although most of the developed countries are well equipped with detailed and consistent energy consumption data, the absence of energy consumption data at the urban scale still occurs in China and other developing countries, which makes the monitoring and analysis of energy consumption more difficult. Moreover, prediction and comparison of future energy consumption can provide an important support for decision making in implementation of appropriate energy saving and emission reduction measures. Most studies only considered the time-series prediction, while less attention has been given to the longitudinal and cross comparisons of energy consumption under different scenarios. Considering these challenges and limitations in previous studies, it is urgent to develop and apply modified methods for better understanding the effect of urban form on energy consumption in order to make viable and scientific energy saving policies.

1.2 Research objectives and key questions

1.2.1 Research objectives

Urban form, normally referring to the spatial pattern and structural feature of urban land use, has experienced significant variation along with the rapid industrialization and urbanization (Tsai, 2005). Compact or dispersed development is a hot topic in urban form study. A wide variety of spatial metrics were developed to quantify the urban form, such as largest patch index (LPI), number of patches (NP), Euclidean nearest neighbor distance (ENN), and Shape index (SHAPE). Compared with the progress in quantification of urban form, the impact of urban form on energy consumption is not fully understood. The main objective of this dissertation is to propose an improved methodology to estimate energy consumption at the urban scale and analyze the impact of urban form on energy consumption in order to understand them better and to support effective urban planning and policy to promote energy efficiency. The focus is on the investigation of urban spatial pattern from remote sensing (RS) images; estimation of energy consumption at the urban level; assessment of the relationships between energy consumption and urban form; forecasting of future energy consumption. The specific objectives are:

1) To derive and analyze the historical urban form within the investigation areas using RS data and a series of spatial metrics. As the first step in this study, it is urgent to derive accurate classification data from RS images as well as to effectively represent the urban form by adopting selected measures.
2) To estimate the multi-regional energy consumption at the urban scale. The data collection at the urban scale is the first step for analysis of the relationship between urban form and energy consumption, as well as for adaptation and mitigation of climate change by local governments. However, it is limited by the

absence of the comprehensive, consistent, and reliable data on energy consumption at the urban scale.

3) To explore and quantify the relationship between urban form and energy consumption during the rapid urbanization process. The question is that multiple time points data are usually involved in the exploration of relationship. In addition, the spatial heterogeneity can cause the relationship to change among individuals. Therefore, it is important to recognize and solve this problem in this study.
4) To forecast future energy consumption under different urban development scenarios based on the relationship between the urban form and energy consumption. The design of the scenarios is strongly linked to the current concerns of policy makers of the region. The result can provide an answer to “what if” question. Furthermore, forecasting future energy consumption will provide an important reference for policy makers in urban planning and implementation of appropriate energy conservation measures under the consideration of differences of the specific scenarios.

1.2.2 Research questions

In this context, the main challenge of this study is to better understand the effect of urban form on energy consumption and to provide guidance for the formulation of future urban planning and decision making. Under this challenge, the following questions are raised and need to be answered:

1) How to accurately estimate the energy consumption at the urban scale?
2) How to quantify the urban form effectively?
3) How to explore the relationship between urban form and energy consumption, dealing with data from multiple individuals over multiple periods?
4) How to predict the future urban energy consumption?

1.3 Organization of the dissertation

This dissertation consists of six chapters that cover the logical framework of the study. After the introduction presented in this chapter, a theoretical framework for this study is given in chapter 2. First, it covers the conceptual basis in the context of urban form, urban energy consumption and the relationship between them. Following the related approaches and their advantages and limitations are introduced.

Chapter 3 is concerned with the study areas in China. After the establishment of the theoretical framework, the socioeconomic characteristics of the study areas are introduced briefly in the national context of China. Additionally, the database for this study is described, which includes several types of RS data as well as other statistical data.

Chapter 4 focuses on methodology in this study, presenting the methods used for quantifying urban form, estimating energy consumption at the urban scale, exploring the relationship between urban form and energy consumption, as well as developing simulation model to predict the future energy consumption. In detail, this chapter consists of three parts. In the first part, RS classification method is proposed in order to derive urban land coverage from multi-temporal Landsat images. Furthermore, a set of spatial metrics for quantifying the urban form are described. In the second part, the nighttime light imagery and statistical energy data are applied to estimate the energy consumption at the urban scale. The panel data analysis is further used to explore the relationships between urban form and energy consumption. The last part proposes cellular automata (CA) model to simulate the future development scenarios and calculate the future energy consumption under specific scenarios. Three scenarios are developed to present different urban forms under various development strategies. Moreover, the energy consumption under different scenarios are evaluated and compared in order to assess the impacts of different urban forms on urban energy consumption.

Chapter 5 presents the results generated by using the methods. In addition, the discussions are given in this chapter. In chapter 6, the answers to the research question proposed in chapter 1 are summarized. Based on the results in this study, the implications of future development are provided.

2. Theoretical background

Since the focus of this study is on analyzing the relationship between energy consumption and urban form, this chapter presents a brief outline of the theoretical background of this theme. The important concept associated with the sustainable urban form is explained. Moreover, the related methods are introduced and compared to provide a general impression about the strength and limitation of these methods.

2.1 Conceptual basis

2.1.1 Sustainable urban form

Urban form can be defined as the spatial configuration of human activities, which reflects economic, environmental, technological and social processes at a certain time (Tsai, 2005). This consists of the spatial pattern and density of land uses as well as the spatial design of transport and communication infrastructure (Anderson et al., 1996). The urban form has a direct impact on habitat, ecosystems, water quality through land consumption, urban fragmentation, and the conversion from natural cover to urban land use (Camagni et al., 2002), Moreover, a growing body of literature support the notion that urban form strongly influence the energy consumption and the related CO_2 emission. It can be explained by a variety of factors, such as topography, planning efforts, and environmental development. The analysis of urban form can reveal the problems and challenges during the urban development.

With the increasing acceptance of sustainable development as a guiding concept, studies have focused on the urban form that trace back to the start of modern planning and urban studies (Conzen, 2001). The most widely cited definition of sustainable development is “development that meets the needs of the present without compromising the ability of the future generations to meet their own needs” (World Commission on Environment and Development, 1987). The current rapid urban growth brought about a series of environmental as well as socioeconomic problems which form a great challenge for sustainable development.

The links between urban form and sustainable development is one of the most hotly debated issues at present. Is there actually a connection between urban form and sustainable development (Holden & Norland. 2005). Breheny (1996) argued that since the late 1980s, urban form would be central to the promotion of sustainable development. Echenique et al. (2012) tested rigorously and realistically the relative performance of spatial options for three distinct kinds of English city regions. They argued that urban form policies can have important impacts on local environmental quality, economy, crowding, and social equity, but their influence on energy consumption and land use are very modest. Jenks et al. (1996) pointed out that there is a significant relationship between urban form and sustainable development, although it is not simple and straightforward. From this point of view, the sustainable form "must be of a form and scale appropriate to walking, cycling and efficient public transportation, and with a compactness that encourages social interaction" (Elkin et al., 1991).

Concerning the energy consumption, much extensive research has found that a dominant share of urban energy consumption belongs to transportation energy, which has a strong relationship with urban form in the intra-city level (Long et al., 2013). Ewing and Rong (2008) present a conceptual framework linking urban form to residential energy use via three causal pathways: electric transmission and distribution losses, energy requirements of different housing stocks, and space heating and cooling requirements associated with urban heat islands. From this point of view, the impact of urban form on energy consumption are mainly reflected by two aspects, transportation energy use and residential energy use.

A growing number of studies searched for a sustainable urban form aiming at reducing the negative effects of rapid urbanization. Undoubtedly, it motivated researchers in different disciplines to look for suitable urban forms for human settlements that will enable built environments to function in a more constructive way than at present and meet the requirements of sustainability development. However, many indicators evaluating the sustainable urban form have been described only in concept. The translation of descriptive indicators into quantifiable measure remains a major challenge.

Normally, urban form is divided into two types: dispersed form and compact form. The dispersed form remains the dominant pattern of development in China and is an increasing common phenomenon around the world. A series of problems are associated with dispersed development, including wasteful use of land resources, increase in energy consumption and development costs (Li et al., 2008). In contrast to dispersed form, the compact city has received much attention around the world. The term of compact city was firstly proposed by Dantzig and Satty (1973) as the alternative planning objective in dealing with the problems caused by the dispersed city. It is a relative high density and mixed land use city, which is based on efficient public transport system and dimensions that encourage walking and cycling (Burton, 2002). With the unprecedented and ongoing growth of urban areas globally accompanying by negative impacts, there has been tremendous opportunities to apply this concept in order to achieve the sustainable urban form. Hillman (1996) argued that compact city can reduce travel distances, and therefore reduce emissions and greenhouse gases, thus curb global warming. In addition, urban residence in compact city could enjoy lower heating costs and less pollution. Jenks et al (1996) pointed out that compact development should be promoted in order to consume less land during the development period. The study by Banister et al (1997) indicated that there are significant relationships between less energy consumption in transport and compact cities. The compact form is suggested as an urban form for sustainable development (Westerinka et al., 2013).

However, limitations and problems of compact form have been argued, such as road congestion, higher housing prices, reduced access to open space. The question of what kind of urban form should be more sustainable was hotly debated. Some researchers argued that there does not exist one ideal urban form for all cities, depending on the local context, existing urban structure, and political possibilities (Guy & Marvin, 2000). While some researchers argued that dispersed urban form is attractive at an individual level since it satisfies individual preferences, such as more space for per housing unit and quick access to open space, and lower housing prices (Gordon & Richardson, 1997). Therefore, how to select a suitable urban form is an important issue for sustainable development.

2.1.2 Spatial metrics

Luck and Wu (2002) suggested that spatial patterns of urban areas can provide a better understanding of the urban form and its effect on environment. Spatial metrics are already commonly used to quantify the shape and pattern of vegetation in landscape ecology (Gustafson, 1998). They were developed in the 1980s and incorporated measures from both information theory and fractal geometry based on a categorical, patch-based representation of a landscape (Herold et al., 2003). Spatial metrics are effective tools for quantifying spatial heterogeneity and providing a better insight on how spatial structures affect the system interaction in a heterogeneous landscape. Planners and policy makers use the spatial metrics to evaluate and promote policies concerning land use and urban development.

Spatial metrics can be grouped into three classes: patch, class, and landscape metrics. Patches are defined as homogenous regions comprising a specific landscape property of interest such as “urban” or “rural” (Dietzel et al., 2005). Patch metrics are computed for each patch in the landscape. Class metrics are calculated for each class, and landscape metrics are applied for the entire landscape. Variation of spatial patterns can be captured and described by the spatial metrics, which categorize complex landscape into identifiable patterns and reveal some ecosystem properties that are not directly observable (Antrop & Van Eetvelde, 2000; McGarigal et al., 2012). Most of spatial metrics are scale dependent and they are determined by the spatial resolution, the extent of spatial domain, and the thematic definition of the map categories (Šímová & Gdulová, 2012). Spatial metrics can be used to describe and analyze the change in the degree of spatial heterogeneity when applying to multi-temporal data. With consideration of study objective, the spatial metrics are selected to quantify the urban form because they can (1) bridge the gap between urban land use patterns and urban planning, (2) improve the reflection of heterogeneous urban spatial patterns (Herold et al., 2005), and (3) promote the analysis of impacts of urban forms on energy consumptions.

Fragstats reports over 100 different metrics (McGarigal et al., 2012). Many studies used and compared a wide variety of different metrics. Their results showed the role of them in representing spatial patterns. However, there are not the best suitable metrics as the significance of specific metrics varies with the objective of the study and the characteristics of spatial patterns under investigation (Parker & Meretsky, 2004). Furthermore, some studies indicated that only a few of these metrics contain unique information, and thus the use of all spatial metrics is redundant (Gustafson, 1998).

2.2 Estimation of urban energy consumption and analysis of the relationship with urban form

2.2.1 Estimation of urban energy consumption

As centers of socioeconomic activities, urban areas play a dominant role in achieving energy efficiency. Therefore, continual, historical and precise information of energy consumption at an urban scale is becoming increasingly important to analyze the relationship between urban form and energy consumption in order to provide a valuable support for making and implementing associated policies towards energy efficiency. Although most of the developed countries are well equipped with detailed and continual energy consumption information, Meng et al (2014) argued that our current understanding of urban energy consumption and the related factors are largely limited by the absence of comprehensive, consistently-defined and reliable data in the developing countries. With the wide requirement and application of urban energy consumption data, there has been an increasing interest in obtaining the data. According to the literature review, there are three widely used ways:

(1) Obtain energy consumption data from previous studies. Banister et al. (1997) conducted the comprehensive analysis of the relationship between urban form and energy consumption for the study areas based on the data obtained from a sample of previous studies. Similarly, Mindali et al (2004) used the data in the study of Newman and Kenworthy (1989).

(2) Collect the surveyed data. Examples can be found in (Banister, 1996; Dieleman et al., 2002).

(3) Approximate energy consumption by related statistical data. The third way is a widely used method for those study areas like China where energy consumption data

are not accessible. An increasing number of studies are conducting their own estimates at city level, addressing the lack of local energy statistics. Dhakal (2009) applied the statistics of energy consumption per unit Gross Region Product (GRP) to estimate the urban energy consumption. Chen et al. (2011) also used the method to estimate the energy consumption in order to conduct future analysis. This method is applied based on the assumption that the parameters or coefficients are relatively stable across different scales (Dhakal, 2009). This estimated method is to downscale socioeconomic data as well as energy consumption data into scale of interest where direct data is not available (van Vuuren et al., 2010).

Numerous methods have been developed to estimate energy consumption, which may be classified into two ways, bottom-up and top-down methods. Generally, the bottom-up method is an ideal approach for urban energy consumption at urban scale, which could provide reliable estimated data and thus is much preferred by local authority. First step is to determine the energy consumption of each designated city and then divide them into district and town energy consumption. However, it faces challenges in developing countries that lack in local energy data. This is the particular case for urban areas in China, where district's and town's energy data are difficult to access, often incomplete and inconsistent (International Energy Agency, 2008). Energy consumption information is available only for a few large cities. Thus, an aggregated and top-down method is necessary to downscale socioeconomic data as well as energy consumption data into scale of interest where direct data is not available (Chen et al., 2011).

However, most of the studies mainly depended on the statistical data published by China national, provincial and municipal Bureau of Statistics. As the statistical approach on data collection, reporting and validation was opaque, there were always significant discrepancies between national, provincial and city level official statistics of energy consumption, which thereby led to unreliable conclusions.

The Defense Meteorological Satellite Program/Operational Linescan System (DMSP/OLS) was originally used to observe clouds by moonlight (Elvidge et al., 1999). DMSP/OLS can also be applied to detect artificial lighting at night in clear conditions without moonlight. The nighttime light (NTL) data collected by the DMSP/OLS uniquely measures light on Earth's surface such as light generated by settlements and fires (Zhang et al., 2013). A number of studies have proved that NTL data has informational value for countries without consistent and accurate statistical data to monitor the socioeconomic activities and to estimate socioeconomic data such as population (Doll & Pachauri, 2010), income (Chen & Nordhaus, 2011), GDP (Wu et al., 2013) as well as electricity consumption (Letu et al., 2010). Doll et al. (2000) is the first researcher to explore national-level relationships between lit areas and GDP at national level, claiming that over 90 % of the quoted total are properly mapped. Based on this study, Doll et al (2006) proposed further insights into the application of NTL data to downscale national GDP into sub-national scales, revealing linear relationship between total brightness value and GRP. Other studies were also conducted to prove that NTL data can be used as informational value at subnational scale for developing countries (Wu et al., 2013; Meng et al., 2014). Mellander et al. (2013) indicated that NTL data are best applied as a proxy for assessing population and density, and can therefore monitor and quantify urbanization indirectly.

Besides the previous studies focused on the quantified relationship between NTL value and socioeconomic data, some studies also revealed the application of nighttime light data in estimating energy consumption globally. The question is how good is NTL as a proxy to map energy consumption? Few studies have conducted the validation analysis of the quantified relationship, except the pioneering studies by Doll et al (2000) and Ghosh et al (2010), showing the R^2 values of 0.84 and 0.73 respectively, when the NTL was used to map global energy consumption. Although high correlations were found, these studies still focused on the energy consumption at global or national scale. The mapping and estimation of energy consumption by using NTL data at urban scale has attracted few attentions.

Despite the NTL data was widely used in previous studies, there are still some inherent shortcomings of NTL data source, including satellite orbit difference, sensor degradation, and limited radiometric range, limit the ability of NTL data for many applications. Six satellites were used to produce NTL data from 1992 to 2013, and

Operational Line-scan System (OLS) sensors are lack of on-board calibration (Elvidge et al., 2009). Moreover, there is not strict intercalibration for NTL data acquired by different satellites. Therefore, a large number of inconsistent lit pixels are found in NTL data without on-board calibration and intercalibration (Liu et al., 2012).

2.2.2 Factors contributing to energy consumption

It is important to understand factors directly or indirectly contributing to the rising energy consumption. There has been an increasing interest in identifying and understanding the effects of different factors on energy consumption because this knowledge is important for effective urban planning towards energy efficiency and sustainable development. Most of the studies focused on the technical characteristics of energy consumption machinery such as vehicles, space conditioning systems and industrial processes. Still other research efforts have addressed related behavioral issues such as choice of transport mode and adoption of energy-conserving equipment.

Under the background of the rapid urbanization around the world, a large number of studies were concerned with the relationship between urbanization and energy consumption. Most of studies nominated urbanization as one of the most important factors contributing the increase in energy consumption (Zhang & Lin, 2012; O'Neill et al). In addition, Poumanyvong and Kaneko (2010) found that urbanization promotes the increase in energy consumption in the high income countries, while urbanization suppressed the increase in energy consumption in low-income countries. The same results were also supported by the study which indicates that urbanization increases transport consumption and the relationship gets significant in high income countries (Poumanyvong et al., 2012). On the other hand, a negative relationship between urbanization and energy consumption was also found. Paul and Bhattacharya (2004) found that the economic growth is positively related with the decline of CO_2 emissions in all the major economic sectors. The inverted U-shaped relationship was demonstrated by Martinez-Zarzoso and Maruotti (2011).

With the rapid urbanization and growing pressures of energy saving and emission reducing, research on Chinese situation has attracted widespread concerns. Li et al.

(2012b) and Liu et al. (2011) found that urbanization played an important role in the increasing energy consumption in China. At the national level, some studies found the positive relationship between urbanization and energy consumption. Liu (2009) found a long term link between urbanization and energy use, and Shen et al. (2005) further pointed out that China will face a challenge of resource shortage if the speed of future urbanization is faster than forecasted. In addition to national level, a number of empirical results were also reported at the city level in China. It is clear that the city contribution will increasingly determine energy consumption of China in the future because the rate of urbanization is rapid and the energy consumption per capital in cities is growing (Dhakal, 2009). Concerning the Yangtze River Delta, one of the most developed areas in China, Gu et al. (2011) found that urbanization contributed to the increase in CO_2 emission due to the industrial activities, transportation, and household. The cities in Yangtze River Delta contribute to 78 % of CO_2 emission. In both urban and rural areas in China, the residential CO_2 emission increases in response to income effects and decreases in response to energy intensity (Zha et al., 2010). Moreover, the urban household energy consumption was higher than that for the rural household (Feng et al., 2011). For the transportation sector, the study conducted by Zhou et al. (2013b) indicates that urbanization in China increased the level of energy consumption of transportation.

A large number of existing studies decomposed the urbanization process into several indicators, such as population growth, economic growth, technology progress when analyzing the relationship between urbanization and energy consumption. These issues have been analyzed and discussed from different aspects. However, it is widely acknowledged that urbanization is a key cause of the significant change in urban form (Herold et al., 2005). In many Chinese cities, the urban form is undergoing dramatic changes that the compact urban form has been replaced by a more dispersed form along with the urbanization process (Wu & Yeh, 1999). Therefore, the changing urban form also needs to be regarded as one of the main indicators that represent urbanization process.

Urban form is proved as a significant contributor to energy consumption. One important aspect of the debate over sustainable urban form is the relationship between urban form and energy consumption. The efforts to understand the relationship between urban form and energy consumption have been highlighted in recent decades. Previous studies have addressed a number of influencing factors which can be used to explain the relationship between urban form and energy consumption, especially in terms of the effects of urban form on transportation (Hankey & Marshall, 2010), residential energy demand (Liu & Sweeney, 2012), and heat island effects (Stone & Rodgers, 2001). Several aspects of urban form can significantly influence urban energy consumption, such as the size, shape, the mixing of land uses and travel patterns (Owens, 1986). Banister et al (1997) explored the relationship between transport energy use and urban forms for the six study areas in United Kingdom and Netherland. Urban form represented by density and employment was proved to be able to affect transportation energy consumption. However, the coarse data and the inconsistency of variables make the comparison of different cities difficult. Additionally, Ratti et al (2005) analyzed the effects of urban texture on the energy consumption of buildings using digital elevation model (DEM).

The relationship between urban form and energy consumption could be complex. In addition to the previous studies, some other studies indicated that the compact urban pattern can effectively reduce energy consumption from the perspective of spatial patterns of urban land use. Harmaajarvi (2000) found that a compact urban pattern could reduce as much as 35 % of the total energy consumption in 2010, in terms of changes in urban transport and district heating. Ou et al (2013) found similar results that compact and polycentric development patterns help to reduce energy consumption. The finding is consistent with the results of similar studies conducted for Canada by Christen et al. (2011), for China by Wang et al. (2014b), and for U.K by Banister (1997). Taking Beijing as a case study, Ma et al. (2015) explored the impact of urban form on individual's travel behavior and estimated CO_2 emission from work and non-work travel. The study concluded that people living in neighborhood with higher job density produced less CO_2 during work travel and residents living in neighborhood with higher retail density emitted less CO_2 during non-work travel.

Addressing the sustainability of urban form, Ye et al (2015) investigated that urban sprawl aspects of compactness have positive link with urban household energy consumption. By selecting and analyzing the 125 largest urbanized areas in USA, the study conducted by Lee and Lee (2014) investigated how urban form affect household energy consumption and CO_2 emission. The results show that it is necessary to implement smart growth policy in order to reduce household energy consumption. Liu and Sweeney (2012) examined the link between household energy and urban form. The result suggests that the energy consumption could be reduced by developing compact cities.

From the studies above, we could find that urban planning and spatial optimization methods are therefore required to save energy consumption besides the traditional methods (Van de Wal et al., 2011). Urban form, an important variable involved in the urban planning, plays an increasingly important role in achieving an energy efficient city and sustainable development. Although previous studies can provide an insight into how the urban form affects energy consumption, a limited number of studies addressed the quantitative analysis of the impact of the temporal changes in urban form on energy consumption.

In addition, the existing studies mainly analyzed the energy consumption from the perspectives of public transportation, home heating, driving and household electricity usage. However, the impact of urban spatial structure on energy consumption is ignored. Moreover, the role of spatial metrics in representing the spatiotemporal dynamics of urban form was neglected.

The link between urban form and energy consumption at the large scale has been widely analyzed. However, the link at the urban scale has been questioned (Dodman, 2009). The existing study mainly concentrates on investigating the relationships from a national perspective without consideration of regional differences. The study analyzing the relationship between urban form and energy consumption only at a national perspective which could ignore the impacts of spatial heterogeneity, resulting in systematic bias in the estimation and analysis of the relationship (Zhang & Lin, 2012), as well as the inconsistent results that cannot be meaningfully interpreted

(Brunnermeier & Levinson, 2004). China is vast in territory, with significant regional differences in urban development and urban form (Shen et al., 2005). Energy consumption is impacted by regional features both on gross level and the per capita level. So far, little empirical work has been conducted to establish or compare the magnitude of the relationship between urban form and energy consumption across regions in a country with consideration of spatial heterogeneity. Therefore, a further study on the impact of urban form on energy consumption in terms of regional aspects needs to be conducted in order to obtain insight into the regional differences and establish a solid foundation for decision makers to design and implement effective energy consumption policies.

2.2.3 Panel data analysis

In the field of estimating the relationship between energy consumption and driving factors, the existing studies can be classified into several categories, which can be distinguished in terms of their distinct methodological perspectives (Du et al., 2012). Among them, the index decomposition analysis is widely applied based on national level time series data. It was reported that several new decomposition methods have been increasingly used in energy related environmental analysis (Ma, 2014; Ang et al., 1998). A lot of previous studies indicate that index decomposition methods have the ability to estimate the relationship between energy consumption and related factors.

The second category is bottom-up sector based analysis. Typically, this method requires one year of data as the baseline. Based on the results of last step, bottom-up sector based analysis predicts future energy consumption by simulating scenarios. Using this method, He et al (2005) and Wang et al (2007) attempted to predict future trends of oil consumption in transportation sector in China. Cai et al (2008) analyzed five energy intensive industries in China, including iron and steel, pulp and paper, electricity, transportation, and cement. The results indicated that energy demand will increase continuously in the next decades in China.

The third category is system optimization. The main idea of this method is to simulate the dynamics of the energy market via linear or non-linear mathematical programming. Once the systems optimization is developed, the energy demand is able to be projected by scenario simulations. Although the analyses of the system models are based on mathematical systems of equations, the parameters used in these equations are estimated by using historical data (Jiang & Hu, 2006; Du et al., 2012).

The fourth category is the input-output analysis and the computable general equilibrium model. Some studies were conducted to analyze the trend of energy demand in China using this method (Garbaccio et al., 1999; Liang et al., 2007).

From the above literature review, it is found that most of previous studies are based on national time-series or cross regional data. The panel data model has many advantages over conventional time series or cross-regional model (Al-mulali, 2012; Du et al., 2012). By using panel data analysis, more data points can be involved for analysis so that the degrees of freedom are increased while the collinearity among the variables are decreased (Hsiao, 2003). The estimation efficiency can be therefore improved. In addition, conventional methods failed to address the spatial heterogeneity in the effects of related factors which could lead to the relation to vary among individuals (Seto & Kaufmann, 2003). However, this problem can be solved by varying intercepts in panel data analysis. Moreover, analyzing the relationship for one period would overlook the fact that the factor on energy consumption is not necessarily static, but could change within the specific period, so that the effects of related factors cannot be fully captured by using traditional methods.

2.3 Prediction of future energy consumption

2.3.1 Urban growth model

Models are simplifications of reality, theoretical abstractions that represent systems. Models of complex systems with geographic properties, such as cities, involve spatiotemporal processes which are difficult to handle using traditional way (Batty et al., 1999). Urban growth models are computer based simulations which can be applied to simulate the spatial location and interaction between urban land use and the related activities. In addition, they can provide an effective way to test the consequence of planning policies on the future urban form. Urban growth models have the ability to simulate reasonable and reliable scenarios about the future development of urban growth. It is valuable for urban planners and decision makers to understand how urban growth occurs through the visualization of different growth scenarios. Developing models for simulating the different energy consumption scenarios by adopting different land use development strategies is increasingly important because it can provide a better understanding of the causes and mechanisms influencing energy consumption.

In recent decades, a large number of urban growth models have been developed and applied to better understand and forecast urban growth. Early studies of urban growth used the model of transportation and land use which is based on the gravity theory or optimizing mathematics, but soon evolved into more dynamic models. Many spatially explicit urban growth models have been used to assess the effects of driving factors on urban growth and to simulate the future scenario. As Geographic Information System (GIS) based models, CLUE (Conversion of Land Use and its Effects) model (Verburg et al., 2001) and UrbanSim model (Waddel, 2002) have been widely applied in previous studies. Among the many different urban growth models, CA model has been widely used by scholars and city planners for urban growth modeling. CA model has the strong capacity in representing non-linear, spatial and stochastic processes (Batty et al., 1997). CA model is a discrete dynamic system, and its structure supplies a capacity of performing dynamic and complex spatial modeling. The spatial structure of CA can be easily incorporated with GIS and RS data. Due to its flexibility, CA model can be extended to involve the flexibility of neighborhoods and shapes and size of cells. Moreover, the simplicity of CA enables it to effectively model complex system by using simple transition rules. In addition, the lattice structure and the link to geographic data make the results of CA model highly visual. The users can view urban systems growing over time in increments.

2.3.2 Development of cellular automata model

The application of CA model in geographical modeling was first proposed by Tobler (1979). Since then many urban growth models were developed to better understand and analyze the urban growth process and the impacts of related factors. According to Yeh and Li (2003), there are at least three types of urban CA models: (1) simulation of urban growth that are explained by urban theories; (2) simulation of the pattern of future urban growth using historical data; (3) generation of different urban patterns with consideration of planning objectives.

CA are discrete dynamic systems whose behavior is completely controlled in terms of local interactions (White & Engelen, 1997). CA model consists of four elements: cell, state of cell, neighborhood, and transition rule (Yeh & Li, 2003). Cells are the smallest units during the CA modeling. It is widely defined as a grid square with the specific size (Wu & Webster, 1998). Each cell is considered to be an automaton and to behave independently from each other. At any given time, transition rules are applied at discrete time step to determine the state of each cell in each iteration.

In CA models, the state of each cell characterizes the attribute of finite state machine in a CA cell. The states are commonly defined in a binary value. However, each cell can only take one state at a time. In the context of urban growth modeling, various land use types can be represented by the different cell states (Thapa & Murayama, 2012).

A neighborhood comprises a CA cell itself and the cells in a given configuration around the cell. In the basic CA model, a neighborhood is only defined as the immediate adjacent set of cells that are close to the cell in question (Santé et al., 2010). There are two neighborhood configurations: Moore neighborhood of the eight cells that form a square around a cell, and the von Neumann neighborhood of the four directly adjacent cells. For modeling the urban growth, it is too limiting by considering the strict neighborhood configuration. A large number of studies have modified neighborhood parameters in order to simulate the urban growth more accurately.

The transition rule is regarded as the core of a CA model. They are the driving forces in the model in terms of defining the behavior of cells based on a set of transition rules (Santé et al., 2010). Transition rules are generally formulated as IF, THEN and ELSE statements that rely on input from a neighborhood effect to evaluate their results. In the context of urban systems, transition rules serve as an important role in explaining how city grows (Hammam et al., 2004). In addition to the neighborhood effect, the other factors significantly affecting urban growth are also involved in the urban CA models.

2.3.3 Design and generation of scenarios

To analyze the future using the CA model, a range of different future scenarios need to be developed and simulated. The design and development of urban scenario has become increasingly important tool for the assessment of land use change in a lot of studies. Xiang and Clarke (2003) stated “land-development scenarios are composed images of an area’s land-use patterns that would result from particular land-use plans, policies, and regulations if they were actually adopted and implemented at a certain point of time”. Petrov et al. (2009) pointed out that scenarios are not prediction but an effective method to assist policy decision and urban planning. Different future development strategies can be represented by developing scenarios to question what we could do if the scenario assumption occurs. The wide interest of using scenarios in the planning process can be explained in several ways: (1) planners can apply a set of scenarios representing different futures to test the consequence by adopting different urban development strategies; (2) planners can construct different set of alternatives by incorporating explicit assumptions; (3) planners can use scenario strategically to achieve specific goals (Song, et al., 2006). The development of scenarios not only provides a support for modeling and planning of alternative developments, but also assists decision making.

By applying different transition rules and parameters, CA models are able to explore how the urban system has been developed and how this system changes under different certain rules or forces. Therefore, it provides an effective environment for “what if” experiments. This enables users to explore various possible futures and develop insights that may be of use in urban planning. Many studies of applied CA modeling to develop various scenarios have been extensively described in the existing literature. For example, Petrov et al. (2009) simulated four urban growth scenarios (business as usual, two different scattered developments, compact development) for Algarve, Portugal. Thapa and Murayama (2012) designed three scenarios (spontaneous, environment-protecting, and resources-saving) to simulate spatial patterns of future urban growth in Kathmandu, Nepal. Considering the forecast of future energy consumption, few studies applied CA model to conduct scenario analysis besides Chen et al. (2013). They developed four different scenarios of development strategies (baseline, preferring industries in the intensive energy consuming sector, preferring industries in the low energy consuming sector, preferring industries in the tertiary sector) to predict future energy consumption in Pearl River Delta in China. However, the scenarios were developed based on the varying economic structures, which failed to capture the effects of the specific urban form on energy consumption.

3. Introduction of the study area

This chapter firstly mainly introduces the study area. In order to achieve the objectives of the study, the database used in this study is further described, which includes the RS images and statistical data.

3.1 Overview of energy consumption in China

China, as the largest developing country in the world, has been experiencing remarkable growth of GDP since the implementation of "Reform and Open Policy" in 1978. The rapid development poses tremendous challenges for China. One of the challenges lies in the significant rising in the energy demand, which in fact lies behind China's increasing energy consumption and related CO_2 emissions over the three decades (Al-mulali et al., 2013). According to the United Nations Statistics of 2010, China has surpassed the U.S. and became the largest CO_2 emitter, sharing 24.2 % of the world's total amount (Zhang, 2011). The fossil fuel-relate emissions increased from 671.1 million metric tons of carbon in 1990 to 2247.5 million metric tons of carbon in 2010 in China (Zhang & Lin, 2012). The energy consumption rapidly increased from 172.45 million in 1978 to 669.78 million tons of SCE in 2010. If the current rate of development will continue, China would produce even larger CO_2 emissions in the future, which draw greater international concerns. Facing dramatically increase in energy consumption and related CO_2 emissions, China government's 12th Five Year Plan (2011-2015) sets a goal that energy consumption per unit of GDP will be reduced by 16 % and CO_2 emissions per unit of GDP will be reduced by 17 % compared with the level in 2010 (Zhang & Lin, 2012). The current emphasis on energy consumption and CO_2 emission reductions provides a stimulus for identifying the driving factors and exploring the relationships between the explanatory factors and the increasing energy consumption in China.

The dramatic development observed in the last three decades in China has shared a similar pattern with that in other developing countries at a comparable stage of socioeconomic development (Ma, 2014). Urban areas experienced significant change in urban spatial patterns which are accompanied with rapid urbanization. This change has significant impact on provincial as well as national energy consumption due to changing resource endowments, lifestyles, economic activities and technology transfer. As shown in Figure 3-1, the energy consumption of each province in China has experienced rapid increasing process.

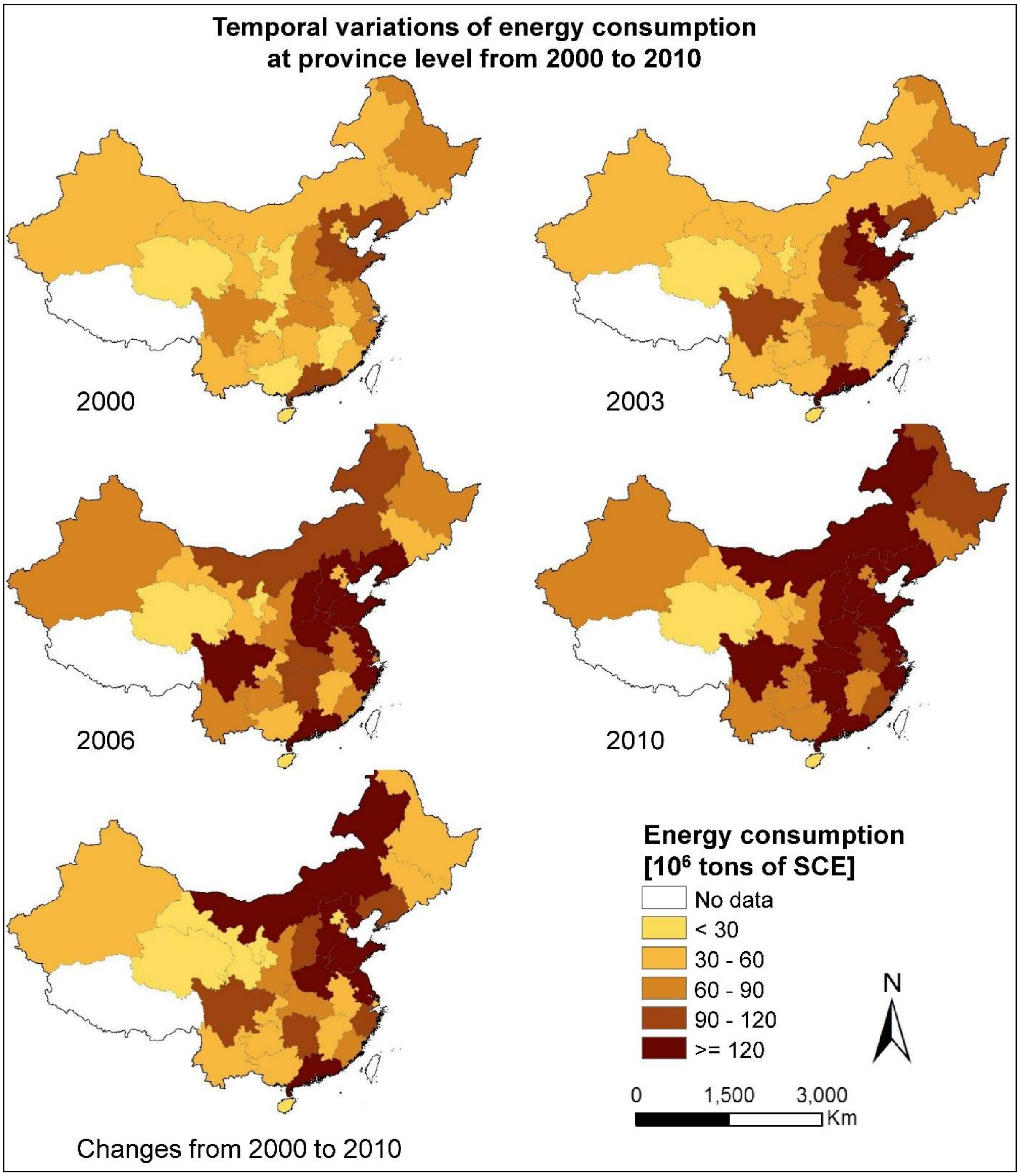

Figure 3-1 : Temporal variations of energy consumption at province level from 2000 to 2010 (Source：Own illustration; the energy consumption data is based on China Energy Statistical Yearbook 2001-2011)

3.2 Study area

In China, urban areas contributed to 75.15 % of the total energy consumption, and the energy use per person for urban areas was 6.8 times as that for rural areas in 2008

(Dhakal, 2009). The 35 largest cities in China, including capitals of each province and metropolis, which contained only 18 % of the total population, emitted 40 % of CO_2 in 2010 (Zhang & Lin, 2012). Urban areas play a significant role in energy consumption and CO_2 emissions in China.

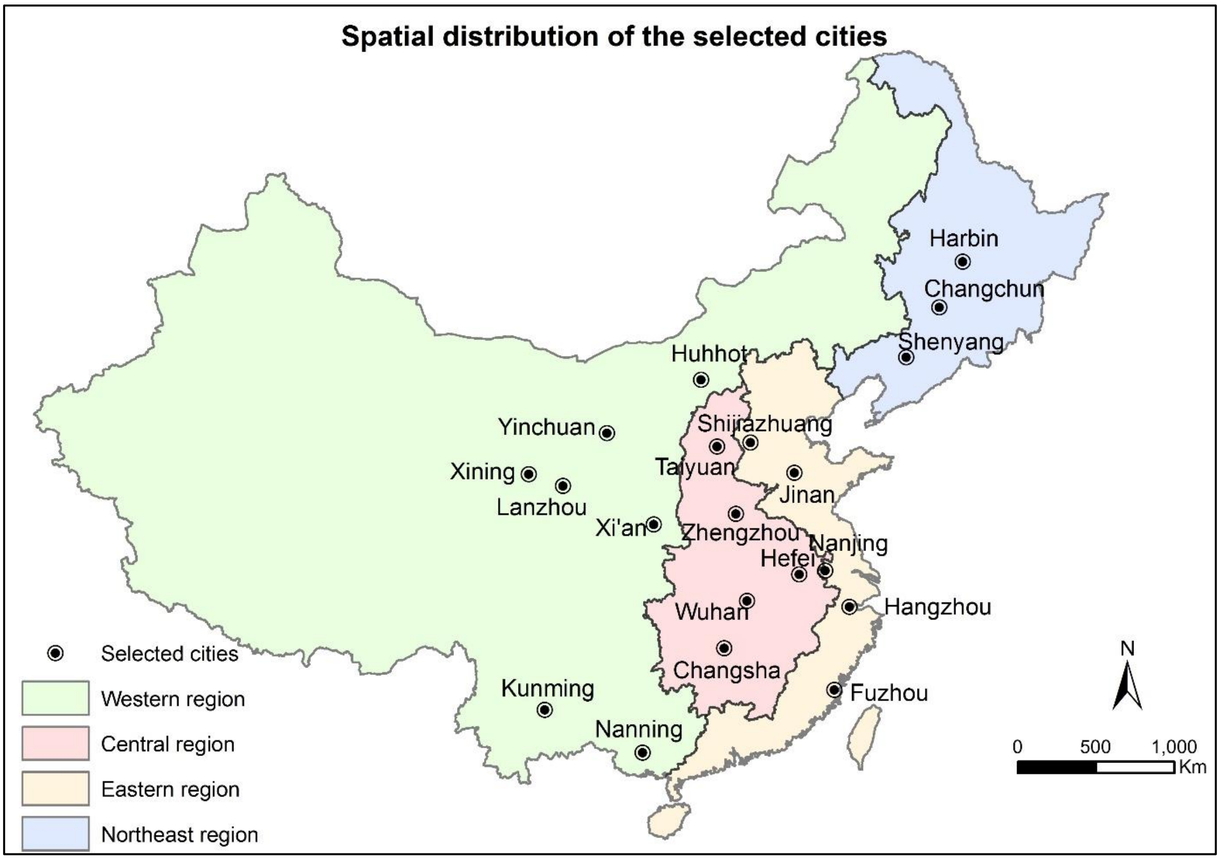

Figure 3-2: Spatial distribution of the selected cities

At present, the speed of development of some province capitals has exceeded that of Metropolis like Beijing and Shanghai in China. Besides six municipalities and special administrative regions (Beijing, Chongqing, Hong Kong, Macau, Shanghai and Tianjin), the total number of province level cities is 28, including 23 province capital cities and five autonomous regions' capitals in China. In the study, due to the data limitation we select the 20 province capital cities which constitute the fast growing areas. Their spatial distributions are presented in Figure 3-2. As shown in Figure 3-3, the total population of the 20 cities was 50.00 million in 2000, and further increased to 65.07 million in 2010. In addition, the sum of the GDP of these 20 cities increased rapidly from 960.18 billion RMB to 4525.36 billion RMB during the period of 2000-2010.

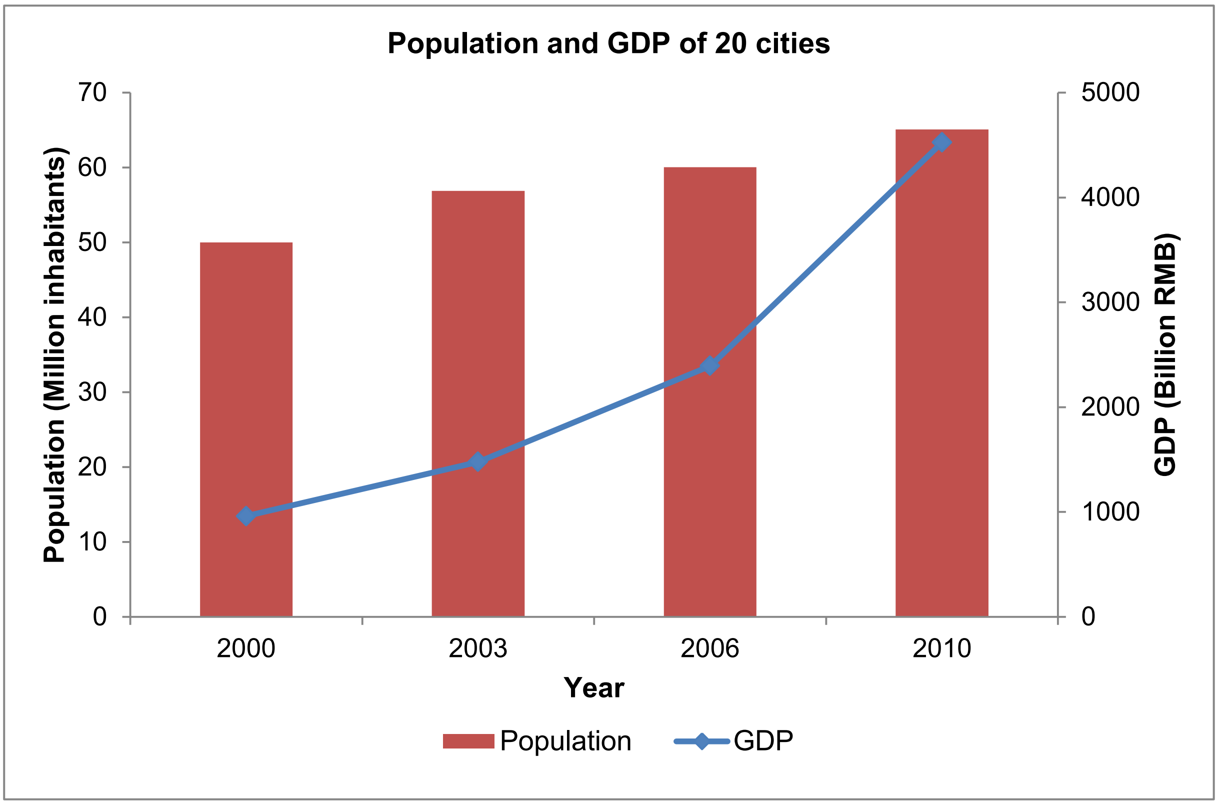

Figure 3-3: The Population and GDP of 20 cities (Source: Own illustration; based on China City Statistical Yearbook 2001-2011)

Besides the rapid growth of population and economic size, the significant differences in their energy consumption trends as well as urban forms are witnessed simultaneously. The selected province capital cities are considered as the representatives of the rapid development in urban areas. It is necessary for this study to create a sample that distributes geographically and composes of different urban forms. Moreover, not as the great global megalopolis, such as Shanghai, Hong Kong etc., these study areas have typical characteristics for the second-tier cities in China.

Since the implementation of “Reform and Open Policy”, rapid urbanization has taken place across China. Due to the imbalances in socioeconomic level and resource distribution among cities, the regional characteristics of energy consumption also show different patterns. According to the degree of socioeconomic development and geographical distribution, Mainland China is divided into four major economic regions: eastern region (ER), central region (CR), western region (WR) and northeast region (NR). This division can provide the basis for the development of regional development policy of the Chinese government. Based on this division, there are three selected cities located in the northeast economic region, namely, Harbin, Changchun and

Shenyang. In China, the northeast economic region was once the most advanced industrial base in northeast Asia due to the complete industrial system in 1930s. At present, it is the second developed economic region, in where Shenyang is the economic center. While the three major economic regions, which is marked as the Bohai Sea region, the Yangtze Delta region and the Pearl River Delta region, distribute in the eastern economic region. It makes the eastern economic region the most developed among the four regions.

Eastern economic region, the most developed area in China, only occupies 13.63% of the nation's territory. More than 50 % big cities and nearly 40 % population, however, allocated to this economic zone area, as well as most of ports in China are mainly concentrated in the region. In this study, five selected cities belong to the eastern region, i.e. Shijiazhuang, Jinan, Nanjing, Hangzhou and Fuzhou. Since 1978 the reform policy from a command economy to a market economy was implemented, the coastal regions of eastern China benefited greatly from this form, and their economies quickly raced ahead. The western region of China, however, lagged behind severely. The western region contains 70 % of China's territory, but only 25 % of China total population, and 13 % of its total economic output in 2009. For balancing the economic development between eastern and western regions, exploration of western region is pretty valuable to obtain the extremely rich land and nature resources from the perspective of urban land use. Seven province capital cities are chosen in order to achieve an energy efficient urban pattern to meet the sustainable development strategy.

The central economic region has a moderate region area and economic development. All of these province cities have a long and rich history. Until now these cities are the transportation hubs to connect the eastern and western regions. Wuhan and Zhengzhou are the most important transportation junctions in China. In this economic region, Wuhan is the largest city on industrial, commercial and political aspects. Five province capital cities are selected to analyze the relationship between urban forms and energy consumption in this study.

Despite the fact that urban development can improve the living standards of residents, it should be acknowledged that such development can also result in the increase in energy consumption and related CO_2 emission, and consequently bring about a lot of environmental problems (Qu et al., 2013). This is particularly clear when considering the total urban built-up areas in the 20 cities, which increase from approximately 4,631 km^2 in 2000 to 10,357 km^2 in 2010 with an annual rate of 572.6 km^2. The rapid growth not only led to the conversion of natural to artificial land cover but also caused a series of environmental problems including urban heat island effect and global warming (Clarke et al., 1997). It is therefore urgent to identify the related factors which lie behind the emissions of CO_2 in rapid development cities for mitigating climate change effects. Moreover, a deep insight into this relationship is also important to assist policy makers and urban planners to reduce energy consumption and curb CO_2 emissions.

3.3 Data

3.3.1 Landsat image

Continual, historical and precise data on the urban growth pattern serves as one of the major input criteria in this study. Satellite remote sensing is the most common data source which can provide a powerful data basis for analyzing spatial and temporal dynamics of urban land cover (Herold et al., 2003). Although urban growth can be detected by traditional survey ways, RS data provide greater amounts of information on the urban growth pattern, along with advantages of time and cost savings. Urban growth pattern extracted by RS data involves the usage of multi-temporal images to detect the differences occurring in urban spatial pattern between the specific time points.

Multi-temporal RS images of 20 cities for 2000, 2003, 2006 and 2010 were applied to obtain the dynamics of land cover. In the study, Landsat TM image and Landsat ETM+ image (U.S. Geological Survey) under clear sky conditions were obtained and employed to analyze the dynamics of land cover. To stay consistent with the same middle resolution of 30m, bands 1, 2, 3, 4, 5, 7 are stacked to further classification. In order to assess the accuracy of classified images, a set of reference data which include topographic maps, high-resolution aerial photography, and field survey data are necessary. Before being classified, preprocessing and enhancement steps (including calculation of reflectance values, atmospheric normalization and geometric correction) had to be conducted to make the images more interpretable. In the study, image processing was implemented using ERDAS IMAGINE 2011 software.

3.3.2 Nighttime light data (NTL)

In addition to the Landsat image for obtaining land cover information, time series NTL data from DMSP/OLS is also applied in this study. The OLS sensor is different from those used to detect ground objects based on the reflection characteristics of solar radiation such as Landsat TM, SPOT HRV, and NOAA AVHRR. The National Geophysical Data Center (NGDC) processed and published NTL, which contains lights from cities, towns, and other sites with persistent lighting. Sunlit, moonlit, and ephemeral events such as wildfires have been discarded (Elvidge et al., 1999). Stable light is one of the most important components for monitoring electric power consumption and economic activity, factors that rely mainly on statistical data. The data presents the global annual average brightness in units of 6-bits digital number (DN) ranging from 0 (background) to 63 (brightest). A DN value for a geographical place represents the average light intensity. The spatial resolution is a 30 arc second grid, which is approximately 0.86 km^2 at the equator. The high contrast between lighted and unlighted areas and the sensor’s spatial resolution makes it become a useful tool to identify areas of intense human activity (Croft, 1973). Figure 3-4 shows the NTL data obtained from satellite F18 for China in 2010. The images of multi-temporal nighttime lights for the study period were collected by four individual sensors (Table 3-1): F14 (1999-2003), F15 (2000-2007), F16 (2004-2009), F18 (2010-2011).

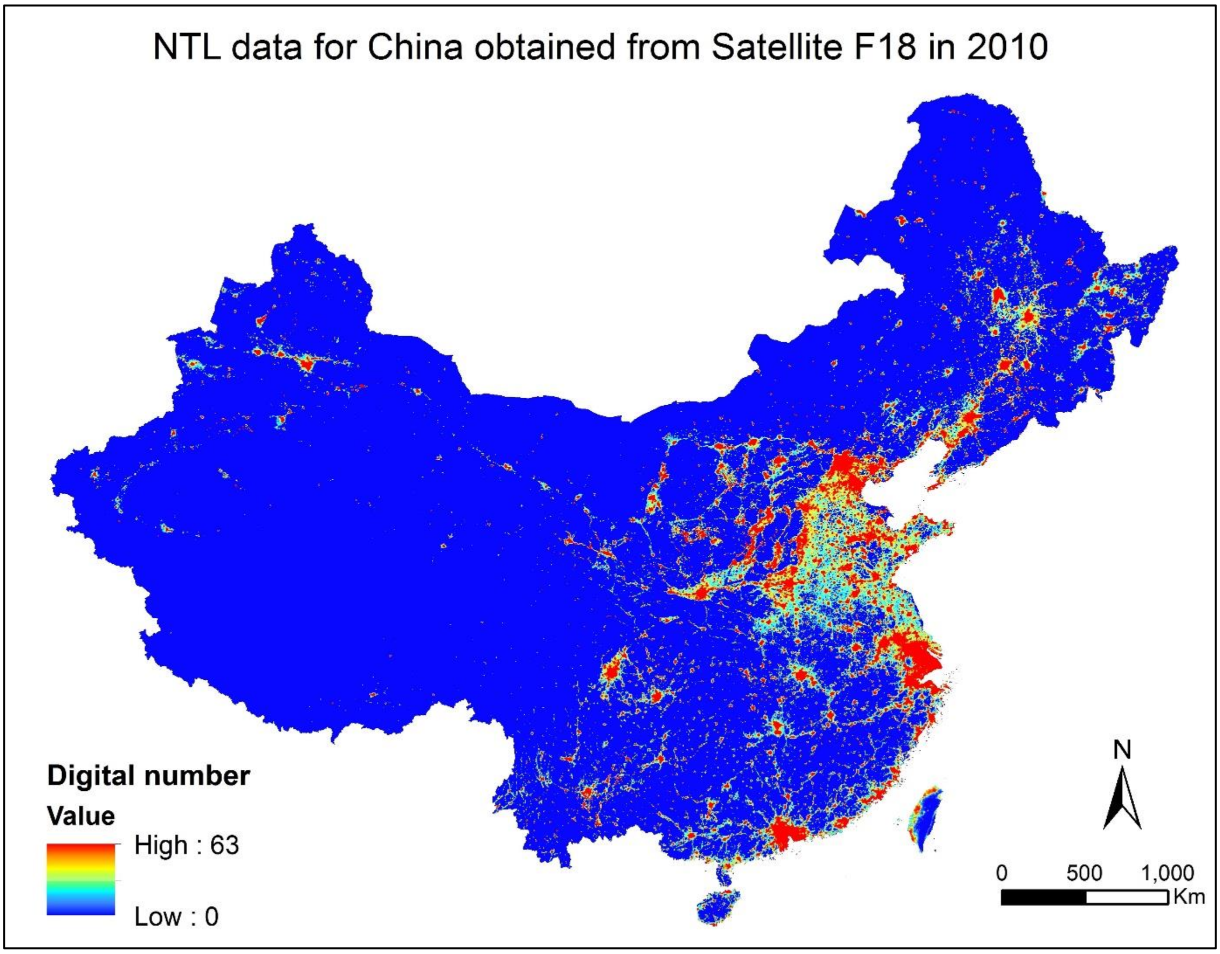

Figure 3-4: NTL data for China obtained from Satellite F18 in 2010

Table 3-1: Nighttime light data used in the study

Year/Satellite	F14	F15	F16	F18
1999	F141999			
2000	F142000	F152000		
2001	F142001	F152001		
2002	F142002	F152002		
2003	F142003	F152003		
2004		F152004	F162004	
2005		F152005	F162005	
2006		F152006	F162006	
2007		F152007	F162007	
2008			F162008	
2009			F162009	
2010				F182010
2011				F182011

3.3.3 Statistical data

Due to the absence of urban energy consumption statistics in China, it is difficult to acquire precise data officially. As only the province energy consumption is available from China Energy Statistical Yearbooks in China, a top-down method was adopted to downscale province energy consumption into urban energy consumption. Coal accounts for 60-70 % of China's primary energy supply (China Energy Statistical Yearbooks, 2001-2011). A common practice in China's energy statistics is to convert all fuel consumption to standard coal equivalent (SCE) (Ma, 2014). By using standard conversion factors provided by the China Energy Statistical Yearbooks (Table 3-2) and the Eq. 1, the physical units of various energy sources are converted to SCE. The conversion is required to aggregate different fuels.

$$EC_{sce} = \sum_{i=1}^{m} cf_i \times EC_i \tag{1}$$

where cf_i indicates the conversion factor for the fuel source i. EC_i is the energy consumption of fuel source i which is measured by physical units. The total number of fuel sources is m. EC_{sce} is the energy consumption measured by SCE.

Table 3-2: Standard conversion factors for different fuels (Source: China Energy Statistical Yearbooks, 2001-2011)

Energy type	**SCE conversion factor**
Raw coal	0.7143 kgSCE/kg
Cleaned coal	0.9 kgSCE/kg
Other washed coal	0.285 kgSCE/kg
Briquettes	0.6 kgSCE/kg
Gangue	0.2857 kgSCE/kg
Coke	0.9714 kgSCE/kg
Coke oven gas	6.143 kgSCE/cu.m
Blast Furnace gas	1.286 kgSCE/cu.m
Converter gas	2.714 kgSCE/cu.m
Other gas	3.5701 kgSCE/cu.m
Other coking products	1.3 kgSCE/kg
Crude oil	1.4286 kgSCE/kg
Gasoline	1.4714 kgSCE/kg
Kerosene	1.4714 kgSCE/kg
Diesel oil	1.4571 kgSCE/kg
Fuel oil	1.4286 kgSCE/kg
Naphtha	1.5 kgSCE/kg
Lubricants	1.4143 kgSCE/kg
Petroleum waxes	1.3648 kgSCE/kg
White spirit	1.4672 kgSCE/kg
Bitumen asphalt	1.3307 kgSCE/kg
Petroleum coke	1.0918 kgSCE/kg
LPG	1.7143 kgSCE/kg
Refinery gas	1.5714 kgSCE/kg
Other petroleum products	1.2 kgSCE/kg
Natural gas	1.33 kgSCE/cu.m
LNG	1.7572 kgSCE/kg
Heat	0.03412 kgSCE/10^3kJ
Electricity	0.1229 kgSCE/kW•h

4. Methodology

The methods presented in this chapter can be categorized into three parts. Section 4.1 introduces Landsat image classification and urban form quantification using several spatial metrics. Section 4.2 presents the estimation of urban energy consumption based on NTL data and province energy consumption. Regarding the nighttime light data, regression models are adopted to investigate the links between DN value of NTL data and total energy consumption within specific province. The links are further used to estimate the urban energy consumption by involving DN value of NTL data within the urban area. Furthermore, the relationship between urban form and energy consumption is also investigated. Section 4.3 illustrates the methods associated with the prediction of the future urban energy consumption, which includes development of CA models and the simulation of future scenarios. Figure 4-1 shows the schematic diagram of workflow.

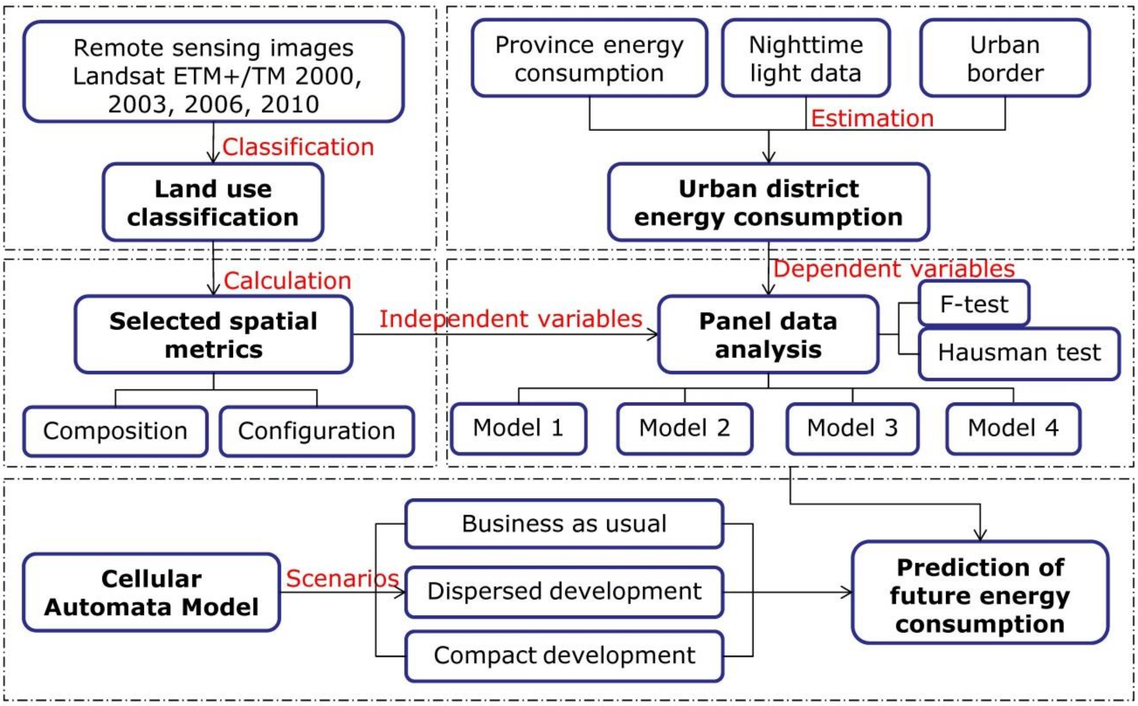

Figure 4-1: Schematic diagram of workflow

4.1 Quantification of urban form

4.1.1 Landsat image classification

RS image is the most common data source for detection, quantification and mapping of land use change patterns (Yuan et al., 2005). It provides a huge amount of information on the geographic distribution of land use and change, along with the advantages of cost and time saving for regional size areas (Dewan & Yamaguchi, 2009).

Maximum Likelihood Classification (MLC) was used to derive land cover information for the study area. Prior to the classification, training samples were selected for each of the pre-determined land cover types by delimiting polygons around representative sites. Using the pixels enclosed by these polygons, the spectral signatures for the respective land cover types recorded by the satellite images would been derived. Once the spectral signature was deemed satisfactory, MLC was selected to extract land use information from Landsat data. Because of the relatively coarse spatial resolution and spectral similarities of the Landsat images, some pixels were misclassified in the initial classification results after MLC supervised classification. The post classification refinement can greatly improve the accuracy of results. Some further data, such as brightness, greenness and wetness layers from the tasseled cap transformation (TCT) were incorporated to refine classified results (Li & Thinh, 2013). In order to evaluate performance of the classification methods and check whether the results are correct for further study, error matrix was carried out to assess the accuracy of classification results.

4.1.2 Spatial metrics

The combination of RS images and spatial metrics can provide more spatially consistent and detailed information about urban structure and change, and consequently, allow for improving representations and understanding the impact of urban structures on the energy consumption.

Following the land cover classification, quantification of urban form was carried out. In this study, the spatial temporal dynamics of urban forms of the 20 province capital cities were characterized quantitatively using a series of landscape indicators and the above mentioned classified data. The application of quantitative indicators is a part of methodologies showing greatest potential in characterizing urban form. According to the achievement of current investigations on this theme (Chen et al., 2011; Long et al., 2013; Seto & Fragkias, 2005; Thinh, 2002), 14 indicators are widely used, namely, Class Area, NP, LPI, Edge Density (ED), AERA, ENN, Perimeter Area Ratio (PARA), SHAPE, Fractal Dimension Index (FRAC), Jaggedness degree, Landscape Shape Index (LSI), Patch Cohesion Index (COHESION), Landscape Division Index (DIVISION), and Aggregation Index (AI). Compactness is an important index that reflects the urban form. Some indicators were used to measure and monitor urban compactness, such as SHAPE, Jaggedness degree, and FRAC. Out of a large portfolio of partly redundant landscape metrics, five metrics were chosen in the study. Both complementary and diverse are considered in order to provide deep insights into the characteristics of urban form. Class Area, LPI are used to describe the composition of the landscape. Class Area represents the total urban area in study area. Class Area approaches 0 as the patch type becomes increasingly rare in the landscape. Class Area =Total Area when the entire landscape consists of a single patch type. LPI is the largest urban patch divided by the total urban area. LPI approaches 0 when the largest patch of the corresponding patch type becomes increasingly smaller. LPI = 100 when the entire landscape consists of a single patch of the corresponding patch type; that is, when the largest patch comprises 100% of the landscape (McGarigal et al., 2012). NP, ENN and SHAPE are used to describe the structure and configuration. NP is equal to the number patches in urban area. NP = 1 when the landscape contains only one patch of the corresponding patch type; that is, when the class consists of a single patch. In order to consider the different influence of patches according to the areas, ENN_AM and SHAPE_AM are calculated by incorporating weighting in this study. ENN_AM is the area weighted mean straight line distance from one patch to the closest patch. SHAPE_AM means the irregular degree of urban patches. SHAPE_AM = 1 when all patches of the corresponding patch type are circular (vector) or square (raster); SHAPE_AM increases without limit as the patch shapes become more irregular (McGarigal et al., 2012). Table 4-1 shows the detailed description of five selected landscape metrics.

Table 4-1: The description of selected landscape metrics (Source: McGarigal et al., 2012)

Landscape Metric	Formula	Description
Class Area	$\text{Class Area} = \sum_{j=1}^{n} a_j \left(\frac{1}{10{,}000}\right)$	a_j=area(m^2) of urban patch j
Number of Patches	$NP = n$	n=number of urban patches
Largest Patch Index	$LPI = \frac{\max_{j=1}^{n} a_j}{A}(100)$	A=total landscape area (m^2) a_j= area(m^2) of urban patch j
Area-weighted Mean Euclidean Nearest Neighbor	$\text{ENN\_AM} = \frac{\sum_{j=1}^{n}\left[(h_j)\left(\frac{a_j}{\sum_{j=1}^{n} a_j}\right)\right]}{n}$	h_j=distance (m) from urban patch j to the nearest neighbouring urban patch n=number of urban patches a_j= area(m^2) of urban patch j
Area-weighted Mean Shape Index	$\text{SHAPE\_AM} = \sum_{j=1}^{n}\left[\left(\frac{0.25p_j}{\sqrt{a_j}}\right)\left(\frac{a_j}{\sum_{j=1}^{n} a_j}\right)\right]$	p_j= perimeter (m) of patch j a_j= area(m^2) of urban patch j

4.2 Exploration of the relationship between urban form and energy consumption

4.2.1 Calibration of nightlight time data

As mentioned in chapter 2, there are several challenges in using NTL data for the urban study. NTL data are lack of continuity and comparability, so that they cannot be used directly for the study. The cumulative DN value are different between two satellites for the same year. As shown in Figure 4-2, for example, in 2007 the cumulative DN value generated by the satellite F15 was 19,370,921, while the value was 25,350,343 acquired from the satellite F16. In addition, the DN value acquired from the same satellite decreased abnormally over time. For example, the cumulative DN value generated from satellite F15 decreased from 19,635,305 in 2002 to 15,054,477 in 2003. This phenomenon cannot accurately reflect the urban development process in developing countries, especially in China, which shows a rapid development of urban socioeconomic condition. Considering these shortcomings, it is important to improve the continuity and comparability of NTL data. In this study, a method was developed to calibrate the data systematically which involves three steps: intercalibration, intra-annual correction, and inter-annual correction. The workflow is shown in Figure 4-3.

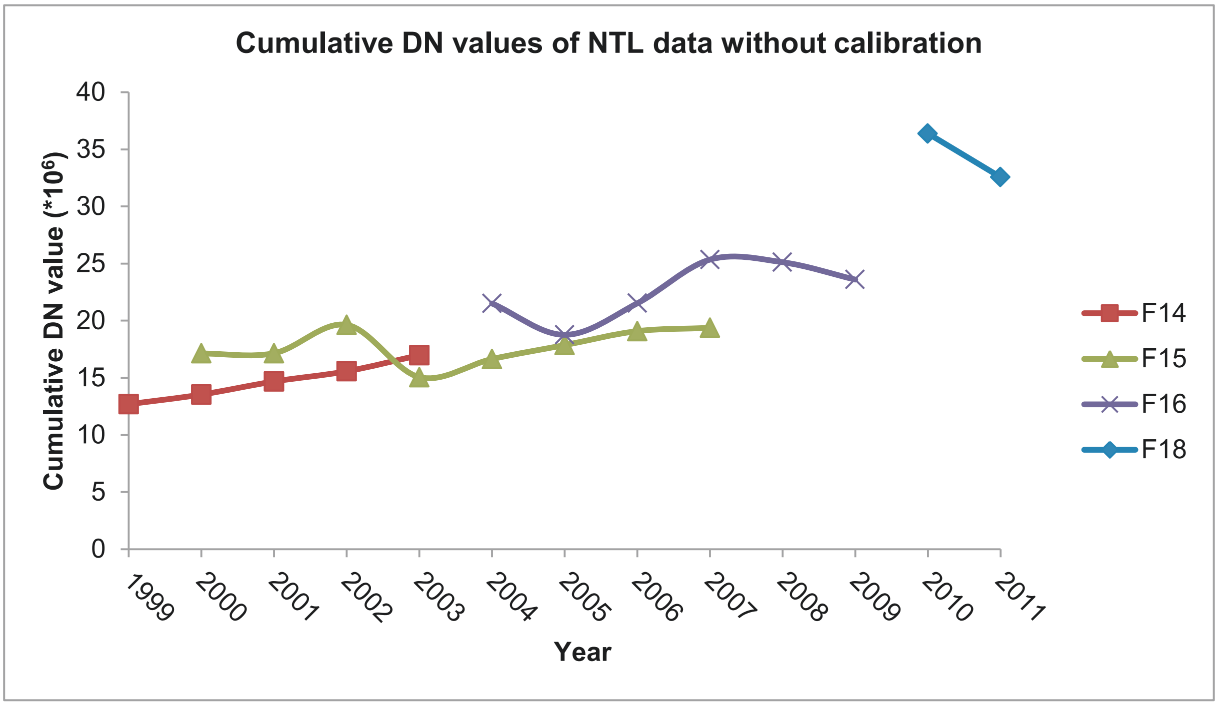

Figure 4-2: Cumulative DN values of NTL data without calibration

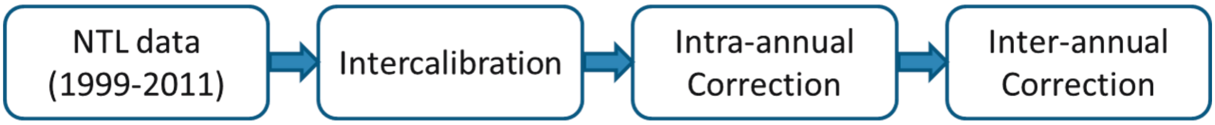

Figure 4-3: The flow chart of NTL calibration

The objective of intercalibration was to improve the continuity and comparability of NTL data in China. Based on the method developed by Elvidge et al. (2009) and the actual situation of China development, intercalibration was carried out firstly in this study. Sicily in Italy was selected as the referenced area because it experienced stable development over time and has an even spread of data across the full dynamic range (Elvidge et al., 2009). Furthermore, the data from satellite F18 in the year of 2010 was selected as reference data due to the highest cumulative DN value for data F182010. The second-order regression model was developed for each satellite using the following equation, which adjusted the other data to match F182010.

$$DN_{intercalibrate} = ar \times DN^2 + br \times DN + cr \tag{2}$$

where DN is the raw DN value of the NTL data, $DN_{intercalibrate}$ indicates the DN value after the intercalibration, ar, br, and cr represent the coefficients of the model. They could be empirically derived by comparing the DN values of other NTL data in Sicily with the reference data from the satellite F18 in 2010. The scatterplots for each data versus F182010 and the second order polynomial trend lines are shown in Figure 4-4. The generated coefficients for each image are shown in Table 4-2. Then the Eq. 2 with the coefficients was used to calibrate the NTL data of China.

For the NTL data acquired from two satellites of the same year, the DN value of the corresponding pixel in NTL image should be the same. Otherwise, the pixel is defined as the unstable lit pixel. The intra-annual correction was conducted by using the information extracted from two different satellites of the same year in order to remove any intra-annual unstable lit pixels. The correction was conducted using Eq. 3 and Eq. 4:

$$DN_{i,n} = (DN_{i,n,a} + DN_{i,n,b})/2 \quad (DN_{i,n,a} \neq DN_{i,n,b} \neq 0) \tag{3}$$

$$DN_{i,n} = 0 \qquad (DN_{i,n,a} = 0 \; or \; DN_{i,n,a} = 0) \tag{4}$$

where $DN_{i,n}$ represents the DN value of corrected unstable lit pixel i of the year n. $DN_{i,n,a}$ and $DN_{i,n,b}$ indicate the DN value of the unstable lit pixel acquired from satellite a and satellite b, respectively.

According to the characteristics of NTL data, the lit pixel detected in earlier NTL images should be maintained in the later images. In addition, the urban nighttime light would grow continuously over time because of the rapid urban growth in China. Therefore, the cumulative DN value of earlier NTL should not be larger than that of later NTL data. With the consideration of problem in original NTL data that the decrease of the cumulative DN value along with the development, inter-annual correction was applied to remove inconsistencies of NTL data for different years and to correct DN value for consistently lit pixels in order to ensure the accurate reflection of urban development process in China. The inter-annual correction was conducted by using the following equations:

$$DN_{i,n} = DN_{i,n-1} \qquad (DN_{i,n-1} > DN_{i,n}) \tag{5}$$

$$DN_{i,n} = DN_{i,n} \qquad otherwise \tag{6}$$

where $DN_{i,n}$ and $DN_{i,n-1}$ represent the DN value of the lit pixel i in the year n and $n-1$, respectively. If the DN value of lit pixel in early NTL image is larger than the DN value in latter NTL image, the DN value will be replaced by the DN value in the early NTL image. Otherwise, the DN value keeps constant.

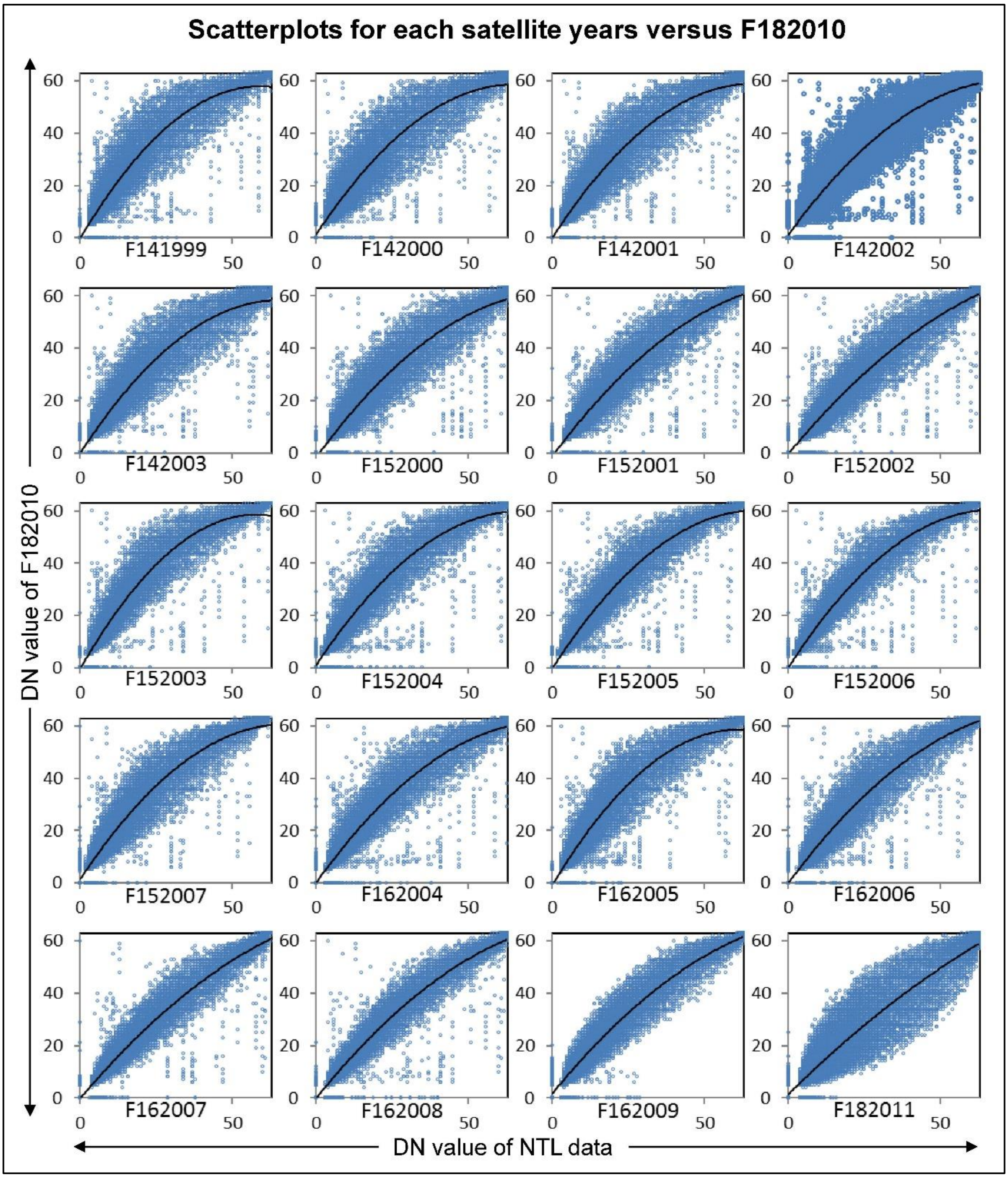

Figure 4-4: The scatterplots for each of the satellite years against F182010 for the NTL data of Sicily

Table 4-2: Coefficients of the regression models for intercalibrating NTL data

Satellite	Year	ar	br	cr	R^2
F14	1999	-0.01663	1.967345	-0.29037	0.905756
	2000	-0.01353	1.762671	1.193656	0.900797
	2001	-0.01366	1.794458	-0.09667	0.917788
	2002	-0.01084	1.605158	1.039629	0.921041
	2003	-0.01364	1.787297	-0.19619	0.921131
F15	2000	-0.00995	1.588583	-1.74908	0.916182
	2001	-0.0093	1.571802	-1.46342	0.931216
	2002	-0.00681	1.402674	-0.46023	0.93278
	2003	-0.01758	2.037701	-0.43726	0.930373
	2004	-0.01303	1.751665	1.03161	0.932972
	2005	-0.01351	1.807911	-0.33229	0.93881
	2006	-0.0135	1.804926	0.029792	0.947785
	2007	-0.01306	1.760759	1.316008	0.929061
F16	2004	-0.01066	1.620645	0.096814	0.93153
	2005	-0.01586	1.94515	-0.97436	0.922514
	2006	-0.00919	1.564644	-0.04688	0.927581
	2007	-0.00642	1.377027	-0.24938	0.949998
	2008	-0.00766	1.449428	-0.18681	0.949827
	2009	-0.00748	1.425348	1.595096	0.948678
F18	2010	0	1	0	1
	2011	-0.0037	1.150797	1.361174	0.893451

4.2.2 Estimation of energy consumption

As mentioned in section 2.2.1, an aggregated and top-down method is useful and effective in estimating urban energy consumption in China. The estimation of urban energy consumption starts with a hypothesis: a pixel based NTL value is correlated with the energy consumption from the location that the pixel occupies. In addition, energy consumption is a complicated consequence of socioeconomic development. The main challenge for estimating urban energy consumption using NTL data is to quantify the relationship between the DN value of NTL data and energy consumption within the specific area over time.

Three simple statistical models (linear regression model, exponential regression model, and power law regression model) were applied to fit the energy consumption to the DN value of calibrated NTL data over time (Eqs. 7-9). The linear regression model with a straight-line shape assumes a constant proportional response of DN value of NTL to the energy consumption (Ma et al., 2012). The exponential regression model is used to quantify a gradually increased response rate of DN value to the increased energy consumption over time. The power-law regression model with the convex shape is applied to quantify variation of DN value which may show gradually decreased response rate to the increase in energy consumption over time.

$$EC_p = a \times NTL_p \tag{7}$$

$$EC_p = a \times \exp(b \times NTL_p) \tag{8}$$

$$EC_p = a \times (NTL_p)^b \tag{9}$$

where EC_p is the amount value of province energy consumption. NTL_p is the sum of DN value within the defined province. a and b are the parameters of regression models. A major concern in estimation of urban energy consumption is the components of a and b.

It was assumed that the relationship between DN value and energy consumption keeps constant within a specific province under the consideration of province differences. The available province energy consumption were plotted against the cumulative DN values of NTL data within the specific province. Furthermore, the relationship between these two variables was fitted using three models. The best fitting regression model can be identified and evaluated by comparing the R^2 values of three different regression models. Once the best fitting regression model is determined, it is valid to use NTL data within a specific urban area as a proxy to estimate corresponding energy consumption.

4.2.3 Investigation of effects of urban form on energy consumption

Panel data analysis is a type of regression models that can deal with observations from multiple individuals over multiple periods. It has more advantages compared with conventional statistical analysis using only either cross-regional or time series data. Panel data usually give researchers a large number of data points, increasing the degrees of freedom and reducing the collinearity among explanatory variables-hence improving the efficiency of estimates (Hsiao, 2003). More importantly, the spatial heterogeneity in the relationship can be explored by varying the intercepts and coefficients in panel data analysis (Raufer, 2007). Therefore, the efficiency and accuracy of estimation can be improved greatly by using panel data analysis.

Normally, panel data analysis can be divided into three major types according to different assumptions: pooled regression model (constant intercepts and constant coefficient), variable intercepts and constant coefficients model, variable intercepts and variable coefficients model (Hsiao, 2003). The specific formulas can be described as Eqs. 10-12, respectively:

$$y_{it} = \alpha + \beta x_{it} + \varepsilon_{it} \ (i = 1,2, \dots N; t = 1,2, \dots T) \quad (10)$$

where i and t are individuals and time; N and T are total number of observed individuals and periods respectively; x_{it} and y_{it} represent the exogenous and endogenous variables, which are also called independent and dependent variables; and ε_{it} is the error term. α denotes the intercepts. β is the coefficients of the variables. The formula expresses the pooled regression model. In this formula, the constant intercepts and coefficients indicate that there are no individual and structural changes in regression model.

If it is assumed that there are some effects not considered by the variables and vary among samples but time invariant, the variable intercepts can be introduced as α_i (Chen et al., 2011). However, there is no structural change due to the constant coefficient in this model form.

$$\alpha_1 \neq \alpha_2 \neq \cdots \neq \alpha_N; \ \beta_1 = \beta_2 = \cdots = \beta_N$$

$$y_{it} = \alpha_i + \beta x_{it} + \varepsilon_{it} \ (i = 1,2, \dots N; t = 1,2, \dots T) \quad (11)$$

where α_i is specified as fixed effects or random effects.

In fixed effects model, the intercept α_i is uncorrelated with x_{it}, and is a constant for individual i. While in random effects model, it is affected by x_{it}. α_i involves not only a constant but also a random term caused by x_{it}.

Moreover, when coefficients are variable as well, it can be denoted as β_i.

$$\alpha_1 \neq \alpha_2 \neq \cdots \neq \alpha_N; \ \beta_1 \neq \beta_2 \neq \cdots \neq \beta_N$$

$$y_{it} = \alpha_i + \beta_i x_{it} + \varepsilon_{it} \ (i = 1,2, \dots N; t = 1,2, \dots T) \quad (12)$$

where β_i means the coefficient of explanatory variable x_{it}, which can vary among individuals. This regression model implies that there also are structural changes besides individual effect. β_i can be treated as fixed or random effects like the specification of α_i.

In this study, the estimated urban energy consumption data of several time points could serve as dependent variables, and a set of spatial metrics calculated based on the urban land use maps were used as independent variables. The implementation of panel data analysis consists of three steps.

The first step is to select a suitable model form from the different model forms in panel data analysis based on the result of a F-test. To avoid the deviation of models and improve the validity of parameter estimation, these two hypotheses are tested:

$H_1: \beta_1 = \beta_2 = \cdots = \beta_N$

$H_2: \alpha_1 = \alpha_2 = \cdots = \alpha_N;\ \beta_1 = \beta_2 = \cdots = \beta_N$

If H_2 is accepted, the pooled regression model should be used. If H_2 is rejected, H_1 should be further tested. If H_1 is accepted, variable intercepts and constant coefficients model is more appropriate; otherwise both intercepts and coefficients are variable.

The F-test is conducted by comparing the Residual Sum of Squares (RSS) values of Eqs. 10, 11, 12:

$$F_2 = \frac{(S_3 - S_1)/[(N-1)*(K+1)]}{S_1/[NT - N*(K+1)]} \sim \mathrm{F}[(N-1)*(K+1), N(T-K-1)] \tag{13}$$

$$F_1 = \frac{(S_2 - S_1)/[(N-1)*K]}{S_1/[NT - N*(K+1)]} \sim \mathrm{F}[(N-1)*K, N(T-K-1)] \tag{14}$$

where F_2 is the statistic for H_2 that both intercepts and coefficient are constant for all individuals over the entire period; F_1 is the statistic for H_1 that intercepts are variable and coefficients are constant. S_1, S_2, S_3 are RSS values of Eqs. 12, 11, 10. K represents the total number of explanatory variables. N is the number of individuals. T denotes the number of the periods. If F_2 is less than the critical value, H_2 is accepted and the pooled regression model should be used; otherwise H_1 should be further tested. If F_1 is less than the critical value, H_1 is accepted and intercepts are variable and coefficients are constant; otherwise variable intercepts and variable coefficients model should be used.

After that, if the test results suggest that the intercepts and coefficients should not be constant, the Hausman test needs to be carried out to decide whether such effects are fixed or random (Chen et al., 2011). Hausman test, which was proposed by William (1997), is used to decide whether effects are fixed or random.

$$W = \left(\hat{b}_{cv} - \hat{b}_{GLS}\right)' \left[var\left(\hat{b}_{cv}\right) - var\left(\hat{b}_{GLS}\right)\right]^{-1}\left(\hat{b}_{cv} - \hat{b}_{GLS}\right) \sim \chi^2(k-1) \quad (15)$$

$\hat{b}_{cv}$ and $\hat{b}_{GLS}$ are generated value from fixed effect model and random effect model, respectively. k is the degree of freedom. W represents the Wald statistics value, if W does not equal to zero, the fixed effect model should be used; otherwise the random effect model should be used.

Finally, the model is performed using Generalized Least Squares (GLS). After the use of panel data analysis, the coefficients of the dependent variables (spatial metrics) are estimated. By analyzing the coefficients, we can understand the relationship between urban spatial pattern and energy consumption.

In order to address the concern whether the spatial heterogeneity is involved in the impact of urban form on energy use in China, the estimation by using panel data analysis is conducted into two steps. The whole sample of the 20 cities is firstly used to examine the relationship between spatial metrics and energy consumption at the national level. As mentioned in Chapter 3, the mainland China can be divided into four economic regions: eastern region, central region, western region and northeast region. Therefore, the whole sample can be divided into four regional samples according to the division. The panel data model needs to be developed for the four regional samples to analyze the regional differences as well as to identify more accurate model for the specific region.

4.3 Prediction of energy consumption

4.3.1 Development of Cellular Automata model

For better achieving a realistic representation of the urban system, the critical issue is how to define the transition rules. The process of realistic urban growth can be defined as an iterative probabilistic system (Barredo et al., 2003). Based on the CA model developed by Li and Thinh (2014), the probability $P_{x,y}^{t}$ of a cell (x,y) be converted to urban land use at time t can be expressed using the following equation. It represents the integration of the intrinsic suitability value $S_{x,y}^{t}$, neighborhood effect $N_{x,y}^{t}$, constraints value $C_{x,y}^{t}$ and random value $V_{x,y}^{t}$.

$$P_{x,y}^{t} = S_{x,y}^{t} * N_{x,y}^{t} * C_{x,y}^{t} * V_{x,y}^{t} \tag{16}$$

The intrinsic suitability value represents the intrinsic suitability of urban development. A logistic regression function was used to calculate global suitability value:

$$S_{x,y}^{t} = \frac{1}{1+\exp(-z)} \tag{17}$$

where $S_{x,y}^{t}$ is the intrinsic suitability value. It varies from 0 to 1 on a S-shape curve. z represents the linear combination of global variables which are regarded as driving forces of urbanization. It can be expressed as follows:

$$z = b_0 + b_1 v_1 + b_2 v_2 + \cdots + b_n v_n \tag{18}$$

where b_0 is the intercept of the model, b_i (i=1, 2,…, n) represents the coefficient of the logistic regression model to be estimated, and v_i is a variable representing driving factor of urban growth, which can be of interval, ordinal or categorical. In this study, the related factors associated with the driving forces of urban growth were selected and involved in the model. These factors are: distance to city center (D2CityC), distance to district center (D2DisC), distance to major road (D2MajR), distance to minor road (D2MinR), slope (SLOPE). The factors need to be standardized into a normalized scale since the above variables are measured in different units. The linear transformation approach was adopted to conduct the standardization.

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

$$N_{x,y}^{t} = \frac{\sum_{n^2-1} con(state_{x,y}^{t} = developed)}{n^2-1} \tag{19}$$

where con() is a conditional function that returns true if the state of a cell within the neighborhood is currently developed. n represents the size of the neighborhood. The neighborhood size is the central element of CA model. It identifies the extent of interaction between land use and the dynamics of the system (Caruso et al., 2005). In this study, Moore neighborhood type with the size of 5 cells was used to analyze the neighborhood effect.

The total constraint score was calculated as:

$$C_{x,y}^{t} = \prod_{f=1}^{n} ec_{x,y,f}^{t} \quad (20)$$

where $ec_{x,y,f}^{t}$ represents the binary value of environmental and ecological constraint factor f that cause the cell (x, y) can not be converted to urban land use at time t. $C_{x,y}^{t}$ is the product of some binary variables representing the constraint to urban growth for the cell (x, y). If $C_{x,y}^{t}$=0, cell (x, y) is restricted by some environmental and ecological constraint factors, such as cell is located within environmental protected area, which is not likely to be converted to urban land use in simulation. Otherwise, $C_{x,y}^{t}$=1.

Urban growth usually involves complex elements. In order to generate patterns that are closer to reality, a stochastic disturbance is introduced (Barredo et al., 2003). It was calculated with Eq. 21:

$$V_{x,y}^{t} = 1 + (-\ln(rand))^{\alpha} \quad (21)$$

where $rand$ (0<$rand$<1) is a uniform random value, and α represents the parameter that allows the degree of the perturbation to be adjusted.

All the spatial data involved in the CA model were unified to the Universal Transverse Mercator (UTM) coordinate system and sampled to the same cell size of 30 m * 30 m. It aims to keep consistent with the spatial resolution of urban land use map and the scale of the calculation of the spatial metrics.

Once the probability $P_{x,y}^{t}$ that cell (x,y) is converted to urban land use at time t is calculated, CA model can be applied to spatially and explicitly simulate urban growth patterns according to the total urban growth area. In order to simplify the operation of the CA model, only the transformation process from non-urban to urban is considered. In each iteration, $P_{x,y}^t$ for all cells are calculated. The cells are then ranked by their transition probability values. The transitions from non-urban cells to urban cells begin from the cell with the highest value and proceed downward until a sufficient number of cells are reached. The transition rule is applied to each cell in each iteration. The non-urban cells with relatively low values remain unchanged. The iteration will continue until the total urban expansion area is satisfied.

Validation of CA model is conducted by comparing the predicted map to the observed map in order to evaluate the accuracy of parameters and the performance of CA model. Batty et al. (1999) argued that the validation of CA model should depend on the purpose of the simulation. The urban spatial pattern similarity between reference map and simulation map was applied to validate the model with the consideration that the objective of the CA model is to make the simulated urban spatial pattern as close as the reference spatial pattern. A total of four spatial metrics (NP, LPI, ENN_AM, and SHAPE_AM) were selected to capture the urban spatial pattern. The spatial pattern similarity (SS) is estimated as follow (Li et al., 2008):

$$SS(\%) = 1 - \frac{1}{4} \times \sum_i \left| \frac{SM_{s,i} - SM_{r,i}}{SM_{r,i}} \right| \times 100\% \quad (22)$$

where $SM_{s,i}$ is the value of the ith spatial metric derived from the simulated urban spatial pattern, and $SM_{r,i}$ refers to the value derived from the observed urban spatial pattern. A larger of value of SS implies that the simulated urban spatial pattern is closer to the observed spatial pattern.

Calibration of CA model is the basis of the effective simulation. The performance of CA model is highly dependent on the adequacy of transition rules which involves several parameters that must be estimated accurately (Wu & Webster, 1998). In this study, it is necessary to calibrate the proposed CA model with the help of historical data before using it to predict future urban growth pattern and corresponding energy consumption. After the calibration, the weights in Eq. 18 and the parameters in Eq. 21 involved in the transition rule can be obtained, so that the model can be applied to conduct the future simulation with high accuracy.

By using the trial and error method, the random parameter can be generated. It is conducted by running the model many times with different random parameter values. The SS value was obtained for each simulated result to measure and compare the overall performance of the model with different random parameter values. A set of weights for the variables can be calculated by using logistic regression approach.

4.3.2 Simulation of development scenario

Previous studies demonstrated the capability of CA model in reproducing historical urban growth (Silva & Clarke, 2005) and in simulating future urban spatial pattern when coupled with spatial optimization models (Li & Thinh, 2014). In this study, the urban spatial metrics under different scenarios could be quantified from the simulation of urban forms. Based on these spatial metrics, the identified panel data model is adopted to predict the corresponding energy consumption for each scenario. Simulating different urban development scenarios in the future is the first step to predict the energy consumption. How to predict the future development is determined by the building of the scenarios. Due to the complexity of the urban system, it is impossible to generate entirely accurate prediction of the future urban spatial pattern. The scenarios are more likely predict various possibilities of potential development (Fuglsang et al., 2013).

The scenarios should closely link to the current existing concerns of the policy makers of the region addressing the key question as well as the historical urban growth trend. Based on the development trend extracted from the historical urban growth analysis and strategic development objectives of the city plan, three scenarios in 2020 were simulated for each selected city. Various urban growth patterns in the study areas were involved in scenarios with a view to explore the possible future evolution of these cities. The land demand values for the cities during this period were obtained according to the urban plan of corresponding cities.

The three scenarios are: Business As Usual (BAU) scenario, Compact Development (CD) scenario, and Disperse Development (DD) scenario. The BAU scenario involves no urban forms constraint, which means the model simulates the future consequences of current urban growth trends without any limitation and alternation.

By contrast, the other scenarios incorporate the constraint of different urban forms, modified neighborhood size as well as the random variables. Each scenario can emphasize one of the most important growth tendencies for each area. CD scenario aims to develop compact urban form, which is more efficient in the use of natural resources and sustainability (Li et al., 2008). It is assumed that the spatial policies are strictly implemented with focus on the concentrating urbanization within existing urban areas. The construction is orientated more to regenerate existing buildings within the city core. In addition, development should be allocated in areas with high accessibility to the city core to encourage the adoption of other means of travel instead of by car. While, the DD scenario is designed to show a dispersed urban growth without any urban planning against this trend. The dispersed development pattern has been observed in some rapid developing cities in China. It results in a large use of land resources because of the increasing demand for residence, shopping and recreation facilities as well as the development in industry and services sectors. An outwards spreading of the city and to a growth in lower density areas constitute of the main development direction.

In addition to simulate the future urban forms, the objective of using cellular automata model is to calculate the related energy consumption and to assess the impacts of different development strategies on the energy consumption. For each scenario, a set of spatial metrics were calculated. Based on the quantitative relationship between spatial metrics and energy consumption, the related future energy consumption for each scenario could be calculated. Through the comparison of the energy consumption for 2020 under different scenarios, scenario-based analysis could help in further understanding the effects of urban development strategy on the energy consumption environment.

5. Results

In the previous chapters, the attempt was made to illustrate the importance of the exploring and analyzing the relationship between urban form and urban energy consumption and how to conduct this work by using related methods. In order to evaluate the performance of the proposed methods described in previous chapter, the methods have been applied based on the available data. The chapter presents and discusses the major findings of this study.

5.1 Urban forms

Multi-temporal Landsat images of the study areas during 2000-2010 were classified into two land cover categories (urban and non-urban) using ERDAS IMAGINE 2011. The classification accuracy for each study area is shown in Table 5-1. A total of 100 random points were generated by using stratified random sampling for each area. The accuracies of urban land are over 82 % for all images. Therefore, the classified maps can be used for the further analysis.

Table 5-1: The overall accuracies of classification results for 20 cities (%)

	2000	2003	2006	2010
Changchun	87	84	90	85
Changsha	85	86	88	84
Fuzhou	89	87	89	91
Hangzhou	88	83	83	91
Harbin	86	90	82	87
Hefei	87	85	86	85
Huhhot	86	86	87	83
Jinan	89	85	90	84
Kunming	89	91	87	88
Lanzhou	88	83	86	85
Nanjing	82	88	84	86
Nanning	89	84	87	91
Shenyang	82	87	90	85
Shijiazhuang	88	84	83	86
Taiyuan	90	89	91	89
Wuhan	83	90	82	89
Xi'an	89	85	86	84
Xining	85	89	84	90
Yinchuang	92	88	86	83
Zhengzhou	87	86	85	86

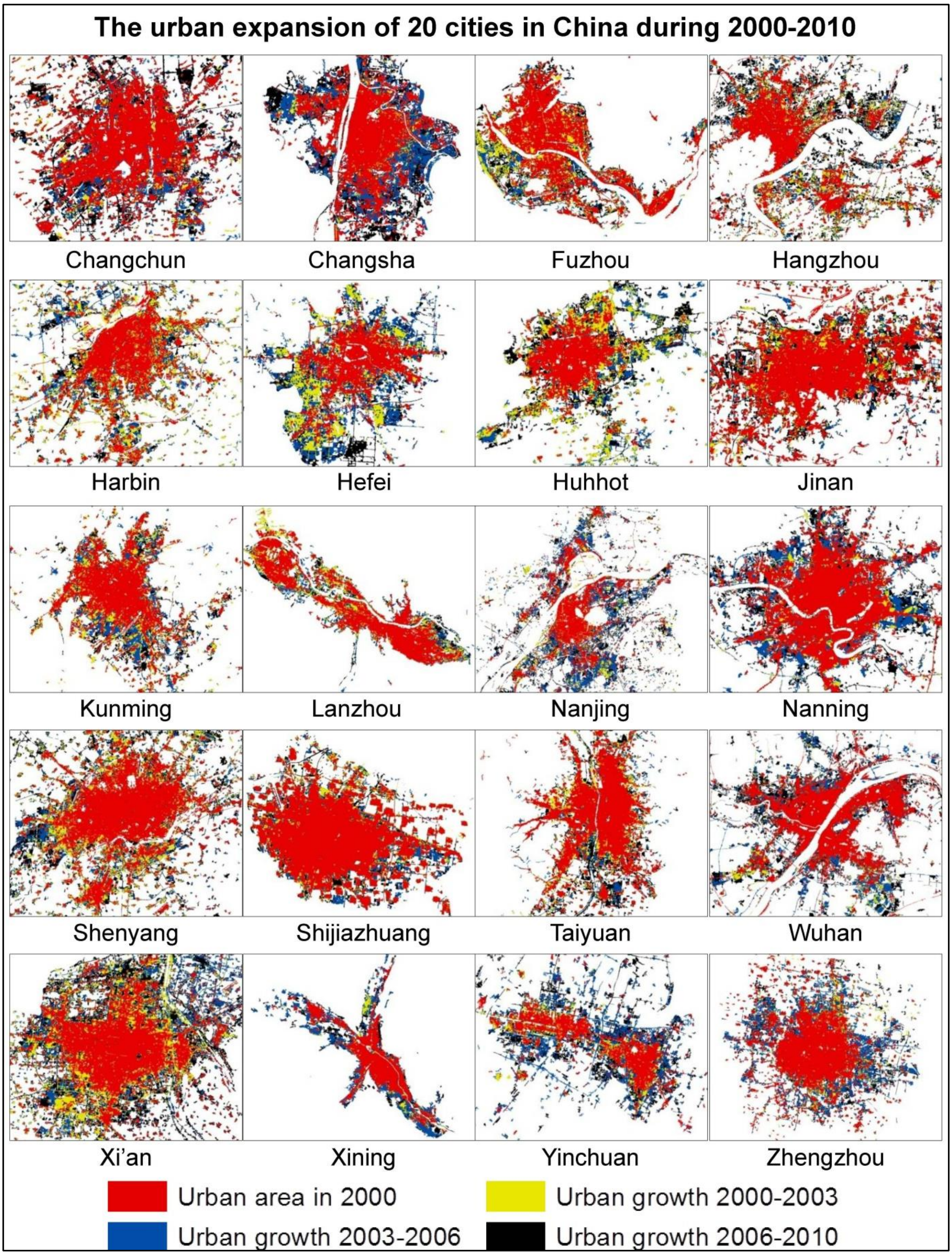

Figure 5-1: The urban expansion of 20 cities in China during 2000-2010

After the classification of urban land cover, urban land cover change detection was carried out. Figure 5-1 shows the spatial patterns of urban expansion for different period, 2000-2003, 2003-2006, and 2006-2010. The urban growth detection clearly identifies the dynamic development path of the urban area during the study period.

Based on classified images and five selected metrics (Class Area, NP, LPI, SHAPE_AM and ENN_AM), urban forms of 20 cities were quantified using FRAGSTATS (McGarigal et al., 2012). Figure 5-2 shows the calculated results of these metrics for the 20 cities in 2000, 2003, 2006 and 2010. The results indicate the significant differences between cities in the changing trend and magnitudes of the indicators. The growth of total urban area is shown in Figure 5-2, which can be considered as a strong evidence to indicate this fact. It can be found that the Class Area value rapidly increased in four different regions during the study period. It is widely acknowledged that almost all of the cities in China have been experiencing the rapid urbanization since the implementation of “Reform and Open Policy” in China. The urbanization process accelerates in a high rate with the fast economic development. The calculation results of Class Area in this study indicate that the urbanization process is still accelerating from 2000 to 2010. According to the degree of socioeconomic development and geography, China can be divided into four economic regions. Class Area values reveals significant difference among the four regions. The higher average value of urban area is found in eastern and northeastern region compared with two other regions (central region and western region). This can be attributed to the rapid economic development in eastern and northeastern region.

As shown in Figure 5-2, the increase and decrease in both NP and LPI values are found in 20 cities during the study period. The increased LPI reflects the growth of historical city core. The allocation of new urban area consists of the developing outward from the original city core and the growth of new urban patches, which are illustrated by the increases in the both of LPI and NP values. The slight increase in NP value is found in central and western regions except Wuhan city. Although there are many land resources in these regions, the economic and natural limitations are the main restriction to the city development. Most of the cities are developed irregularly along the available valley, such as Lanzhou, Huhhot, Yinchuan etc. The inverse trends, however, occur in some eastern and northeastern cities. Many patches were developed for the industrial development as well as the infrastructures construction. As a special case, Wuhan experienced the dramatic increase in NP value, and achieved the highest NP value in 2010. While the relatively lower LPI value is found in

2010. A larger proportion of urban expansion in Wuhan focused on the development of new urban patches, rather than the expansion of the existing urban patches. Higher NP value of 2681 and lower LPI value of 6.866 may suggest a more scattered pattern. In contrast to Wuhan, Shijiazhuang in eastern region has the highest LPI value of 50.176 and lower NP value of 53, which indicates that the continued growth in Shijiazhuang focused on the extension of historical city cores and the increasing connection of recent individual urban patches already close to the center. Over time, few new urban patches were allocated, whereas the present individual urban patches grew together.

The change in SHAPE_AM is presented in Figure 5-2 as well. SHAPE metric measures the compactness of urban form. A value close to one indicates the corresponding patch has a compact form. Otherwise, the patch is more complex and fragmented. As the increasingly rapid urbanization process, the cities' diffusely sprawling development is illustrated by the continuous increases in SHAPE_AM. This is a particular case for the central and northeastern regions, which experienced the significant increase in SHAPE_AM from 2000 to 2010. It implies that the cities in the two regions have more dispersed urban forms.

Figure 5-2 shows that the ENN_AM value decreased in all cities, indicating that the urban patches became more proximate. The distance between patches decreased as the urban patches became larger. In addition, the small patches are more connected with central urban patches, which can be confirmed by the decreasing ENN_AM value. This could result in the loss of open space between the urban patches. As evidenced by Figure 5-1, the vacant land between patches was filled by the new developed land. The new urban areas were found very close to the existing urban areas.

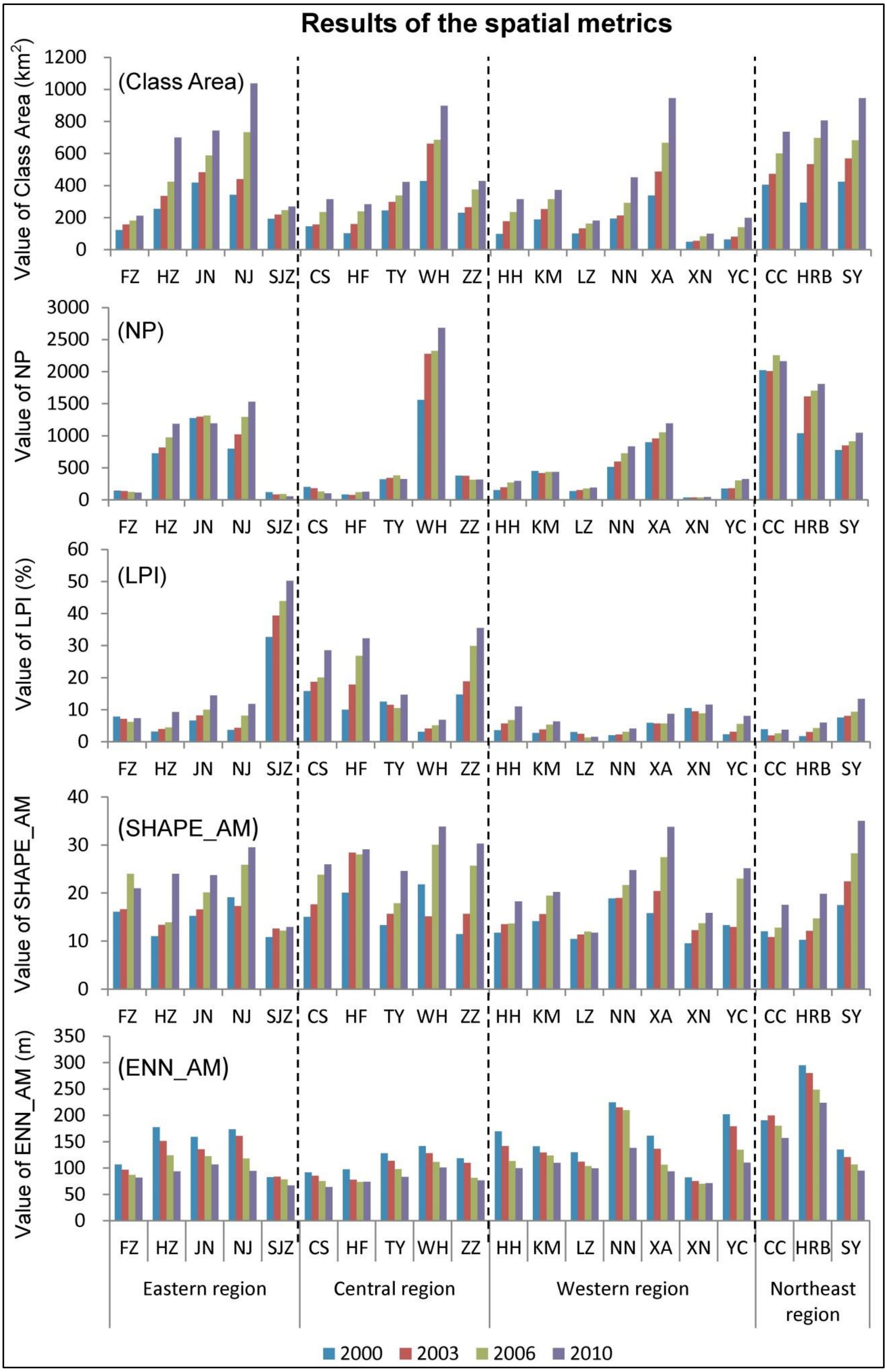

Figure 5-2: Results of spatial metrics (FZ: Fuzhou; HZ: Hangzhou; JN: Jinan; NJ: Nanjing; SJZ: Shijiazhuang; CS: Changsha; HF: Hefei; TY: Taiyuan; WH: Wuhan; ZZ: Zhengzhou; HH: Huhhot; KM: Kunming; LZ: Lanzhou; NN: Nanning; XA: Xi'an; XN: Xining; YC: Yinchuan; CC: Changchun; HRB: Harbin; SY: Shenyang)

5.2 The quantitative relationship between urban form and energy consumption

5.2.1 Calibrated nighttime light data

Figure 5-3 shows the cumulative DN values of multi-temporal NTL data after the intercalibration. In this study, the objective of intercalibration is to improve the continuity of NTL data in China from 2000 to 2010. The discrepancies in DN value of NTL data acquired from different satellites in the same year can be effectively reduced. For the raw NTL data, the cumulative DN value in 2001 acquired from satellite F14 is 14,682,227, while the DN value is 17,153,402 from F15 (Figure 4-2). By conducting intercalibration, the corresponding DN values are 23,130,731 from F14 and 23,280,413 from F15, respectively. Furthermore, the intercalibration method reduces the abnormal change of cumulative DN value acquired from the same satellite over time. For example, the cumulative DN value acquired from F15 inaccurately decreased from 19,635,305 in 2002 to 15,054,477 in 2003. After the conduction of intercalibration, the cumulative DN value increased from 24,483,902 to 25,889,593.

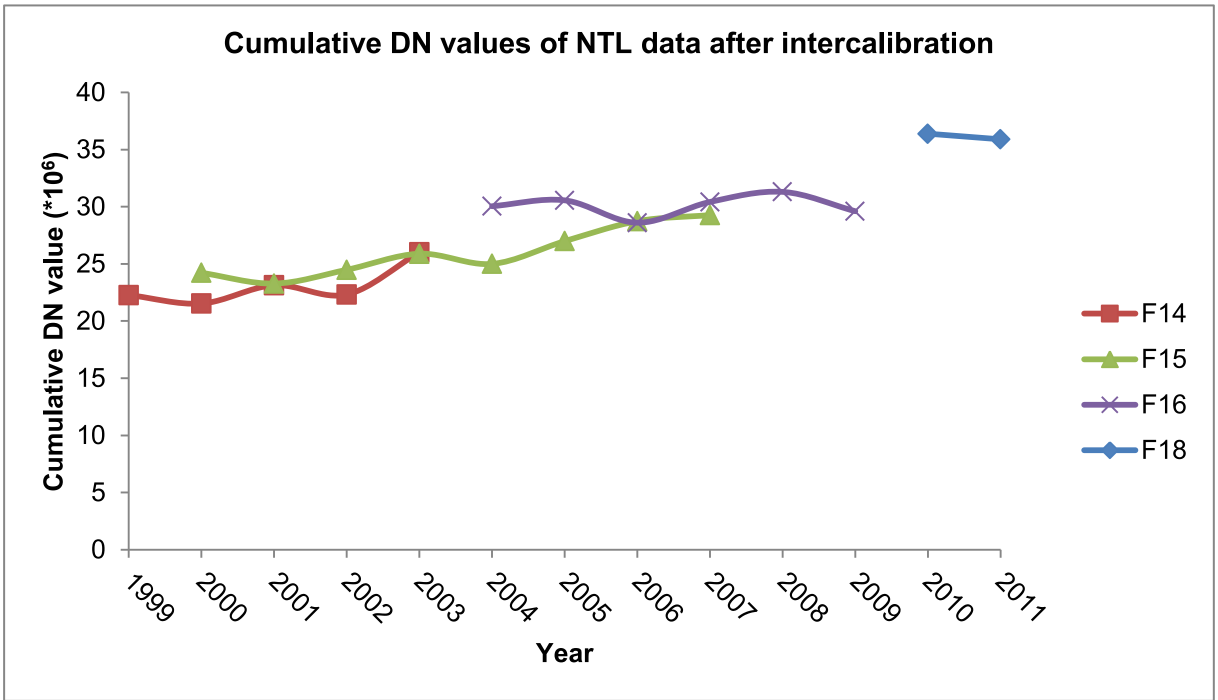

Figure 5-3: Cumulative DN values of NTL data after the intercalibration

The continuity and comparability of NTL data was further improved for the study period by using intra-annual correction. The cumulative DN value after intra-annual correction is shown in Figure 5-4. For the same year, the DN values acquired from different satellites should keep the same. The inter-annual correction was carried out to remove the abnormal fluctuations in cumulative DN value of NTL data. As shown in Figure 5-5, the variation trend of cumulative DN value keeps the continuous increase from 2000 to 2010 with the annual increase rate less than 15 %. After the calibration, the calibrated NTL data in China was generated during the study period (Figure 5-6). It can be seen from Figure 5-6, the area with high DN value grows from 2000 to 2010. In addition, the DN values of some pixels increase over time. The calibrated NTL data was used for the further analysis, including exploring the relationship between the cumulative DN value of NTL data and energy consumption within a specific province as well as the estimation of urban energy consumption.

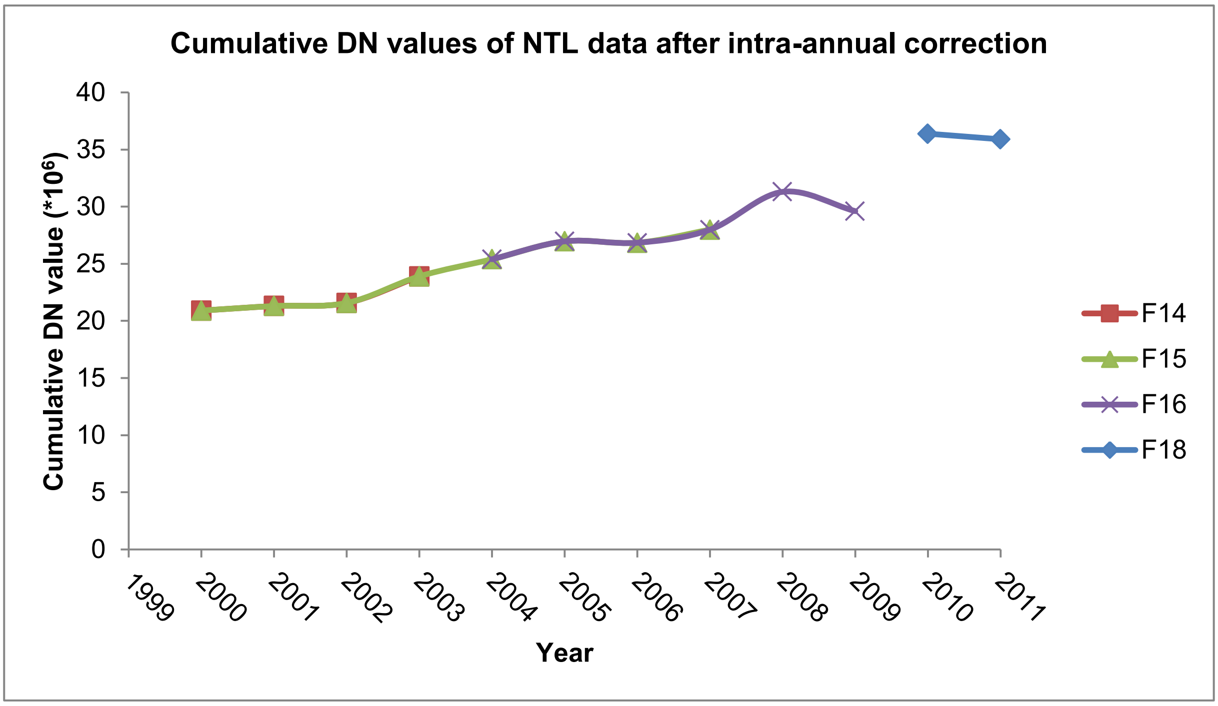

Figure 5-4: Cumulative DN values of NTL data after intra-annual correction

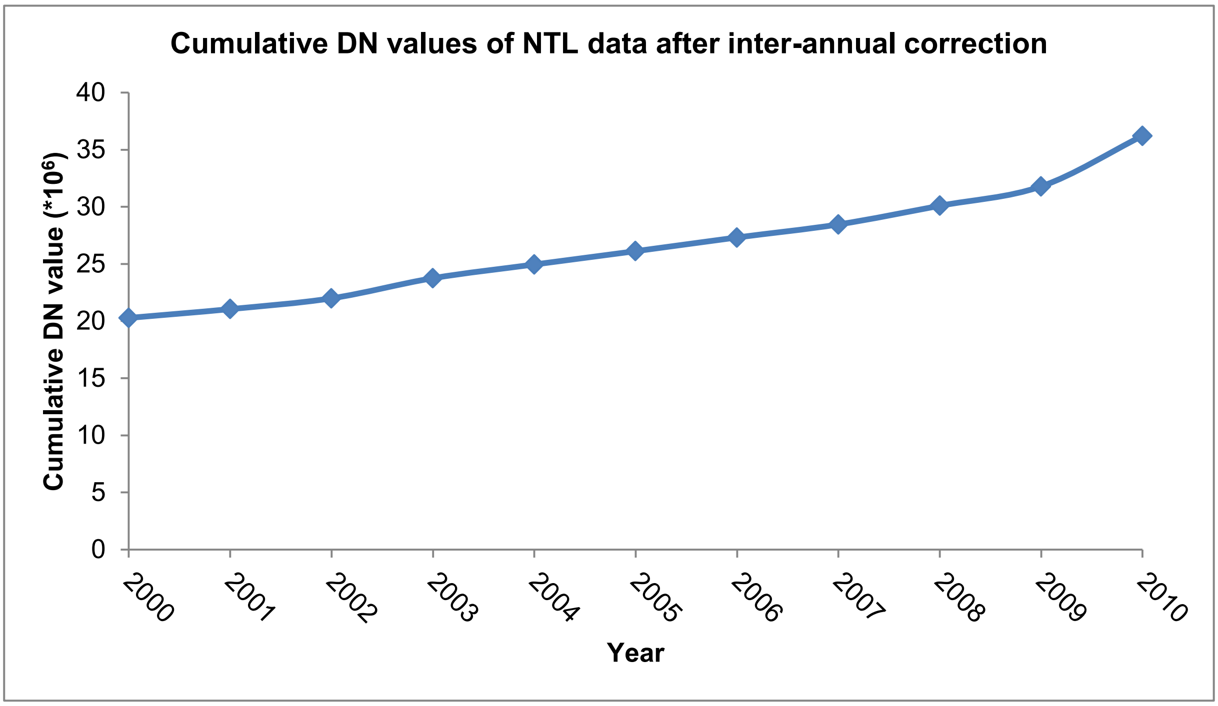

Figure 5-5: Cumulative DN values of NTL data after inter-annual correction

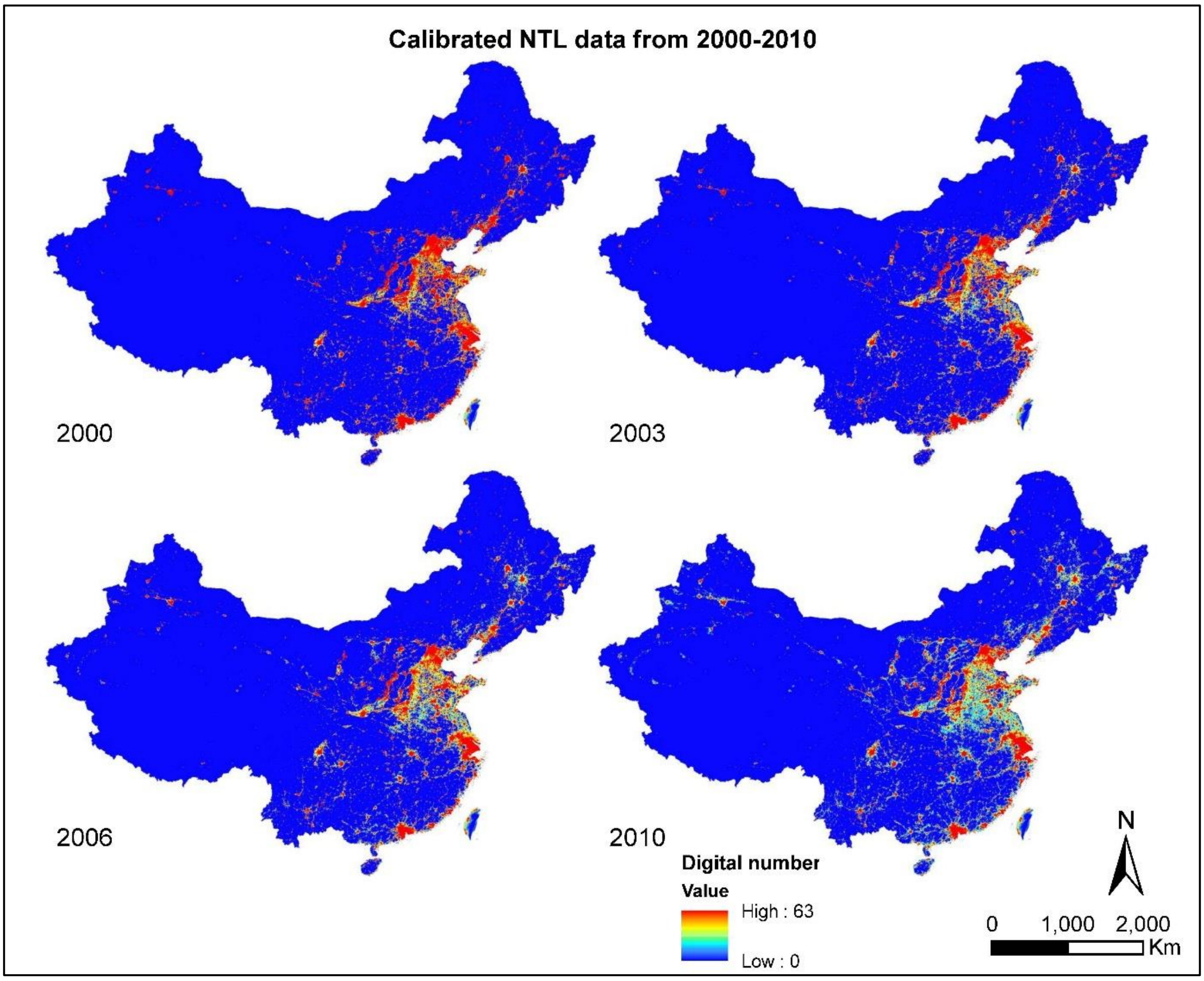

Figure 5-6: The calibrated NTL data from 2000 to 2010 in China

5.2.2 Urban energy consumption

The primary challenge for estimating urban energy consumption using NTL data is to obtain quantitative relationships between cumulative DN value of NTL data and energy consumptions across different provinces.

NTL data have been widely used to analyze global and regional distributions in socioeconomic development. Previous studies revealed a significant positive linear relationship between NTL data and statistical measures of socioeconomic development at global or regional scale (Doll et al., 2006; Elvidge et al., 1999). In order to determine the suitable regression model for estimating the urban energy consumption, three different regression models were developed and compared.

As shown in Figure 5-7, the results indicate that all of the selected provinces show remarkable links between the increased DN value and the rising energy consumption. Particularly noteworthy, the power law responses of cumulative DN value of NTL data to energy consumption occur in all 20 provinces through the comparison of R^2. In addition, the regression model for all provinces are statistically significant ($p < 0.001$). The highest R^2 value of 0.9775 for Zhejiang province suggests that the NTL data significantly correlated with the overall energy consumption in Zhejiang province. While provinces with a high concentration of energy-consuming industries were found with relatively lower R^2. The lowest R^2 of 0.8447 was found in Shanxi province. The coal mining has been the main source of the strong economic activity of Shanxi province. The lowest R^2 value could be attributed to the fact that energy is consumed by the coal mining activities without generating any lights. In summary, the findings support the previous studies that concluded the cumulative DN value has statistically correlation with socioeconomic activities (Doll et al.,2006; Meng et al., 2014). Furthermore, the study improves the understanding of the effectiveness of NTL in correlating with energy consumption at province level. In conclusion, the result shows that there is a significant relationship between energy consumption and NTL data for individual province.

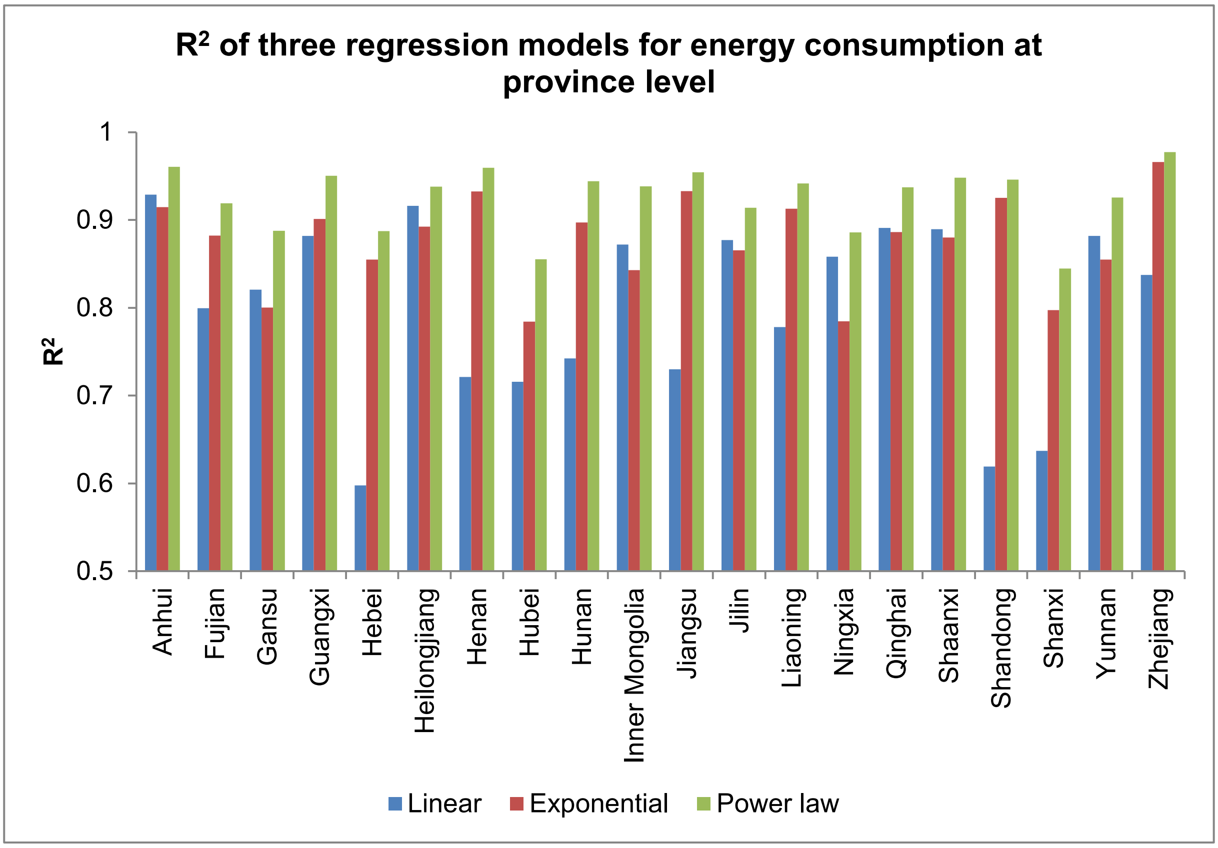

Figure 5-7: R^2 of three regression models (linear, exponential, power law) for energy consumption at province level

Figure 5-8 shows the scatter plots of cumulative DN value of NTL data and statistical province energy consumption. Positive relationships with some outliers are found in the result. Root Mean Square Error (RMSE) has been widely used as a paramount indicator to validate the accuracy of the estimated value by comparing with the statistical value. However, RMSE can only express the magnitude of the error comparing with statistical value. It fails to compare the accuracy among several groups when the statistical values are not the same. In order to improve the validation, the relative Root Mean Square Error (rRMSE) by percentage between estimated energy consumption and statistical energy consumption at province level was calculated to validate the regression model. rRMSE can be calculated using the following equation:

$$\mathrm{rRMSE} = \sqrt{\textstyle\sum_{i=1}^{m} {d_i}^2 / m} \tag{23}$$

$$d_i = \left| \frac{EC_{e,i} - EC_{s,i}}{EC_{s,i}} \times 100\% \right| \tag{24}$$

where d_i is the relative error of estimated energy consumption; m is the number of samples; d_i can be calculated by the Eq. 24. $EC_{s,i}$ is the statistical energy consumption at province level for the sample i; $EC_{e,i}$ represents the energy consumption estimated by using regression model for the sample i.

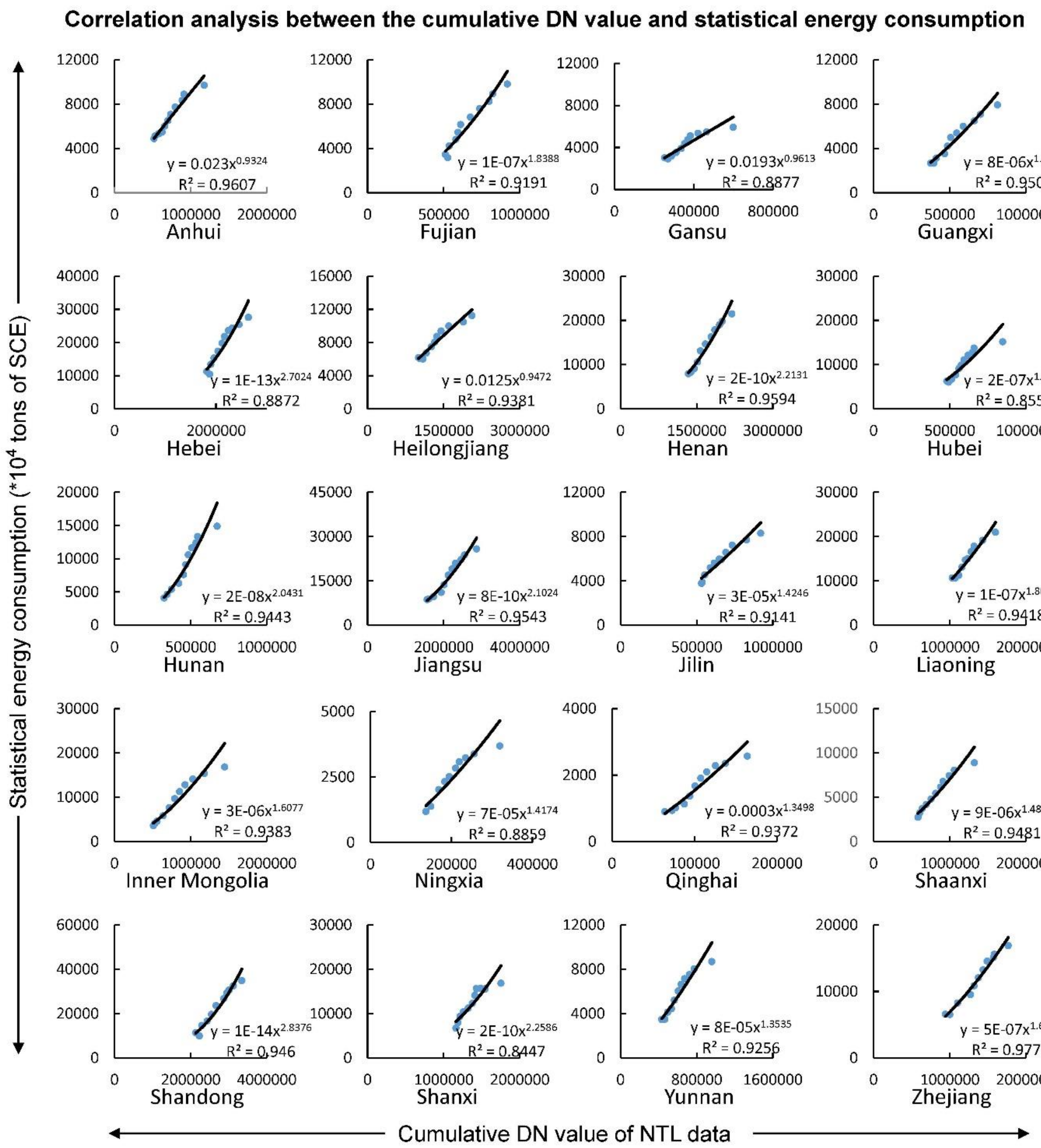

Figure 5-8: Correlation analysis between the culmulative DN value of NTL data and statistical energy consumption for individual province

Figure 5-9 shows the calculation results of rRMSE between estimated and statistical energy consumption for each province. It provides a general insight into the accuracy of the estimated energy consumption by comparing with statistical consumption. From the result it is possible to see that the rRMSE value ranges from 4.55 % to 13.93 % for the estimated energy consumption.

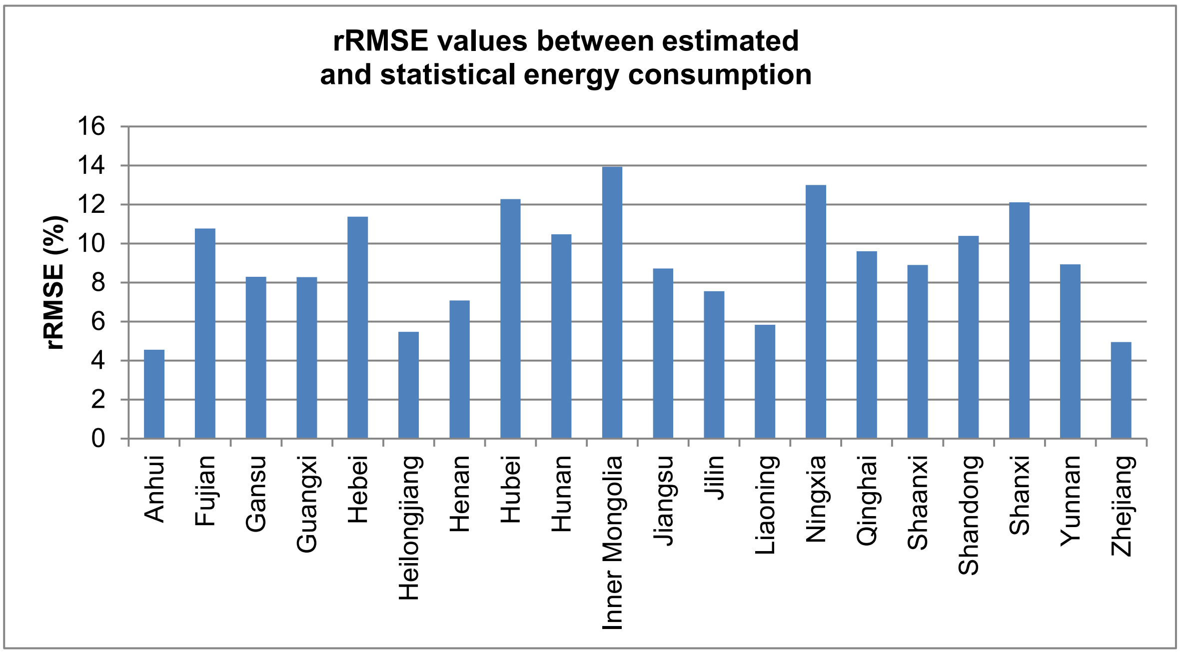

Figure 5-9: rRMSE values between estimated and statistical energy consumption for 20 provinces using the power law regression models

For each province, there are 11 samples of energy consumption during the study period of 2000-2010. In addition to the general information acquired from rRMSE, the relative error (d) of estimated energy consumptions were calculated and presented to achieve the clear descriptive of the effectiveness of identified models in estimating province energy consumption at spatiotemporal scale. Figure 5-10 displays the distribution overlay of the relative error of calculated province energy consumption compared with the statistical energy consumption in the form of a box plot. The bottom and top of the box represents the 25th and 75th percentiles. The space between the different parts of the box implies the degree of dispersion (spread) and skewedness in the estimated results. It also shows the outliers. From Figure 5-10, it is noteworthy that the relative error of estimated energy consumption varies conspicuously within a specific province over time. The relative error of estimated energy consumption in Ningxia province falls in the largest range from 0.42 % to 26.10 %. While the relative error of estimated energy consumption in Anhui province has a narrow range. The estimated consumptions with large range of relative error and some outliers are evident, which are probably caused by diversities of factors affecting the relationships between NTL and energy consumption. It demonstrates that the performance of identified models on estimating energy consumptions is not stable over time. Moreover, the ranges of relative error vary significantly from one province to another. This can be explained by the spatially differences in socioeconomic development, and energy intensity. Overall, the effectiveness of regression model in estimating the energy consumption differs spatially.

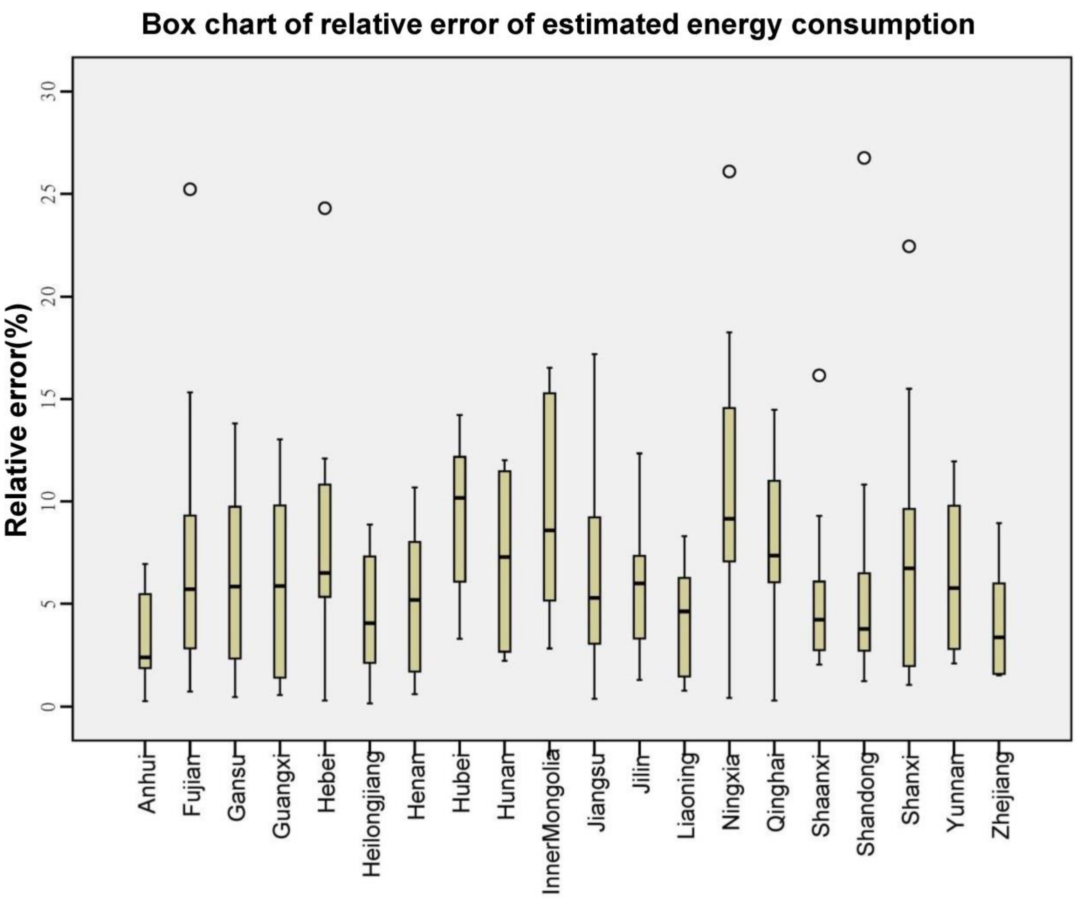

Figure 5-10: Box chart of relative error of estimated energy consumption.

The distribution of the relative error is summarized in Figure 5-11. This clearly depicts that 38 % of the total samples have a relative error between 0 % and 5 %. If the error is further extended until 10%, more than 70 % of the total samples fall in the range of 0-10 %. It indicates that energy consumptions for most of time points can be estimated with high accuracy. The proportion value decreases continuously as the relative error increases. Only 4 % of the total samples have the relative error larger than 20 %.

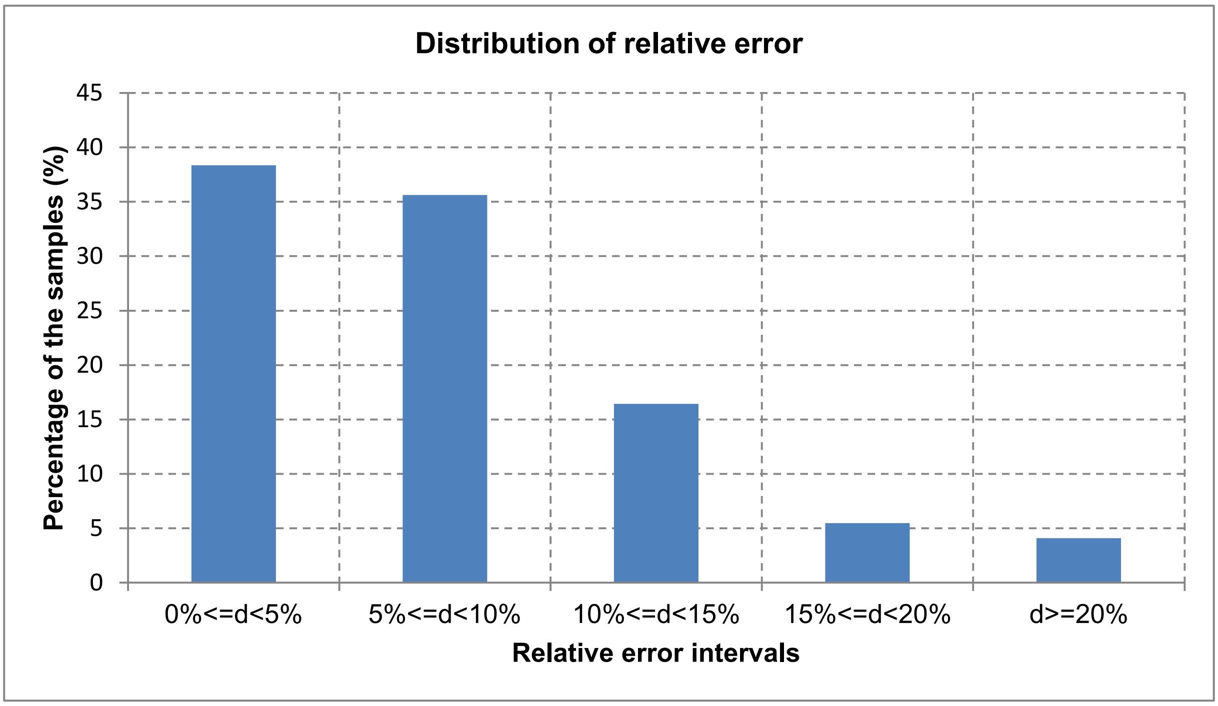

Figure 5-11: The distribution of the relative error

After a series of validation procedures, the results indicate that the selected regression models were feasible and reliable to estimate province energy consumption in China using NTL data.

The assessment result of regression models verifies the utility of NTL data for estimating long-term trend in energy consumption through power law regression model for 20 provinces in China during 2000-2010. Moreover, the results reveal the same quantitative responses of DN value to the variation in energy consumption over time. In most of previous studies, only one regression model was used to quantify the relationship between socioeconomic activities and DN value of NTL data without considering and comparing with other regression models (Meng et al., 2014). Particularly, most of the related studies only focused on the application of linear regression model. Although observationally-based assessment of NTL could be applied for tracing energy consumption, the different quantitative models should be used for different types of urban development in order to obtain more accurate estimation values. Therefore, there is an urgent need to test different models and select a suitable one according to their performance. In this study, three different models (linear, exponential, and power law regression models) were involved to quantify the relationship. The suitable model was identified by using R^2. Particularly noteworthy, the relationship between energy consumption for all provinces and cumulative DN value of NTL can be effectively quantified by power law regression model rather than linear model and exponential model. Thus, the power law regression model was selected as the best fitting model. The comparison of different regression models can avoid the bias and inaccuracy that is caused by considering only one model. The study can improve the previous studies by proposing three different models and identifying the suitable one based on the measure of goodness of fit.

The quantification of the relationship between energy consumption and NTL suggests that the NTL data can be considered as a proxy for estimating the energy consumption. In order to achieve the consistent result within a specific province, the power law regression model needs to be modified in order to estimate the urban energy consumption. The original regression model for fitting energy consumption to NTL data is shown as Eq. 25.

$$ECe_{p,t} = a \times NTL_{p,t}^{b} \tag{25}$$

where a is the coefficient of power law regression model. $NTL_{p,t}$ is the cumulative DN value of NTL data for the province p in the year t. $ECe_{p,t}$ is estimated energy consumption for the province p in the year t. According to the validation result, the relative error is observed by comparing the estimated energy consumption with statistical energy consumption. In order to make sure the estimated value is consistent with statistical value, relative error $d_{p,t}$ was involved to correct the estimated value. The equation is expressed as Eq. 27, which is generated by transforming Eq. 25.

$$d_{p,t} = (ECe_{p,t} - ECs_{p,t})/ECs_{p,t} \tag{26}$$

$$ECs_{p,t} = ECe_{p,t}/(1 + d_{p,t}) = a \times NTL_{p,t}^{b}/(1 + d_{p,t}) \tag{27}$$

where $d_{p,t}$ is the relative error between estimated energy consumption and statistical energy consumption for the province p in the year t. $ECs_{p,t}$ is statistical energy consumption for the province p in the year t.

Eq. 27 can be further transformed into the following equation:

$$ECs_{p,t} = (a \times NTL_{p,t}^{b-1}/(1 + d_{p,t})) \times NTL_{p,t} \quad (28)$$

where $a \times NTL_{p,t}^{b-1}/(1 + d_{p,t})$ can be regarded as a new coefficient of the linear regression model at the time t for a specific province p. The coefficient indicates the amount of energy consumption for the pixel with DN value of 1. It is not fixed and it increases as the cumulative DN value of NTL data increases.

In order to keep the amount of energy consumption consistent within specific province, the cumulative DN value of NTL data for the specific province should equal to the sum of the cumulative DN value for all cities in the specific province. This can be expressed by the following equation:

$$NTL_{p,t} = \sum_{i=1}^{n} NTL_{u,t,i}. \quad (29)$$

where $NTL_{u,t,i}$ is the DN value for the city i in the year t. It is assumed that the total number of cities in the province is n. $NTL_{p,t}$ should be the sum of $NTL_{u,t,i}$ (i=1,2,…n).

According to the Eq. 29, the Eq. 28 can be transformed to Eq. 30:

$$ECs_{p,t} = (a \times NTL_{p,t}^{b-1}/(1 + d_{p,t})) \times \sum_{i=1}^{n} NTL_{u,t,i} \quad (30)$$

where $NTL_{u,t,i}$ represents the cumulative DN value of city i in the year t within the specific province. Based on the Eq. 30, the energy consumption can be estimated by the Eq. 31 for the individual city.

$$EC_{u,i} = (a \times NTL_{p,t}^{b-1}/(1 + d_{p,t})) \times NTL_{u,t,i} \quad (31)$$

where $EC_{u,i}$ is the energy consumption for the city i. The coefficient varies over time, and it is different for each province because of the regional differences involved in the characteristics of energy consumption. The urban energy consumption can be estimated by using the linear regression model with variable coefficients.

The study proposed linear regression model with variable coefficients on the basis of the power law regression model to estimate the total energy consumption at an urban level. Recently, different models were developed to estimate the socioeconomic statistics. For example, Meng et al. (2014) proposed panel linear model to estimate the city CO_2 emissions in China based on the assumption that the relationship is constant within a specific province. According to the proposed model for urban level, however, the sum of CO_2 emissions for all cities in the specific province is not equal to the total CO_2 emissions in the province. It is a common problem in the studies related to the estimation of socioeconomic statistics. The problem could lead to the overestimation or underestimation of the actual value at the urban level. In reality, the total statistical data of a specific province should be constituted of the sum of the statistical data of the individual cities within the province. This study proposed the linear regression model with variable coefficients which ensures that the sum of estimated energy consumption for each city within a specific province equals to the total statistical energy consumption for the province. By applying this method, the accuracy of the estimation can be improved.

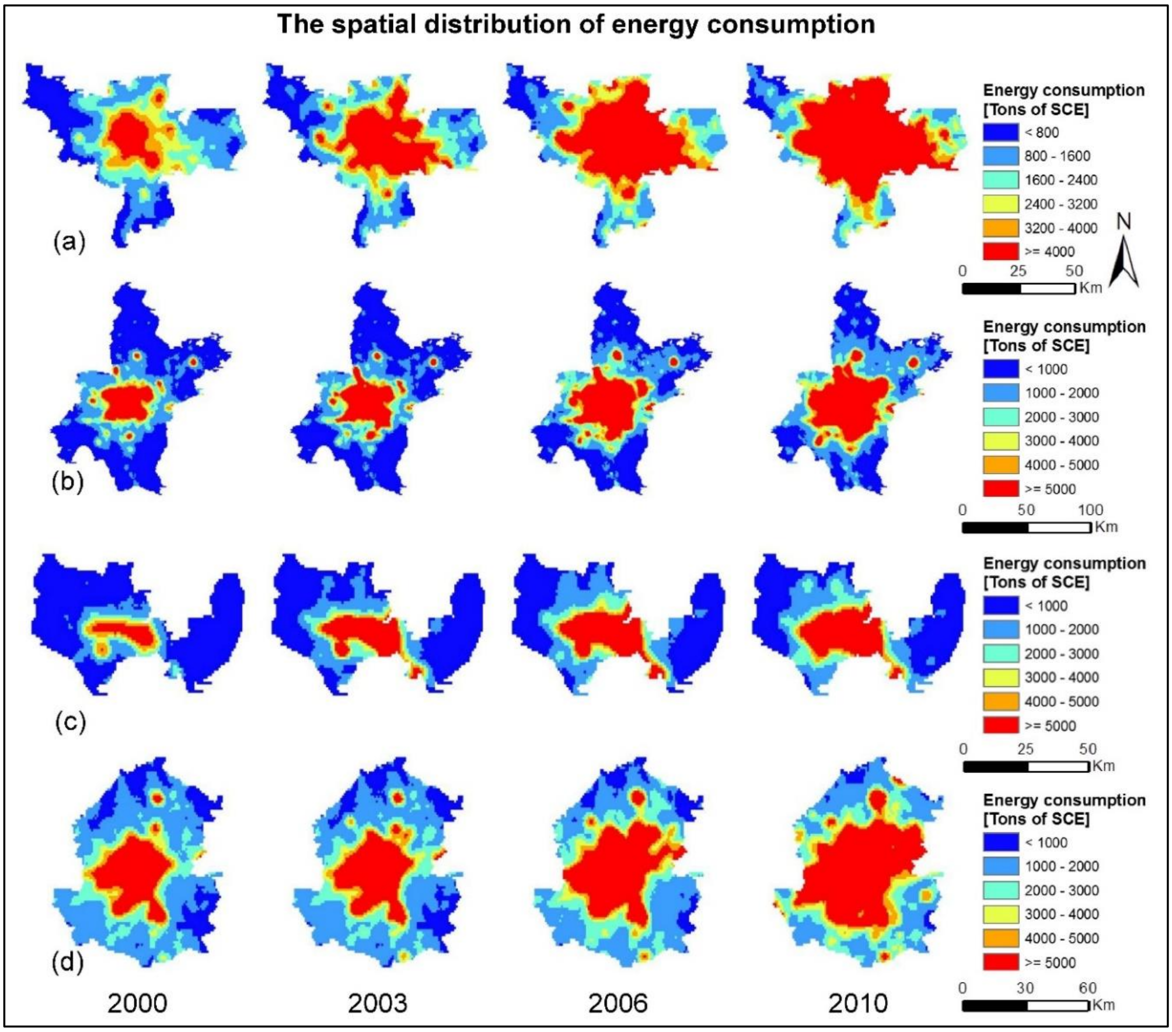

Figure 5-12: The spatial distribution of energy consumption in 2000, 2003, 2006, and 2010: (a) Hangzhou, (b) Wuhan, (c) Yinchuan, (d) Shenyang.

The urban energy consumptions were estimated using Eq. 31. Taking the four cities (Hangzhou, Wuhan, Yinchuan, Shenyang) in four regions as an example, the estimation method was applied to downscale statistical province energy consumptions into grid format within the cities. The spatial distribution of energy consumption in Figure 5-12 is expressed as tons of SCE per pixel of NTL data during the study period. Visually, energy consumption in each city increased significantly from 2000 to 2010. As indicated by the figure, the area with high energy consumption value expanded around the city core. This is the particular case for Hangzhou, where the area with high value increased significantly, which could be attributed to the expansion of urban area and the increase in population. In addition, it is found that much more energy intensive activities were aggregated in the city core than in suburban area. On one hand, much more socioeconomic activities were concentrated within the city core, which is the dominant energy consumer in China, increasing the energy intensity of city areas. On the other hand, the income level and lifestyle of city residents changed, leading to increasing energy consumption.

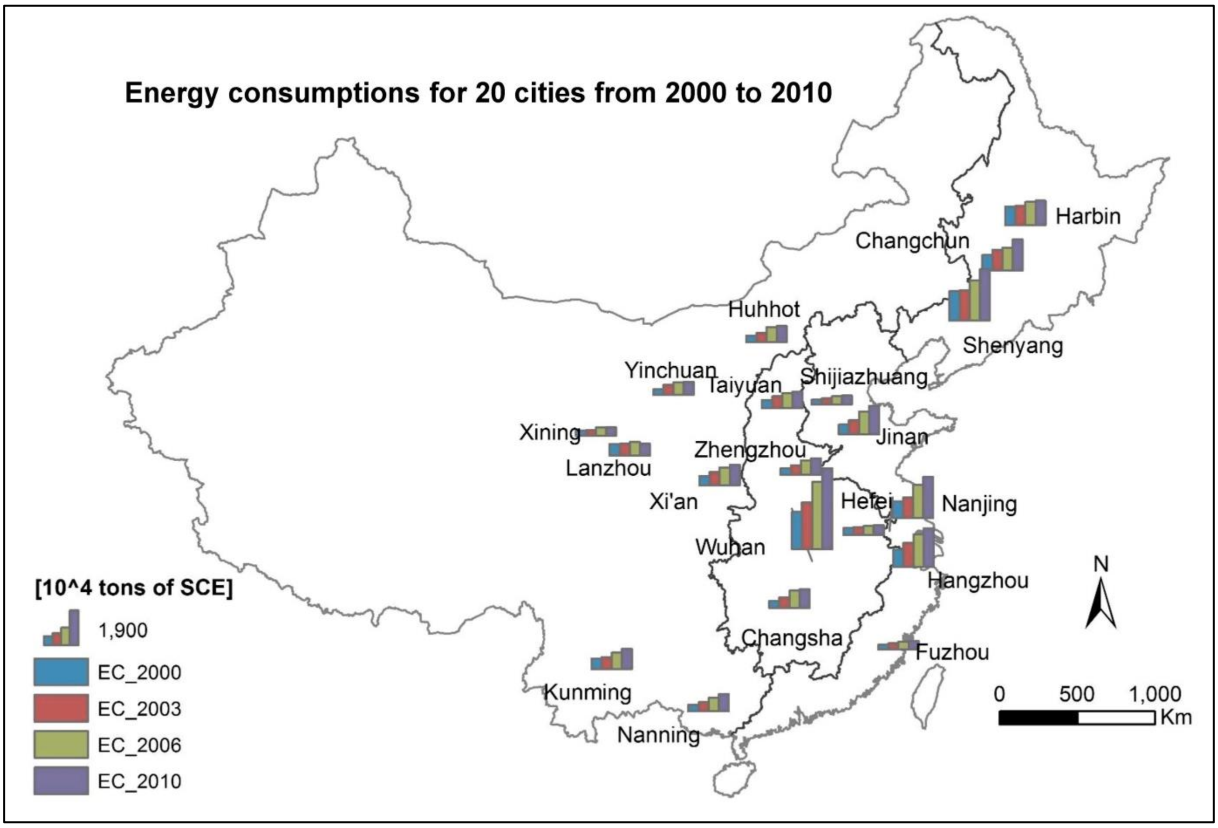

Figure 5-13: The bar chart of energy consumptions for 20 cities from 2000 to 2010

Figure 5-13 presents the estimated energy consumption values in 20 cities from 2000 to 2010. It indicates that energy consumption of each city increased gradually during the period. The sum of energy consumption of the 20 cities grew by approximately 102 % from 10,902.89*10^4 tons in 2000 to 22,121.36*10^4 tons of SCE in 2010. In Jinan, the energy consumption increased by approximately two times from 2000 to 2010, which shows the highest increase rate over 20 cities. Wuhan is found to be the largest energy consumer, with its rising energy consumption rising dramatically from 1,708.09*10^4 tons in 2000 to 3,702.64*10^4 tons of SCE in 2010. Similarly, as shown in Figure 5-14, the energy consumption per capita of Wuhan is higher than that of other cities in 2010. Each person in Wuhan city consumed 7.11 tons of SCE. In contrast, Xining in western region of China is proved to be the smallest consumer, with its energy consumption of 378.04*10^4 tons of SCE in 2010. Although the energy consumption in Yinchuan is not the highest in the western region, the urban energy consumption per capita is higher than that of other cities. In addition to the variation of energy consumption, the energy consumption per capita varies across cities.

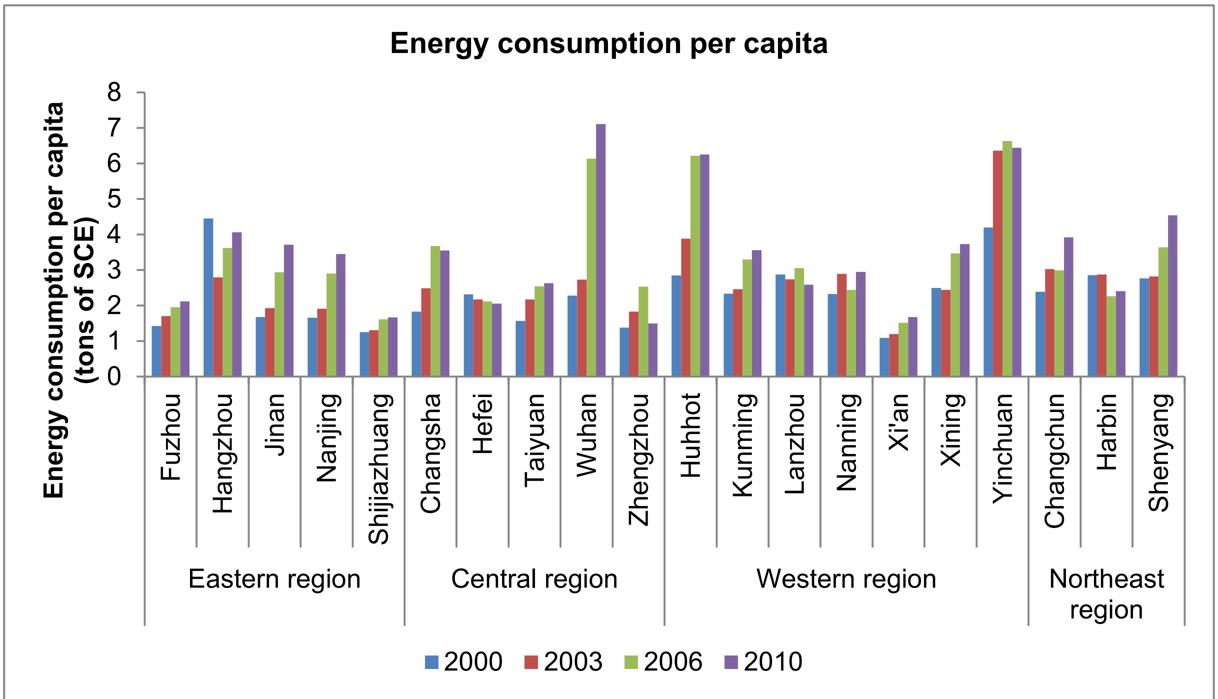

Figure 5-14: The energy consumption per capita for 20 cities from 2000 to 2010

Moreover, spatiotemporal differences of energy consumption are also reflected in Figure 5-15. The average energy consumption for seven cities in western region is lower than that of other areas during the period of 2000-2010. In contrast to the western region, the northeast region can be regarded as the largest consumer with the average consumption of 1,632.09*10^4 tons of SCE in 2010. However, the average overall energy consumption for three cities in northeast region increased by 68 %, lower than that of other regions. The energy consumption in eastern region increased significantly with the highest rate of 137 %. The increase rate of energy consumption decreases gradually from the eastern region to the central region, and from the central region to the western and northeast region. This is in accordance with the findings of Wang et al. (2014a). It may be due to the different urbanization level and regional socioeconomic development. During the period of 2000-2010, the regional socioeconomic and urbanization level in eastern region maintained high growth rate. It is also indicated by the Figure 5-12 (a), in which the expansion of area with high energy consumption value is more remarkable in Hangzhou, a city within eastern region. The economy, population, urbanization, car ownership, and other related factors play a crucial role in rising energy consumption. In western region, however, the above factors experienced relative slow growth during the period. As an important base of old industry with equipment manufacturing, the urbanization and economic growth in northeast region lag far behind the development in eastern region (Wang et al., 2016). For both western and northeast regions, rural development is the most important factor affecting growth in energy consumption, followed by economic growth, transportation and nonagricultural industry development. Because of its geographical proximity to the eastern region, the central region experienced industrial transition process, in which some industries shifted from eastern region to central region, which resulted in the dramatic increase in energy consumption during the study period.

During this period, a large number of energy saving and emission reduction policies have been proposed mainly through the adjustment of industrial structure and the usage of new technologies. It was proved that the improvement in energy efficiency via current measures cannot offset the increase of energy consumption. This is similar to opinions of Chen et al. (2013) as well as Güneralp and Seto (2012). As we mentioned above, changing urban structures may be another effective way to reduce the energy consumption, hence improving the energy efficiency.

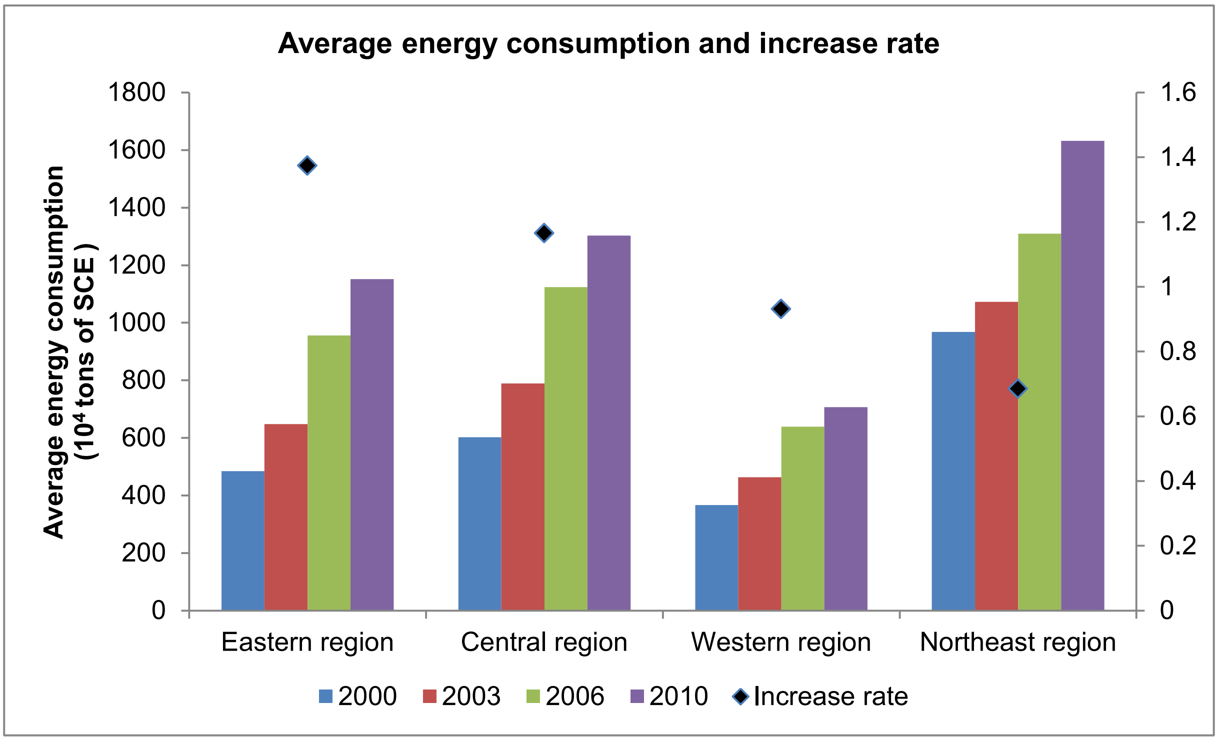

Figure 5-15: Average energy consumption and the increase rate for four regions

5.2.3 The links between urban form and energy consumption

In order to examine the links between urban form and energy consumption, the estimated urban energy consumption and calculated spatial metrics served as dependent variables and independent variable, respectively. Panel data model was then applied to conduct the estimation. To address the concern whether the impact of urban form on energy consumption differs across the regions in China, we divided the exploration of relationship into two steps. First, the whole sample without consideration of regional differences was adopted to explore the relationship between urban form and energy consumption. Second, the sample of different regions was used to estimate the relationships for the four regions.

Given the condition that T > K+1 in panel data model, here T means the number of time points. K is the number of independent variable. In this study, T is 4. Therefore the maximum value of K should be 2. This indicates that the regression model has at most two independent variables. All five metrics cannot be involved in one regression model due to this condition. In order to properly estimate the relationship between energy consumption and urban form, these metrics can be divided into several combinations. The combination should include two metrics with low correlation. Prior to estimating parameters of panel data model, the Pearson's correlation analysis was implemented in order to test the correlation among the metrics and to select the combination of non-correlated metrics in each estimated model. Table 5-2 presents the results of correlations among the spatial metrics in this study. Based on the computed correlation coefficients in Table 5-2, four pairs of metrics meet the requirement: (Model 1) Class Area and LPI; (Model 2) Class Area and ENN_AM; (Model 3) NP and SHAPE_AM; (Model 4) LPI and SHAPE_AM. Therefore, four combinations of metrics are used to establish four regression models to quantify the relationship between urban form and energy consumption.

Table 5-2: Correlation coefficients of the selected spatial metrics

	Class Area	**NP**	**LPI**	**SHAPE_AM**	**ENN_AM**
Class Area	1				
NP	0.795**	1			
LPI	-0.098	-0.376**	1		
SHAPE_AM	0.557**	0.198	0.164	1	
ENN_AM	0.116	0.447**	-0.561**	-0.347**	1

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

F-test was conducted firstly for these four models in order to identify a suitable regression form from the three different potential forms in panel data analysis. Based on S_1, S_2, S_3 of each model, F_2 and F_1 results were obtained according to the Eqs. 13 and 14. The results are listed in Table 5-3. Table 5-4 shows the F-test results. Given the significance level of 0.001 %, F (57, 20) is approximate 6.75. F_2 values for models 1-4 are greater than F (57, 20), which indicates that the pooled regression model should be rejected, then F_1 should be further tested. All of the values of F_1 are less than the F (38, 20) which is about 7.11 at the same significance level. It demonstrates that the variable intercepts and constant coefficients model should be adopted for these four models.

The Hausman test was further conducted to identify whether the fixed or random effects will be applied. According to the Eq. 15, W value can be calculated. The result of the Hausman test for the four models are presented in Table 5-5. The result shows that the values of W for models 1-4 are greater than zero. Hence, the fixed effect model for estimation was selected for the further analysis.

Table 5-3: RSS and F values for models 1-4

	S_1	S_2	S_3	F_2	F_1
Model 1	347560	3720910	15577742	15.37553	5.10831
Model 2	130136	1881693	12045403	32.12620	7.08387
Model 3	135688	1422976	9618751	24.52236	4.99322
Model 4	267641	2338407	20700320	26.78713	4.07214

Notes: The combinations of metrics in these four models are: Class Area and LPI (Model 1); Class Area and ENN_AM (Model 2); NP and SHAPE_AM (Model 3); LPI and SHAPE_AM (Model 4).

Table 5-4: F-test results for models 1-4

F-test	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Pooled regression	15.38 > F(57,20)	32.13 > F(57,20)	24.52 > F(57,20)	26.79 > F(57,20)
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Variable intercepts and constant coefficients	5.11 < F(38,20)	7.08 < F(38,20)	4. 99 < F(38,20)	4.07 < F(38,20)
	(0.00001)	(0.00001)	(0.00001)	(0.00001)

Table 5-5: Hausman test results for models

	Model 1		**Model 2**		**Model 3**		**Model 4**	
	Fixed	**Random**	**Fixed**	**Random**	**Fixed**	**Random**	**Fixed**	**Random**
Class Area	1.778	1.888	1.618	1.804				
NP					0.845	0.715		
LPI	2.990	-1.936					-4.492	-8.887
SHAPE_AM					36.887	38.488	52.655	54.736
ENN_AM			-1.476	-0.535				
W	1.372		1.584		1.769		1.079	

The test results indicate that there exists a relationship between spatial metrics and energy consumption:

$$EC_{u,i} = \alpha_i + \beta_1 * x_{1,t} + \beta_2 * x_{2,t} + \varepsilon_{it} \tag{32}$$

where $EC_{u,i}$ is the energy consumption of the city i, α_i is the city fix coefficient, to capture the differences between different cities, $x_{1,t}$ and $x_{2,t}$ represent the two spatial metrics for city i at time t. β_1 and β_2 are the coefficient of the selected spatial metrics, respectively. The coefficients keep constant over time and different study areas. ε_{it} is the error term.

Based on the four different combinations of spatial metrics, four fixed effect models for estimating overall energy consumption were estimated accordingly (Table 5-6). The first model examines the effect of the composition of Class Area and LPI on energy consumption. Similarly, the other three models investigate the effect of compositions of Class Area and ENN_AM; NP and SHAPE_AM; LPI and SHAPE_AM on energy consumption respectively. The parameters of the relationship between energy consumption and urban form were estimated by using panel data analysis. As shown by the result, the variables coefficients exhibited that urban spatial pattern has important but different impacts on the energy consumption. It is found that all the estimated coefficients are statistically significant at the level of 1 %. All the selected spatial metrics are correlated significantly with energy consumption. Class Area, NP, LPI, SHAPE_AM are positively correlated with energy consumption when we using 80 samples (coefficient of LPI is negative in Model 4, but it is not significant), while ENN_AM is negatively correlated with energy consumption.

Table 5-6: Coefficients estimated from panel data analysis for 20 cities

	Model 1	**Model 2**	**Model 3**	**Model 4**
Class Area	1.8423**	1.5458**		
t-statistic	19.4988	10.5044		
NP			0.9854**	
t-statistic			13.1153	
LPI	3.4824**			-1.1637
t-statistic	2.9295			-0.3902
SHAPE_AM			31.2928**	49.4246**
t-statistic			10.8085	15.8986
ENN_AM		-2.1379**		
t-statistic		-3.2791		
Constant	112.9817**	528.0465**	-458.4887	-91.1109*
t-statistic	3.8604	3.9970	-10.7452	-2.3742
Number of samples	80	80	80	80

** Significant at 0.01 level

* Significant at 0.05 level

The positive correlation between Class Area and overall energy consumption indicates that urban expansion was related to the increase of energy consumption.

From Table 5-5, it can be seen that the coefficient of Class Area in Model 1 is 1.8423. It is indicated that 1 km^2 increase in urban land area would lead to $1.8423*10^4$ tons of SCE increase of the energy consumption when other elements remain constant in Model 1. The positive relationship can be explained from the perspectives of population growth and economic development (Fan et al., 2008; Chen et al., 2011). The sum of population of these 20 cities increased significantly from 2000 to 2010 due to the dramatic urbanization. The increase in urban population, which is the main driver of urban growth, is responsible for the increase in energy consumption. Along with the rapid urbanization process in China, many people are moving from less developed areas to more developed areas. Among the different kinds of migration, the migration from rural areas to urban areas is the foremost reason for the significant population growth. The migration pattern has a significant impact on energy consumption. The new urban migrants consume greater energy than their rural settlements. Firstly, a large percentage of energy supply in rural area relies on biomass while urban energy consumption mainly comes from commercial fuels. In addition, the change in migrants' lifestyle due to the rural-to-urban migration would cause the change in typical energy consumption profile of these migrants (Ma, 2014). The socioeconomic activities of rural-to-urban migrants shift from agricultural to service, construction and industrial activities, which have significantly different energy intensity compared with agricultural activities in rural areas.

The main goal of most developing countries, especially China, is to accelerate the economic development, which should be another reason of growing energy consumption. The rapid economic development contributes to the dramatic urbanization and urban expansion. As shown by the land cover change detection in section 5.1, a large amount of non-urban land was converted into urban land such as industrial land and commercial land. In China, the manufacturing industries, especially the processing industries, which are characterized as low energy efficiency and high labor intensive, normally play an important role in regional economy in most Chinese cities (Ma and Stern, 2008). It makes more energy-consuming sectors concentrate into the urban areas. From the statistical data, the secondary industry and the tertiary industry of the 20 province capital cities contributed more than 97 % of total urban district GDP in 2010. In these 20 cities, the proportion of secondary industry accounted almost 45 % in these four years (China City Statistical Yearbook, 2001, 2004, 2007, 2011). Therefore, the development of regional economy should be one of the most important factors affecting the increase of energy consumption. Moreover, rising income makes urban residents' lifestyles more energy intensive (Dhakal, 2009). Based on the total population and estimated energy consumption, the average energy consumption per capita of 20 provincial cities was about 2.18 tons of SCE in 2000, and rapidly increased into nearly 3.39 tons of SCE in 2010. It is inevitable that China will face a significant challenge if the urban expansion in the future remains at the high rate. It is predicted that shortage between supply and demand of oil will be 193 million tons by 2020 (Shen et al., 2005).

As indicated by the estimated result, NP has noticeably positive effect on the energy consumption. The higher of the value of NP is, the more disperse the spatial pattern of urban is. The result suggests that the development of the new urban patches may lead to the rising energy consumption. The massive construction formed many new urban patches, which has been a key factor contributing to the rapid expansion of urban areas. The development of new urban patches may lead to the accelerated development of private and public transport, requiring more energy. Particularly, private transport increases significantly due to the new developed patches (Jones, 1991). For example, the scatter pattern of residential and working areas leads to long movements of people from residences to their work places (Muller, 2004). In addition, the new urban patches require more public infrastructures compared with the development within existing urban patches. The construction, operation and maintenance of the infrastructure could increase the energy consumption (Zhang & Lin, 2012). As a consequence, the increase in number of patches could result in rising energy consumption.

SHAPE_AM provides a measure of the jaggedness or shape of the urban patches. Less compact urban form with highly complex, irregular boundaries can be expected to increase the traveling distance. As indicated by Table 5-6, SHAPE_AM is found to have a significant positive impact on energy consumption, which is consistent with previous studies. A large number of studies concluded that a compact urban form is highly beneficial for sustainable development due to the increased accessibility, lesser need for car transport, reuse of existing infrastructure, and regeneration of urban areas (Thinh et al., 2002; Burton, 2002). Makido et al (2012) suggested that less fragmented cities consume less energy and emit less CO_2 from the perspective of transportation. The main reason for the positive relationship between SHAPE_AM and energy consumption lies in the process of fast industrialization. Many factories and industrial parks were established in urban areas which were developed during rapid industrialization process because the local governments want to attract investments and promote economy. In the process, however, the rapid development was lack of the effective land use planning and management. The general consequence was the tangled and disordered distribution of factories. As indicated by the estimation results, a compact urban structure plays an important role in reducing energy consumption.

It is worth noting that the spatial metric LPI has significant positive impact on overall energy consumption. In contrast to the previous studies conducted by Chen et al. (2011), the study found that overall energy consumption would decrease with the growth of percentage of largest urban patch (city core). The difference of urbanization and socioeconomic situation between the two different study areas could be used to explain the different findings. Many researchers believe that compact cities have environmental, social and fiscal advantages and result in energy saving (Burton, 2002; Hillman, 1996). In some degree, the negative relationship between LPI and energy consumption can support the viewpoint of compact urban form and can consume less energy. However, the traffic congestion associated with compact cities, which was ignored by previous studies, has become a serious problem in saving energy consumption. Traffic congestion is commonly characterized by the longer trip time, lower speed, and increased vehicular queuing (Ang, 1990). Certainly, it is true that more activities would be concentrated into larger city core because more functions can be provided by that (Yeh & Li, 2001). However, larger city core can result in a traffic congestion due to the high density of settlement and insufficient road resources. Therefore, the traffic congestion plays a crucial role in rising energy consumption. In addition, Makido et al. (2012) concluded that the monocentric urban form with high density settlements may lead to high energy consumption. From this point of view, therefore, the development of polycentric urban form can decrease the energy consumption.

One interesting finding is the negative correlation between ENN_AM and energy consumption, which differs from the previous studies. Yin et al (2013) pointed out that decreased distance to city center is the most influential fact to improve the energy efficiency. Chen et al (2011) argued that the ENN_MN is positive correlated with energy consumption in the Pearl River Delta. In this study, ENN_MN is replaced by ENN_AM, which reflects the area weighted mean Euclidean Nearest Neighbor distance. ENN_AM averages the distance by weighting patch area so that larger patches weigh more than smaller patches. This improves the measure of ENN_MN at the global level because the structure of smaller patches is often determined more by image pixel size than by characteristics of natural or manmade features found in the landscape (Milne, 1991). It may be the reason for the different correlation results. Additionally, the number of private cars is also increasing along with the increase of income and change of lifestyle. Therefore, the explanation of negative correlation between ENN_AM and energy consumption may be that potential traffic will increase for shopping and leisure activities when the spatial connection between relatively smaller patches and city core is strong. More energy would be consumed due to the increasing will of traveling. This is particular the case in the fast developing regions, many newly residential areas are built within new urban patches, which are distant from the city core. The road connecting with the city core are constructed after the building of new residential areas. However, the construction of the facilities such as hospital, school and market is lagged behind. Thus the residents have to travel long distance between city core and where they live.

Most of the existing studies concern with the relationship of energy consumption and explanation variables in China, while the study at the regional level is increasingly important for design and implementation of urban spatial planning and energy policy (Zhang & Seto, 2011). With consideration of regional differences, the same procedure was used to examine the relationship between urban form and energy consumptions for the cities in eastern region, central region, western region, and northeast region, respectively. The estimated parameters for the four regions are listed in Table 5-7, 5-8, 5-9 and 5-10. As shown in these tables, the coefficients of spatial metrics (Class Area, NP, LPI, SHAPE_AM) are statistically significant correlated with energy consumption under the level of 5 % or lower in eastern, central, and western regions. The coefficient of ENN_AM is significant in eastern and western regions but is not noticeable at the level of 5 % in central region, which indicates that the increasing energy consumption cannot be explained by the variation of ENN_AM value in central region. Because of the limited samples in northeast region, only Class Area and LPI have remarkable correlation with energy consumption.

Focusing on the four regions, some results of estimated coefficients suggest that it is similar with the result generated by the models at the national level. Moreover, it can be found from the tables that the impact of the spatial patterns on energy consumption varies across regions. From model 1 for the four regions, it can be seen that the coefficients of Class Area are 1.8419, 4.1585, 1.0872, and 1.5370, respectively. With urban land area increasing by 1 km^2, urban energy consumption will increase by $1.8419*10^4$, $4.1585*10^4$, $1.0872*10^4$ and $1.5370*10^4$ tons of SCE in eastern, central, western and northeast regions in China, respectively. The impact of increasing urban land area on energy consumption varies across regions, with the greatest impact on the central region, followed by the eastern, western and northeast regions. In central region, the increase of the urban land can be mainly attributed to the rapid development of industry with high energy intensity. This could lead to the significant increase in energy consumption.

The results indicate that the effects of other explanation variables on energy consumption also differ across regions. With a 1 increase in SHAPE_AM value in Model 3, the energy consumption in eastern, central, and western regions will increase $41.8031*10^4$, $36.1556*10^4$, and $14.2506*10^4$ tons of SCE, respectively. The effect of compact urban form in eastern region is more marked than that in other regions. Furthermore, the impact of NP on urban energy consumption in central region is more significant than that of other regions.

The effect of LPI on energy consumption is significant and positive in eastern, western, and northeast regions, while it is noticeable and negative in central region. As mentioned in previous paragraphs, the congestion caused by compact development is highlighted as an important influencing factor to the positive relationship. However, the dominance of the largest urban patch is negatively correlated with energy consumption, which is consistent with the viewpoint of compact development as suggested by Jenks et al. (1996). The compact urban form can reduce energy consumption through the reduction of interactions among different patches. As a result, the compact development may have lower energy consumption. The regional differences could be attributed to the differences in the economic and infrastructure level among different regions. The cities in eastern region are characterized by the rapid urbanization and economic development as well as the high population density. Although the relatively complete infrastructure and transportation system in the city core provide a good opportunity for development, the fast growing number of private cars could cause the serious congestion. In western region, the transportation system is not complete due to the relatively lower economic level and natural limitations. Therefore, the congestion is also significant. In central region, however, the congestion is not as serious as that in other regions.

Table 5-7: Coefficients estimated from panel data analysis for 5 cities in eastern region

	Model 1	**Model 2**	**Model 3**	**Model 4**
Class Area	1.8419**	0.5019**		
t-statistic	12.5977	3.2555		
NP			0.9229**	
t-statistic			5.5859	
LPI	3.5999*			11.2365
t-statistic	2.4055			1.3296
SHAPE_AM			41.8031**	69.9353**
t-statistic			4.7976	6.2613
ENN_AM		-9.9416**		
t-statistic		-7.6785		
Constant	14.0176	1750.464**	-592.8746**	-593.4334**
t-statistic	0.2683	8.3090	-7.1441	-3.4696

Number of samples	20	20	20	20

** Significant at 0.01 level

* Significant at 0.05 level

Table 5-8: Coefficients estimated from panel data analysis for 5 cities in central region

	Model 1	Model 2	Model 3	Model 4
Class Area	4.1585**	2.7182*		
t-statistic	5.5174	2.6012		
NP			1.3567**	
t-statistic			7.6790	
LPI	-22.5420**			-8.3881
t-statistic	-3.0637			-1.0348
SHAPE_AM			36.1556**	47.7420**
t-statistic			8.8497	5.2764
ENN_AM		1.2017		
t-statistic		0.2379		
Constant	-101.4677	-100.0705	-702.0447**	38.0871
t-statistic	-0.6874	-0.1193	-5.0798	0.3390
Number of samples	20	20	20	20

** Significant at 0.01 level

* Significant at 0.05 level

Table 5-9: Coefficients estimated from panel data analysis for 7 cities in western region

	Model 1	Model 2	Model 3	Model 4
Class Area	1.0872**	0.4990**		
t-statistic	5.0936	3.1419		
NP			1.1830**	
t-statistic			6.6968	
LPI	25.9779*			10.8051
t-statistic	2.2129			0.8242
SHAPE_AM			14.2506**	28.5075**
t-statistic			2.8738	6.5706
ENN_AM		-3.5386**		
t-statistic		-4.3267		
Constant	136.6374*	886.1985**	-173.8587**	-2.5220
t-statistic	2.4498	6.2931	-3.1627	-0.0378
Number of samples	28	28	28	28

** Significant at 0.01 level

* Significant at 0.05 level

Table 5-10: Coefficients estimated from panel data analysis for 3 cities in northeast region

	Model 1	Model 2	Model 3	Model 4
Class Area	1.5370*	0.2243		
t-statistic	3.0651	0.3434		
NP			-0.2980	
t-statistic			-0.5863	
LPI	7.7880			144.1321*
t-statistic	0.1489			2.5967
SHAPE_AM			-10.3860	0.7350
t-statistic			-2.1444	0.1554
ENN_AM		49.2399		
t-statistic		2.0731		
Constant	285.6944	237.0680	3627.8850	323.2328
t-statistic	1.4698	1.4159	2.2951	0.2830
Number of samples	12	12	12	12

** Significant at 0.01 level

* Significant at 0.05 level

One of the objectives in this study is to predict future energy consumption at urban level by using generated models and a set of spatial metrics. Therefore, it is necessary to evaluate the performance of different models prior to the prediction of future energy consumption. The rRMSE between reference energy consumption and calculated energy consumption using panel data model was applied to assess the performance of the panel data models and to validate if the selected spatial metrics are correlated with the energy consumption. In addition, the representative city in each region needs to be identified in order to conduct the further analysis by using cellular automata model for these cities. With consideration of the urban energy consumption per capita, Hangzhou in eastern region, Wuhan in central region, Yinchuan in western region, and Shenyang in northeast region were selected for the further analysis. As shown in Figure 5-14, the four cities have the largest urban energy consumption per capita compared to other cities within the corresponding regions. There is an urgent need to predict the future energy consumption and test the consequences of different energy saving policies in these cities.

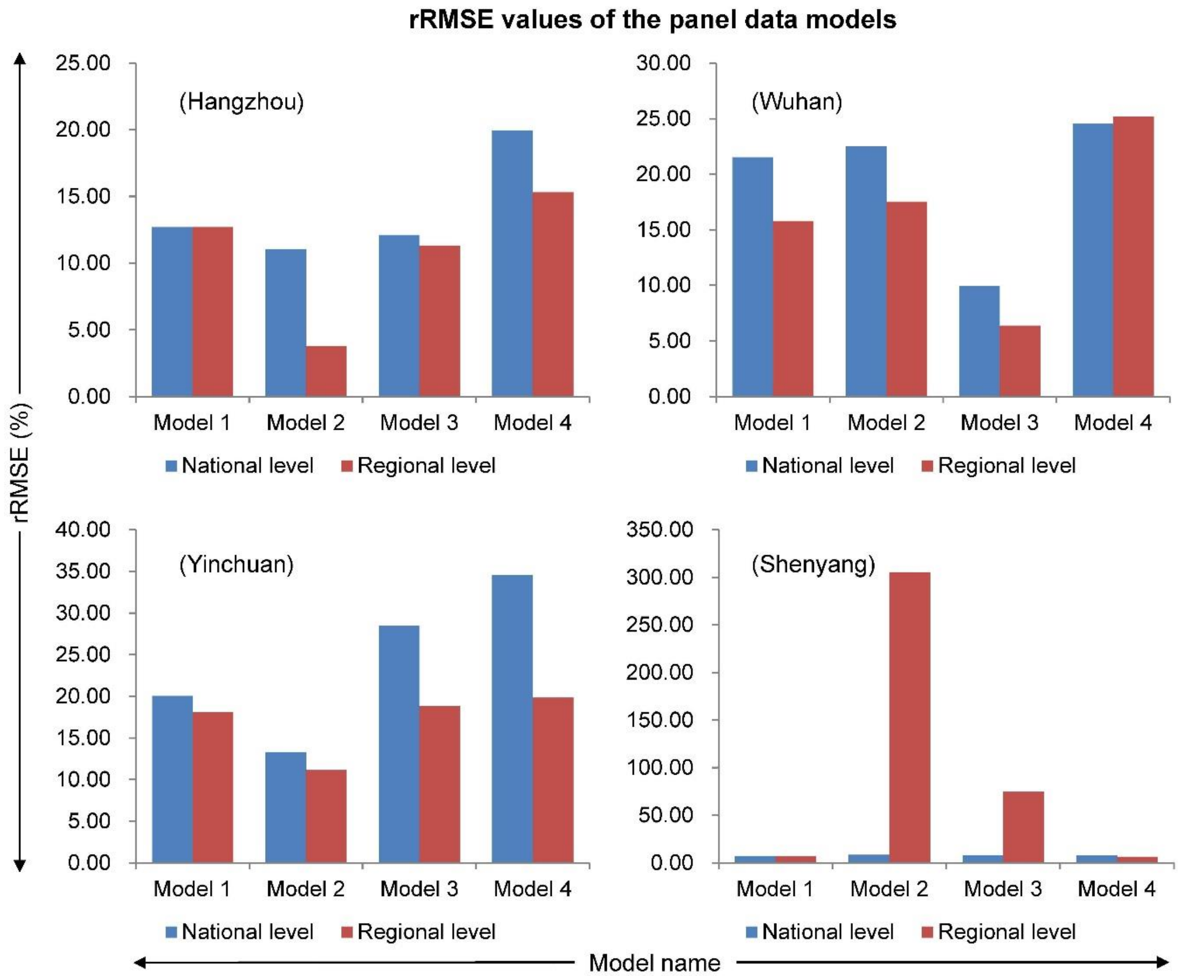

Figure 5-16: rRMSE values of the panel data models for four cities (Model1-4)

Based on the Eqs. 23 and 24, the rRMSE could be generated. Figure 5-16 shows the rRMSE values between the calculated energy consumption by using panel data models and the reference energy consumption for the selected four cities. The relatively low rRMSE generated by the panel data models suggests that the selected spatial metrics present a high ability as a proxy of energy consumption. The panel data models are proved to be able to generate urban energy consumption with low rRMSE value. Furthermore, the models were classified into two categories (models at national level and regional level) in order to compare the performance of two types of models. As indicated by the results, the models for three cities (Hangzhou, Wuhan, and Yinchuan) at regional level perform better than the models using whole sample in generating accurate energy consumption. Moreover, the models at regional level are more accurate than that at national level in terms of exploring the impact of the spatial pattern on energy consumption. This can be attributed to the regional differences in energy consumption characteristics among different regions. As shown in

Figure 5-16 (Shenyang), however, the rRMSE values of the Model 2 and Model 3 at regional level are much higher than the models at national level because of the limited samples in northeast region. Although Model 4 at regional level performs better than other models, the SHAPE_AM is not significantly correlated with the urban energy consumption when regional sample was used.

In addition, it is found that the rRMSE values vary significantly when different models are used. This could be partly attributed to the fact that each panel model is developed by using only two different spatial metrics, which are measured from different aspects. This could lead to a bias in predicting future urban energy consumption. Therefore, the prediction values of energy consumption generated by different models should be averaged to avoid the bias and remove the abnormal fluctuation. The impacts of all spatial metrics on energy consumption can be fully considered. The following equation is used for the averaging:

$$ECp_{u,i} = \frac{1}{4} * \sum_{n=1}^{4} EC_{u,i,n} \quad (33)$$

where $EC_{u,i,n}$ represents the calculated energy consumption value by using panel model n (ranging from 1 to 4). $ECp_{u,i}$ is the prediction value for urban i, which is calculated by averaging the results generated by four panel models.

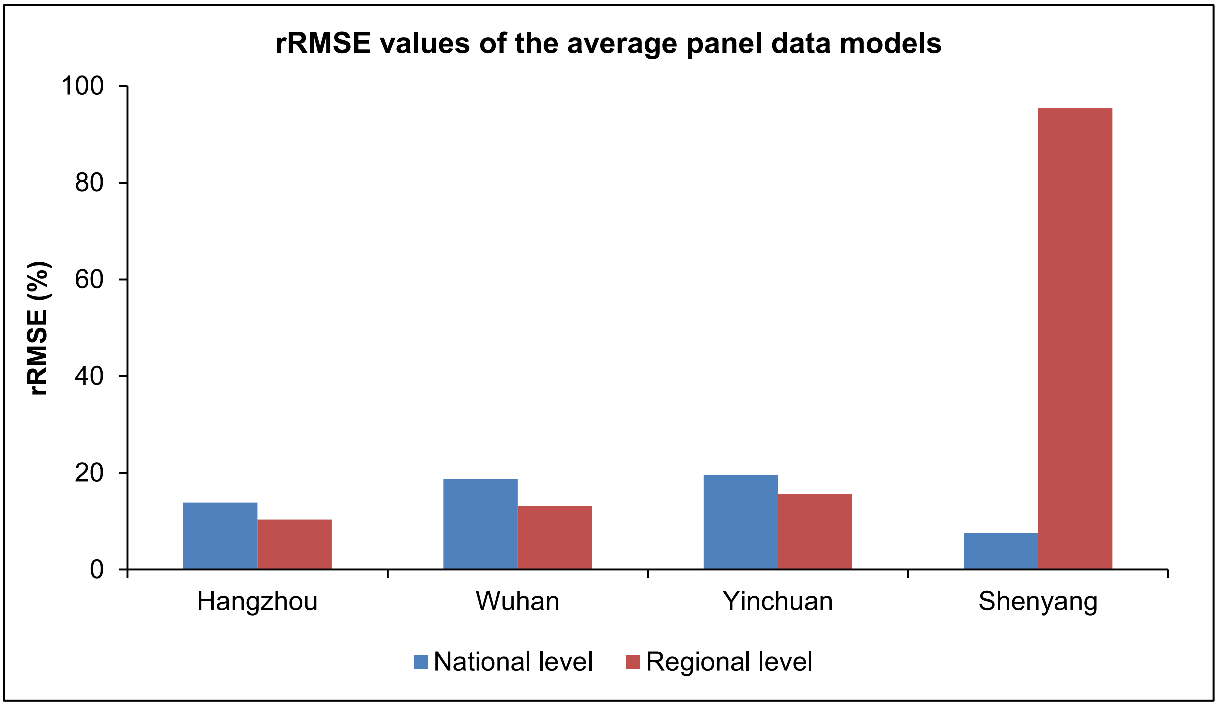

Figure 5-17: rRMSE values of the average panel data model

Here, rRMSE was applied to compare the difference between reference value and calculated average energy consumption in order to verify the reliability of this method (Figure 5-17). Although the rRMSE of average values are higher than some results generated by using single model, the method of averaging different models could generate more reliable prediction results by considering all spatial metrics. Nevertheless, the fairly low values of rRMSE (rRMSE<20 %) suggest that the averaging method can be used to generate and predict the reliable energy consumption values. In this study, the future energy consumptions for Hangzhou, Wuhan, and Yinchuan were predicted by averaging the energy consumption values generated by four models at regional level. While the future energy consumption for Shenyang can be generated by averaging the four models results at national level.

5.3 Future energy consumption

The exploration of the relationship between urban form and energy consumption, allows us to better understand whether dynamic change of urban form is a major factor underlying the increasing energy consumption in China. Forecasting future energy consumption under different urban development scenarios based on the relationship between urban form and energy consumption can provide an important reference for decision makers in supporting their design and implementation of suitable and effective energy conservation policies.

5.3.1 Cellular Automata model

The urban land cover maps of 2003, 2006 and 2010 for the selected four cities were used to calibrate the CA model with the land cover map in 2000 as the beginning of the simulation.

By using logistic regression model, the weights of a set of factors affecting urban growth were generated. In addition, the historical urban growth during the period of 2000-2003, 2003-2006, 2006-2010 was simulated respectively. For each simulation, the result was compared with the observed urban land cover map in the last year of the period, and the spatial pattern similarity value was calculated using Eq. 22 to assess the overall performance of the model. Based on similarity value, the optimal parameters involved in the CA model were identified which enables the model to simulate more accurate result. Figure 5-18 shows the spatial pattern similarity between the simulated and observed maps, which can be used to evaluate the performance of the CA models for different cities. As evidenced by visual comparison and the relatively higher similarity value, the simulated results from the model are generally very similar to the observed spatial pattern, with the SS value ranging from 90 % to 95 %. The validation result indicates that the proposed CA model can reproduce the historical urban spatial pattern with high accuracy. Therefore, it can be further used to simulate the future urban development scenario.

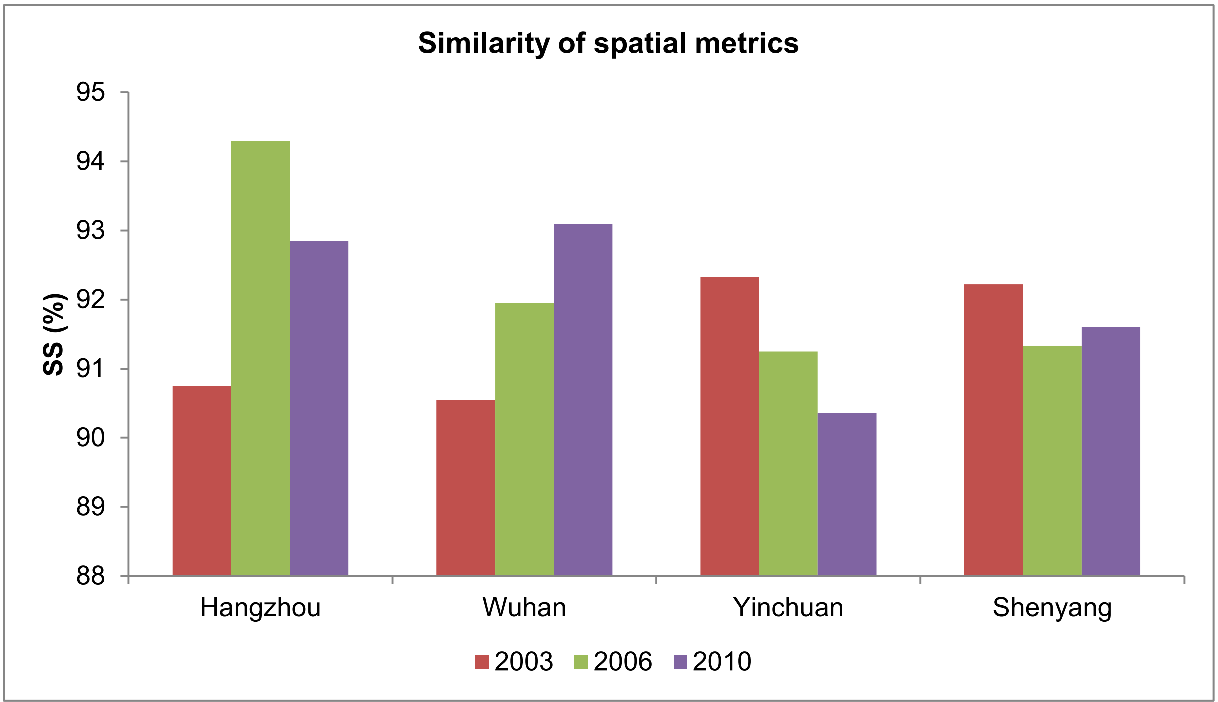

Figure 5-18: Validation of CA models for different cities using the similarity of spatial metrics

5.3.2 The future scenario

Once the calibration results were accepted, the simulation of future urban spatial pattern were conducted for the year 2020. Based on the panel data analysis for each region, this study proceeded to set up different urban development scenarios for forecasting the future energy consumption. The development of different scenarios is dependent on the variation of parameters involved in the CA model (Table 5-11).

Table 5-11: The configurations of CA model for each scenarios (BAU: Business As Usual; CD: Compact Development; DD: Dispersed Development)

	Parameters	BAU	CD	DD
Hangzhou	Neighborhood Size	5*5	3*3	9*9
	Random variable	2.1	1.2	3.0

Wuhan	**Neighborhood Size**	5*5	3*3	9*9
	Random variable	1.8	1.2	3.0
Yinchuan	**Neighborhood Size**	5*5	3*3	9*9
	Random variable	1.8	1.2	3.0
Shenyang	**Neighborhood Size**	5*5	3*3	9*9
	Random variable	2.0	1.2	3.0

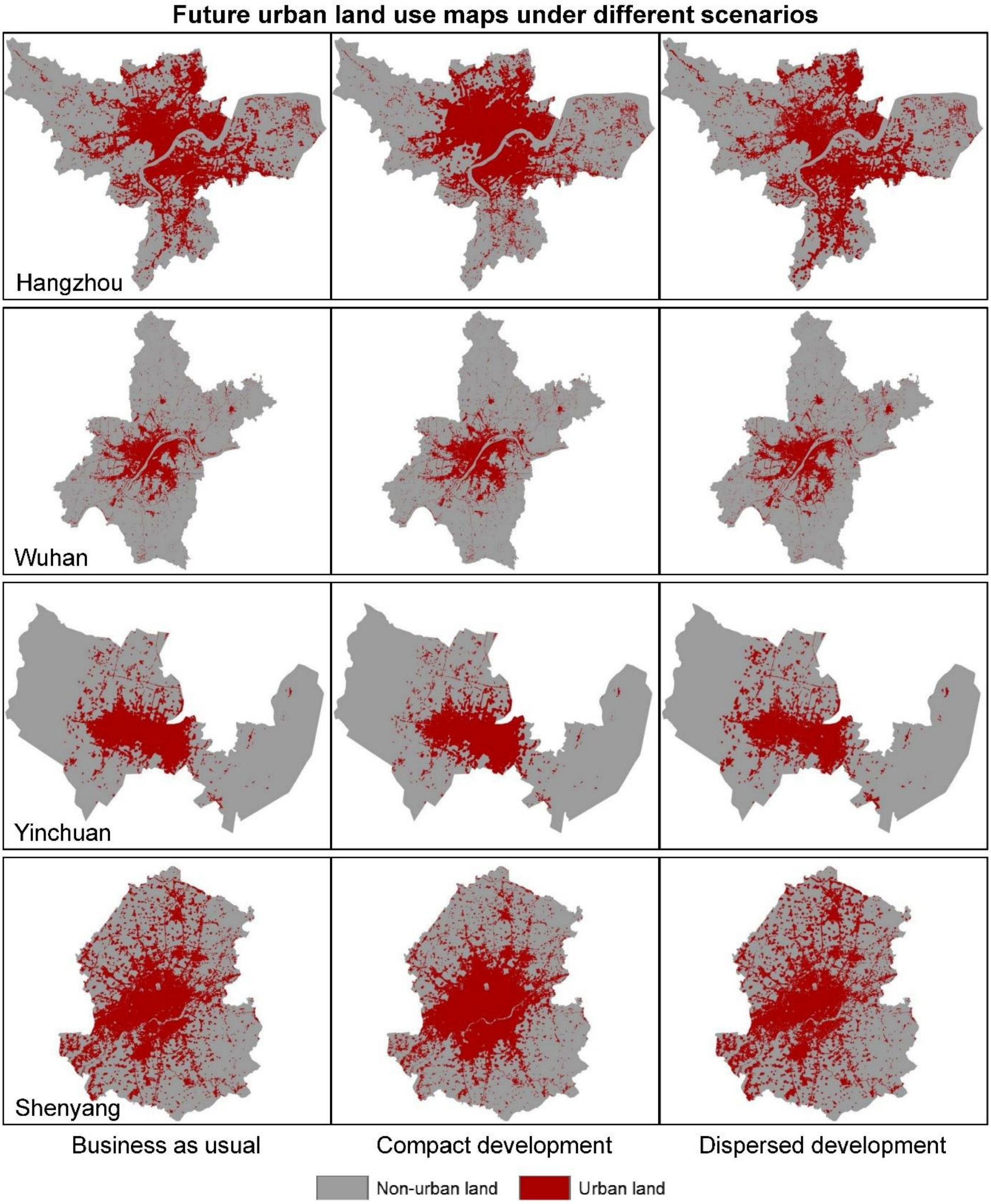

Figure 5-19: Future urban land use maps under different scenarios

Figure 5-19 shows the future urban development scenarios of 2020 for the selected four cities. Although the scenarios for the same city have the same urban land area as that of the 2010-2020 urban planning, the urban growth patterns vary significantly. We can visualize how different development strategies cause differences in urban spatial pattern for each scenario. Then, spatial metrics were further calculated to quantify the differences among the simulated spatial patterns (Table 5-12).

Table 5-12: The spatial metrics values for each city under different scenarios

		Class Area	NP	LPI	SHAPE_AM	ENN_AM
Hangzhou	BAU	1100	3663	26.21	39.53	66.64
	CD	1100	863	25.14	13.60	83.65
	DD	1100	6539	14.01	40.40	62.26
Wuhan	BAU	1200	6124	10.24	34.79	82.33
	CD	1200	2901	10.56	25.83	107.49
	DD	1200	8282	9.77	41.36	72.80
Yinchuan	BAU	300	1163	13.05	15.24	79.68
	CD	300	233	13.57	8.90	95.05
	DD	300	1990	12.21	21.44	65.80
Shenyang	BAU	1200	3511	25.91	37.34	67.63
	CD	1200	870	28.23	19.33	87.04
	DD	1200	8655	24.84	45.52	63.32

Sprawl patterns were observed in the dispersed development scenario because of the weak spatial restriction on development and the increasing demand in living on the fringe areas. The largest values of NP and SHAPE_AM were found in this scenario. Due to the rapid development of new patches near the existing patches, the values of ENN_AM in the dispersed development scenario are the lowest. In the CD scenario, the growth of new urban area tends to connect with the city core or the existing urban patches. Therefore, the highest values of LPI are found in this scenario. The SHAPE_AM decreases as the urban patches grow and form larger urban patches. By using the proposed CA model, the different spatial patterns under scenarios can be simulated as expected.

The integration of panel models and CA models was used to explore the impacts of different development strategies on urban growth and energy consumption. Figure 5-20 shows the predicted energy consumption values calculated by using panel data models and Eq. 33 for four cities under different scenarios. The energy consumption varies under different scenarios. Compared with the urban energy consumption in 2010, the BAU and DD scenarios in 2020 will consume more energy. Moreover, the largest consumption values are found under DD scenario for all selected cities. This indicates that dispersed development could result in a significant increase in energy consumption. As shown in Figure 5-19, a large number of new patches are developed around the city core or at fringe areas. This could lead to the construction of a number of facilities and roads in order to meet the requirement of the residents living outside the city core. Thus the construction could result in an increase of energy consumption. In addition, the potential transportation requirements increase when socioeconomic activities are distributed in many scattered urban patches. Recently, many new residential areas are developed at fringe areas where the living environment is better than that in the city core. Muller (2004) concluded that the irregular pattern of new patches can lead to recurrent long communicating distance of residents from residences to their place of work. As a result, the significant increase in travelling distance plays an important role in the rising energy consumption.

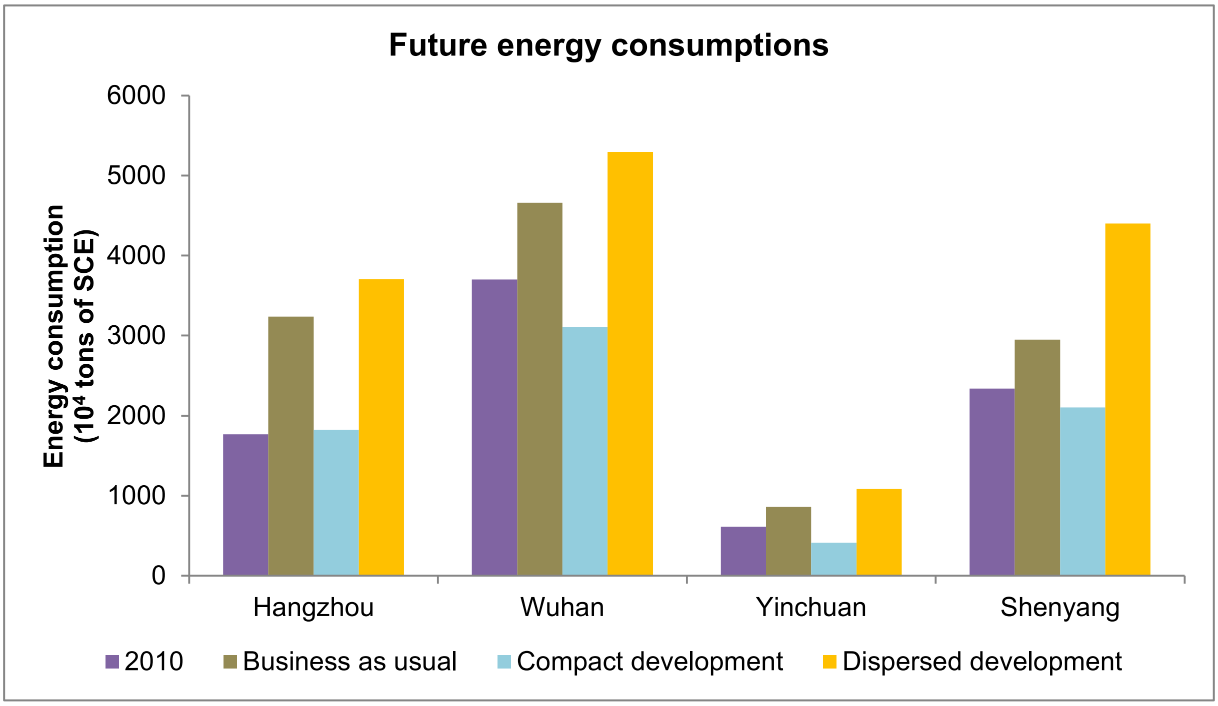

Figure 5-20: Future energy consumptions under different scenarios

In addition, the predicted result indicates that the CD scenario with an aggregated and continuous pattern is conducive to the reduction of the energy consumption. The result is in line with the results of a number of previous studies. The spatial metrics of NP and SHAPE_AM are measures of the scattered and complexity of the urban pattern. The lower the values both NP and SHAPE_AM are, the more compact the spatial pattern of urban is. The compact urban can decrease the complexity of the traffic. Although the largest ENN_AM values are found under compact scenarios, the development of new urban patches is strictly limited. The most of facilities are located within the city core. Concentration of employment within the city core can reduce commuting distance. The residents, who live within the city core, have easy access to facilities and services related to daily life, for example schools, markets, and hospitals. The results of previous studies have also proved that more compact urban form can lead to shorter travelling distance, less use of private vehicle (Wang et al., 2014(b)), a higher utilization efficiency of urban facilities (Jenks et al., 1996), and higher urban land use intensity (Li et al., 2008). Therefore, the advantages brought by the compact development could be the less consumption of energy. The findings indicate that a compact urban development is highly beneficial for fast growing cities in China in order to achieve high efficiency of energy use and sustainable development. In addition, the result could provide a better understanding for the decision makers and urban planners to identify effective development strategies and urban land use planning.

6. Discussion and conclusion

Chapter 2 represented the theoretical background with the concepts and methods for estimating energy consumption and exploring the links between urban form and energy consumption. The study areas in China (20 province capital cities) and the related RS data and socioeconomic data were described in chapter 3. Chapter 4 introduced the related methods for this study. By applying the methods in the study areas, the results could be obtained in chapter 5. This chapter aims to address the research questions and the major findings. Based on the results future development recommendations and an outlook is provided.

6.1 Methodology implications

Recently, it is universally acknowledged that urban form has a significant impact on the global climate change through the energy consumption and related CO_2 emission. Therefore, it is necessary to implement appropriate spatial planning and urban development strategies in order to mitigate the negative impact of global warming. However, the existing studies engaging in the tasks of estimating the urban energy consumption and quantifying the relationship between urban form and energy consumption are limited. Focused on the gap, this study aimed to investigate a new method to estimate urban energy consumption and to explore the impact of urban form on energy consumption using Landsat data, NTL data, and socioeconomic data for 20 province capital cities in China during the period of 2000-2010.

This study has made efforts to understand the impact of urban form on the urban energy consumption. In this study, the built-up area of each city was extracted using Landsat images. In addition, five selected spatial metrics were applied to quantify the urban form for each city. The historical energy consumption of 20 province capital cities in China were estimated by using NTL data and statistical province energy consumption. In order to explore the links between urban form and energy consumption, panel data analysis was subsequently adopted with consideration of regional differences. In order to obtain additional insights into the impact of different development strategies on urban growth and energy consumption, CA model was further used to simulate urban spatial patterns and predict corresponding energy consumption under different scenarios.

Estimating urban energy consumption is the first step for adaptation and mitigation of climate change but also one which is hampered by the lack of reliable statistical data on urban energy consumption. In section 2.2.1, the methods of estimating urban energy consumption and their shortcomings were outlined based on existing references. It served as background knowledge of the possible method that could be applied effectively to estimate energy consumption at the urban scale. Section 4.2.2 proposed the detailed estimation method used in this study, which provided an answer to the first research question. These sections constitute one of the main innovations in this study.

1) How to accurately estimate the energy consumption at the urban scale?

Previous studies presented that there are several challenges to estimate urban energy consumption in China. Generally, the bottom-up method can be regarded as an ideal way for estimating urban energy consumption, which could provide accurate estimated results. However, it faces difficulties in developing countries especially in China. Satellite remote sensing has the advantage to provide efficient and accurate spatial data for various research purposes because of its extensive spatial coverage and high temporal resolution (Dewan & Yamaguchi, 2009). Compared with other satellite products mainly focusing on monitoring land cover and land use, an important feature of night-time light data is that night-time lighting signals can be quantitatively connected to simultaneous alterations in the socioeconomic activities and urban extent (Ghosh et al., 2010). Many efforts have been made to successfully capture the relationship between NTL data and socioeconomic statistics at global scales (Doll et al., 2006; Elvidge et al., 2012).

In this study, the accuracy of estimated urban energy consumption was improved in terms of three steps: (1) preprocessing of NTL data; (2) exploration of the quantitative relationships between the province energy consumption and NTL data using different regression models; and (3) estimation of the urban energy consumption based on the correlations between NTL data and province consumption. In order to improve the continuity and comparability of NTL data, the study proposed three steps to correct NTL data systematically: intercalibration, intra-annual correction, and inter-annual correction. The result indicates that the abnormal discrepancies of NTL data can be greatly reduced. Additionally, the primary challenge for estimating energy consumption using satellite-based data was to identify the correlation between remotely sensed signals and energy consumption over time. Three different regression models (linear, exponential, and power law) were applied to fit the response of NTL to energy consumption over time with consideration of the regional differences. The best-fitting model for quantifying the relationship were obtained by the comparisons of R^2, a measure of goodness-of-fit. The validation result suggests that the identified model can be used to effectively estimate the province energy consumption. Moreover, the NTL data is a suitable proxy of energy consumption in China. Different from other unique models proposed in previous studies, new models were proposed to estimate urban energy consumption by considering the regional difference among 20 provinces. Focusing on each study area, the study proposed a linear regression model with variable coefficients by modifying the identified regression models within the specific province. It could avoid the underestimation or overestimation of the energy consumption existing in previous studies.

The accuracy of the proposed model is largely dependent on the original energy data and intensity of nighttime light brightness as a proxy of energy consumption. The province energy balances tables were used as the data sources. Improving the accuracy of the statistical data on energy in China would surely increase the reliability of the proposed method. In addition, it has been proved that the variations in energy consumption can be accurately explained by NTL data. The methodological error of utilization NTL as a proxy to estimate urban energy consumption is therefore regarded as an acceptable limitation because of its capacity of accurate estimation with limited data source. The validation proved that urban energy consumption can be estimated by applying the proposed method. More importantly, it can build a systematic energy consumption data set for developing countries, which face the challenges in estimating energy consumption due to the lack of energy data at the urban scale.

In addition to the estimation of urban energy consumption, it is necessary to quantify the urban form for the study areas in order to provide the independent variables for exploring the relationship between urban form and energy consumption.

2) How to quantify urban form effectively?

As described in section 2.1.1, the definition of urban form refers to the spatial configuration of human activities (including the density of land uses, spatial pattern and spatial distribution of transport infrastructure), which can reflect socioeconomic and environmental processes (Tsai, 2005). Urban form can affect economic efficiency and urban environment, ultimately affecting both the design and regulation of the use of urban space (Fang et al., 2015). It is increasingly being regarded as an important potential role in the promotion of energy efficiency and the coordination of urban sustainable development.

In order to characterize the spatial and temporal dynamics of urban form of each city in this study, Landsat images were used to derive the urban land coverage for four time periods: 2000, 2003, 2006, and 2010. RS data is useful in obtaining the spatial distribution of urban land use through the classification of RS image (Yuan et al., 2005). Based on the research objective, the classified land cover types were further converted into two classes: urban and non-urban land.

Although some previous studies focused on the quantification of urban form by calculating ratios between two related variables (for example, urban population density measures, compactness ratios), such studies neglected the process-based character of urban development and cannot reflect the spatial characteristics of urban form (Qin & Shao, 2012; Yin et al., 2013). Different from the studies mentioned above, this study attempted to estimate the relationship between urban energy consumption and urban form from the perspective of spatial patterns. The literature review pointed out that a number of studies have demonstrated the utilization of spatial metrics to quantify the spatial patterns and the change of urban spatial patterns. Spatial metrics have been also proved useful in representing urban form and supporting urban planning (Herold et al., 2005). However, less attention has been paid to exploring the relationship between energy consumption and urban spatial patterns. In this study, the integration of RS and spatial metrics reveals the characteristics about urban form and their changes, allowing for quantitative estimation of the link between energy consumption and urban form. In this study, several spatial metrics were utilized to quantify urban form with focusing on three aspects of spatial pattern: the urban size, complexity, and continuity. The spatiotemporal change of spatial metrics for each city could provide a better understanding of the urban spatial pattern and the regional differences.

In the next step, section 4.2.3 provided the answer to the third question and section 5.2.3 gave the results that proved the effectiveness of the proposed methods.

3) How to explore the relationship between urban form and energy consumption, dealing with data from multiple individuals over multiple periods?

As concluded in chapter 2.2.2, the efforts to understand the relationship between urban form and energy consumption have been made. In order to effectively capture and analyze the impact of urban form on energy consumption, it is necessary to explore the quantitative relationships between urban growth patterns and urbanization considering the characteristics of the variables. In this study, panel data analysis was employed to estimate whether and to what extent the spatial patterns of urban form are correlated with energy consumption. The spatial metric values were defined as the independent variables, and the energy consumption were set as dependent variables. Panel data analysis is a regression approach for studying observations from multiple entities over multiple periods. It has several major advantages over conventional statistical analysis using only cross regional or time series data. The results in section 5.2.3 indicate that panel data analysis is capable of capturing the relationship between urban form and energy consumption using cross regional and time series data. The estimation of efficiency can be improved by using panel data analysis. In addition, spatial heterogeneity not accounted by independent variables in the previous study could cause variation of the relation among individuals. This could be solved by varying the intercepts and coefficients in panel data analysis.

The forms of the regression model for panel data analysis vary with different assumptions. In order to explore the reliable relationship between urban form and energy consumption, a suitable model form was identified based on the results of F-test. The selected model was finally evaluated using generalized least squares. Furthermore, the panel data analysis was conducted not only at the national level but also at the regional level in order to provide a deeper insight into the differences of the impact of energy consumption among different regions.

The last research question deals with the future energy consumption. Section 4.3 provided the answer to this question and section 5.3 presented the results of the application of the proposed approaches.

4) How to predict the future energy consumption?

In this study, a model that integrated panel data model and CA was proposed to simulate the future urban form and to predict the corresponding energy consumption. The main efforts were made to illustrate a way in which CA model could be used to provide support for the design and implementation of energy efficiency policy. CA model can generate various urban spatial patterns by modeling different local interactions and the impacts of factors on urban growth. As concluded in section 2.3, the strengths of CA in simulating realistic urban growth and in solving urban planning problems have been demonstrated by previous studies. In order to provide alternative context for the decision makers, the logistic CA model was developed and further applied to simulate various urban form under three different development scenarios in 2020 for four representative cities, which were strongly linked to the current concerns of the policy makers in China. The three scenarios were: business as usual scenario, compact development scenario, and dispersed development scenario, respectively.

The spatial variables in terms of selected spatial metrics were obtained through the analysis of multiple future scenarios of urban growth. Using these metrics values, the panel data model was adopted to calculate the future energy consumption for each scenario. The integration model was useful for exploring the impacts of different development strategies on urban growth and energy consumption.

The combination of scenario simulation and the panel data model has proved to be capable of predicting the future energy consumption with focus on the historical development trend and various strategies. The analysis of the future scenarios and corresponding energy consumption under different “what-if” conditions can assist decision makers in evaluating the impact of different development strategies on urban form and the corresponding energy consumption. The result can form a basis for urban development policy recommendations towards sustainable urban development.

6.2 Recommendations

Considering the dramatic speed of urban growth in China, it is important to assess the environmental impact of the significant change in urban spatial pattern and to mitigate the negative impact in order to achieve sustainable development (Yin et al., 2015). Given the significant contribution of urban area to energy consumption, the impact of different urban spatial patterns on energy consumption intensifies in the context of rapid urbanization. Covering 20 province capital cities over the period 2000-2010, the study analyzed the impact of urban form on urban energy consumption by exploring the quantitative relationship between them and predicting future energy consumption under different development scenarios. The results provide deep insights into the energy consumption at the urban scale and the impact of urban form on urban energy consumption. It also suggests some theoretical and policy implications related to the energy efficiency.

In the context of rapid urbanization, it is becoming increasingly important to develop and implement a strict policy to control the rapid expansion of urban area in some cities. The results in this study indicate that the growth of urban land area is the major driver for the tremendous increase in energy consumption in the study areas during the study period. It was found by a large number of studies that the rapid economic growth can increase energy consumption although it can improve living standards (Dhakal, 2009; Zhang & Lin, 2012). In order to reduce energy consumption and combat global climate change, slowing down the economic growth process could be the most effective measure. However, it must be recognized that the fast economic growth and urbanization are currently the main goal of the Chinese government (Fang et al., 2015). Since the implementation of “Reform and Open Policy”, China has made remarkable achievements in terms of the economic development (Wang et al., 2016). Therefore, the prerequisite of reducing energy consumption must be maintenance of rapid urbanization. Given this situation, the government faces the tremendous challenge of both balancing continuously increasing urban energy consumption and rapid economic growth with environmental responsibility (Dhakal, 2009; Zhang & Lin, 2012).

The study result reveals that the design of rational urban form through spatial planning and urban land use management can be an effective way in fulfilling the requirement of reducing urban energy consumption and maintaining rapid economic growth. As concluded in section 2.2.2, however, rapid urbanization influences energy consumption in a number of ways. Different from the previous studies, the result suggests that the dynamics change of urban spatial pattern underlying the rapid urbanization has a significant impact on the energy consumption.

The urban areas of the selected cities have experienced rapid urban expansion during 2000-2010, with significant differences in both the character and magnitude of the changes in urban form. The urbanization not only significantly promotes the urban growth but also results in more fragmented and irregular spatial pattern. Chinese government should make effort to optimize the urban spatial pattern in order to reduce the energy consumption because the irregular urban pattern contributes to the increase of energy consumption. The future urban development strategies should be designed taking into the consideration of urban shape complexity. According to the results in this study, the lower energy consumption level can be achieved when the city is more compact. This knowledge can help the decision makers to address energy consumption reduction and to achieve sustainable development. However, as indicated by the negative impact of LPI on energy consumption, various environmental problems resulting from the compact city may appear when the development is only concentrated within the single city core. It could result in longer travel distance and traffic congestion in the city core. There are still residents living in the suburban area although most of people are concentrated within city core. The people who live on the fringe areas need to travel far to obtain the services in the city core. Thus, the polycentric urban development with high compactness should be encouraged in order to prevent the disadvantages of monocentric development.

Finally, the policy measures in energy saving should not be the same in the different regions in China. In this study, 20 cities were divided into four regions (eastern, central, western, and northeast regions). Although the significant increases in energy consumption were found in all cities, the increase rates of energy consumption varied across regions and declined continuously from eastern region to central region, and from central region to western and northeast region, which can be explained by the different speed of urbanization and economic growth. The panel data analysis also suggests that the significant differences exist among the different regions in terms of the urban spatial patterns and their impact on energy consumption. In the central region, the increasing urban land had the greatest impact on urban energy consumption compared to other regions. In eastern region, the impact of increasing NP value was not as strong as that in other regions because the urban infrastructure and road system were more advanced compared with other regions. Therefore, the planning and land use management should consider the disparities of regions in order to lessen regional disparities and realize balanced development.

In summary, the empirical findings of this study can provide important implications for the action on the path towards developing high energy efficiency cities in China.

6.3 Outlook

The methods proposed in this study have proved to be useful in estimating energy consumption and analyzing the impact of urban form on energy consumption in 20 province capital cities in China. The findings of this study provide a support for decision making towards sustainable urban development. However, there are several limitations and shortcomings that should be recognized regarding present study.

The spatial metrics for quantitative spatial patterns were calculated at the resolution of 30 m. However, it has been widely recognized that the spatial pattern is scale dependent since it changes with the scale of analysis. The further analysis need to be conducted at different resolutions to provide additional insights into the impact of scales on spatial pattern analysis as well as the links between urban form and energy consumption.

Considering the relatively low spatial resolution of Landsat image, the study only generated the urban land data without considering the detailed land use classes, i.e. industrial, residential and commercial land. However, the spatial distributions of the detailed land use categories are also important in analyzing the impact of urban form on energy consumption. It would be valuable to extract these land use categories by using high spatial resolution RS images and to examine the relationship between spatial distributions of the detailed land use categories and energy consumption.

Based on the different scenarios simulated by CA model, the corresponding future energy consumption were calculated in this study. The urban growth process is a complex process which can be affected by many variables. Due to the lack of some variables that affects the urban growth, only limited variables were involved in the CA model. It is necessary to consider more potential variables in the future studies in order to improve the performance of CA model. In addition, more urban development scenarios should be developed based on not only the compactness degree but also the other elements such as population distribution, economic structures, and current policies in order to provide more comprehensive results for the future development.

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Appendix

Table 7-1: The total population of the 20 cities from 2000 to 2010 (Unit: Million inhabitants) (Source: China City Statistical Yearbook 2001-2011)

	2000	2003	2006	2010
Changchun	2.93	3.10	3.49	3.63
Changsha	1.75	1.96	2.15	2.42
Fuzhou	1.48	1.66	1.82	1.89
Hangzhou	1.79	3.93	4.14	4.35
Harbin	3.04	3.15	4.73	4.72
Hefei	1.35	1.56	1.93	2.16
Huhhot	1.06	1.10	1.12	1.21
Jinan	2.64	3.35	3.52	3.48
Kunming	2.11	2.24	2.32	2.60
Lanzhou	1.82	1.95	2.04	2.10
Nanjing	4.62	4.90	5.25	5.48
Nanning	1.36	1.46	2.55	2.71
Shenyang	4.85	4.88	5.00	5.15
Shijiazhuang	1.67	2.11	2.31	2.44
Taiyuan	2.33	2.50	2.71	2.85
Wuhan	7.49	7.81	5.01	5.21
Xi'an	3.93	5.10	5.41	5.63
Xining	0.94	1.00	1.05	1.01
Yinchuan	0.64	0.72	0.88	0.95
Zhengzhou	2.19	2.40	2.61	5.10

Table 7-2: The GDP of the 20 cities from 2000 to 2010 (Unit: Billion RMB) (Source: China City Statistical Yearbook 2001-2011)

	2000	2003	2006	2010
Changchun	61.82	99.82	128.66	236.39
Changsha	41.53	55.24	106.66	262.78
Fuzhou	46.41	62.55	80.44	154.36
Hangzhou	67.79	161.78	273.78	474.08
Harbin	54.99	82.13	141.06	258.20
Hefei	23.52	38.18	81.78	192.05
Huhhot	12.45	29.85	62.69	119.49
Jinan	66.14	105.37	165.93	295.98
Kunming	48.33	63.08	91.32	154.87
Lanzhou	27.06	37.93	57.34	87.73
Nanjing	94.57	145.31	255.90	451.52
Nanning	21.52	30.36	62.46	130.39
Shenyang	93.79	139.07	228.17	418.49
Shijiazhuang	41.77	59.18	80.47	123.98
Taiyuan	29.48	43.27	89.11	162.23
Wuhan	120.68	166.22	223.83	455.91
Xi'an	60.15	85.85	132.73	276.29
Xining	6.26	9.54	18.85	44.04
Yinchuan	7.56	11.16	24.41	51.20
Zhengzhou	34.35	53.01	88.58	175.39

Table 7-3: The spatial metrics values of the 20 cities from 2000 to 2010

		Class Area (km^2)	NP	LPI (%)	SHAPE_AM	ENN_AM (m)
Changchun	2000	405.32	2,022	3.87	12.01	190.58
	2003	473.32	2,006	1.93	10.83	199.50
	2006	600.77	2,255	2.59	12.81	179.96
	2010	734.96	2,161	3.72	17.52	156.86
Changsha	2000	144.70	202	15.78	15.04	92.02
	2003	157.23	179	18.67	17.63	85.37
	2006	234.55	130	20.04	23.81	75.21
	2010	314.36	103	28.50	25.95	63.76
Fuzhou	2000	123.06	145	7.86	16.10	106.64
	2003	156.30	138	7.15	16.62	96.75
	2006	180.63	123	6.18	23.98	86.87
	2010	210.92	113	7.36	20.97	81.88
Harbin	2000	292.88	1,038	1.73	10.26	294.80
	2003	532.81	1,613	3.05	12.11	280.02
	2006	697.50	1,701	4.24	14.72	248.45
	2010	806.03	1,805	5.97	19.82	223.63
Hangzhou	2000	253.81	726	3.20	11.01	177.28
	2003	334.67	815	3.99	13.38	151.24
	2006	423.77	972	4.49	13.90	124.14
	2010	699.98	1,187	9.30	23.98	93.75
Hefei	2000	101.93	82	9.98	20.06	97.49
	2003	158.99	77	17.86	28.37	77.65
	2006	238.53	118	26.80	28.03	73.27
	2010	282.70	127	32.25	29.06	73.75
Huhhot	2000	98.04	150	3.61	11.72	169.35
	2003	177.26	193	5.68	13.50	141.51
	2006	234.37	269	6.76	13.66	113.24
	2010	315.24	296	11.04	18.27	99.46
Jinan	2000	418.39	1,276	6.60	15.22	159.15
	2003	482.54	1,298	8.21	16.56	135.36
	2006	587.81	1,315	10.03	20.12	122.33
	2010	742.38	1,191	14.45	23.72	106.65
Kunming	2000	187.73	450	2.75	14.11	141.14
	2003	252.82	419	3.82	15.62	129.45
	2006	314.39	434	5.33	19.46	123.83
	2010	372.60	434	6.30	20.20	109.76
Lanzhou	2000	100.86	138	3.06	10.46	129.92
	2003	132.99	151	2.44	11.34	111.78
	2006	161.89	176	1.33	11.99	103.41
	2010	181.90	191	1.54	11.75	99.06
Nanjing	2000	341.75	797	3.68	19.11	173.26
	2003	439.81	1,021	4.34	17.31	160.67

	2006	732.24	1,293	8.16	25.86	118.19
	2010	1,036.80	1,530	11.81	29.50	94.56
Nanning	2000	194.01	514	2.06	18.86	224.33
	2003	213.35	598	2.25	18.99	214.85
	2006	291.93	725	3.13	21.67	209.51
	2010	451.86	832	4.09	24.77	138.16
Shenyang	2000	423.29	777	7.58	17.51	134.85
	2003	569.56	848	8.02	22.40	120.45
	2006	683.01	912	9.37	28.26	106.60
	2010	945.73	1,044	13.37	34.99	94.82
Shijiazhuang	2000	192.60	118	32.67	10.82	82.74
	2003	218.40	82	39.35	12.62	83.61
	2006	246.20	89	43.91	12.18	78.30
	2010	268.19	53	50.18	12.94	66.95
Taiyuan	2000	244.15	322	12.48	13.33	127.86
	2003	297.68	342	11.49	15.69	113.60
	2006	337.20	381	10.48	17.87	97.85
	2010	423.00	323	14.69	24.55	83.16
Wuhan	2000	428.93	1,559	3.14	21.78	141.56
	2003	661.47	2,278	4.14	15.12	128.07
	2006	685.13	2,324	5.10	30.01	111.30
	2010	898.00	2,681	6.87	33.82	100.95
Xi'an	2000	338.24	897	5.88	15.79	161.31
	2003	486.68	954	5.70	20.40	136.28
	2006	666.92	1,054	5.67	27.44	106.14
	2010	945.83	1,192	8.73	33.75	93.70
Xining	2000	48.51	38	10.48	9.53	82.41
	2003	54.43	37	9.49	12.27	75.17
	2006	83.35	38	8.87	13.69	70.11
	2010	99.56	45	11.55	15.86	71.43
Yinchuan	2000	63.68	178	2.32	13.30	201.80
	2003	80.85	179	3.13	12.92	179.12
	2006	139.33	303	5.54	23.00	134.58
	2010	198.30	324	8.03	25.14	109.99
Zhengzhou	2000	229.36	379	14.72	11.45	118.50
	2003	265.14	374	18.84	15.67	109.90
	2006	374.97	313	29.89	25.67	81.54
	2010	428.34	317	35.47	30.25	76.43

Table 7-4: The energy consumption for 20 provinces from 2000 to 2010 (Unit: 10^4 tons of SCE) (Source: China Energy Statistical Yearbook 2001-2011)

Province	Capital	2000	2003	2006	2010
Jilin	Changchun	3,766	5,174	5,908	8,297
Hunan	Changsha	4,071	6,298	10,581	14,880
Fujian	Fuzhou	3,463	4,808	6,828	9,809
Zhejiang	Hangzhou	6,560	9,523	13,219	16,865
Heilongjiang	Harbin	6,166	6,714	8,731	11,234
Anhui	Hefei	4,879	5,457	7,069	9,707
Inner Mongolia	Huhhot	3,549	5,778	11,221	16,820
Shandong	Jinan	11,362	16,625	26,759	34,808
Yunnan	Kunming	3,468	4,450	6,621	8,674
Gansu	Lanzhou	3,012	3,525	4,743	5,923
Jiangsu	Nanjing	8,612	11,060	19,041	25,774
Guangxi	Nanning	2,669	3,523	5,390	7,919
Liaoning	Shenyang	10,656	11,253	14,987	20,947
Hebei	Shijiazhuang	11,196	15,298	21,794	27,531
Shanxi	Taiyuan	6,728	10,386	14,098	16,808
Hubei	Wuhan	6,269	7,708	11,049	15,138
Shaanxi	Xi’an	2,731	4,170	6,129	8,882
Qinghai	Xining	897	1,123	1,903	2,568
Ningxia	Yinchuan	1,179	2,015	2,830	3,681
Henan	Zhengzhou	7,919	10,595	16,232	21,438

Table 7-5: The cumulative DN values of NTL data for each province from 2000 to 2010

Province	Capital	2000	2003	2006	2010
Jilin	**Changchun**	531,601	589,126	662,161	920,047
Hunan	**Changsha**	326,124	421,493	484,246	673,332
Fujian	**Fuzhou**	511,248	579,704	675,618	917,842
Zhejiang	**Hangzhou**	942,040	1,272,820	1,439,352	1,768,417
Heilongjiang	**Harbin**	1,006,283	1,155,829	1,364,963	2,056,301
Anhui	**Hefei**	519,055	625,493	737,830	1,178,124
Inner Mongolia	**Huhhot**	509,325	638,094	854,774	1,445,831
Shandong	**Jinan**	2,132,579	2,430,751	2,869,067	3,345,342
Yunnan	**Kunming**	433,109	534,781	637,301	958,475
Gansu	**Lanzhou**	252,683	310,965	369,268	598,438
Jiangsu	**Nanjing**	1,565,024	1,936,266	2,220,393	2,862,223
Guangxi	**Nanning**	374,563	466,150	545,589	814,239
Liaoning	**Shenyang**	1,033,395	1,118,787	1,234,905	1,602,086
Hebei	**Shijiazhuang**	1,819,637	1,959,828	2,168,371	2,638,056
Shanxi	**Taiyuan**	1,161,395	1,257,660	1,408,676	1,752,315
Hubei	**Wuhan**	480,587	539,723	593,225	847,928
Shaanxi	**Xi’an**	584,001	692,706	881,152	1,323,341
Qinghai	**Xining**	64,083	87,618	107,468	163,974
Ningxia	**Yinchuan**	136,720	168,977	210,287	319,416
Henan	**Zhengzhou**	1,337,302	1,516,963	1,784,616	2,191,819

Table 7-6: The cumulative DN values of NTL data for each city from 2000 to 2010

	2000	2003	2006	2010
Changchun	98,704	106,735	116,874	157,593
Changsha	25,697	32,676	36,098	38,861
Fuzhou	31,166	34,044	35,086	37,325
Harbin	141,552	155,846	167,170	207,785
Hangzhou	114,596	146,957	163,232	185,250
Hefei	33,165	38,745	42,597	53,620
Huhhot	43,355	47,002	52,829	64,801
Jinan	83,108	94,321	110,776	124,195
Kunming	61,416	66,182	73,624	102,285
Lanzhou	43,831	47,016	48,512	54,858
Nanjing	138,763	163,764	177,558	210,065
Nanning	44,285	55,697	62,980	81,957
Shenyang	129,871	136,774	149,815	178,963
Shijiazhuang	33,915	35,395	37,004	38,988
Taiyuan	63,230	65,917	68,662	78,094
Wuhan	130,944	149,499	165,078	207,397
Xi'an	91,389	101,294	117,534	140,542
Xining	16,800	18,965	20,589	24,139
Yinchuan	31,223	38,293	43,374	53,021
Zhengzhou	51,061	62,793	72,670	78,170

Table 7-7: The estimated urban energy consumption from 2000 to 2010 (Unit: 10^4 tons of SCE)

	2000	2003	2006	2010
Changchun	699.24	937.40	1,042.79	1,421.18
Changsha	320.78	488.25	788.76	858.79
Fuzhou	211.11	282.36	354.59	398.89
Harbin	867.36	905.28	1,069.30	1,135.17
Hangzhou	798.00	1,099.50	1,499.12	1,766.69
Hefei	311.74	338.02	408.11	441.80
Huhhot	302.10	425.61	693.51	753.86
Jinan	442.78	645.10	1,033.18	1,292.24
Kunming	491.77	550.71	764.89	925.66
Lanzhou	522.47	532.96	623.10	542.95
Nanjing	763.58	935.42	1,522.65	1,891.61
Nanning	315.56	420.94	622.19	797.08
Shenyang	1,339.18	1,375.70	1,818.18	2,339.91
Shijiazhuang	208.67	276.29	371.92	406.88
Taiyuan	366.29	544.36	687.17	749.07
Wuhan	1,708.09	2,135.06	3,074.63	3,702.64
Xi'an	427.37	609.78	817.53	943.29
Xining	235.16	243.07	364.58	378.04
Yinchuan	269.25	456.63	583.72	611.02
Zhengzhou	302.36	438.57	660.97	764.57

Table 7-8: The energy consumption per capita for 20 cities from 2000 to 2010 (Unit: tons of SCE)

	2000	2003	2006	2010
Changchun	2.39	3.02	2.99	3.92
Changsha	1.83	2.49	3.68	3.55
Fuzhou	1.42	1.70	1.95	2.12
Harbin	2.86	2.87	2.26	2.41
Hangzhou	4.45	2.80	3.62	4.06
Hefei	2.31	2.17	2.11	2.05
Huhhot	2.84	3.88	6.22	6.25
Jinan	1.67	1.93	2.93	3.71
Kunming	2.33	2.46	3.30	3.56
Lanzhou	2.88	2.73	3.06	2.58
Nanjing	1.65	1.91	2.90	3.45
Nanning	2.33	2.89	2.44	2.94
Shenyang	2.76	2.82	3.64	4.54
Shijiazhuang	1.25	1.31	1.61	1.67
Taiyuan	1.57	2.18	2.54	2.63
Wuhan	2.28	2.73	6.13	7.11
Xi'an	1.09	1.20	1.51	1.68
Xining	2.50	2.44	3.47	3.73
Yinchuan	4.20	6.36	6.64	6.44
Zhengzhou	1.38	1.83	2.53	1.50

EIDESSTATTLICHE VERSICHERUNG

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

"Analysis of Urban Form Parameters with a Focus on Energy Consumption"

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

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

Dortmund, 15.07.2016 Jie Zhao