RETAIL INTERNATIONALIZATION AND URBAN RESTRUCTURING IN CHINA: A STUDY OF FOREIGN HYPERMARKETS AND URBAN LAND WITH GEOGRAPHIC INFORMATION SYSTEM AND REMOTE SENSING

by

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ABSTRACT

China’s retail sector has undertaken tremendous transformation since its opening to foreign investment in 1992. Retail transnational corporations have expanded rapidly in this emerging market. Yet relatively little is known about how they have embedded in the Chinese market and expanded spatially and temporally. China has experienced unprecedented urbanization since the onset of economic reform in 1978. Dramatic land use and land cover (LULC) change and urban expansion have taken place in the past three decades. Detailed time-series analysis of LULC change and urban growth in Chinese cities is still scant.

This dissertation focuses on the expansion of foreign hypermarket retailers in China and the urban growth in one Chinese city, Suzhou. This research analyzes the penetration strategy and local embeddedness of foreign hypermarket retailers, examines their spatial inequality and dynamics at different geographical levels, and identifies their location determinants through binary logistic regression models. This study applies random forest classification to multitemporal Landsat Thematic Mapper (TM) images of Suzhou for LULC change analysis, employs landscape metrics and Geographic Information System (GIS) analysis to investigate urban growth patterns, and develops global and local logistic regression models to identify determinants of urban growth.

The results indicate that spatiotemporal expansion of foreign hypermarket retailers has been largely dictated by the gradual liberalization policy of the Chinese government. Their local embeddedness has been impacted by both home and host economies. Relative gaps in foreign hypermarkets among three macro regions are narrowing while absolute gaps are widening. Provincial foreign hypermarket distribution has shown significant clustering in the Yangtze River Delta since 2005. Their distribution in Shanghai has changed from dispersion to intensified clustering and shown a clear trend of suburbanization. This study confirms that the random forest algorithm can effectively classify the heterogeneous landscape in Suzhou and LULC change has accelerated from 1986 to 2008. Three urban growth types, edge-expansion, infilling, and leapfrog are identified. Compared with the global model, the geographically weighted logistic regression model has overall better goodness-of-fit and provides more insights to spatial variations of the influence of underlying factors on urban growth.

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CHAPTER 1

INTRODUCTION

1.1 Background

China's miraculous rise has been spearheaded by selected coastal localities, and the development and transition have been driven by interplays of the state, global capital, and localities, empowered by the triple transition of decentralization, marketization, and globalization (Wei, 2000). Economic transformation and spatial restructuring in urban China have been important research fields for economists, geographers, and urban planners since the economic reform and open-up policy began in the late 1970s. Among the multifaceted economic transformations, retail transformation has received less attention compared to manufacturing industry, which actually reflects the traditional low status of the retail sector in China (Wang & Jones, 2001). Spatial restructuring has been another characteristic of Chinese cities in the reform era. Rapid urbanization following the economic reform has greatly influenced land use and land cover (LULC) change in China through urban expansion. Urban growth pattern derived from remote sensing and Geographic Information Systems (GIS) analysis has been a reliable source for delineating spatial restructuring in urban China.

The internationalization of retailing is one of the most salient characteristics of the global service economy today. Since the mid-1990s, a group of retail transnational corporations (TNCs) from Western Europe and North America has expanded globally and risen rapidly in the world economy. Since the onset of economic reform in 1978, rapid economic growth has transformed China into one of the world's largest consumer markets. China has become an attractive target market for international retailers. However, foreign retailers were not allowed to engage in retail trade in China until 1992. Since then, many international retailers have established their presence in this emerging market. They have introduced a variety of modern retail formats, transferred advanced retail know-how and technology, and played an important role in the retail transformation in China. However, little is known about the spatiotemporal expansion pattern and location determinants of these foreign retailers.

Anthropogenic LULC change is increasingly affecting the environment of the Earth's surface and atmosphere. Changes in LULC can influence the climate, affect the biodiversity, disrupt socio-cultural practice, and increase natural disasters (Dewan & Yamaguchi, 2009; Kindu, Schneider, Teketay, & Knoke, 2013). To mitigate the detrimental effects of urban growth on the environment, accurate and reliable information on spatial and temporal patterns of LULC change is therefore particularly important for developing rational and sustainable economic, social, and environmental policies (Long, Tang, Li, & Heilig, 2007). Tremendous LULC change and urban growth has taken place in China since 1978, especially in the eastern coastal region (Seto & Kaufmann, 2003; Weng, 2002). The massive conversion of arable land to nonagricultural use has been a major feature in this region (Li, Chen, & Sun, 2007; Yeh & Li, 1999). Most extant models tend to reveal urban growth patterns from a global view and assume that the influence of various factors can be applied uniformly throughout the whole study area without consideration for spatial variation. Detailed analyses about the spatiotemporal dynamics and spatial determinants of urban growth in Chinese cities are still scant (Liao & Wei, 2014; Luo & Wei, 2009).

This dissertation aims to explore the expansion patterns and location determinants of foreign hypermarket retailers in China and examine the spatiotemporal dynamics and spatial determinants of urban growth in Suzhou, China based on the LULC change analysis derived from remote sensing images. With the assistance of spatial statistics, spatial modeling, GIS analytical tools, and remote sensing techniques, spatiotemporal expansion patterns of foreign hypermarkets in China and urban growth in Suzhou will be mapped and analyzed, and their spatial determinants will be identified.

1.2 Literature Review and Research Objectives

1.2.1 Literature Review

This dissertation mainly draws upon two strands of literature, including the issues related to retail internationalization and transformation in China, and the methods and models for monitoring LULC change and urban growth in Suzhou.

In response to the rapid rise of retail TNCs, an interdisciplinary research agenda has emerged to examine various aspects of their activities, including stages and entry strategy in retail internationalization (Coe, 2004; Dawson & Mukoyama, 2006; McGoldrick, 1995), impact of host economies on local embeddedness (Coe & Lee, 2006; Coe & Wrigley, 2007; Hess, 2004; Wrigley, Coe, & Currah, 2005), the structural paradox between enforcing standardization and conducting localization (Aoyama, 2007; Chuang, Donegan, Ganon, & Kan, 2011), and spatial dynamics of market penetration in emerging economies (He, Li, & Yin, 2011; Wang, 2009).

The success of retail TNCs in new markets largely depends on localization. A key conceptualization in TNC-local relations is the notion of local embeddedness, which includes three interrelated types – societal, network, and territorial (Hess, 2004). Territorial embeddedness deals with how economic actors are "anchored" in different places – from the nation state to the local level (Wrigley et al., 2005), and describes the extent to which firms' strategic behavior is influenced by the institutional characteristics of the host economies (Tacconelli & Wrigley, 2009). Local embeddedness can be constrained by a series of institutional, structural, technological, and spatial mismatches (Wei, 2015). Underlocalized retail TNCs may fail to gain customer acceptance. However, there are problems and costs associated with the implementation of localization, which often goes against the rationale of economies of scale and may challenge the corporate identity of TNCs. Aoyama's (2007) case study of Wal-Mart and Carrefour in the advanced Japanese retail market revealed a structural paradox inherent in retail TNCs, which lies in the balance between their objective in enforcing standardization (at the supranational level) and the need to conduct localization (at the subnational level) to ensure customer acquisition.

The geographic literature on retailing in China has also been quite limited until very recently. A few studies of China's retail transformation gradually appeared after 2000. These studies examined retail internationalization (Wang, 2003), strategic responses of retail TNCs (Tacconelli & Wrigley, 2009), diversification of retail format (Wang, 2011), and locational dynamics of international retailers (He et al., 2011). Scholars have also revealed the political economy and institutional changes underlying the retail transformation (Wang & Song, 2008). They confirm that the expansions of retail

TNCs were dictated by the gradual liberalization policy of the Chinese government (Wang, 2009).

Spatial dynamics of retail TNCs, and to a large extent service TNCs, in China has been an understudied topic. Previous studies of TNCs were predominantly focused on the manufacturing sector. Only a few studies have looked into location determinants and spatial patterns of service TNCs (He et al., 2011; Hong, 2007; Wu & Strange, 2000). The postwar retail suburbanization in Western countries described the flow of retailing out of traditional city centers to newly constructed suburban shopping centers, followed by the decline of the inner city (Jones & Simmons.1993). Suburbanization of retailing in China has been a trend in major cities since the mid-1990s but also showed characteristics different from Western countries (Chai, Shen, & Long, 2007; Qian, 2008)

The retail sector in China was a rigidly state-monopolized distribution system before the onset of economic reform in l978. China's retail industry has undergone a profound transformation since the economic reform in the late 1970s. Foreign retail ownership has increased significantly since 1992. A variety of modern retail formats were imported to China in the 1980s and 1990s (Wang, 2011). Most of the new formats were introduced by foreign retailers, who have considerably intensified their operation in the Chinese market. Among all the new retail formats, the hypermarket is the most popular because of its wide assortment of goods and competitive pricing. In the Chinese retail sector, a hypermarket is defined as a one-stop retail store with comprehensive merchandise and at least 6000 square meter floor space and a parking space greater than or equal to 40% of floor space (GBT18106-2004). The hypermarket retailing in China is dominated by foreign retailers (Moreau, 2008). The largest international retailers in China, namely Carrefour, Wal-Mart, and RT-Mart, are all hypermarket operators.

Any understanding of China's retail transformation requires an appreciation of the institutional changes that have trigged it. After 1978, a series of liberalization, privatization, and internationalization gradually transformed the retail sector (Wang & Zhang, 2005). Several stages of progressive liberalization can be identified in China's retail industry. Shortly after the opening of the retail sector in 1992, the Chinese central government imposed strict regulations on foreign retailers in terms of geographic distribution of foreign stores and their ownership. In 1999, retail foreign direct investment (FDI) was permitted to all provincial capitals and subprovincial cities. Retail chains were also allowed through joint ventures. China joined the World Trade Organization (WTO) in 2001 and consequently lifted all remaining restrictions in retailing in 2004.

On the other hand, remote sensing and GIS have been widely used as cost-effective tools in detecting LULC change and urban expansion. Remote sensing can provide valuable multitemporal data to monitor land use change pattern and process while GIS technology can analyze and map these changes (Long et al., 2007; Weng, 2002; Yuan, Sawaya, Loeffelholz, & Bauer, 2005). Tremendous LULC change and urban growth has taken place in China since 1978, especially in the eastern coastal region (Seto & Kaufmann, 2003; Weng, 2002). Rapid urbanization in China is accompanied by arable land loss, landscape fragmentation, and sustainability challenges (Wei, 2007; Xie, Yu, Bai, & Xing, 2006; Yeh & Li, 1999).

Accurately classifying remotely sensed data into a thematic map remains a challenge because many factors may affect the success of a classification, such as the complexity of the landscape, selected remote sensing data, and image processing and classification approaches (Lu & Weng, 2006). Urban areas are typically a complex combination of buildings, roads, vegetation, and water and so on and are very difficult to classify accurately. Random forest (RF) is a novel classification algorithm developed in the field of machine learning (Breiman, 2001), which has been successfully applied to classify heterogeneous landscapes (Basnet & Vodacek, 2015; Ghimire, Rogan, & Miller, 2010; Ghosh, Sharma, & Joshi, 2014). Compared with other classification methods, RF is easy to implement and fast in computation.

Many efforts have been made to analyze the complex pattern of urban land expansion and understand the underlying factors. Scholars have attempted to understand the driving forces of urban growth in China from institutional and political economy perspectives (Deng & Huang, 2003; Lin & Ho, 2005; Lin & Wei, 2002; Wei, 2012, 2015). They find that urban growth in China is driven by economic reform and globalization and led by the state and transnational corporations. With the advances in spatial modeling, GIS, and remote sensing, various models have been developed to analyze urban growth patterns in Chinese cities (Li & Yeah, 2000; Xie et al. 2007). Nevertheless, these models are often inadequate to incorporate socioeconomic factors and institutional analysis to explain the underlying mechanism of urban growth.

Most extant models such as the orthodox logistic regression model tend to analyze urban growth from a global view, which assumes that the influence of various factors can be applied uniformly throughout the whole study area without consideration for spatial variation. However, urban growth is in fact a nonstationary process over space. A few recent studies have taken account of the spatial nonstationary relationship between urban growth and explanatory factors and address this issue by using spatially explicit models such as geographical weighted regression (GWR) and spatial expansion method (Liao & Wei, 2014; Luo & Wei, 2009).

1.2.2 Research Objectives

Based on the review above, there are four areas that deserve further research efforts: first, the impacts of home and host economies on retail TNCs' local embeddedness in China and how they resolve the structural paradox between enforcing standardization and conducting localization; second, the spatiotemporal expansion patterns of major foreign hypermarket retailers and their location determinants; third, the applicability of random forest algorithm in classifying multitemporal Landsat Thematic Mapper (TM) images of Suzhou and LULC change analysis derived from the image classification; fourth, the spatiotemporal dynamics and spatial determinants of urban growth in Suzhou.

Specifically, this dissertation aims to achieve the following four research objectives: (1) to investigate how home country effect and host market institution jointly influence foreign hypermarket retailers' local embeddedness and identify strategies that they adopt to resolve the inherent structural paradox; (2) to examine the spatial dynamics of foreign hypermarket at regional, provincial, intercity, and intraurban level and identify location determinants of major foreign retailers; (3) to use random forest classification and postclassification change detection to identify the magnitude, location, and nature of LULC change in Suzhou; (4) to investigate the urban growth pattern in Suzhou and relate them to the socioeconomic transitions that Suzhou experienced and to uncover the spatial variation of location determinants of urban growth through the logistic GWR model.

1.3 Data and Methodology

1.3.1 Study Area

This dissertation aims to conduct research on foreign hypermarket retailers at multiple geographical levels, ranging from regional and provincial, to intercity and intraurban. Consequently, the study area includes Shanghai Municipality, prefectural and higher level cities, 31 provincial-level administrative divisions, and 3 macro regions (eastern, central, and western) in mainland China. Shanghai was chosen for the case study of spatial clustering and suburbanization of foreign hypermarkets because it is the headquarter city for most foreign retailers and has a large number of foreign hypermarkets. As a rapidly industrializing and urbanizing city, Suzhou was chosen for the study of land use and land cover (LULC) change and urban growth because it is representative of fast changing coastal cities that have experienced dramatic spatial restructuring during the past 3 decades.

1.3.2 Data and Data Resources

This research incorporates a variety of data, including retailer data, store data, city data, remote sensing data, and GIS data. Data about entry time, entry strategy, and store location of foreign hypermarket retailers were collected from corporate websites, company annual yearbooks, statistical yearbooks, retail industry almanacs, academic articles and books, and news reports. Store-level data of foreign hypermarkets are analyzed by their establishment date and administrative division. City-level data such as FDI, retail sales, and urban salary were collected from the China City Statistical Yearbook (SSB, 2011). Population data including both registered population and migrant population for each city were collected from the 2010 population census (SSB, 2012).

Remote sensing data, mainly Landsat TM images, were exclusively downloaded from the website of the USGS (United States Geological Survey, http://earthexplorer.usgs.gov/). GIS data such as administrative divisions of Suzhou, Shanghai, and China and the transportation network of Suzhou were provided by Nanjing Institute of Geography and Limnology and Suzhou Planning Bureau.

1.3.3 Analysis Methods

In order to examine the spatiotemporal dynamics of foreign hypermarket retailers in China and urban growth in Suzhou, a combination of statistical and spatial modeling, remote sensing technique, and GIS analysis are applied in this research.

First, five spatial statistical indices are employed to investigate the spatial dynamics of foreign hypermarkets. Two global statistics, global Moran's I and Getis-Ord General G, are used to analyze whether the spatial distribution of foreign hypermarkets is dispersed or clustered. Two local statistics, local Moran's I and Getis-Ord G^*, are employed to identify whether there is any local spatial autocorrelation or clustering. Furthermore, the Average Nearest Neighbor (ANN) index is employed to examine the point pattern of foreign hypermarkets in Shanghai.

Second, binary logistic regression models are employed to identify the spatial determinants of three major foreign hypermarkets Carrefour, Wal-Mart, and RT-Mart at the intercity level in 2010.

Third, the random forest classification method is applied to multitemporal Landsat TM images of Suzhou. Then postclassification comparison is used to five independently classified thematic maps for LULC change analysis.

Fourth, a variety of landscape metrics are employed to analyze the overall changes in the urban land pattern in Suzhou. Landscape metrics were originally developed in the field of landscape ecology and have been recently applied to urban morphology.

Fifth, GIS analysis is used to identify types, magnitude, direction, and location of urban growth in Suzhou. Three types of urban growth, namely infilling, edge-expansion, and leapfrog, are identified. Sector analysis is employed to characterize the quantity and spatial distribution of urban land in terms of angular orientation relative to the urban center. Concentric analysis is used for analyzing the relationship between the area of urban growth and the distance from the urban center.

Lastly, global logistic regression and logistic GWR models are employed to identify the spatial determinants of urban growth in Suzhou. The logistic GWR model aims to reveal the spatial variation of urban growth patterns.

1.4 Organization of the Dissertation

This dissertation is organized into six chapters. Following the introductory chapter, Chapter 2 examines the development and embeddedness of foreign hypermarket retailers in China. This chapter analyzes the general spatial penetration pattern of foreign retailers, the impacts of home and host economies on their local embeddedness, and how they resolve the structural paradox between enforcing standardization and conducting localization.

Chapter 3 investigates the spatial inequality and dynamics of foreign hypermarket retailers at different geographic scales in China. This chapter analyzes the relative and absolute gaps in foreign hypermarkets among Chinese regions and provinces, identifies the location determinants of foreign retailers at the intercity level through binary logistic regression models, and examines the intensified spatial clustering and suburbanization of foreign hypermarkets in Shanghai.

Chapter 4 applies the random forest classification method to multitemporal Landsat TM imagery in Suzhou in 1986, 1991, 1995, 2002, and 2008; uses postclassification comparison method for LULC change analysis; and relates the changes to major socioeconomic driving forces.

Chapter 5 analyzes spatiotemporal dynamics of urban growth and models its spatial determinants in Suzhou. This chapter applies GIS analysis to land use data to identify types, magnitude, direction, and location of urban growth; uses landscape metrics to quantify the trend of urban growth; and employs global logistic regression and logistic GWR models to identify the spatial determinants of urban growth in Suzhou.

Chapter 6 concludes the major findings and contributions of previous chapters, discusses the limitations of this dissertation, and highlights the directions for future research.

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CHAPTER 2

FOREIGN HYPERMARKET RETAILERS IN CHINA: SPATIAL PENNETRATION, LOCAL EMBEDDEDNESS, AND STRUCTRUAL PARADOX[1]

2.1 Introduction

Since the deepening of globalization in the 1980s, the world economy has been increasingly shifting towards the service economy. Many developing countries have gradually removed restrictions on service industries (for example, retail, finance and insurance, logistics, and transportation) to attract foreign direct investment (FDI). Transnational corporations (TNCs) in the service sector have expanded globally. While China is known as the world factory, FDI in China has also undergone significant structural transformation. Service FDI in China increased from 24 percent of the total realized FDI in 2001 to more than 50 percent in 2011. Retailing has been at the frontier of international expansion of service TNCs.

The internationalization of retailing is one of the most salient characteristics of the

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global service economy today. Since the mid-1990s, a group of retail TNCs mainly from Western Europe (for example, Carrefour, Tesco, and Metro) and North America (such as Wal-Mart) has expanded globally and risen rapidly in the world economy. During the past two decades, these retail TNCs have intensified their strategic expansion in emerging markets across East Asia, Eastern Europe, and Latin America for prospective growth and profits. The global expansion of retail TNCs has become an increasingly important topic in economic geography (Coe, 2004; Coe & Wrigley, 2007; Wrigley, 2000).

Since the economic reform began in the late 1970s, rapid economic growth in China has brought wealth to its people and transformed the nation into one of the world's largest consumer markets. With retail sales growing at a double-digit per year, China has become an attractive target market for many international retailers. However, foreign retailers were not allowed to engage in retail trade in China until 1992. Since then, most international retailers have established their presence in China. These foreign retailers introduced a variety of modern retail formats, transferred advanced retail know-how and technology, and played an important role in the retail transformation in China.

Although retail TNCs can greatly transform the host economies, their spatial and temporal processes underlying the retail transformation in China are little studied. Among all the new retail formats in China, the hypermarket is the most popular, thanks to its wide assortment of goods and competitive pricing. The hypermarket retailing in China, especially in large cities, is dominated by foreign retailers (Moreau, 2008). The largest international retailers in China, namely Wal-Mart, Carrefour, and RT-Mart, are all hypermarket operators. Focusing on the hypermarket retailing sector, this chapter aims to analyze the spatial penetration patterns of major foreign hypermarket retailers in China, the impacts of home and host economies on their local embeddedness, and how these retail TNCs resolve the structural paradox between enforcing standardization and conducting localization in the Chinese retail market.

2.2 Literature Review

In response to the rapid rise of retail TNCs, various aspects of their activities have been studied, including stages and entry strategy in retail internationalization (Coe, 2004; Dawson & Mukoyama, 2006; McGoldrick, 1995), impact of host economies on local embeddedness (Coe & Lee, 2006; Coe & Wrigley, 2007; Hess, 2004; Wrigley, Coe, & Currah, 2005), the structural paradox between enforcing standardization and conducting localization (Aoyama, 2007; Chuang, Donegan, Ganon, & Kan, 2011), and spatial dynamics of market penetration in emerging economies (He, Li, & Yin, 2011;Wang, 2009).

The process of retail internationalization can be hypothesized as composing of a sequence of five key stages: pre-entry, entry, post-entry, assimilation, and exit (Dawson & Mukoyama, 2006). To understand the complex activities associated with the post-entry stage, Dawson (2003) proposes a four-phase model of stabilization, consolidation, domination, and control. Based on the level of control and risk, the entry strategy to foreign retail markets can range from licensing, concessions, franchising to joint venture, acquisition and merger, and start-up (McGoldrick, 1995). Wang (2003) specifies the entry strategy into entry mode and entry path. Firms can take one of the two modes to enter a foreign market: wholly owned subsidiaries or joint ventures. Both modes can be realized through either green-field development (organic growth) or acquisition and merger.

The literature on economic globalization has focused much on production-based manufacturing industry and shown a myopic neglect of distribution-based retail industry (Wrigley, 2000). In recognition of the spatially and temporally complex dynamics of retail TNCs, Coe (2004) and Coe and Lee (2006) propose the global production network (GPN) approach to examine the globalization of retailing. This approach argues that retail TNCs should be positioned as complex configurations of intra-, inter- and extra-firm relational networks which are highly embedded in and shaped by the economic, political, and institutional contexts of both home and host economies (Wrigley et al., 2005). The notion of global commodity chain (GCC), which the GPN approach draws on has also been utilized to examine the emergence of global retailers and the buyer-driven global commodity chains (Gereffi, 1994).

The success of retail TNCs in new markets largely depends on localization. The "distribution-based" nature of retail TNCs requires them to become embedded in the host market and rapidly understand the nuance of local customer culture to an extent not needed for "production-based" manufacturing firms (Currah & Wrigley, 2004; Wrigley et al., 2005). A key conceptualization in TNC-local relations is the notion of local embeddedness, which includes three interrelated types – societal, network, and territorial (Hess, 2004). Societal embeddedness refers to the legacy that a firm derives from the cultural, institutional, and economic environment of its home market. This "genetic code" (Hess, 2004) plays an important role in shaping a firm's international strategies. Wei, Zhou, Sun, and Lin (2012) emphasize the home country effect in TNC's local embeddedness. Network embeddedness refers to a firm's relationships, both horizontal and vertical, with other organizations—including suppliers, customers, competitors, and other entities (Henderson, Dicken, Coe, & Yeung, 2002). Territorial embeddedness deals with how economic actors are “anchored” in different places – from the nation state to the local level (Wrigley et al., 2005), and describes the extent to which firms’ strategic behavior is influenced by the institutional characteristics of the host economies or societies (Tacconelli & Wrigley, 2009).

Unlike manufacturing TNCs which were pseudo-embedded in host economies through establishing their own glocal networks with other TNC suppliers (Wei 2015; Wei & Liao, 2013), Wrigley et al. (2005) argue that it is the necessarily high territorial embeddedness in markets and cultures of consumption, planning and property systems, and logistical and supply chain operations that defines the distinctive theoretical and organization challenge of retail TNCs. Retail TNCs must invest in territorial embeddedness to achieve what Bianchi and Arnold (2004) describe as “organizational legitimacy” in host markets in both the economic domain and the broader sociocultural network. Coe and Lee (2006) have found that Samsung-Tesco has secured sustained growth through strategic localization of product design, sourcing networks and employees, and strategic decision making to become territorially embedded in the South Korean economy and society. Coe and Wrigley (2007) explore the host economy/society impacts of the retail TNCs and stress the mutual transformations of the host economies by the retail TNCs and reciprocally, of the retail TNCs themselves.

There are also problems and costs associated with the implementation of localization, which often goes against the rationale of economies of scale and may challenge the corporate identity of TNCs (Aoyama, 2007). Aoyama’s case study of the world’s two largest retailers, Wal-Mart and Carrefour, in the advanced Japanese retail market revealed a structural paradox inherent in retail TNCs. This paradox lies in the balance between retail TNC's objective in enforcing standardization (at the supranational level) and the need to conduct localization (at the subnational level) to ensure customer acquisition. Standardization or the direct transfer of retail TNC's strategic assets such as formats, commodities and retail practices, and know-how is a cost-effective means to achieve economies of scale (Aoyama, 2007). Nevertheless, standardization can be hindered in many situations in the host economies. For example, the stringent German land use policy, competition, and labor regulations made Wal-Mart unable to replicate its effective Big-Box store development, marketing strategies, and wage practice in Germany as it did in the U.S. (Aoyama & Schwarz, 2006; Christopherson, 2007).

Local embeddedness can be constrained by a series of institutional, structural, technological, and spatial mismatches (Wei, 2015). Underlocalized retail TNCs may fail to gain customer acceptance. The strong market power of manufacturers/suppliers in South Korea, Japan, and Germany made it difficult for Carrefour and Wal-Mart to exercise their power to dominate the retail distribution system and suppliers (Aoyama, 2007; Christopherson, 2007; Coe & Lee, 2006). Carrefour and Wal-Mart's inadequate localization to adapt to South Korean customers' tastes and preferences eventually contributed to their failure in South Korea (Gandolfi & Strach, 2009; Kim, 2008). Underdeveloped infrastructure and logistics system, highly fragmented retail market, and a lower level of purchasing power made retail TNCs unable to practice their home market standardization in the Chinese market (Chuang et al., 2011). Retail TNCs may also face challenges in penetrating the Chinese market and embedding within the Chinese economy.

The geographic literature on retailing in China has been quite limited. Studies of retail transformation in urban China did not appear until the 2000s. These studies have examined retail internationalization (Wang, 2003, 2009), challenge of embeddedness and strategic responses of retail TNCs (Tacconelli & Wrigley, 2009), and diversification of retail ownership and format (Wang, 2011; Wang & Chan, 2007). Scholars have revealed the political economy and institutional changes underlying the retail transformation (Wang & Song, 2008). They have also confirmed that the growth and expansion of retail TNCs in China were constrained by the slow-paced retail deregulation. The spatial dynamics of retail TNCs and to a large extent service TNCs in China has been an understudied topic. Existing studies on foreign firms are predominantly concentrated on the manufacturing sector (Huang & Wei 2014; Liefner & Wei 2014; Zhou, Sun, Wei, & Lin, 2011). Only in the recent years did a few studies look at the spatial pattern of service FDI in China. Wang (2009) and He et al. (2011) find that market-oriented retail FDI has followed China's urban hierarchy and diffused into inland cities. This is different from manufacturing FDI, which is highly concentrated in the coastal regions.

The limited extant studies on the retail transformation in China warrant further investigations of retail TNCs in this emerging market. This study examines the hypermarket retailing sector in China as this retail channel is concentrated with foreign retailers and has experienced rapid growth. We investigate three largest foreign hypermarket retailers, namely Carrefour, Wal-Mart, and RT-Mart, to provide more detailed analysis. We adopted data triangulation, the use of multiple sources of data, in this study. We collected data about entry time, entry strategy, and store location of foreign retailers from corporate websites, statistical yearbooks, and news reports. Store-level data of foreign hypermarkets are analyzed by their establishment date and administrative division.

2.3 Research Background and Context

Before 1978, the retail sector in China was a rigidly state-monopolized distribution system. Private retail ownership was banned and retail chains were nonexistent (Wang, 2003). Since the late 1970s, China's retail sector has undergone a profound transformation: retail ownership has diversified considerably; various modern retail formats have been imported; and international retailers have come to play an important. Over the past 36 years, domestic retail ownership has been substantially diversified. More importantly, since 1992, foreign retail ownership has increased rapidly (Wang & Chan, 2007). A variety of modern retail formats, such as convenience store, supermarket, hypermarket, warehouse club, and factory outlet, were imported in the 1980s and 1990s (Wang, 2011), Most of the new retail formats were introduced by foreign retailers, who have considerably intensified their operation and increased market share in China.

Institutional changes have trigged the retail transformation in China. In the era of planned economy, the retail industry was monopolized by the state. After 1978, a series of liberalization, privatization, and internationalization have gradually transformed the retail sector (Wang & Zhang, 2005). Several stages of progressive liberalization can be identified in the retail sector. In the early stage of opening the retail sector (shortly after 1992), the Chinese central government imposed strict regulations on foreign retailers. The geographic distribution of foreign retail stores was highly restricted to a few coastal cities and special economic zones. In addition, foreign retailers could only have a minority ownership. In 1999, retail FDI was permitted to all provincial capitals and sub-provincial cities. Retail chains were also allowed through joint ventures. In 2001, China joined the World Trade Organization (WTO) and consequently lifted all remaining restrictions in retailing in 2004.

Many foreign retailers in China were actually approved by local governments who took the liberty of approving retail joint-ventures independently. Such an inconsistent retail regulatory system and the fragmented administrative structure are the characteristics of China's "fragmented developmental state" (Wang & Song, 2008). At the local level, international retailers could enjoy many privileges in tax preferences and obtaining free use of land. Consequently, many of them took advantage of this discrepancy between the central and local governments in China and strategically expanded their business in this emerging market. Most foreign hypermarket retailers came to China shortly after the opening of retail sector to foreign investment in 1992. Carrefour entered China in 1995, Walmart in 1996, and RT-Mart in 1998.

Among all the new retail formats that foreign retailers adopt in China, the hypermarket is the most popular and most successful one as it can provide a variety of consumer goods at competitive prices. According to Top 100 Retailers in China 2012 (CCFA, 2013), the largest three foreign retailers by sales, RT-Mart (5^{th}), Wal-Mart (6^{th}), and Carrefour (10^{th}), are all hypermarket operators. The concept of hypermarket originated in France in the early 1960s (Dawson, 1976). In 1963, the French retailer Carrefour opened the world's first hypermarket near Paris. The hypermarket is a classic retail innovation, combining price competition with a varied product range (Guy, 1998). It typically sells a complete range of food and convenience items and a wide range of clothing, footwear, and household items. The Retail Format Classification

(GBT18106-2004) in China defines a hypermarket as a one-stop retail store with comprehensive merchandise and at least 6000 square meter floor space and a parking space greater than or equal to 40 percent of floor space.

Since the first hypermarket in China opened by Carrefour in Beijing in 1995, hypermarkets have expanded rapidly in the Chinese retail market. Foreign retailers, especially two early entrants Carrefour and Wal-Mart, played an important role in promoting and popularizing this retail format. In the mid-1990s, armed with advanced information technology and effective supply networks, these two international retailers introduced hypermarkets to China as well as the concept of “one stop shopping” and the slogan of “everyday low price”. Compared with other retail formats, such as the noisy and crowded wet markets and the standard supermarkets with limited assortment of goods, hypermarkets can provide a complete range of goods at competitive prices in a clean and tidy shopping environment. Therefore, this new retail format soon gained popularity in China. The hypermarket strategy of Western retailers was emulated by international retailers from Asia and Chinese domestic retailers. As a result, many other foreign and domestic hypermarket operators opened their first stores in the late 1990s.

Hypermarket retailing in China is more concentrated with foreign retailers than any other retail channel. This is in contrast to supermarkets, which is a highly segmented retail channel and controlled by domestic players (Moreau, 2008). While some domestic hypermarket operators such as Wu-Mart in Beijing and Yonghui Supermarket in Fujian have a significant presence in their regional market, foreign retailers such as Carrefour, Wal-Mart, and RT-Mart dominate the nationwide hypermarket retailing. For example, 82 foreign hypermarkets in Shanghai accounted for 78.6% of the total hypermarket sales in

2008 (Wang, Liu, & Wang, 2012).

Since the opening of the retail sector in 1992, ten foreign retailers have operated hypermarkets in China (Table 2.1). International hypermarket retailers adopted a variety of strategies to enter the Chinese market. These include start-up, joint venture, and merger and acquisition (M&A). Foreign retailers who came to China in the mid-1990s enjoyed the advantages of being the first movers. They usually preferred organic growth and opened stores at prime locations in large Chinese urban centers. Earlier entrants such as Carrefour, Wal-Mart, Auchan, Hymall, Trust-Mart, and RT-Mart all chose this strategy. To overcome the scarcity of prime locations, the latecomers such as Tesco and Lotte Mart resorted to the M&A strategy. Tesco's acquisition of Hymall and Lotte Mart's acquisition of the Dutch warehouse clubs Makro and Jiangsu-based Times Supermarket enabled them to access prime sites in the nearly saturated property market in large Chinese cities. Even the first movers such as Wal-Mart and Carrefour used M&A strategy to consolidate their market positions. Wal-Mart's acquisition of Trust-Mart in 2007 not only increased its store number substantially but also gave it the access to large retail space that would have been otherwise difficult to obtain. Carrefour's acquisition of the Hebei-based regional retailer Baolongcang Group in 2010 enabled it to penetrate the conservative retail market in Hebei Province.

Although the hypermarket is a popular retail format, not all foreign hypermarket operators are doing well in China. As Table 2.1 and Table 2.2 show, RT-Mart, Wal-Mart, and Carrefour are clearly leading the hypermarket retailing sector. They have achieved a national wide distribution network, whereas Tesco, Lotte Mart, Auchan, Lotus, and E-mart remain as regional retailers. Western and Taiwanese hypermarket retailers are

Table 2.1 Major foreign hypermarket chains in China, 2012

Retailer	Country	Year of entry	Year of acquisition	Market penetration Stores	Cities	Provinces
Carrefour	France	1995		219	71	24
Wal-Mart	U.S.	1996		280	150	25
Lotus	Thailand	1997		72	27	14
E-Mart	South Korea	1997		16	4	3
Trust-Mart	Taiwan	1997	2007	(101)	(35)	(16)
Hymall	Taiwan	1998	2006	(43)	(16)	(6)
RT-Mart	Taiwan	1998		219	147	25
Auchan	France	1999		55	30	9
Tesco	U.K.	2004		111	48	11
Lotte Mart	South Korea	2008		102	71	10

Note: Wal-Mart stores not including the acquired Trust-Mart stores

Sources: Compiled by the author from various cooperate websites

Table 2.2 Rank and retail sales of foreign hypermarket chains in China, 2012

Retailer	Rank in Top 100 Retailers	Stores	Total Sales (billion Yuan)	Average Store Sales (million Yuan)
RT-Mart	5th	219	72.47	330
Wal-Mart	6th	387	*58	150
Carrefour	10th	219	45.27	207
Tesco	24th	111	*20	180
Lotte Mart	36th	102	16.32	160
Auchan	38th	55	16.30	296
Lotus	50th	72	*12.5	173
E-Mart	-	16	*2.4	150

Note: Wal-Mart stores include 99 Trust-Mart stores and 8 Sam's club; * indicates estimation.

Source: Adapted from Top 100 Retailers in China 2012 (CCFA, 2013) doing relatively better than their East and Southeast Asian counterparts. Among the foreign hypermarket operators who entered China in the 1990s, only Wal-Mart was officially approved by the central government (Wang & Zhang, 2006). All the other foreign hypermarket retailers strategically bypassed the state approval and got permission from the local governments.

2.4 Spatial and Temporal Penetration of Foreign Hypermarket Retailers

Carrefour, Wal-Mart, and RT-Mart are the most successful foreign hypermarket chains with a national wide distribution in China. Therefore, their penetration processes are the best examples to illustrate the changing spatial and temporal dynamics of foreign hypermarket retailers

We analyzed the numbers of Carrefour, Wal-Mart, and RT-Mart stores from 1995 to 2012 to illustrate their expansion processes (Figure 2.1).The majority of their stores were the results of organic growth except seven former Baolongcang stores in Hebei, which were acquired by Carrefour. Wal-Mart's acquired Trust-Mart stores were not included in this analysis. Restricted by retail regulations, Wal-Mart and RT-Mart didn't make much progress before 2001. On the contrary, Carrefour bypassed state regulations and aggressively expanded its business in the late 1990s. China's accession to the WTO in 2001 greatly encouraged foreign retailers' expansion as China promised to remove all restrictions in retailing within three years. Both Wal-Mart and RT-Mart increased their stores significantly in 2001, while Carrefour was admonished by the State Economic and Trade Commission and temporarily suspended for further expansion (Wang, 2003). In December 2004, China lifted all remaining restrictions in retailing to fulfill its WTO obligations. The three foreign hypermarket chains all accelerated their expansion after

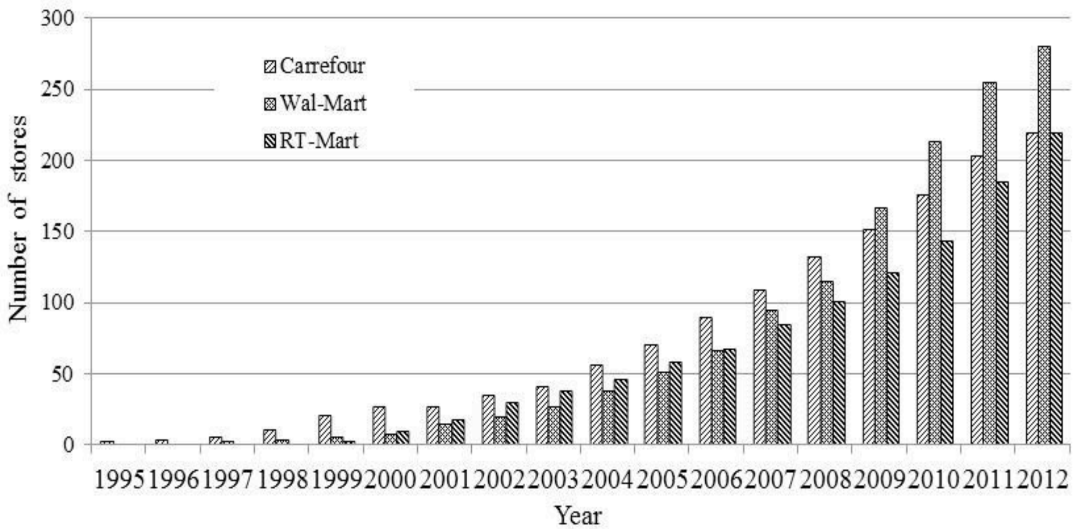

Figure 2.1 Hypermarkets of Carrefour, Wal-Mart, and RT-Mart, 1995-2012

2004, especially after 2008 when provincial governments were delegated the authority to approve wholly foreign funded retail enterprises. Wal-Mart opened 52 new hypermarkets in 2009, which accounted for nearly one third of its total number of stores (167 at that time). By the end of 2009, Wal-Mart had surpassed Carrefour to become the No.1 foreign hypermarket chain in terms of number of stores. RT-Mart expedited its expansion after 2008 and achieved the same number of stores as Carrefour at the end of 2012.

Insights can be gained into the spatial expansion pattern of each foreign hypermarket chain by examining the differences in the city tier composition of their stores (Figure 2.2). Deloitte's definition of different tiers of Chinese cities is adopted here (Deloitte, 2011)[2]. Clearly, the three foreign retailers all started from the first-tier cities in the coastal (Carrefour in Beijing, Wal-Mart in Shenzhen, and RT-Mart in Shanghai) and

[2] First-tier cities: Beijing, Shanghai, Guangzhou, and Shenzhen. Second tier cities: Tianjin, Chongqing, sub-provincial cities, the majority of provincial capitals, and economically developed prefecture level cities. Third-tier cities: provincial capitals in less developed provinces and the majority of prefecture level cities. Fourth-tier cities: mainly county-level cities and county towns.

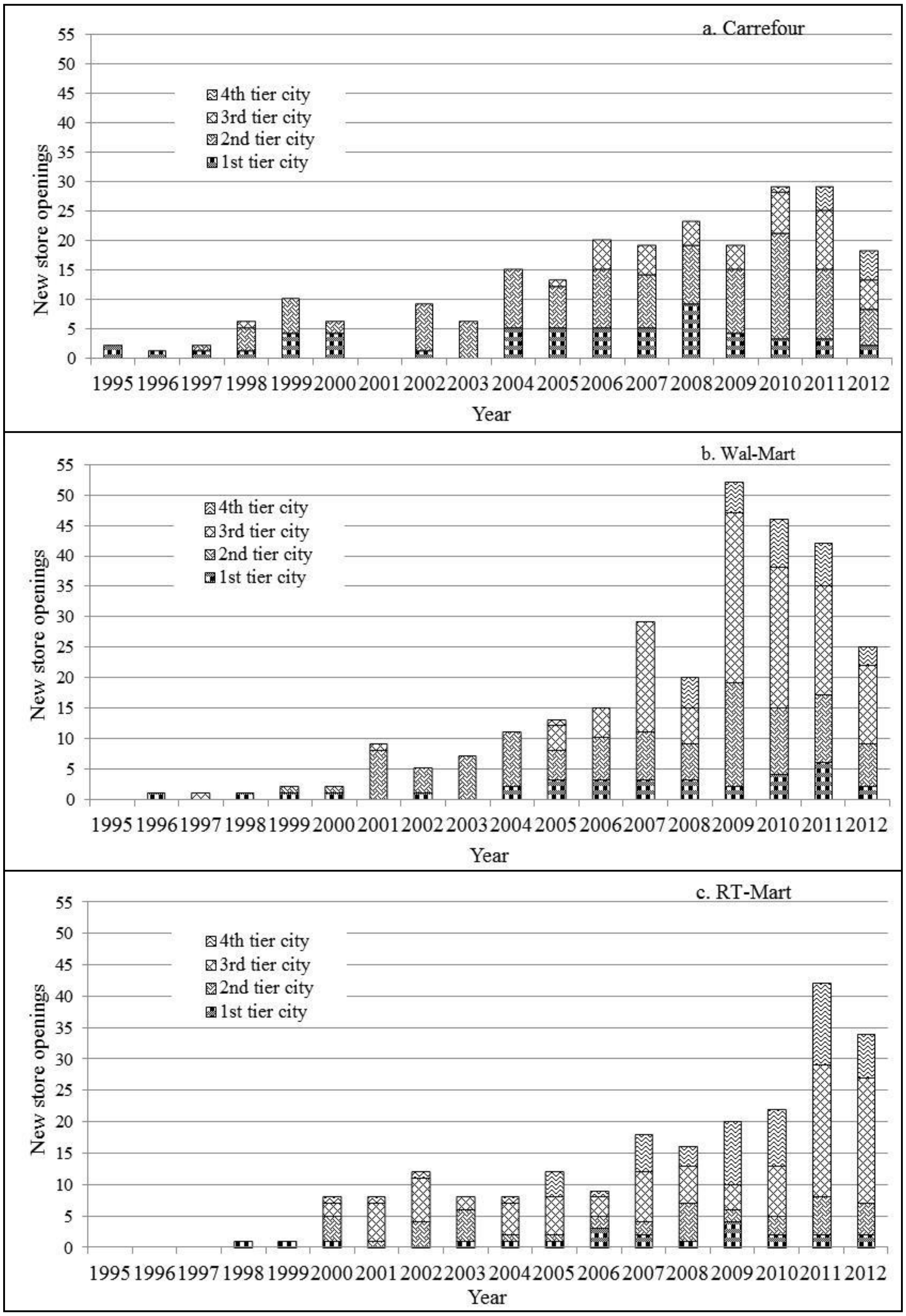

Figure 2.2 New store openings by city tier in China: a. Carrefour b. Wal-Mart c. RT-Mart

gradually expanded to the second-, third- and fourth-tier cities. Carrefour had focused exclusively on the first- and second-tier cities until 2005. Then it began to open stores in the third-tier cities and later expanded to the fourth-tier cities in 2010. However, lower tier cities were never the focus of Carrefour and its current stores are mostly concentrated in large cities.

Wal-Mart was initially engaged in expanding to the second-tier cities in its early development in China. Since 2005, Wal-Mart has significantly increased its stores in the third-tier cities. In recent years, Wal-Mart also opened a few stores in the fourth-tier cities. Wal-Mart's expansion largely followed the Chinese urban hierarchy from large cities to medium and small cities. This is totally different from Wal-Mart's spatial diffusion in the United States, where it expanded contagiously from its headquarter in Arkansas to neighboring states and reversely from small towns into large urban areas (Graff and Ashton, 1993).

RT-Mart clearly adopted a different expansion strategy. After a short period of expanding in large cities, since 2001 RT-Mart has largely focused on the third-tier cities. The importance of the fourth-tier cities increased when RT-Mart began to open stores in those cities in 2007. Stores in the large cities only account for a small proportion of RT-Mart's total number of stores.

In order to further investigate their temporal and spatial expansion patterns, the locations of the three foreign hypermarkets chains were mapped (Figures 2.3-2.5). Their spatial penetration has taken place in two directions: from the eastern costal region to the central and western hinterland; and along China's urban hierarchy from the first- and second- tier cities to the third- and fourth-tier cities.

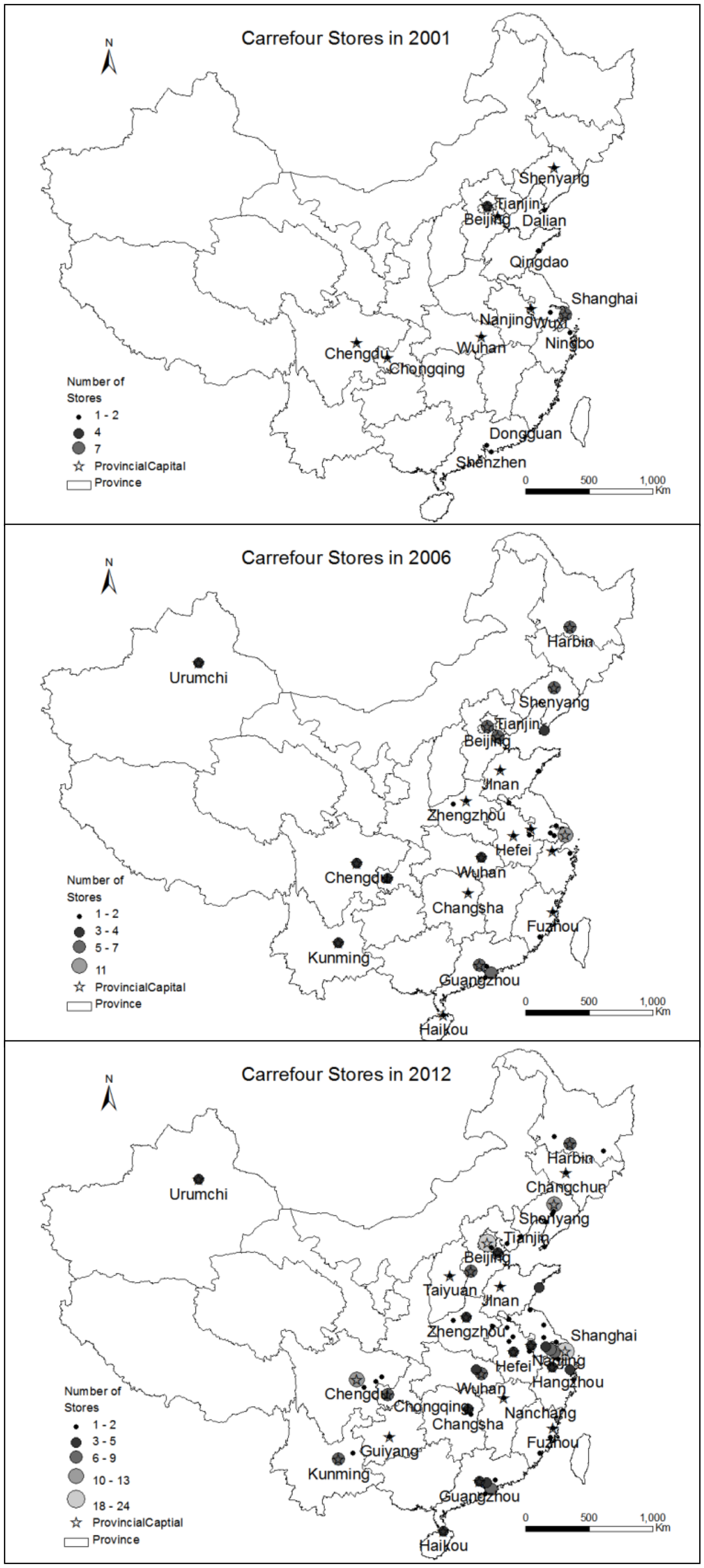

Figure 2.3 Spatial expansion of Carrefour stores, 2001- 2012

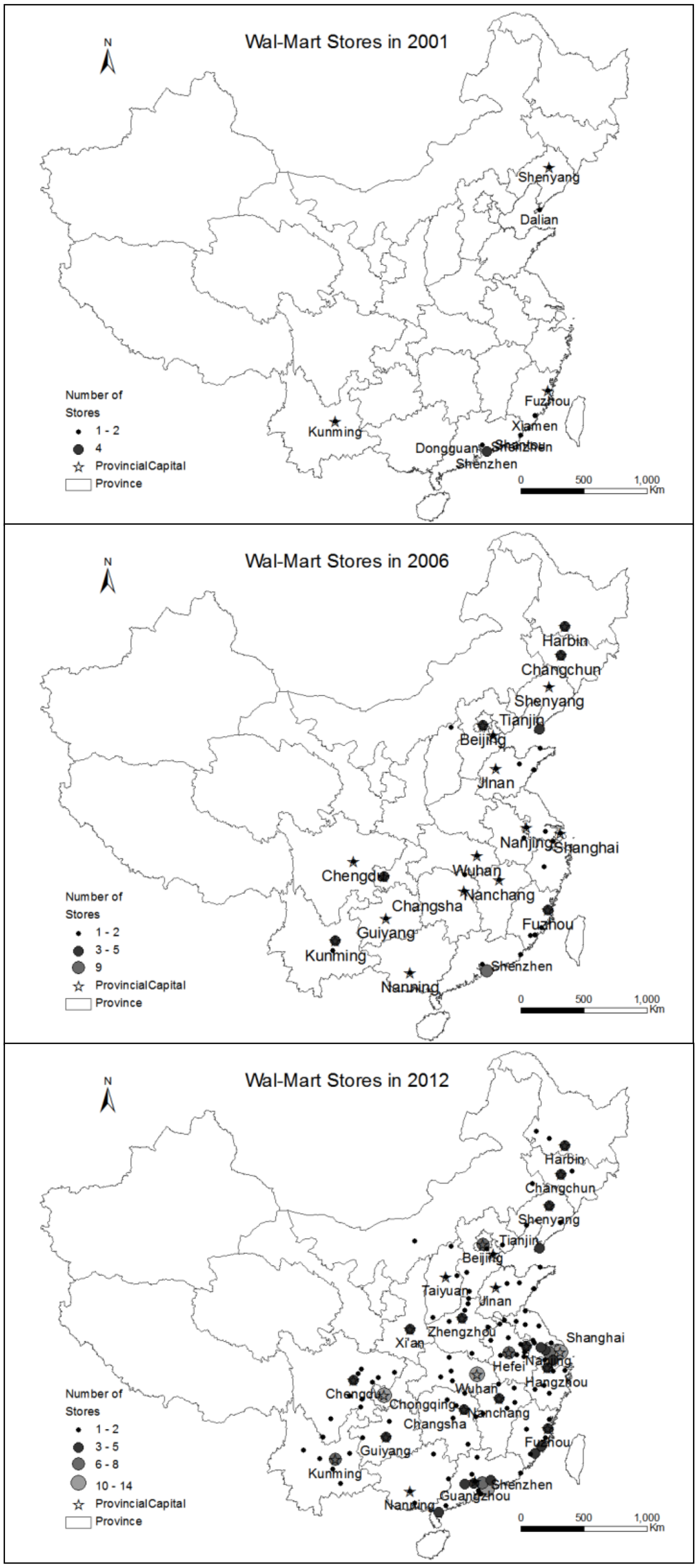

Figure 2.4 Spatial expansion of Wal-Mart stores 2001- 2012

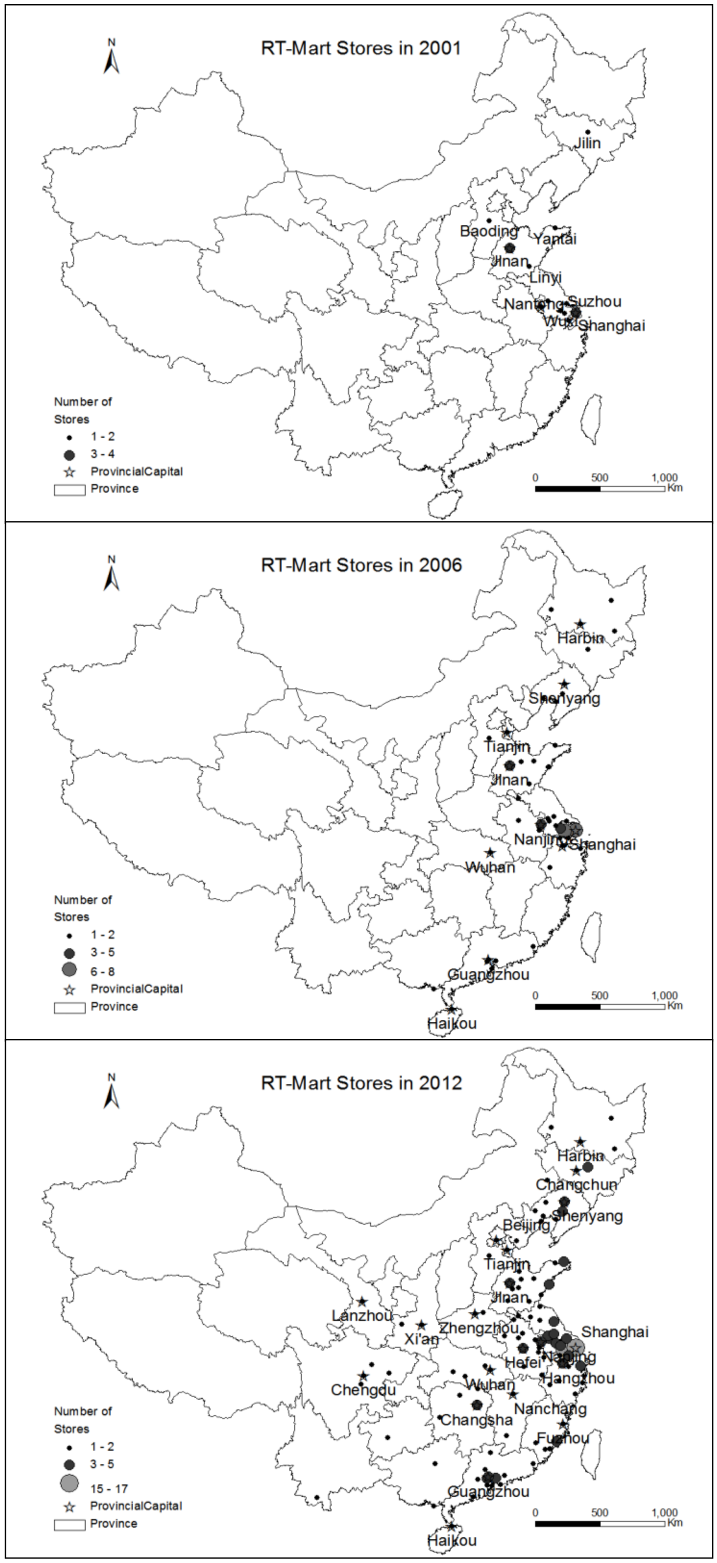

Figure 2.5 Spatial expansion of RT-Mart stores, 2001- 2012

In 2001, Carrefour had the largest number of stores and the broadest distribution, thanks to its aggressive expansion. Carrefour opened stores in the northeast region (Shenyang and Dalian), north region (Beijing and Tianjin), east region (Shanghai, Wuxi, Nanjing and Ningbo), central region (Wuhan), and south region (Dongguan and Shenzhen). Wal-Mart and RT-Mart hadn't made much expansion by 2001 as they largely followed the state regulations. Wal-Mart stores were primarily distributed along the coastal line in the south region (Shenzhen, Dongguan, Shantou, Xiamen, and Fuzhou) and the northeast region (Dalian and Shenyang) except Kunming in the southwest region. RT-Mart stores were mainly concentrated in the east region (Shanghai, Jiaxing, Suzhou, Wuxi, and Yangzhou) and Shandong Province (Linyi, Jinan, and Yantai).

By 2006, Carrefour had almost established its nationwide distribution network. It expanded from coastal region towards the central region (Zhengzhou and Changsha) and western region (Kunming and Urumchi). Carrefour stores were mainly located in centrally administered municipalities and provincial capitals of developed provinces. Wal-Mart had a similar distribution network as Carrefour, but its average number of stores in a city (1.9) was much smaller than that of Carrefour (3.5). As Wal-Mart mainly focused on the second-tier cities before 2005, it lost the first-mover opportunities to Carrefour in most first-tier cities (Beijing, Shanghai, and Guangzhou) except in its headquarter Shenzhen. While RT-Mart was still concentrated in the east, north, and northeast coastal regions, it was making inroads to some inland provinces such as Anhui, Hubei, and Heilongjiang.

By 2012, Carrefour had added only a few new cites to its distribution network. Instead, it significantly increased stores in the cities where it already had a presence.

Carrefour tended to over-concentrate in large urban centers, especially provincial capitals (Figure 2.3). It has fewer cities in the distribution network than Wal-Mart and RT-Mart (Table 2.2). Carrefour stores were clustered across the Yangtze River Delta. In 2012, Wal-Mart had the largest number of stores and the deepest market penetration. It had dramatically expanded into lower-tier cities and simultaneously increased stores in large cities. South and central regions had the largest number of Wal-Mart stores (Figure 2.4). RT-Mart had expanded to the central and west regions and established a nationwide distribution network by 2012. But it had fewer stores in the inland regions than in the coastal regions (Figure 2.5). Many inland provinces had only one or two RT-Mart stores, whereas more than one third of its stores were clustered in the eastern coastal region. Retail TNCs in other developing countries also show clear spatial expansion strategies. For example, Wal-Mart stores were first heavily concentrated in the Mexico City metropolitan area and then aggressively expanded into cities throughout Mexico (Iacovone, Javorick, Keller, & Tybout, 2009).

Market performance of foreign retailers is closely related to their expansion strategies. Carrefour has focused on the first- and second-tier cities since its entry. More than half of its stores are located in the second-tier cities (Table 2.3). In the early years of opening up the retail sector, these large cities were first opened to foreign retailers. They had greater profit potential because of a larger population size with a higher disposable income. Therefore, they attracted most of the early foreign hypermarkets. However, in recent years, the retail market in large Chinese cities has become saturated as a result of the intensified competition. The cost of maintaining stores in large urban centers has greatly increased. At the same time as China’s urbanization speeds up, the third- and

Table 2.3 Distribution of foreign hypermarkets along China's urban hierarchy, 2012

Retailer	1st tier cities	2nd tier cities	3rd tier cities	4th tier cities
Carrefour	**24.23%**	**52.86%**	18.50%	4.41%
Wal-Mart	11.74%	**36.30%**	**41.64%**	10.32%
RT-Mart	10.05%	19.18%	**44.75%**	**26.03%**

fourth-tier cities are thriving with huge market potential. Carrefour didn't pay enough attention to this trend, nor changed its strategy accordingly. As a result, it began to fall behind Wal-Mart and RT-Mart.

On the contrary, Wal-Mart shifted its focus from the second-tier cities to the third-tier cities in 2005 and gradually included the fourth-tier cities in its store network. This accelerated its expansion easily in the lower-tier cities with less competition. RT-Mart has focused on the third-tier cities since 2001. Its unique expansion strategy enabled it to avoid fierce direct competition with other foreign retailers in large cities and helped it to lay a firm foundation in small and medium sized cities, where nearly 70% of its stores were located (see Table 2.3). Consequently, RT-Mart surpassed Carrefour and became the No. 1 foreign retailer in retail sales in 2010.

2.5 Local Embeddedness and Structural Paradox of Foreign Retailers

Foreign hypermarket retailers managed to embed in the Chinese retail market and resolve their inherent structural paradox. Based on Hess' (2004) notion of three types of embeddedness (societal, network, and territorial), we specifically examine how Carrefour, Wal-Mart, and RT-Mart are influenced by home and host economies to balance between standardization and localization in their store location, supply chain management, and network relationships in China.

Carrefour and Wal-Mart are both world-renowned international retailers. Much of their success can be attributed to their standardized operation, which often entails centralized procurement and distribution based on highly developed infrastructure and advanced information technology. However, the underdeveloped infrastructure in distribution and logistics, an immature information technology environment, the vast variety of consumer behaviors, and the highly fragmented retail markets in China impeded Carrefour and Wal-Mart' effective enforcement of global standardization (Chuang et al., 2011). Instead, these retail TNCs have to localize their operation to accommodate the local culture and satisfy the preferences of Chinese customers.

Compared to Carrefour and Wal-Mart, which have a long history of international expansion in many countries, RT-Mart started its first store in 1996 in Taiwan and expanded its first international operation into mainland China in 1998. RT-Mart developed almost simultaneously in the two markets. It didn't have a standardized operation strategy when it entered mainland China. However, this seemingly disadvantage actually enabled RT-Mart to quickly adapt to the complex Chinese retail market. Table 2.4 summarizes the standardization and localization strategies that Carrefour, Wal-Mart, and RT-Mart have adopted in home and/or host economies.

2.5.1 Carrefour

Most of Carrefour's outlets in France are located in suburban areas. This suburban location strategy enabled it to quickly acquire cheap land for developing large floor area and parking space, which catered well to the shopping behavior of automobile-oriented French customers. When Carrefour came to China in 1995, it did not inherit this "genetic code" of suburban location. In the mid-1990s, commercial districts in Chinese cities were still in the urban center. Most Chinese people depended on public transit and were used to

Table 2.4 Standardization and localization of retail TNCs in home country and China

Foreign retailer	Operation standards in home country	Embeddedness and changes in China
Carrefour	Suburban location	Located near residential area or public transit route
	Centralized purchasing	Decentralized purchasing
	Centralized distribution	Supplier delivery
	Charge suppliers additional fees to compensate costs	Charge suppliers additional fees to compensate costs
Wal-Mart	Small-town start and reverse hierarchical diffusion	From large city to medium and small cities
	Centralized purchasing	Centralized purchasing
	Centralized distribution	Centralized distribution & supplier delivery
	Dominate suppliers & direct purchase without middlemen	Partially purchase through intermediaries
RT-Mart		Concentrate in small and medium cities
		Centralized purchasing with local autonomy
		Centralized distribution & supplier delivery
		Good relationship with local government

shopping in a wet market for grocery. To adapt to the local Chinese market conditions, Carrefour opened its first few hypermarkets in urban centers or adjacent to residential areas. Although at the national level Carrefour is over-concentrated in large cities, at the local urban level, its stores are usually well located at prime locations. Carrefour conducted extensive ethnographic research on the Chinese wet markets to understand the kind of products, methods of display, and customers' typical purchases (Tacconelli & Wrigley, 2009) and adapted the fresh-market style in its Chinese hypermarkets. The convenient store location and familiar wet-market display quickly made Carrefour hypermarkets popular with Chinese urban consumers.

Carrefour has a lean retail model in its home country, which is synonymous to standardization and requires the minimization of logistics costs. This model has an effective supply chain including centralized procurement and distribution. However, the underdeveloped highway system and the vast size of China's territory made a speedy delivery system impossible in the mid-1990s. Carrefour initially decentralized its procurement system when it came to China. It gave autonomy to local store managers, who were sensitive to local consumer preference and behavior, to do their own procurement (Cambra-Fierro & Ruiz-Benitez, 2011; Chuang et al., 2011). This decentralized procurement strategy enabled local store managers to "identify and respond more efficiently to the different needs of customers across China" (Tacconelli & Wrigley, 2009) and helped Carrefour quickly establish its leading position. Nevertheless, this decentralized strategy also brought in the problem of commercial corruption. In 2007, several procurement officers in Carrefour's Beijing stores were arrested because of accepting bribes from suppliers. At the same time as Carrefour's stores increased rapidly, the economies of concentration began to emerge. Carrefour began to centralize its procurement. Its procurement system now has three levels: national headquarter, regional purchasing center, and City Commission Units (CCU) (Chuang et al., 2011). CCU is used to bridge individual stores and purchasing centers. Carrefour doesn't have a centralized distribution system in China. It requires suppliers to deliver products directly to the outlets. Suppliers are also responsible for replenishing the stock as needed. By switching logistics and distribution responsibility to suppliers, Carrefour's costs are much smaller than its competitors.

Carrefour's lean retail model requires cost-effective relationships with suppliers. Its low-price strategy is one of the reasons why Carrefour is popular in France. To be able to offer low price to customers, Carrefour in France charges suppliers/manufacturers various fees as compensation (Wang, 2001). When Carrefour came to China, it also brought this strategy. Profit in retail industry is usually generated from the mark-up price at which a product is sold. Nevertheless, a large portion of Carrefour's profit comes from the additional fees paid by suppliers/manufacturers (Tao, 2007). These fees are charged for entry, display, shelf space, promotion, advertisement, and new store openings and so on. Carrefour is reported as the first retailer to generate profit by charging vendor fees in China. It has also been constantly ranked the most expensive foreign retailer to do business with (Wang, 2009). Chinese manufacturers/suppliers' profit margin has been severely squeezed by Carrefour. In 2003, there was a high profile conflict regarding slotting fees between Shanghai Seed and Nut Roasters Association (SSNRA) and Carrefour (Wang, 2006). The increasingly tense relationship with manufacturers/suppliers is one of the major problems that led to the underperformance of Carrefour in recent years.

2.5.2 Wal-Mart

Wal-Mart originally had a small-town location strategy in its home country. Wal-Mart's first store was opened in a one-horse town in Arkansas (Farhoomand, 2006). By starting from rural backwaters, Wal-Mart acquired cheap land and avoided direct competition from stronger players such as Kmart (Graff & Ashton, 1993). Wal-Mart supercenters are primarily located in suburban and exurban areas in the U.S. When Wal-Mart came to China in 1996, it encountered the same situations as Carrefour did. Wal-Mart could not replicate its small-town location strategy in China. The lower purchasing power and the absence of infrastructure in small Chinese cities made a Wal-Mart supercenter impossible let alone the fact that these cities were not open to foreign retailers then. Consequently, Wal-Mart had to start from a tier-one city, Shenzhen. Some of Wal-Mart China's outlets are actually located in the most expensive commercial districts such as its Jianguolu branch in Beijing.

Despite the stark contrast between the U.S. and Chinese markets, Wal-Mart still aimed to implement its centralized procurement and distribution concept in China. This standardized operational strategy was challenged by the local market conditions. The rigid and centralized procurement strategy gave Wal-Mart little flexibility to respond quickly to the volatile Chinese market. In recent years, Wal-Mart has gradually modified its procurement system and added regional purchasing centers and purchasing offices in provincial capitals (Chuang et al., 2011). In its home market Wal-Mart has a network of over 4000 outlets. The interstate highway system, advanced information technology, and Wal-Mart's own truck fleet make the centralized distribution (from distribution center

(DC) to outlets) a cost-effective operation in the United States. However, the small number of outlets and underdeveloped infrastructure do not permit Wal-Mart to enjoy the same economies of scale in China. On the contrary, the inefficient use of Wal-Mart's DCs made its logistics cost higher than its competitors (He et al., 2011). In addition to its centralized distribution, Wal-Mart now also uses supplier direct delivery and third-party logistics to accommodate the local market.

Wal-Mart is regarded as one of the toughest and shrewdest negotiators in the world. It never stops pressing suppliers for a lower price but requires high quality at the same time. Wal-Mart is well known for its relentless cost control. In the U.S., Wal-Mart successfully drives costs down in the supply chain by pushing out middlemen and buying directly from manufacturers (Christopherson, 2007; Farhoomand, 2006; Gereffi & Christian, 2009). Wal-Mart attempted to implement this factory-direct purchasing mode in China. However, most Chinese manufacturers/suppliers rejected this plan because of risks and concerns. In China where manufacturers can be easily overpowered by retailers because of the problem of oversupply, Wal-Mart, a foreign retailer notorious for its relentless cost control and stringent requirement, is not seen as a reliable partner, especially by smaller suppliers. Consequently, Wal-Mart still has to mainly negotiate prices with intermediary trading companies (Chuang et al., 2011).

2.5.3 RT-Mart

Most of RT-Mart outlets in Taiwan are located in large and medium sized cities. RT-Mart has 22 outlets under three banners in Taiwan, a small and different market with affluent customers. RT-Mart's location strategy in mainland China is very similar to that of Wal-Mart in the U.S. Although RT-Mart started from the largest Chinese city Shanghai, most of its stores are in small and medium sized cities to avoid direct competition from other foreign retailers. RT-Mart's Taiwanese managers often take advantage of their cultural and ethnic affinity to develop favorable relationship (*guanxi*) with local Chinese government officials. Therefore, they are able to acquire many prime locations in small and medium cities with favorable terms.

RT-Mart's logistics system is similar to that of Wal-Mart China. RT-Mart's procurement system has a national headquarter and five regional purchasing centers. But it also gives autonomy to store managers to make quick purchase to replenish stocks. RT-Mart's distribution system is a combination of centralized distribution, supplier direct delivery, and third-party logistics. At first sight, RT-Mart seems not to have any advantage in supply chain management. Its effective procurement strategy comes from its emphasis on fresh produce. RT-Mart has a much larger produce department than Wal-Mart and Carrefour. While Wal-Mart is unable to completely implement its factory-direct strategy in China, RT-Mart manages to buy produce directly from contracted farms. Being ethnic Chinese themselves, RT-Mart's Taiwanese managers can better understand local consumer culture and market conditions. Since Chinese people put much emphasis on the freshness of food, RT-Mart usually offers fresh produce and staple food at the lowest price in the market to attract customers.

To summarize, major foreign hypermarket retailers' local embeddedness is impacted by both home and host economies. Although the home country effect may influence their initial strategy, they tried to resolve the structural paradox by constantly adapting to the changing Chinese market. In the early years, Carrefour was better localized in China by locating stores near urban customers. Carrefour initially decentralized its purchasing and distribution activities. With the increasing number of stores and potential economies of scale, Carrefour has added centralized elements to its supply chain management. Wal-Mart initially had a centralized operation largely from its standardization strategy but also modified to incorporate localized elements. Without a standardization strategy when it came, RT-Mart has taken advantage of closer ethnic and cultural affinity to better embed in mainland China.

2.6 Conclusion and Discussion

Foreign retailers have expanded their business in China remarkably since the retail market reform in the mid-1990s. As the most popular retail format, the hypermarket retailing is highly concentrated with foreign retailers. However, none of the foreign retailers completely followed the four-stage post-entry model proposed by Dawson (2003). While Carrefour, Wal-Mart, and RT-Mart can be said to have completed the second phase of consolidation, other foreign retailers are still in the first phase of stabilizing their operation.

The spatial and temporal penetration of foreign hypermarket retailers has been greatly influenced by the gradual liberalization policies of the Chinese government. Their expansion to the inland regions didn't take place until China's accession to the WTO in 2001. The subsequent elimination of restrictions in retailing in 2004 further facilitated their development. Spatially, expansion of major foreign hypermarket chains has taken place in two directions: from the eastern costal region to the central and western hinterland and along China's urban hierarchy from the first- and second-tier cities (large urban centers) to the third- and fourth-tier (small and medium sized) cities.

Foreign retailers' embeddedness in China is impacted by both home and host economies. The home country effect greatly influenced their initial strategies, but they are constantly changing to be better embedded in the Chinese market. Retail TNCs have to confront the structural paradox between standardization and localization in their international expansion. Carrefour's localized strategy enabled it to quickly embed in the diverse Chinese market but also brought in problems as its store network expanded. As a result, it was forced to centralize. Wal-Mart's centralized strategy was slow to accommodate the rapidly changing local market, so it modified to add localized elements. Although RT-Mart didn't bring much experience from its home market, it took advantage of closer ethnic and cultural affinity to embed in mainland China. The three retailers have adopted different strategies and flexibility in dealing with local embeddedness.

While China is continuing to embrace liberalization, we see a highly competitive Chinese market where foreign firms are facing intense challenges from Chinese retailers and no longer enjoy ownership advantages. International retailers have lost most of the privileges that they enjoyed when they entered China in the mid-1990s. Additionally, the Chinese governments at the central and local levels are now nurturing their own retail giants to combat foreign competition (Wang, 2009). The Shanghai-based Brilliance Group and the state-owned China Resource Vanguard, ranked 2nd and 4th in Top 100 Retailers in 2012, are just two examples of such powerful national retail conglomerates (CCFA, 2013). Domestic regional retailers such as Wu-Mart in Beijing and Yonghui Supermarket in Fujian are leading their individual regional market. These national and regional retailers are competitive hypermarket operators gradually grabbing market shares from their foreign counterparts. The prospect of foreign hypermarket retailers in China is closely related to their ability to compete with these strong domestic contenders.

China’s recent economic slowdown is also weighing on foreign retailers (KPMG, 2013), who have been less adaptive than domestic retailers. The year of 2012 witnessed a downturn in retail growth in China (Linkshop, 2013). Foreign hypermarkets also slowed down their expansion, as seen in the sharp decrease in their new store openings in 2012 (Figure 2.2). China’s booming e-tailing, manifested by the amazing rise of online retailers such as Alibaba, Jingdong, and Dangdang, has dramatically lessened the need for physical stores of all formats. Foreign hypermarket retailers have to compete with e-retailers, providing better value and service or emphasizing on goods difficult to replace by e-retailing (e.g. fresh produce). The rising operation costs such as rentals and labor cost are also putting great pressure on foreign retailers (Li & Li, 2013). Several foreign hypermarket chains such as Carrefour, Wal-Mart, Tesco, and Lotte Mart were reported to have closed stores (Linkshop, 2013). Foreign hypermarket retailers may find that their mode of growth largely relying on scale expansion is no longer sustainable. It is not as easy as in the past to generate profit by simply opening new stores. After nearly 20 years of rapid development, foreign retailers have to readjust their development strategies. They may take a variety of measures, such as enhancing the single store retail sales and optimizing their store network. They have to face the fact that China is a highly competitive, increasingly mature market, and have to raise their level of competitiveness to sustain their presence or even increase their market shares in China.

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CHAPTER 3

SPATIAL INEQUALITY AND DYNAMICS OF FOREIGN HYPERMARKET RETAILERS IN CHINA

3.1 Introduction

The world economy has increasingly shifted towards service since the intensification of globalization in the late 1980s. Within the service sector, producer service industries have gained much attention because of their important role in the development of global cities and networks (Sassen, 2001). While advanced producer services such as finance, insurance, and real estate have been an engine for urban growth, retailing as the link between producers and consumers has always been an important part of the urban economy. Although retail activities occupy only a small portion of urban land, they play many important roles such as generating employment and serving as the center for consumption (Wang & Zhang, 2005; Yeats, 1997). Global cities all have a robust and sophisticated retail sector, as manifested from the Fifth Avenue in New York to Ginza in Tokyo, and from the Avenue Des Champs-Elysees in Paris to Causeway Bay in Hong Kong.

The globalization of retailing is one of the most important features of the world economy today. A group of international retailers from Western Europe (e.g., Carrefour and Tesco) and North America (e.g., Wal-Mart) have rapidly risen since the early 1990s and have become the “movers and shapers” of the global economy (Dicken, 2003). In the recent two decades, these retail transnational corporations (TNCs) have intensified their strategic expansion in emerging markets.

The economic reform since 1978 has transformed China into the largest emerging economy. China has therefore become an attractive target market for TNCs (Wei, Zhou, Sun, & Lin, 2012; Zhou, Sun, Wei, & Lin, 2011), including international retailers. Many foreign retailers have established their presence in China since the opening up of the retail sector in 1992. They have introduced various modern retail formats, transferred advanced retail know-how and technology to China, and played an important role in the retail transformation (Wang, 2003; Zhang & Wei, 2015). Among the new retail formats, hypermarket is the most popular because of its wide assortment of goods and competitive pricing. The hypermarket retailing in China is dominated by foreign retailers, especially in large cities (Moreau, 2008).

Retail TNCs can greatly impact the host economies (Coe & Wrigley, 2007). However, studies on international retailers in China are still limited. This chapter aims to analyze spatial dynamics of foreign hypermarket retailers in China at different geographic scales including regions, provinces, and the case of Shanghai. We use logistic regression models to identify location determinants of Carrefour, Wal-Mart, and RT-Mart at the intercity level. Their preferences for different city sizes and different temporal expansion strategies are also analyzed. Last, we examine the spatial clustering of foreign hypermarkets and suburbanization of hypermarket retailing in Shanghai in recent years.

3.2 Theoretical Framework and Research Background

An interdisciplinary research agenda has emerged to examine the roles of retail TNCs in the process of economic globalization, including globalization of retailing (Coe, 2004; Wrigley, 2000), the stages and entry strategy of retail TNCs in foreign markets (Dawson, 2003; Dawson & Mukoyama, 2006; McGoldrick, 1995), and spatial patterns of international retailers in emerging economies (He, Li, & Yin, 2011; Wang, 2009). Dawson and Mukoyama (2006) argue that the process of retail internationalization can be hypothesized as a sequence of five key stages: pre-entry, entry, postentry, assimilation and exit. To describe the complex activities associated with the postentry stage, Dawson (2003) proposes a four-phase model of stabilization, consolidation, domination, and control. Based on the level of control and risk, the entry strategy to foreign retail markets can range from licensing, concessions, franchising to joint venture, acquisition and merger, and start-up (McGoldrick, 1995).

Within the vast body of literature on economic development in China, relatively little attention has been paid to the retail sector, which well reflects the traditional low status of this sector in China (Wang & Jones, 2001). The geographic literature on retailing in China has also been quite limited until very recently. A few studies of China's retail transformation gradually appeared after 2000. These studies examined retail internationalization (Wang, 2003), strategic responses of retail TNCs (Tacconelli & Wrigley, 2009), diversification of retail format (Wang, 2011), and locational dynamics of international retailers (He et al., 2011; Zhang & Wei 2015). Scholars have also revealed the political economy and institutional changes underlying the retail transformation (Wang & Song, 2008). They confirm that the expansions of retail TNCs were dictated by the gradual liberalization policy of the Chinese government (Wang, 2009).

Extant research on foreign hypermarket retailers in China is scant. The majority of the research work was concentrated in business and management studies. Scholars have examined how Wal-Mart and Carrefour balanced the competing demands of standardization and localization (Chuang, Donegan, Ganon, & Kan, 2011) and articulated the organizational response of Western retail TNCs to the changing institutional demands in China (Siebers, 2011, 2016). They mainly look into giant Western retail TNCs and give little attention to the smaller second-tier retail TNCs such as those from East and Southeast Asia and do not notice spatial dynamics of different foreign retailers. .

Spatial dynamics of retail TNCs, and to a large extent service TNCs, in China has been an understudied topic. Previous studies of TNCs were predominantly focused on the manufacturing sector (Liao & Wei, 2013; Lin, Wang, Zhou, Sun, & Wei, 2011). Only a few studies have looked into location determinants and spatial patterns of service TNCs. Wu and Strange (2000) investigate the location choice of foreign insurance representative offices and find that the proximity to headquarters of regulatory authority, current and future market demand, and the presence of other FDI (foreign direct investment) have significant effect. Hong's (2007) study on foreign logistics firms suggests that their location depends on the transportation condition as well as market size, labor quality, agglomeration economies, and government incentives. He et al. (2011) find that market-oriented international retailers have largely followed China's urban hierarchy and diffused into inland cities. Commonly examined location determinants of foreign firms include market size, policies and institutions, and agglomeration economies.

Suburbanization has been a significant phenomenon in postwar Western countries.

Suburbanization of service industries, including producer service and retailing, usually followed population and manufacturing suburbanization (Gong & Wheeler, 2002; Kellerman, 1985). The retail suburbanization in Western countries described the flow of retailing out of traditional city centers to newly constructed suburban shopping centers, followed by the decline of the inner city (Jones & Simmons, 1993). Suburbanization of retailing has been a trend in major Chinese cities since the mid-1990s. Through questionnaires of consumer shopping behavior, Chai, Shen, and Long (2007) find that downtown retailing in Beijing has been threatened by the booming suburban retailing in the course of residential suburbanization. Qian (2008) analyzes retail suburbanization in relation to the spatial restructuring of population in Shanghai and finds that retail and commercial activities still concentrate in the downtown although retailing has rapidly developed in the inner suburbs. However, both studies lack quantitative analyses to support their conclusions.

This chapter aims to fill gaps in the extant literature and advance our understanding of foreign hypermarket retailers in China. First, we apply quantitative analysis to spatial dynamics of retail TNCs, which have been long neglected by the traditional economic-geographic studies. Second, we examine spatial dynamics of foreign retailers at multiple geographic levels ranging from regional and provincial to intercity and intraurban. Existing studies looked into spatial pattern of foreign retailers mainly at regional scales. Third, we explicitly investigate how institutional changes have impacted the spatiotemporal expansion strategies of major foreign hypermarket retailers.

3.3 Data and Methodology

3.3.1 Study Area

The study area includes regions and provinces in China and Shanghai municipality. Suited on the estuary of the Yangtze River, Shanghai is the largest city and the national economic center of China. Shanghai also has the largest urban retail market. Many foreign retailers chose it as their China headquarters and opened their first Chinese store in Shanghai. To keep the consistency for analysis, we use the administrative division of Shanghai in 2008 because Nanhui and Luwan were annexed to other districts in 2009 and in 2011. Shanghai Municipality consisted of 19 district-level administrative divisions in 2008 (Figure 3.1). Three districts, Huangpu, Jing'an, and Luwan, formed the urban core. Six districts, Yangpu, Hongkou, Zhabei, Putuo, Changning, and Xuhui constituted the inner city. The surrounding four districts Baoshan, Jiading, Minhang, and Pudong were in the inner suburb. The other five districts Qingpu, Songjiang, Jinshan, Fengxian, Nanhui, and Chongming County formed the outer suburb.

3.3.2 Data

This study mainly utilizes secondary data. We adopted data triangulation, the use of multiple sources of data, in our research. Data about entry time, entry strategy, and store location of foreign retailers were collected from corporate websites, company annual yearbooks, statistical yearbooks, retail industry almanacs, academic articles and books, and news reports. Such data collection method has been widely used in retail studies (Siebers, 2016; Wang, 2003, 2009). We mainly employed two types of data: store data and city data. Store-level data of foreign hypermarkets are analyzed by their establishment date and administrative division. City level data such as FDI, retail sales,

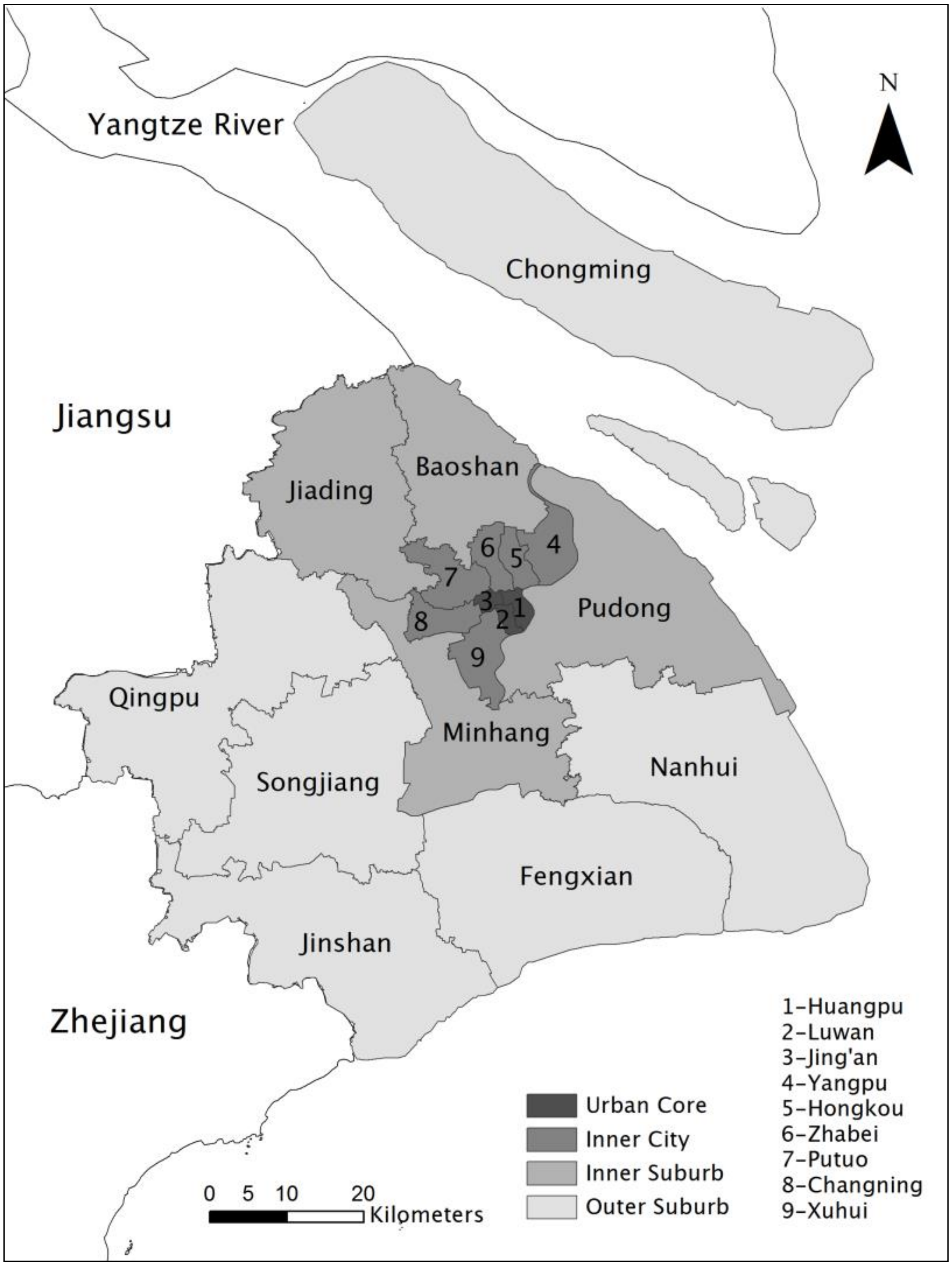

Figure 3.1 Administrative division of Shanghai in 2008

and urban salary were collected from the China City Statistical Yearbook (SSB, 2011). We collected population data from the 2010 population census (SSB, 2012), which includes both registered population and migrant population for each city.

3.3.3 Methods

This study mainly uses quantitative methods, including spatial statistics and regression models, to examine spatial dynamics of foreign hypermarket retailers. We employ global statistics (global Moran's I and Getis-Ord General G) to see whether the spatial distribution of foreign hypermarkets is dispersed or clustered. We use local statistics (local Moran's I and Getis-Ord G^*) to identify whether there are any local spatial autocorrelation or clustering. Furthermore, the Average Nearest Neighbor (ANN) index is employed to examine the point pattern of foreign hypermarkets in Shanghai. We also use logistic regression models to identify location determinants of three leading foreign hypermarket retailers in China.

3.3.3.1 Spatial indicators for autocorrelation and clustering

Global Moran's I is calculated for each year between 2000 and 2012 to assess the degree to which the provincial foreign hypermarket distribution deviates from the null hypothesis of spatial randomness. A statistically significant positive Z-score for global Moran's I means that similar values cluster spatially while a statistically significant negative one means that similar values disperse spatially. Since global Moran's I only detects spatial associations, it cannot identify local clusters or outliers. Local Moran's I, also called Local Indicator of Spatial Association (LISA; Anselin, 1995), is therefore used to detect any local spatial autocorrelation and identify clusters or outliers of foreign hypermarket retailers at the province level.

Getis-Ord General *G*, another global statistic index, is calculated to assess the degree to which the subdistrict foreign hypermarket distribution in Shanghai deviates from the null hypothesis of spatial randomness. A statistically significant positive Z-Score for Getis-Ord General *G* means larger values cluster spatially while a statistically significant negative one indicates smaller values cluster spatially. Similarly, Getis-Ord General *G* cannot identify local cluster of higher values or lower values. The local statistic Getis-Ord *G** is used to identify clusters of larger numbers (Hot Spots) or small numbers (Cold Spots) of subdistrict hypermarkets.

The Average Nearest Neighbor (ANN) index measures the distance between each point feature and their nearest neighboring feature and averages all these as the nearest neighbor distance. By comparing the ratio between the actual average nearest neighbor distance and the distance of a hypothetical random distribution, we can infer whether the spatial point distribution is clustered, random, or dispersed. A statistically significant negative *Z*-Score for ANN means spatial clustering of point features while a statistically significant positive *Z*-Score means dispersion.

3.3.3.2 Regression model for location determinants

Locational advantages are crucial factors for international retailers to succeed in foreign markets. This study analyzes the location determinants of three leading foreign hypermarket retailers—Carrefour, Wal-Mart, and RT-Mart—at the intercity level. The majority of foreign hypermarkets are located in a prefectural or higher level city, which usually has an urban district population (*shixiaqu renkou*) of more than 500, 000. According to the 2010 population census (SSB, 2012), there were 241 such cities in

2010. Binary logistic regressions model is used to capture location determinants of these foreign retailers. The presence of a foreign hypermarket in a city with an urban district population of more than 500, 000 is defined as the dependent variable (1=if at least one foreign hypermarket, 0=if none) (Table 3.1).

Neoclassical economic geography analyzes industrial location based on specific attributes of each location such as market demand and agglomeration economy. Foreign hypermarket chains make their store location choice based on a number of attributes of each city. Market demand is an important consideration when foreign firms choose their location. Extant studies have shown that most commonly used measures of market demand are population, salary, income, or savings (Hong, 2007; Wu & Strange, 2000). Four measures are used in this model to represent market demand. Urban district population (POP) is employed to reflect the current market size. GDP per capita (GDPPC), retail sales of consumer goods per capita (RSALEPC), and average urban annual salary (SALARY) are used to represent the market potential (Table 3.1). It is expected that these four measures will be positively related to the

Table 3.1 Definitions of explanatory variables

Explanatory Variables	Definition	Expected impact
POP	Population in the urban district	+ GDPPC
	GDP per capita	+
RSALEPC	Retail sales of consumer goods per capita	+
SALARY	Average urban annual salary	+
COMSTORE	Number of other foreign hypermarkets in the same city	Uncertain
PSTORE	Number of own hypermarkets in the same province	+
TIME	Number of years being open to foreign retailers	+
UFDIPC	Utilized FDI per capita	+

foreign hypermarket location choice.

Market competition is another important factor that firms have to consider. Firms usually tend to avoid direct competition with their competitors. However, the agglomeration economies in retailing predict that similar stores are usually spatially clustered. The number of other foreign hypermarkets in the same city (COMSTORE) is used to represent market competition. For example, this variable for Carrefour is the total of Wal-Mart and RT-Mart stores combined. The impact of this measure is uncertain.

Internal economies of scale might be another consideration for the distribution-based retail industry. To better share information and reduce logistics costs, retailers tend to locate many stores in one province to achieve internal economies of scale (He et al., 2011). The number of same brand hypermarkets in the same province (PSTORE) is used to see if a foreign retailer aims to achieve internal economies of scale at the provincial level. This measure is expected to have a positive effect on their location choice.

Institutional geography takes influence of institutional factors such as government policies into spatial economy. Government policies are of vital importance to foreign firms in China (Wu & Strange, 2000). The Chinese government adopted a gradual open door policy to the retail sector and extended reform policies from coastal region to central and western regions. Therefore, cities that were opened earlier had advantages over other cities. Two measures, the number of years being open to foreign retailers (TIME) and utilized FDI per capita (UFDIPC), are used to represent the openness of a city and are expected to be positively related to the foreign hypermarket location choice. Finally, to reduce the skewness of independent variables, natural logarithm is used in this model.

3.4 Retail Transformation and Hypermarket Retailing in China

3.4.1 Retail Transformation in China

The retail sector in China was a rigidly state-monopolized distribution system before the onset of economic reform in l978. During the Maoist era, retailing was limited to the distribution of necessities to consumers (Wang & Jones, 2001). Retailing was a passive activity because there was always a shortage of consumer goods within a planned economy before 1978. Private retail ownership was banned and retail chains were nonexistent (Wang, 2003). China's retail industry has undergone a profound transformation since the economic reform in the late 1970s. Foreign retail ownership has increased significantly since 1992. A variety of modern retail formats, such as convenience store, supermarket, hypermarket, warehouse club, and factory outlet, were imported to China in the 1980s and 1990s (Wang, 2011). Most of the new retail formats were introduced by foreign retailers, who have considerably intensified their operation in the Chinese market. China's economy is currently transforming from an export-oriented and investment-based growth model to a consumption-and-service driven model. As the link between producers and consumers, retailing is expected to play an important role in this economic transition.

Any understanding of China's retail transformation requires an appreciation of the institutional changes that have trigged it. In the era of planned economy, the retail industry was monopolized by the state. After 1978, a series of liberalization, privatization, and internationalization gradually transformed the retail sector (Wang & Zhang, 2005). Several stages of progressive liberalization can be identified in China's retail industry. In the early stage of opening up, the Chinese government imposed strict regulations on foreign retailers (Wang, 2003). The geographic distribution of foreign retail stores was restricted to only a few coastal cities and special economic zones. Also, international retailers could only have minority ownership. However, many foreign retailers started their operation in China without the state approval. They were approved by the local governments who independently took the liberty of approving retail joint-ventures. In 1999, foreign retailers was permitted to all provincial capitals and subprovincial cities. Retail chains were also allowed through joint ventures. In 2001, China joined the World Trade Organization (WTO) and promised to remove restrictions in the retail sector with step-by-step changes. China had lifted all remaining restrictions in retailing by the end of 2004 and provided complete legal freedom for foreign retailers (Siebers, 2016; Wang, 2009).

3.4.2 The Retail Format of Hypermarket

Among all the new retail formats, the hypermarket is the most popular and most successful because it can provide a variety of consumer goods at competitive prices. The concept of hypermarket originated in France in the early 1960s (Dawson, 1976). The French retailer Carrefour opened the world’s first hypermarket near Paris in 1963. The hypermarket is a classic retail innovation, combining price competition with a varied product range (Guy, 1998). A hypermarket typically sells a complete range of food and convenience items and a wide range of clothing, footwear, and household items. The definition for hypermarket also varies from country to country in terms of merchandise mix, floor space, and parking space. The Retail Format Classification (GBT18106-2004) in China defines a hypermarket as a one-stop retail store with comprehensive merchandise and at least 6000 square meter floor space and a parking space greater than or equal to 40% of floor space.

Hypermarket is called *damaichang* in Chinese, literally meaning a big marketplace. Hypermarket consumers in Western countries are automobile dependent and often do their shopping on a weekly basis and purchase in bulk. Most Chinese consumers visit hypermarkets on foot, by bike, or by public transit. They also make very frequent visits because of small purchase each time. Therefore, hypermarkets in China are often located adjacent to residential areas or along major public transportation routes and close to bus stops or subway stations (Siebers, 2012). In addition, most hypermarkets offer free shuttle services to their nearby communities.

Since Carrefour opened its first Chinese store in Beijing in 1995, hypermarkets have expanded quickly in the Chinese retail market. Hypermarket retailing is more concentrated with foreign retailers than any other retail channel. While some domestic hypermarket operators such as Wu-Mart in Beijing and Yonghui Supermarket in Fujian have a significant presence in their regional market, foreign retailers dominate the national market of hypermarket retailing in China.

3.5 Foreign Hypermarkets in Regional and Provincial China

Foreign hypermarkets have grown remarkably in China in the past two decades, especially after 2004 when the Chinese government lifted all restrictions in the retail sector. However, this trend has slowed down in the most recent years as China’s economic deceleration began to weigh on foreign retailers (Figure 3.2). Most foreign hypermarket retailers are TNCs equipped with advanced retail technology and effective supply network. Their entry to a new regional or provincial market would usually introduce advanced technology, increase merchandise mix, and force local retailers to

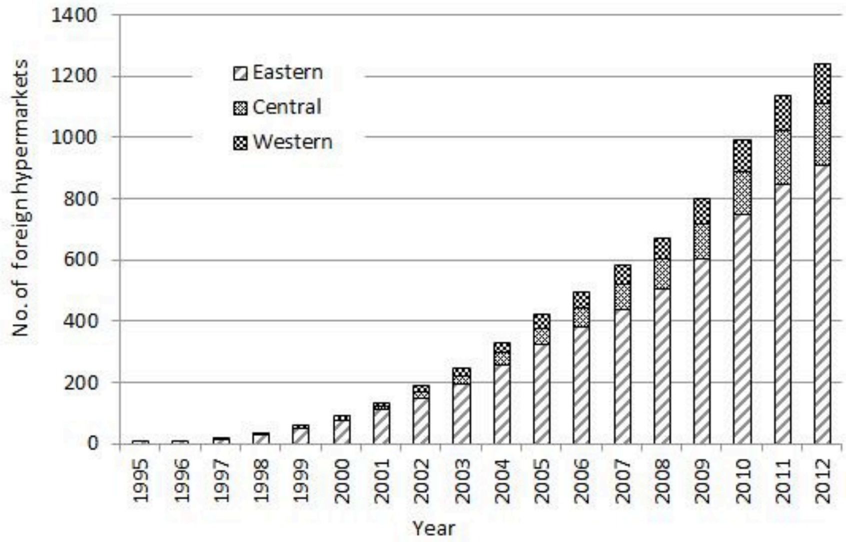

Figure 3.2 Foreign hypermarkets by region in China, 1995-2012

upgrade. Therefore, spatial inequality of foreign hypermarkets has greatly impacted the retail transformation in different regions and provinces across China.

Foreign hypermarkets are unevenly distributed among the regions. Relative gaps in foreign hypermarkets among regions are narrowing while absolute gaps are still widening (Tables 3.2 and 3.3). Relative gaps mean the difference between the percentages of total foreign hypermarkets in each region while the absolute gaps mean the difference between the numbers of stores in each region. Starting from Carrefour's first store in Beijing in 1995, foreign retailers have favored the eastern coastal region as their most important market. The majority of their stores have been located in this region. In 2012, the eastern region still captured more than 70% of total foreign hypermarkets, while the central region had 16.5 % and western region had barely more than 10%. Previous studies identified the continuous spreading of manufacturing-

Table 3.2 Regional distributions (%) of foreign hypermarkets in China, 1995-2012

Region	1995	1998	2000	2003	2006	2009	2012
Eastern Region	100.00	82.35	83.91	78.46	76.77	75.25	73.14
Central Region	0.00	2.94	3.45	10.98	12.32	14.32	16.50
Western Region	0.00	14.71	12.64	10.57	10.91	10.43	10.36

Table 3.3 Growth rates of foreign hypermarkets in three regions, 2000-2012

Year	Eastern region		Central region		Western region		National	
	No.	Growth Rate	No.	Growth Rate	No.	Growth Rate	No.	Growth Rate
2000	73	-	3	-	11	-	87	-
2006	380	420.55%	61	1933.33%	54	390.91%	495	468.97%
2012	904	137.89%	204	234.43%	128	137.04%	1236	149.70%

dominant FDI from the coastal region to the central region and then to the western region (Cheng, 2006; Huang & Wei, 2016). However, foreign hypermarket retailers did not follow this pattern. They actually skipped most of the central region in the very beginning and developed stores in the southwestern region in the late 1990s (Figure 3.3). Therefore, the western region had more foreign hypermarkets than the central region from 1997 to 2002. From 2000 to 2006, the growth rate in the central region was much higher than that in the western region, which had more foreign hypermarkets than the central region from 1997 to 2002. From 2000 to 2006, the growth rate in the central region was much higher than those in the eastern and western regions (Table 3.3). Consequently, foreign hypermarkets in the central region began to outnumber those in the western region in the mid-2000s. The rapid growth rate of the central region might be linked to positive impact of regional development policies such as the “Rise of Central China” Plan in 2004. The different

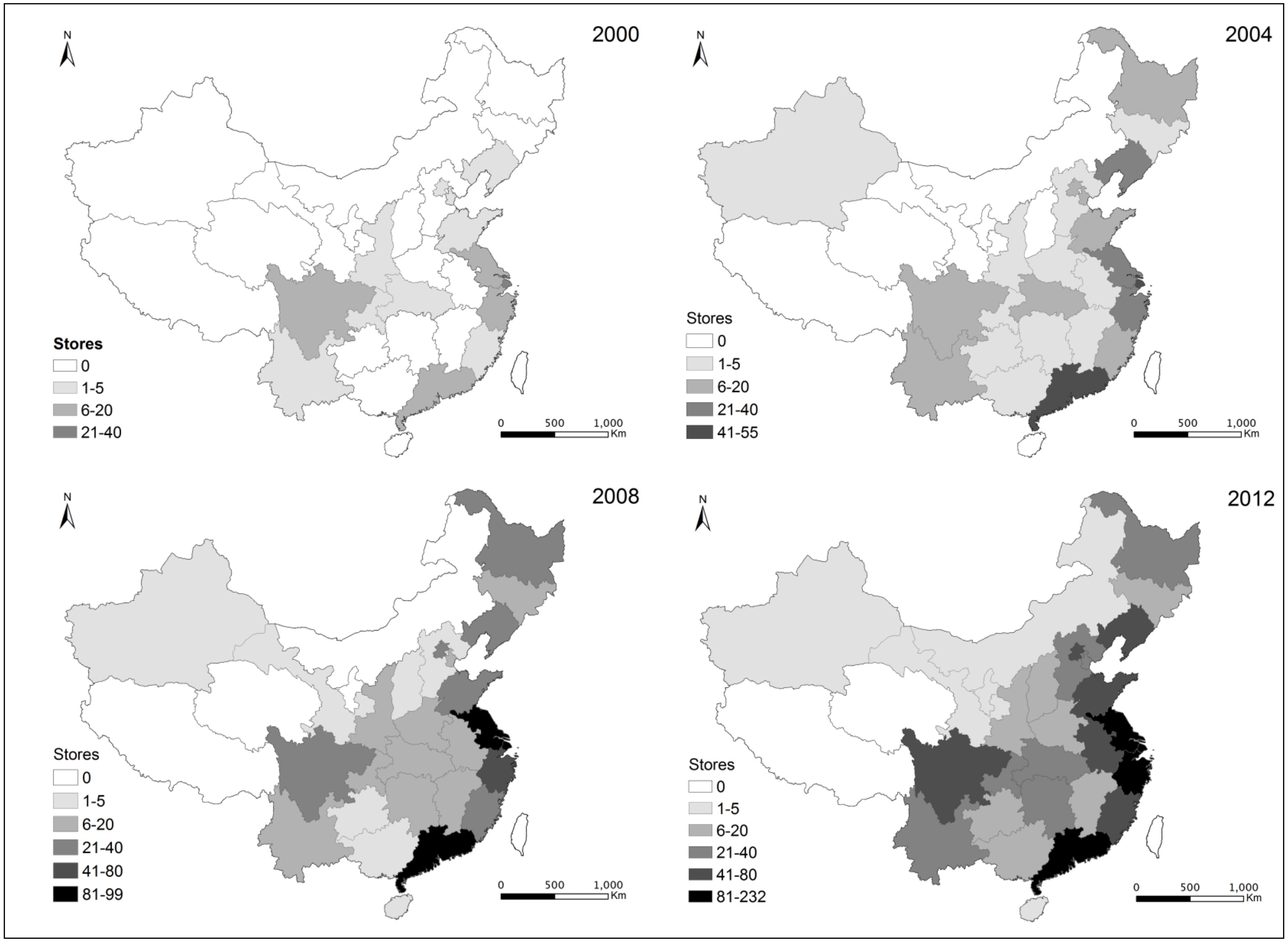

Figure 3.3 Foreign hypermarkets at the provincial level, 2000, 2004, 2008, and 2012

trends in the relative gap and absolute gap of foreign hypermarkets among three regions confirm again that the eastern region was still their most important regional market although they had spatially expanded to the central and western regions.

The spatial inequality of foreign hypermarkets at the provincial level is illustrated in Figure 3.3. In 2000, the majority of stores were located in coastal provinces like Jiangsu, Shanghai, Zhejiang, and Guangdong. Foreign hypermarket retailers avoided most central provinces and expanded in some southwestern provinces in the late 1990s. The southwestern province Sichuan was another favorable location of foreign retailers probably because of its large population and huge market potential. By 2004, foreign hypermarket chains had expanded to most provinces except Inner Mongolia, Shanxi, Ningxia, Gansu, Qinghai, and Tibet. Even Xinjiang had a few hypermarkets. Foreign retailers continued to concentrate in the Yangtze River Delta region and Guangdong Province. Liaoning, Beijing, Shandong, and Fujian also had many foreign hypermarkets. From 2004 to 2008, international retailers only made new inroads into Shanxi and Hainan but greatly intensified their store distribution in most existing provincial markets. Relative provincial inequality of foreign hypermarkets has decreased over the years. By 2012, only Qinghai and Tibet had no foreign hypermarkets. In addition to the coastal provinces, Sichuan and Anhui also attracted a lot of foreign hypermarkets.

Foreign hypermarket distribution at the provincial level has shown statistically significant clustering since 2005. The Z-score of global Moran's I statistics for each year from 2005 to 2012 is greater than 1.65, indicating there has been constant spatial autocorrelation in the provincial foreign hypermarket distribution (Figure 3.4).

Local Moran's I further reveals where the spatial clusters or outliers of foreign

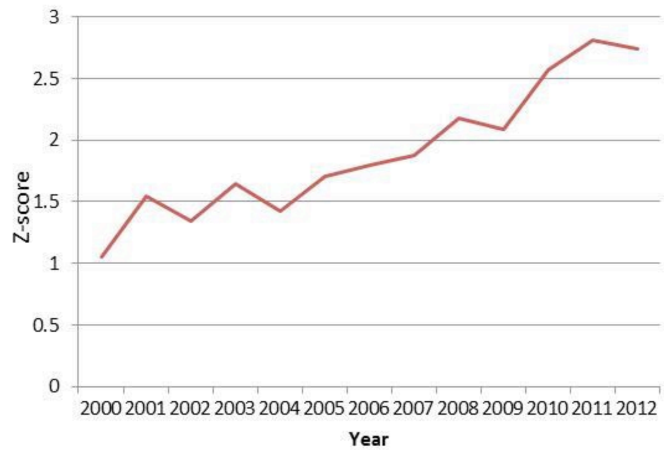

Figure 3.4 *Z*-score for global Moran's *I* of provincial foreign hypermarkets, 2000-2012

hypermarkets were located. From 2000 to 2004, the spatial cluster of high values (HH) was in Shanghai and Zhejiang. In 2005 and 2006 Guangdong stood out as a spatial outlier (HL). From 2007 to 2012, Shanghai, Zhejiang, and Jiangsu formed a spatial cluster of high values of foreign hypermarkets (HH) in the Yangtze River Delta. This pattern was quite different from Huang and Wei's (2016) findings that spatial clusters and/or outliers of FDI tended to spread from the eastern region to the central and western regions as government incentive policies began to promote development of these regions. Over the past two decades, foreign hypermarkets had spatially expanded to the central and western provinces, but they still tended to cluster in the Yangtze River Delta.

3.6 Location Determinants of Major Foreign Hypermarket Retailers

Since the opening up of the retail sector in 1992, ten foreign retailers have operated hypermarkets in China. International hypermarket retailers adopted a variety of strategies to enter the Chinese market. These include start-up, joint venture, and merger and acquisition (M&A). Foreign retailers who came to China in the mid-1990s enjoyed the first-mover advantages. They preferred organic growth and opened stores at prime locations in urban centers. To overcome the scarcity of prime locations, latecomers such as Tesco and Lotte Mart resorted to the M&A strategy. Even the first movers such as Wal-Mart and Carrefour used M&A to consolidate their market positions. Wal-Mart's acquisition of Trust-Mart in 2007 gave it the access to large retail space that would have been difficult to obtain. Carrefour's acquisition of the Hebei-based regional retailer Baolongcang Group in 2010 enabled it to penetrate the conservative retail market in Hebei.

For the convenience of analysis, foreign hypermarket operators are divided into three groups according to their country-of-origin (Table 3.4). Western retailers include Carrefour, Wal-Mart, Auchan, and Tesco. East and Southeast Asian hypermarket operators include Lotus, E-Mart, and Lotte Mart. Taiwanese hypermarket chains include RT-Mart, Trust-Mart, and Hymall, although the latter two were acquired by Wal-Mart and Tesco. The hypermarket is a popular retail format, but not all foreign hypermarket operators are doing well in China. Carrefour, Wal-Mart, and RT-Mart are clearly leading the hypermarket retailing sector (Table 3.5). They have achieved a nationwide distribution network, whereas Tesco, Lotte Mart, Auchan, Lotus, and E-mart remain as regional retailers. Western and Taiwanese hypermarket retailers are doing relatively better than their East and Southeast Asian counterparts.

Carrefour, Wal-Mart, and RT-Mart are the most successful foreign hypermarket chains with an extensive store network (Figure 3.5). Their location determinants can illustrate the strategies of successful foreign retailers. Logistic regression models
illustrate the strategies of successful foreign retailers. Logistic regression models

Table 3.4 Penetration of major foreign hypermarket retailers in China, 2012

Group	Retailer	Country	China Headquarter	Entry Year	Stores	Cities*	Province
Western	Carrefour	France	Shanghai	1995	219	71	24
	Wal-Mart	U.S.	Shenzhen	1996	280	150	25
	Auchan	France	Shanghai	1999	55	30	9
	Tesco	U.K.	Shanghai	2004	111	48	11
East/ Southeast Asian	Lotus	Thailand	Shanghai	1997	72	27	14
	E-Mart	S. Korea	Shanghai	1997	16	4	3
	Lotte Mart	S. Korea	Shanghai	2008	102	71	10
Taiwanese	Trust-Mart	Taiwan	Shanghai	1997	(101)	(35)	(16)
	Hymall	Taiwan	Shanghai	1998	(43)	(16)	(6)
	RT-Mart	Taiwan	Shanghai	1998	219	147	25

Source: compiled by authors from various cooperate websites

Note: *includes cities at centrally administered level, prefectural level, and county level.

Table 3.5 Market performance of foreign hypermarket chains in China, 2012

Retailer	Rank in Top 100 Retailers	Stores	Total Sales (billion Yuan)	Average Store (million Yuan)
RT-Mart	5th	219	72.47	330
Wal-Mart	6th	387	*58	150
Carrefour	10th	219	45.27	207
Tesco	24th	111	*20	180
Lotte Mart	36th	102	16.32	160
Auchan	38th	55	16.30	296
Lotus	50th	72	*12.5	173
E-Mart	-	16	*2.4	150

Note: * indicates estimation.

Source: Adapted from Top 100 Retailers in China 2012 (CCFA, 2013)

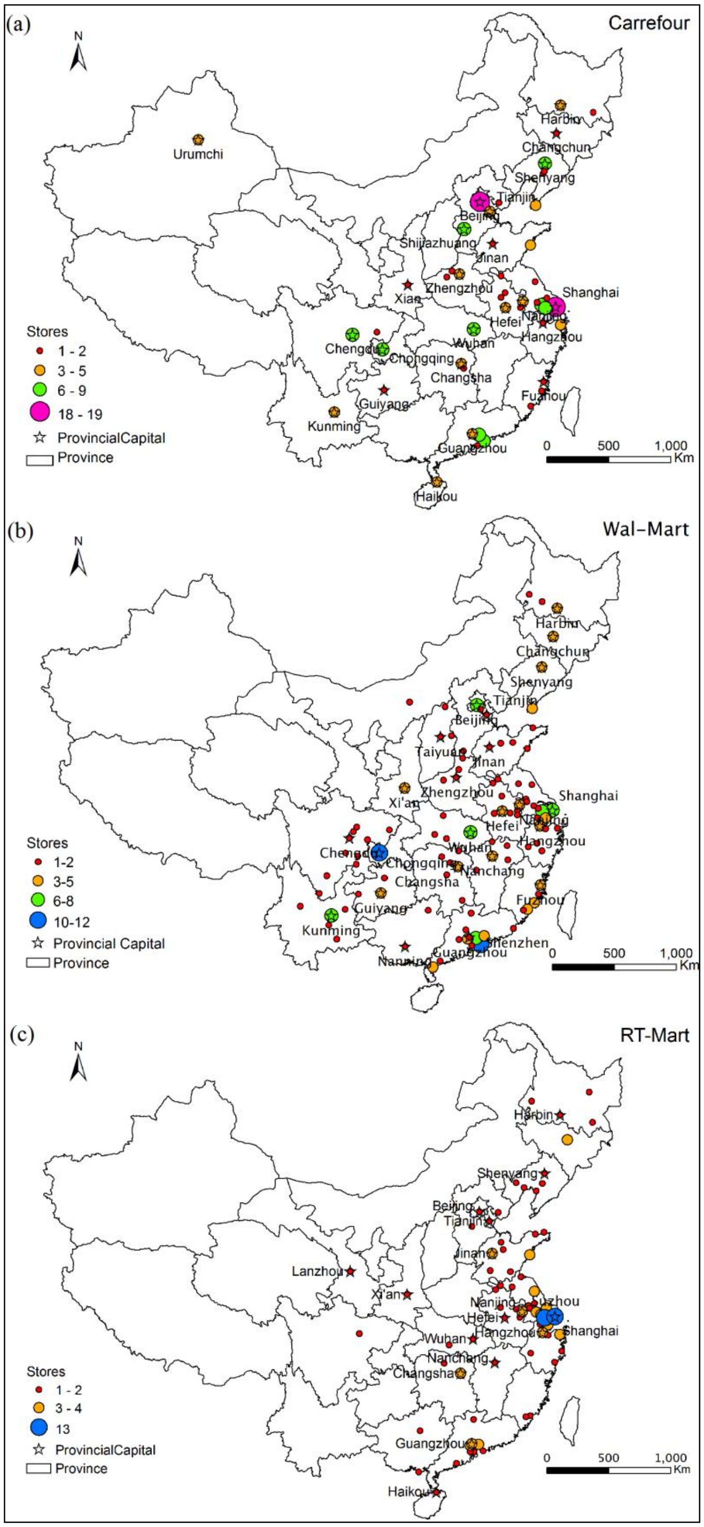

Figure 3.5 Spatial distributions of Carrefour, Wal-Mart, and RT-Mart stores in 2010

estimated by the maximum likelihood method are used to identify their location determinants. Correlation between independent variables indicates no serious problems of collinearity. The estimates produced by the logistic regression models are presented in Table 3.6. All the models are statistically significant. However, the model has more explanatory power for the location determinants of Carrefour than for those of Wal-Mart and RT-Mart. The percentage correctly predicted is 92.1 for Carrefour while it is only 77.6 for Wal-Mart. and 83.0 for RT-Mart.

The estimation results highlight different location determinants of the three foreign retailers. First, the population variable *LnPOP* is positively significant to Carrefour, Wal-Mart, and RT-Mart, indicating that foreign hypermarkets tend to locate in cities with a larger population. Contrary to our expectation, *LnGDPPC* is negatively associated with all three retailers but not significantly. The variable *LnRSALEPC* is alsonot significant to the three retailers. This may indicate that the presence of competitors in the same city does not significantly impact the city-level location choice of foreign hypermarket retailers.

Second, *Ln(PSTORE+1)*, the variable measuring internal economies of scale at the provincial level, is positively significant to Wal-Mart and RT-Mart but not to Carrefour. The larger the number of Wal-Mart or RT-Mart stores in the province, the higher the probability for a city to have a store of either retailer.

Third, the policy variable *LnTIME* is only positively significant to Carrefour. It is negatively related to Wal-Mart and RT-Mart but does not have a significant effect. Cities open to foreign retailers earlier are more likely to have a Carrefour store. LnUFDIPC, another variable reflecting the openness of a city, has a significant effect on Carrefour

Table 3.6 Estimation results for the binary logistic regression models

	Carrefour Model		Wal-Mart Model		RT-Mart Model	
Variables	Coef.	*SE*	Coef.	*SE*	Coef.	*SE*
LnPOP	1.618***	0.624	2.056***	0.446	0.881*	0.468
LnGDPPC	-1.163	1.145	-0.258	0.642	-0.662	0.777
LnRSALEPC	-0.067	0.921	0.351	0.546	0.748	0.652
LnSALARY	2.992	1.935	2.792**	1.200	2.689*	1.470
Ln(COMSTORE+1)	0.076	0.532	-0.108	0.243	0.244	0.431
Ln(PSTORE+1)	0.441	0.337	0.749***	0.211	1.003***	0.213
LnTIME	2.760**	1.224	-1.081	0.930	-1.231	0.943
LnUFDIPC	0.801**	0.372	0.105	0.173	0.466**	0.224
Constant	-38.075**	17.476	-39.974***	10.851	-35.321***	13.103
Sample size	241		241		241	
-2 log likelihood	108.13		213.67		161.99	
Pseudo R-Square	0.551		0.337		0.431	
PCP[a]	92.1		77.6		83.0	

Note: *, ** and *** denotes significance at 0.1, 0.05, and 0.01 level, respectively.
PCP[a]: percentage correctly predicted with cut-value 0.5.

and RT-Mart but not on Wal-Mart. This indicates the larger the utilized FDI per capita in a city, the more likely for this city to have a Carrefour or RT-Mart store.

3.7 Expansion Patterns of Major Foreign Hypermarket Retailers

This section examines how those significant variables play their role in the different expansion patterns of Carrefour, Wal-Mart, and RT-Mart. Since urban district population is the only variable significant to all three retailers, we first look into this factor. According to their urban district population, the 287 prefectural and higher level cities in 2010 could be categorized into six groups: small, small-medium, medium, large, extra-large, and super-large (Table 3.7).

Carrefour stores were highly concentrated in the large, extra-large, and super-large cities (Figure 3.6). The bigger the city size was, the larger the percentage of that city group

Table 3.7 Size and number of prefectural and higher level cities in 2010

Urban District Population (1,000)	Size of city	No. of cities
200-500	Small	46
500-1,000	Small-Medium	103
1,000-2,000	Medium	86
2,000-4,000	Large	30
4,000-10,000	Extra-Large	16
10,000-22,000	Super-Large	6

Source: compiled from the Tabulation of the 2010 Population Census of China (SSB, 2012) and China City Statistical Yearbook (SSB, 2011)

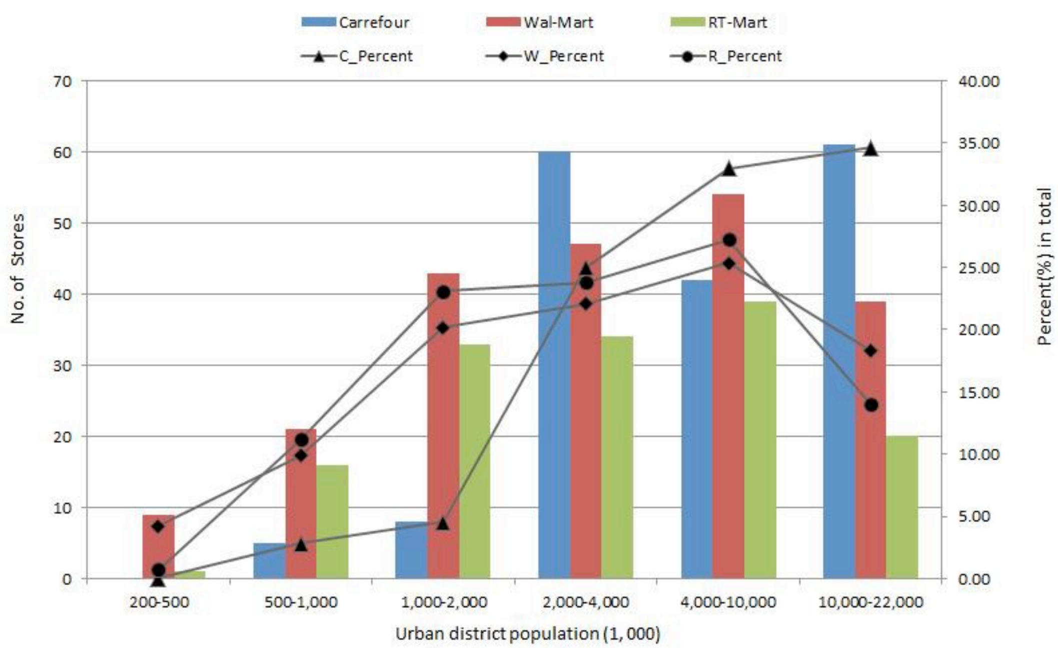

Figure 3.6 Carrefour, Wal-Mart, and RT-Mart stores by urban district population, 2010

was in the total of Carrefour stores. Carrefour had the largest store percentage in the large, extra-large, and super-large city groups (about 25%, 33%, and 35%, respectively) and the smallest percentage in the small, small-medium, and medium cities (0%, 3%, and 5%, respectively). The same pattern could also be found in the number of stores, especially in the large and super-large city groups where Carrefour far outnumbered Wal-Mart and RT-Mart. There existed a dichotomy in Carrefour's store distribution:

a large number of stores in bigger cities and no or few stores in small and medium cities.

Wal-Mart outnumbered the other two retailers in most city groups except in the large and super-large groups. Wal-Mart and RT-Mart had a very similar percentage of stores in the small-medium, medium, large and extra-large city groups where Wal-Mart had a slightly smaller one. The latter three groups were also the common focus of the two retailers where they located the majority of their stores (about 70%). Wal-Mart's percentage of stores in the small city group (about 5%) was the largest among the three retailers and the second-largest (about 18%) in the super-large group. Compared with Carrefour and RT-Mart, Wal-Mart had a more balanced store distribution in different city groups. Wal-Mart managed to avoid an extremely low or high percentage of stores in a single city group.

RT-Mart shared a very similar store distribution pattern with Wal-Mart except that it had a much smaller percentage in the small and super-large city groups (less than 1% and about 14%, respectively). RT-Mart had the second-largest number of stores in small, small-medium, and medium cities and had the smallest in large, extra-large, and super-large cities. RT-Mart showed the most interest in expanding in the small-medium, and medium cities and least interest in the super-large cities.

The logistic regression models reveal the significance of internal economies of scale at the provincial level for Wal-Mart and RT-Mart. Table 3.8 compares the provincial expansion patterns of three retailers and sheds more light on the effect of this variable. First of all, Carrefour had significantly fewer cities (47) than Wal-Mart (100) and RT-Mart (69) in its store network although it had the second largest number of stores. In most provinces, Carrefour concentrated its stores in only one or two cities, usually the

Table 3.8 Provincial expansions of Carrefour, Wal-Mart, and RT-Mart, 1995-2010

Carrefour					**Wal-Mart**					**RT-Mart**				
Province	Entry	First city	Citie	Stores	Province	Entry	First city	Cities	Stores	Province	Entry Time	First city	Citie	Stores
Beijing	1995-12	Beijing	1	18	Guangdong	1996-8	Shenzhen	12	36	Shanghai	1998-7	Shanghai	1	13
Shanghai	1995-12	Shanghai	1	19	Yunnan	1999-12	Kunming	5	10	Jiangsu	2000-4	Nanjing	12	40
Guangdong	1996-11	Shenzhen	4	20	Liaoning	2000-4	Dalian	2	8	Shandong	2000-9	Jinan	8	15
Tianjin	1997-10	Tianjin	1	5	Fujian	2001-1	Fuzhou	5	12	Zhejiang	2000-11	Jiaxing	7	16
Chongqing	1998-1	Chongqing	1	6	Heilongjiang	2002-7	Harbin	3	5	Hebei	2001-5	Baoding	2	2
Hubei	1998-11	Wuhan	1	7	Jilin	2002-12	Changchu	1	4	Jilin	2001-10	Jilin	2	4
Liaoning	1999-6	Shenyang	4	13	Hunan	2003-6	Changsha	6	9	Heilongjian	2002-8	Qiqihar	4	6
Sichuan	1999-9	Chengdu	2	10	Jiangxi	2003-8	Nanchang	5	8	Liaoning	2002-11	Jinzhou	5	7
Jiangsu	1999-10	Nanjing	7	20	Shandong	2003-9	Jinan	5	7	Hubei	2002-12	Wuhan	2	2
Zhejiang	1999-10	Ningbo	2	5	Tianjin	2003-12	Tianjin	1	2	Guangdong	2004-1	Chaozhou	10	18
Shandong	1999-12	Qingdao	2	4	Jiangsu	2004-1	Nanjing	9	17	Tianjin	2005-9	Tianjin	1	2
Hunan	2002-6	Changsha	2	4	Guangxi	2004-4	Nanning	2	3	Anhui	2005-12	Ma'anshan	4	4
Yunnan	2002-9	Kunming	1	5	Guizhou	2004-5	Guiyang	2	6	Hainan	2006-9	Haikou	1	2
Heilongjiang	2002-12	Harbin	2	6	Hubei	2004-11	Wuhan	4	10	Guangxi	2006-10	Beihai	2	2
Anhui	2004-2	Hefei	4	6	Shanxi	2005-3	Taiyuan	2	4	Hunan	2007-8	Changde	2	4
Xinjiang	2004-2	Urumqi	1	3	Beijing	2005-5	Beijing	1	7	Fujian	2008-9	Xiamen	2	2
Fujian	2005-9	Fuzhou	3	5	Chongqing	2005-6	Chongqing	1	10	Gansu	2008-9	Lanzhou	1	1
Henan	2006-2	Zhengzhou	3	5	Shanghai	2005-7	Shanghai	1	7	Jiangxi	2008-12	Nanchang	1	1
Hainan	2006-11	Haikou	1	3	Anhui	2005-12	Wuhu	7	11	Shaanxi	2009-9	Xi'an	1	1
Shaanxi	2007-2	Xi'an	1	1	Zhejiang	2006-6	Jinhua	8	14	Beijing	2010-5	Beijing	1	1
Jilin	2007-11	Changchu	1	2	Sichuan	2006-9	Chengdu	10	11					
Hebei	2010-9	Tangshan	1	7	Hebei	2007-4	Langfang	2	2					
Guizhou	2010-12	Guiyang	1	1	Shaanxi	2007-10	Xi'an	1	4					
					Henan	2007-12	Zhengzhou	4	5					
					InnerMongolia	2010-12	Baotou	1	1					
Total			47	176				100	213				69	143

provincial capital and the second-largest city, while Wal-Mart and RT-Mart expanded to as many cities as possible in a province, especially in developed provinces such as Guangdong, Jiangsu, and Zhejiang. Consequently, the average number of stores in a city was 4 for Carrefour but only 2 for Wal-Mart and RT-Mart. Carrefour was more interested in concentrating stores at the urban level while Wal-Mart and RT-Mart aimed to achieve the internal economies of scale at the provincial level by expanding the numbers of stores and cities simultaneously.

Spatial and temporal expansion patterns of Carrefour, Wal-Mart, and RT-Mart into different provincial markets are summarized in Table 3.8. Before China's accession to WTO in 2001, Carrefour strategically bypassed state policy and aggressively expanded to 11 provinces in North China (Beijing and Tianjin), Northeast China (Liaoning), East China (Shanghai, Jiangsu, Zhejiang, and Shandong), Southwest China (Sichuan and Chongqing), and Central China (Hubei). Carrefour reached half of its provincial markets as early as in 1999. Restricted by retail regulations, Wal-Mart and RT-Mart did not make much progress until 2002. Wal-Mart was mostly developing in Guangdong and expanded to Yunnan, Liaoning, and Fujian. RT-Mart was concentrated in East China (Shanghai, Jiangsu, Zhejiang, and Shandong) and expanded north to Hebei and Jilin. During this period, the first city that Carrefour and Wal-Mart entered in a province was the provincial capital or the second largest city (e.g., Ningbo and Shenzhen) whereas RT-Mart already chose smaller sized cities (for example, Jiaxing in Zhejiang and Baoding in Hebei) as the first city in a respective provincial market.

China's accession to WTO significantly encouraged foreign retailers to expand their business. From 2002 to 2004, Carrefour made inroads into Hunan, Yunnan, Heilongjiang, Anhui, and even the remote Xinjiang Uyghur Autonomous Region in Northwest China. Among the three retailers, Wal-Mart expanded most rapidly and reached provinces in Northeast China (Heilongjiang and Jilin), North China (Tianjin), Central China (Hunan and Hubei), East China (Jiangxi, Shandong and Jiangsu), South China (Guangxi), and Southwest China (Guizhou). However, it was still absent in several important markets such as Beijing and Shanghai. RT-Mart continued its expansion in Northeast China (Heilongjiang and Liaoning) and opened up markets in Hubei and Guangdong. Carrefour and Wal-Mart still kept their provincial-capital-as-the-first-city strategy during these years while RT-Mart opted more for smaller sized cities (e.g., Qiqihar, Jinzhou, and Chaozhou) as the first city to enter a new provincial market.

The Chinese government fully removed restrictions in the retail sector in late 2004. Since then, international retailers have been virtually free to open stores anywhere in China without any restriction in ownership. After 2004, Carrefour only added one provincial market each in East China (Fujian), Central China (Henan), South China (Hainan), Northwest China (Shaanxi), Northeast China (Jilin), North China (Hebei), and Southwest China (Guizhou). Wal-Mart mainly expanded towards North and East and reached four provinces in North China (Shanxi, Beijing, Hebei, and Inner Mongolia), three in East China (Shanghai, Anhui, and Zhejiang), two in Southwest China (Chongqing and Sichuan) and one each in Central China (Henan) and Northwest China (Shaanxi). Wal-Mart finally entered national centers Beijing and Shanghai in 2005. At the same time, RT-Mart was gradually transforming from a regional retailer in the Yangtze River Delta to a national one. RT-Mart made inroads into Northwest China (Gansu and Shaanxi) and reached more provinces in North China (Tianjin and Beijing), East China (Anhui and Fujian), Central China (Hunan), and South China (Hainan and Guangxi). Southwest China (Guizhou). Wal-Mart mainly expanded towards North and East and reached four provinces in North China (Shanxi, Beijing, Hebei, and Inner Mongolia), three in East China (Shanghai, Anhui, and Zhejiang), two in Southwest China (Chongqing and Sichuan) and one each in Central China (Henan) and Northwest China (Shaanxi). Wal-Mart finally entered national centers Beijing and Shanghai in 2005. At the same time, RT-Mart was gradually transforming from a regional retailer in the Yangtze River Delta to a national one. RT-Mart made inroads into Northwest China (Gansu and Shaanxi) and reached more provinces in North China (Tianjin and Beijing), East China (Anhui and Fujian), Central China (Hunan), and South China (Hainan and Guangxi). From 2005 to 2010, Carrefour did not change its first-city strategy while Wal-Mart began to follow RT-Mart's early strategy and chose smaller sized cities (e.g., Wuhu in Anhui, Jinhua in Zhejiang, and Langfang in Hebei). However, RT-Mart itself increasingly chose the provincial capital as its first city during this period. By the end of 2010, Wal-Mart had expanded to 25 provinces, Carrefour to 23, and RT-Mart to 20. Wal-Mart and Carrefour had already established their nationwide store network. RT-Mart was still working to reach this goal, which it soon achieved in the next 2 years (see Tables 3.4 and 3.5).

3.8 Spatial Clustering and Suburbanization of Foreign Hypermarkets in Shanghai

As the national economic center, Shanghai has a large number of foreign hypermarkets. Many international retailers such as Carrefour, RT-Mart, Tesco, Lotus, and Auchan chose Shanghai as their headquarters in China and concentrated their stores in this metropolis (Table 3.4). Since the first hypermarket opened by Carrefour in Hongkou District in 1995, foreign hypermarkets have grown rapidly in Shanghai (Figure 3.7). They have also been the major players in the hypermarket retailing sector. For example, foreign hypermarkets accounted for 78.6% of the total hypermarket sales in Shanghai in 2008 (Wang, Liu, & Wang, 2012).

Spatial distribution of foreign hypermarkets in Shanghai has changed dramatically since 2000. In 2000, foreign hypermarkets were concentrated in the inner city and confined within the Central Ring Road (Figure 3.8). By 2006, foreign hypermarket had significantly increased their store density in the inner city and expanded greatly into the inner suburb, and eventually spread to the outer suburb. By 2012, most new stores had mushroomed in the inner suburban districts like Baoshan, Jiading, Minhang, and Pudong. Each outer suburban district had at least two or three foreign hypermarkets, which grew only in a few selective subdistricts such as administrative towns. There had been very few

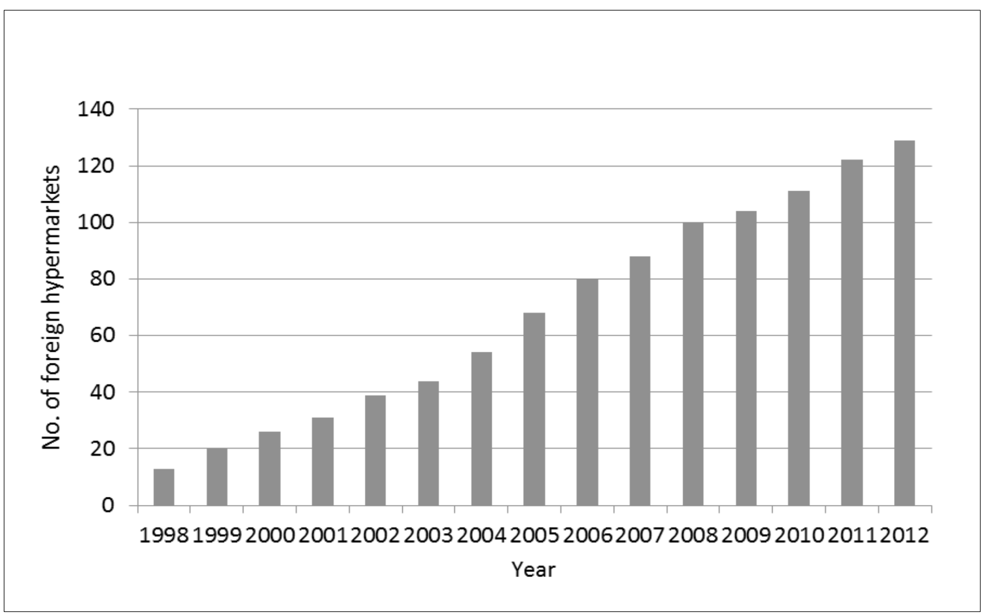

Figure 3.7 Foreign hypermarkets in Shanghai, 1998-2012

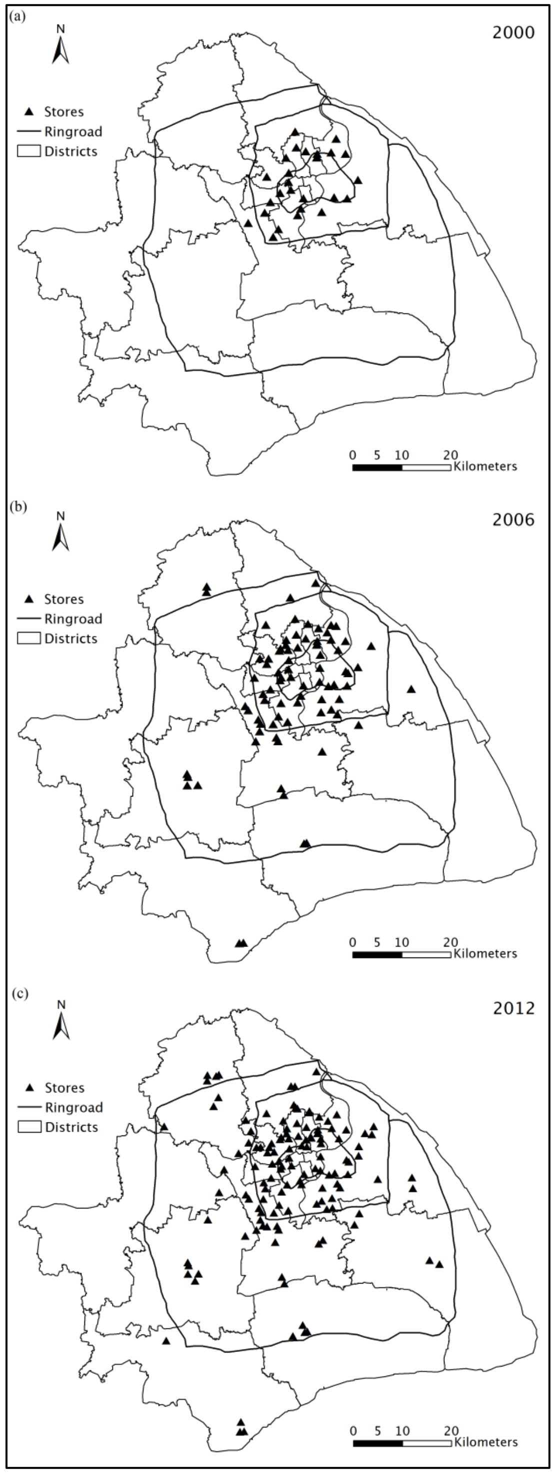

Figure 3.8 Spatial distribution of foreign hypermarkets in Shanghai, 2000, 2006, and 2012

foreign stores in the urban core since the beginning.

Suburbanization of retailing has been a trend in many Chinese cities (Chai et al., 2007; Qian, 2008). The changing distribution of foreign hypermarkets in Shanghai illustrated this trend as well (Table 3.9). More than half of the stores were located in the inner city in 2000. From 2000 to 2006, foreign retailers doubled their stores in the inner city but the share in this area decreased into 36%. At the same time, stores quadrupled in the inner suburb and the share steadily increased to 49%. Outer suburban stores increased to 9 during this period. Between 2006 and 2012, inner city stores only increased by 9 while inner suburban stores increased by 28. Outer suburban stores rapidly increased to 20. There were few changes of stores in the urban core from 2000 to 2012. Over the years, foreign hypermarket retailers gradually moved their focus from the inner city to the inner suburb and steadily expanded into the outer suburb. Suburbanization of hypermarket retailing in Shanghai was closely related to population suburbanization, which actually started in the mid-1990s (Qian, 2008). In addition, the Shanghai government began to restrict development of new hypermarkets in the inner city in 2006 (Shanghai Municipal People's Government, 2006).

Average Nearest Neighbor (ANN) index is employed to examine the point pattern

Table 3.9 Changing distribution of foreign hypermarkets in Shanghai, 2000-2012

Urban Area	2000		2006		2012	
	Stores	Share	Stores	Share	Stores	Share
Urban Core	2	8%	3	4%	4	3%
Inner City	14	54%	29	36%	38	29%
Inner Suburb	10	38%	39	49%	67	52%
Outer Suburb	0	0	9	11%	20	16%

of foreign hypermarkets. ANN index is calculated for each year from 1998 to 2012. An ANN *Z*-score value of less than -1.65 (significant at the 0.1 level) indicates spatial clustering while an ANN *Z*-score value of greater than 1.65 indicates spatial dispersion. As shown in Figure 3.9, the spatial pattern of foreign hypermarkets was dispersed from 1998 to 2003. Then it suddenly became clustered in 2004 when the central government removed all restrictions in the retail sector. This spatial clustering has been intensified in recent years. The most clustered pattern occurred in 2011 with an ANN *Z*-score of -8.43. Spatial clustering of foreign hypermarkets in Shanghai also caused problems for local communities such as traffic congestion and driving small retailers out of business.

ANN *Z*-scores indicate the spatial clustering of hypermarkets but do not tell where the clusters are located. Therefore, hot spot analysis is conducted to the subdistrict foreign hypermarket distribution in 2012. Local statistic index Getis-Ord *Gi** is calculated for each subdistrict. Hot spots of high values of foreign hypermarkets are found in a few adjacent subdistricts in Minhang and Pudong and individual subdistricts in Baoshan, Jiading, and Fengxian (Figure 3.10). Except one in Fengxian District, these subdistricts were almost exclusively located in the inner suburb, which had seen the most rapid expansion of foreign hypermarkets in recent years.

3.9 Conclusion and Discussion

This chapter analyzes spatial inequality and dynamics of foreign hypermarket retailers in China at different geographic scales, which are often neglected in the traditional economic-geographic studies. We utilize quantitative analysis of foreign retailers in conjunction with institutional analysis to understand how state policies

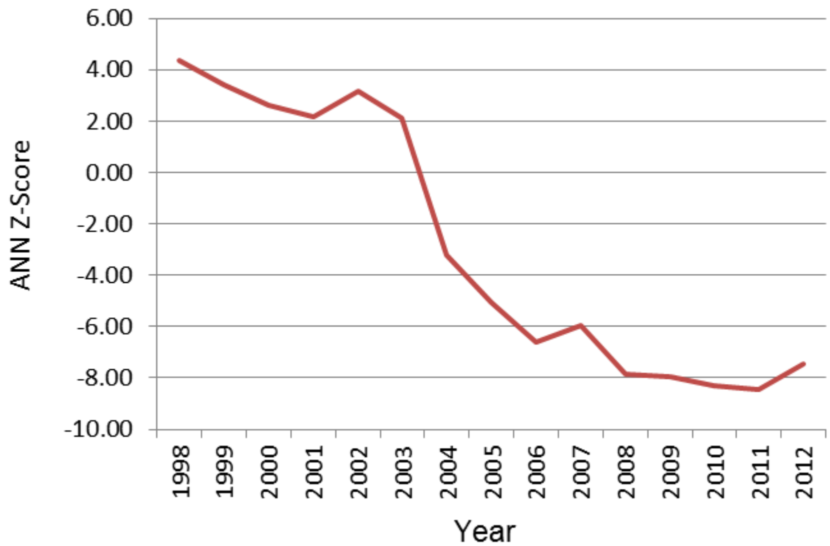

Figure 3.9 ANN *Z*-scores for foreign hypermarkets in Shanghai, 1998-2012

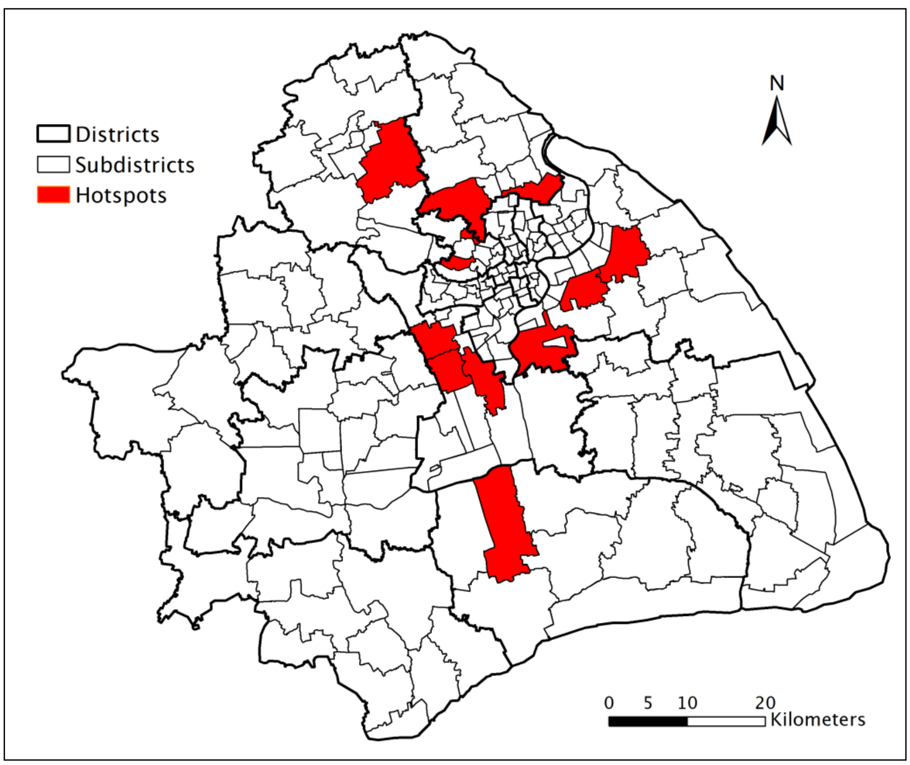

Figure 3.10 Hotspot analysis of subdistrict foreign hypermarkets in Shanghai, 2012

impacted their expansion patterns and location strategies. Our study finds that international retailers have their own spatial strategies in penetrating the Chinese retail market. However, their spatial strategies have been largely dictated by the gradual liberalization policy of the Chinese government. Their major changes in market expansion occurred right after a retail deregulation policy was implemented. China's accession to the WTO in 2001 and the complete removal of restrictions in retailing in market. However, their spatial strategies have been largely dictated by the gradual liberalization policy of the Chinese government. Their major changes in market expansion occurred right after a retail deregulation policy was implemented. China's accession to the WTO in 2001 and the complete removal of restrictions in retailing in 2004 best exemplified how institutional factors influenced the spatial dynamics of foreign retailers. Although none of the foreign hypermarket retailers has passed through the four-stage postentry model proposed by Dawson (2003), Carrefour, Wal-Mart, and RT-Mart can be said to have completed the second phase of consolidation while others are still in the first phase of stabilizing their operation.

Foreign hypermarket retailers have remarkably expanded their business since the mid-1990s. Spatial inequality in foreign hypermarkets among Chinese regions has changed dramatically. The relative gaps among them are narrowing while the absolute gaps are widening. Foreign hypermarket retailers have favored the eastern region and located most of their stores there. Different from manufacturing TNCs, they skipped most of the central region and developed quite a few stores in the southwestern region in the late 1990s. Foreign hypermarkets developed most rapidly in the central region since 2000. At the provincial level, relative spatial inequality has decreased over the years. As the retail deregulation policy proceeded, international retailers expanded their stores from eastern coastal and southwestern provinces to central and western provinces. Since 2005, provincial foreign hypermarket distribution has shown statistically significant clustering in the Yangtze River Delta.

Three leading foreign hypermarket retailers, Carrefour, Wal-Mart, and RT-Mart, have different location determinants at the intercity level. Although urban district population is a significant factor to them all, they have preferences for cities of different population size. Carrefour preferred cites with an urban district population of two million or more (large, extra-large, and super-large cities) and concentrated the majority of its stores there. Wal-Mart had a more-balanced distribution of stores in various city groups but also focused on medium, large, and extra-large cities and owned the largest number of stores in almost every city group. RT-Mart shared a similar focus with Wal-Mart but preferred to expand into small-medium and medium sized cities as well. In addition, Carrefour favored cities with a longer time of being open to foreign retailers while this factor was not statistically significant to Wal-Mart and RT-Mart. Provincial expansion patterns confirmed that Carrefour was more interested in concentrating stores at the urban level while Wal-Mart and RT-Mart aimed to achieve internal economies of scale at the provincial level. Their first-city strategy at different time periods indicated that Carrefour had not changed its bigger city preference while Wal-Mart scaled down to small and medium cities and RT-Mart scaled up to larger cities.

At the intraurban level, foreign hypermarket retailers in Shanghai gradually expanded from the inner city to the suburb. Suburbanization of foreign hypermarkets has been a clear trend in recent years. Foreign retailers have shifted their focus from the inner city to the inner suburb, where most of the new stores were located. Changing ANN *Z*-scores indicate the spatial distribution of foreign hypermarkets has changed from dispersion to clustering in 2004, and the spatial clustering has intensified since then.

The future expansion of foreign retailers is challenging as retail internationalization deepens in China. The recent economic slowdown has already weighed on international retailers. Several foreign hypermarket chains such as Carrefour, Wal-Mart, and Lotte Mart were reported to have closed stores (Linkshop, 2013). British retailer Tesco's Chinese hypermarket business was even merged with a state-owned retail conglomerate China Resource Vanguard in 2014 (Siebers, 2016). The booming online retailing (e-tailing), which has already accounted for about 10% of total retail sales in China (eMarketer, 2014), is putting increasing pressure on physical stores. However, the transformation to a consumer-driven economy can also offer great opportunities to retail TNCs in China, such as the rise of upper-and-middle class and a new generation of free-spending and sophisticated consumers (Kuo, 2016). Foreign retailers have to change their strategies to seize these opportunities and adapt to the highly competitive Chinese retail market. Major foreign hypermarket retailers have already integrated e-tailing or diversified retail formats in their Chinese business. RT-Mart launched its e-tailing platform Feiniu.com in early 2014. Carrefour launched its convenience stores Easy Carrefour in November 2014. Wal-Mart took full ownership of a Chinese e-Commerce venture Yihaodian in July 2015. Nevertheless, how these adaption strategies will influence their spatial dynamics is still unknown. Will the development of e-tailing by retail TNCs eclipse the needs of developing new hypermarkets? Will hypermarkets eventually lose their popularity to other retail formats? We are not sure about answers to these questions at this point. The relatively saturated retail market in large cities might force foreign hypermarket retailers to focus more on small and medium cities in their next round of store expansion.

The limitations of this study actually generate several future research topics. This research mainly uses secondary data. First-hand data from in-depth interviews and qualitative surveys with senior executives of these retail TNCs would provide more insights from the perspective of foreign retailers. Finally, this research only examines foreign hypermarket retailers, which are large general merchandise retailers. The consideration of other types (e.g., clothing retailers) and sizes (e.g., small and medium) of retailers may tell a different story.

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CHAPTER 4

RANDOM FOREST CLASSIFICATION FOR LAND USE AND LAND COVER CHANGE ANALYSIS IN SUZHOU USING MULTITEMPORAL LANDSAT IMAGES

4.1 Introduction

Anthropogenic land use and land cover (LULC) change is increasingly affecting the environment of the Earth's surface and atmosphere. These changes are taking place at an unprecedented rate and at spatial scales ranging from local to global. Changes in LULC can influence the climate, affect the biodiversity, contribute to habitat destruction, lead to the decline in natural vegetation cover, disrupt socio-cultural practice, and increase natural disasters (Dewan & Yamaguchi, 2009; Kindu, Schneider, Teketay, & Knoke, 2013). Urbanization is a major form of anthropogenic land use activity that leads to the loss of arable land (Yeh & Li, 1999). Since ecosystems in urban areas are strongly influenced by human activities, more attention has been recently directed to monitoring urban LULC changes (Yuan, Sawaya, Loeffelholz, & Bauer, 2005). To mitigate the detrimental effects of urban growth environment and ecosystems, accurate and reliable information on spatial and temporal patterns of LULC change is therefore particularly important for developing rational and sustainable economic, social, and environmental policies (Long, Tang, Li, & Heilig, 2007).

Since the onset of economic reform and open-door policy in 1978, tremendous land use and land cover change has taken place in China, especially in eastern coastal regions such as the Yangtze River Delta region (Long et al., 2007; Xu, 2004) and Pearl River Delta region (Seto & Kaufmann, 2003; Weng, 2002). The massive conversion of arable land to nonagricultural use has been a major feature of land use change in these regions (Li, Chen, & Sun, 2007; Yeh & Li, 1999). Rapid industrialization and urbanization following the economic reform have greatly influenced LULC change in China through urban sprawl and the increase of built-up areas. However, environmental problems that result from land use change may undermine the sustainable economic development in China if there is no appropriate planning and management of land resources. To make rational policies for land management, there is an urgent need to evaluate the pattern and magnitude of land use and land cover change.

Remote sensing (RS) and Geographical Information Systems (GIS) have been widely applied and considered as cost-effective tools in detecting land use and land cover change. Remote sensing can provide valuable multitemporal data to monitor land use change patterns and processes while GIS technology can analyze and map these changes (Weng, 2002; Yuan et al., 2005; Long et al., 2007). Satellite remote sensing imagery has been widely used for monitoring land cover types by spectral classification. The widely used method of change detection enables us to identify the structural variation between different LULC patterns.

This chapter describes the methods and results of classification and postclassification change detection of multitemporal Landsat TM imagery of Suzhou city in 1986, 1991, 1995, 2002, and 2008. Our main objectives are to employ the random forest method for image classification, assess the accuracy of classifications, monitor

LULC changes through postclassification change detection, analyze urban expansion patterns, and relate them to major socioeconomic driving forces.

4.2 Materials

4.2.1 Study Area

The study area of Suzhou is located between 30°59’ to 31°33’, and 120°11’ to 120°53’, in southern Jiangsu Province in East China. The city is situated on the eastern shore of Taihu Lake and the lower reaches of the Yangtze River Delta (Figure 4.1). Suzhou is characterized with numerous rivers, canals, and lakes throughout the city and low mountains in the west. The average elevation of Suzhou is about 4 meters. The city has a humid subtropical monsoon climate and receives approximately 1100 mm of rainfall annually.

Suzhou City is the prefectural seat of Suzhou Prefecture, which contains the other four county-level cities. This city has been rapidly industrialized and urbanized since the mid-1990s. The administrative division of Suzhou City has been changing since the 1980s because it kept annexing land from neighboring cities. To maintain the consistency for analysis, we use the administrative division of it in 2008. At the end of 2010, this city covered an area of 1810 sq. km with a population of 4 million.

4.2.2 Data

This study obtained multitemporal Landsat Thematic Mapper (TM) images of Suzhou City from the United States Geological Survey (USGS) GLOVIS website (http://glovis.usgs.gov/). Anniversary dates in late July and early August were targeted because growing season is useful for mapping vegetation. The study area is cloud prone in summer because of its humid subtropical monsoon climate. Therefore, only five scenes with minimum cloud cover were selected within the time period between 1986 and 2008 (Table 4.1). These images were Landsat Level 1 Standard Data in the format of digital numbers (DN). USGS recently implemented the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) to carry out atmospheric correction and produce the Landsat Surface Reflectance Climate Data Record (CDR) product in Hierarchical Data Format (HDF). The Landsat Surface Reflectance CDR for the 1986 scene was downloaded from the USGS website (http://earthexplorer.usgs.gov/) and used for intercalibrating all other scenes.

This study employed the random forest algorithm for image classification, which can incorporate not only spectral data but also spatial data such as Digital Elevation Model (DEM). The DEM we used is the Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global Digital Elevation Model (GDEM), also downloaded from the USGS website (http://earthexplorer.usgs.gov/). The data have a spatial resolution of 30 m, the same as Landsat Level 1 Standard Data. The biggest problem encountered in the data acquisition was the lack of ground truth data from field work or high-resolution images. No field work has been done in the past due to the retrospective nature of this study. A few high-resolution images that covered the entire Suzhou city were available in Google earth, but they were mostly taken after 2008. The high-resolution image taken on March 14, 2009 was the closest and had the best quality. It was selected as the reference image for the classified TM image of July 5, 2008. Although there were phenological differences between them, this was the best reference image that we could find.

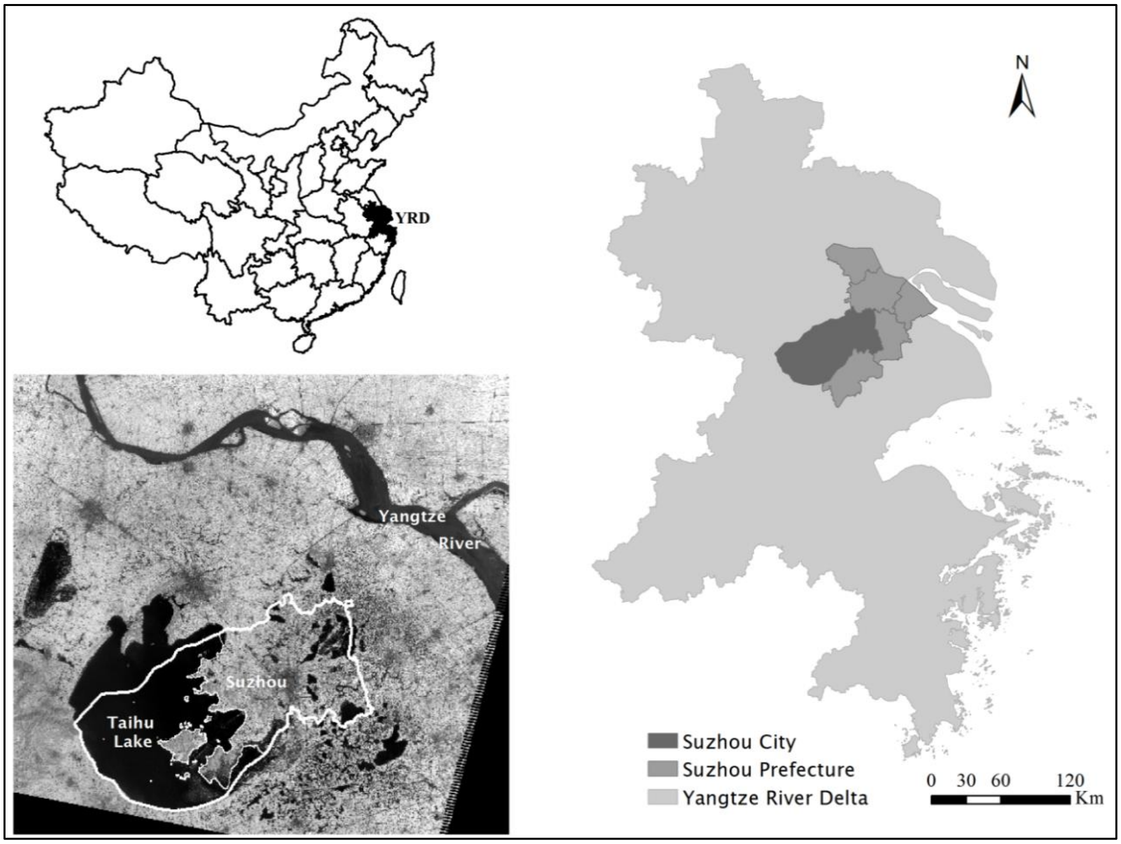

Figure 4.1 Location of Suzhou City

Table 4.1 Dates of Landsat TM scenes used in this study

Path	Row	Date
119	38	July 25, 1986
119	38	July 23, 1991
119	38	August 3, 1995
119	38	August 22, 2002
119	38	July 5, 2008

4.3 Methods

The complete workflow of this study, which describes how the data, methods, and analysis were collected and performed, is shown in Figure 4.2. This flowchart includes data acquisition, data preprocessing, image classification, accuracy assessment, and change detection. The software package ENVI 4.8 (Exelis Visual Information Solutions, Boulder, Colorado) and the public domain software R (R Foundation for Statistical Computing, Vienna, Austria) were used for image processing and land classification.

4.3.1 Data Preprocessing

Due to shifts in the spatial coverage of each TM scene, a mask containing the study area of Suzhou was applied to all years. Since Landsat Level 1 Standard Data in the DN format were not atmospherically corrected, the Landsat Surface Reflectance CDR data for the July 25, 1986 scene was downloaded. All other dates were then intercalibrated using pseudo-invariant pixels found by IR-MAD (Iteratively re-weighted Multivariate Alternation Detection; Canty & Nielsen, 2008).

Ridd’s (1995) vegetation-impervious surface-soil (V-I-S) model has been a major advance in urban LULC classification in recent years. The V-I-S model assumes that the spectral signature of urban land cover is a linear combination of three components: vegetation, impervious surface, and soil. This conceptual model may be implemented by using linear spectral mixture analysis (LSMA), which decomposes the spectral reflectance of a pixel into different proportions (Wu & Murray, 2003). Nevertheless, the use of this model in practice is constrained by several factors: it cannot explain all land cover types such as water and wetlands; impervious surfaces cannot be easily identified as an endmember due to its spectral variability (Lu & Weng, 2004; Wu & Murray, 2003).

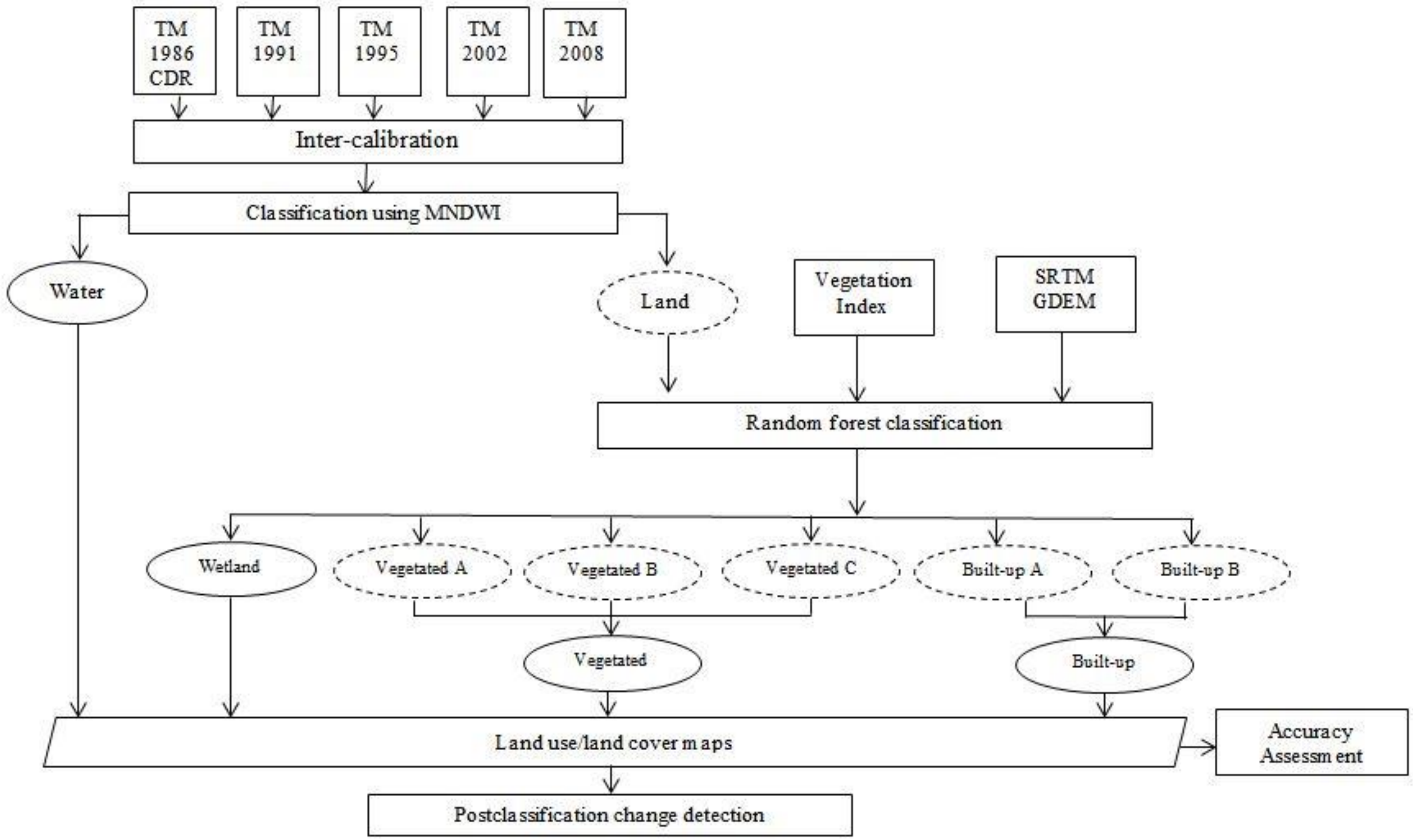

Figure 4.2 Flowchart for the procedures performed and classification scheme (dashed line box for intermediate classes)

Impervious surfaces are anthropogenic features through which water cannot infiltrate into the soil, such as roads, driveways, sidewalks, parking lots, rooftops, and so on (Weng, 2012). The impervious surface estimation may be improved by the addition of low-albedo and high-albedo fractions. However, some low reflectance materials (e.g., water) and high reflectance materials (e.g., cloud) can adversely affect impervious surface estimation (Small, 2001). These materials should be identified and masked in the first place. In this study, we did not directly use the V-I-S model or LSMA for image classification, but used the above method of impervious surface estimation to classify built-up land. Built-up land was divided into two subclasses: low reflectance built-up (Built-up A) and high reflectance built-up (Built-up B). As water features account for a large proportion of Suzhou, we firstly identified and masked them to avoid the confusion between water and low reflectance built-up land.

We broadly classified the whole study area into water and land classes by using the modified normalized difference water index (MNDWI). There are many methods for the extraction of open water from remote sensing imagery. The band ratio approach uses two multispectral bands, one from visible wavelengths and the other usually from near infrared wavelengths, to suppress vegetation and land and enhance water features. McFeeters (1996) proposes the normalized difference water index (NDWI) to achieve this goal. The NDWI is expressed as follows:

$$NDWI = \frac{Green - NIR}{Green + NIR} \tag{4.1}$$

where *Green* is a green band such as TM band 2 and *NIR* is a near infrared band such as TM band 4. Nevertheless, the NDWI cannot effectively suppress the signal from built-up land so that enhanced features are still mixed with built-up land noise. Xu (2006) modified the NDWI by substituting the MIR band for the NIR band. The modified NDWI (MNDWI) can be expressed as follows:

$$MNDWI = \frac{Green - MIR}{Green + MIR} \quad (4.2)$$

where MIR is a middle infrared band such as TM band 5. The use of MNDWI will result in more accurate extraction of open water features as the built-up land and vegetation had negative values while water features have positive values (Xu, 2006). Therefore, a threshold of zero is applied to extract water feature. However, Ji, Zhang, and Wylie (2009) argue that MNDWI threshold actually varies depending on the proportions of subpixel water/nonwater components. We tried several different thresholds of MNDWI for each TM scene until the best extraction result was achieved.

Selection of suitable vegetation indices is very important for successful land cover classification. We performed the Tasseled Cap (TC) Transformation to the six reflective bands of TM images and got three indices, namely Brightness, Greenness. and Wetness (Crist & Cicone, 1984). Normalized difference vegetation index (NDVI), the most widely used vegetation index, was also calculated for each TM image. Lastly, elevation data from SRTM GDEM were incorporated to stack an 11-band dataset for image classification.

4.3.2 Random Forest Image Classification

A modification of the Anderson Scheme Level I method was used to evaluate LULC changes in this study (Anderson, Hardy, Roach, & Witmer, 1976). Four broad land cover classes were identified: water, wetland, vegetated land, and built-up land (Table 4.2). A hierarchical classification scheme of two levels was implemented. We started from Level 2 at which vegetated land and built-up land were respectively divided into

Table 4.2 Land use/cover classification scheme

Land use/cover class	Description
Water	Permanent open water, lakes, rivers, canals, ponds and reservoirs
Wetland	Permanent and seasonal wetland, marshy land, swamps
Vegetated	Agricultural land (crop fields, vegetable land, orchards), forest, grass
Built-up	Residential, commercial and services, industrial, transportation, roads, mixed built-up or other built-up

three and two subclasses, and then aggregated to Level 1 of four general classes (Figure 4.2). We used random forest (RF) image classification in this study. Random forest is an ensemble algorithm developed in the field of machine learning and uses bootstrap samples with replacement to grow a large set of classification trees (Breiman, 2001). The main advantage of RF is its nonparametric nature, which does not require data to follow a particular distribution such as the normal distribution assumed in the maximum likelihood classification (Basnet & Vodacek, 2015). In the context of land cover classification by RF, a pixel is assigned to the class that receives the maximum number of votes from the collection of multiple trees (Ghimire, Rogan, & Miller, 2010).

RF has been shown to increase land cover classification accuracy because the classification error of one permutation can be overcome by the ensemble of permutations (Gilason, Benediktsson, & Sveinsson, 2006; Pal, 2005). RF does not overfit the data because the large number of trees grown reduces generalization error (Breiman, 2001). It is less sensitive to noise and computationally faster than many other ensemble methods. RF can incorporate a diverse variety of data (e.g., DEM and climate data) in addition to spectral data into the classification algorithm (Ghosh, Sharma, & Joshi, 2014; Horning, 2010).

Compared with larger number of parameters required by other classification methods, RF has only two parameters: the number of classification trees (*ntree*) and the number of randomly selected variables (*mtry*) at each split. RF uses approximately two-thirds of random samples for training. The remaining one-third samples, which are left out from the bootstrap sample, are called Out-of-Bag (OOB) samples. The OOB samples help to evaluate the misclassification error and the variable importance (Eisavi, Homayouni, Yazdi, & Alimohammadi, 2015; Ghosh et al., 2014). The variable importance can be used to understand the contribution of specific variables in classification trees (Ghimire et al., 2010). The RF algorithm was implemented in R by Liaw and Wiener (2002). We used ENVI and R for random forest image classification.

Random forest needs training data for land cover classification and test data for accuracy assessment since it is a supervised classification method. An extensive sample set of approximately 7200 pixels was manually selected for the six Level 2 land cover classes for each year in 1986, 1991, 1995, 2002, and 2008. The sample set was then divided into two subsets. The larger subset contained two thirds of the original sample set and was used for training. We used stratified random sampling in this data partitioning step to make sure that land cover classes in each subset were truly representative of those in the sample set. Landsat TM spectral bands (1-5, and 7), four vegetation indices (TC Brightness, TC Greenness, TC Wetness, and NDVI), and elevation were used as input bands for image classification. As a postclassification operation, a 3 x 3 majority filter was applied to smooth the classified image, which could reduce the salt-and-pepper effects in the final classification map.

4.3.3 Accuracy Assessment

Classification accuracy refers to the extent of correspondence between the remotely sensed data and reference information (Congalton, 1991). Accuracy assessment of the 2008 classification map was performed using the high-resolution image on March 14, 2009 as reference data. We used stratified random sampling and selected 500 points from the classified image. Then we exported the 500 points into Google earth and created 30 m x 30 m squares centered at these points and decided the dominant land cover type within each square on the high-resolution image by visual interpretation. The results were then recorded in a confusion matrix. Classification accuracy was evaluated using producer’s accuracy and user’s accuracy for each class, and overall accuracy and Kappa coefficient. Producer’s accuracy is the fraction of correctly classified pixels with regard to all pixels of that ground truth class while the user’s accuracy is the fraction of correctly classified pixels with regard to all pixels classified as this class in the classified image. The overall accuracy is calculated by summing the number of pixels classified correctly and dividing by the total number of pixels. The Kappa coefficient measures the agreement between classification and ground truth pixels. We assessed the classification accuracy at Level 1 of complexity where four general land cover classes were considered.

4.3.4 Change Detection

Many change detection methods have been developed to analyze variations in LULC patterns (Coppin, Jonckheere, Nackaerts, Muys, & Lambin, 2004; Lu, Mausel, Brondizio, & Moran, 2003). These methods can be divided into preclassification and postclassification techniques. In the preclassification approach, various algorithms such as image differencing, image rationing, change vector analysis, and vegetation index differencing are applied to multitemporal satellite images to generate change vs. no change maps (Yuan et al., 2005). These methods are effective in locating changes but do not provide information about the nature of change (Ridd & Liu, 1998). On the other hand, postclassification comparison methods examine changes over time between independently classified land cover maps and generate “from-to” change information (Jensen, 2004). This is the most widely used technique for identifying land use and land cover change (Lu et al., 2003). The accuracy of change detection using postclassification comparison closely depends on the accuracy of each individual classification and is subject to error propagation (Yuan et al., 2005). Nevertheless, this technique is particularly useful in clarifying the magnitude, location, and nature of LULC change (Dewan & Yamaguchi, 2009). A multitemporal postclassification comparison change detection method was used in this study to identify land cover changes in five periods, 1986-1991, 1991-1995, 1995-2002, 2002-2008 and 1986-2008.

4.4 Results

4.4.1 Classification Performance

Random forest chooses the most important variables by internal estimation of variable importance to generate a large ensemble of independent trees (Meng et al., 2012). Variable importance analysis can identify the most important variables for classification and examine how they vary over the years. The result of variable importance for the 5 years was presented in Figure 4.3. Although the most important variables changed from year to year, TC Greenness, TC Brightness, and NIR were constantly among the top four variables for all 5 years. These three spectral bands played the most important role in the classification of the five images.

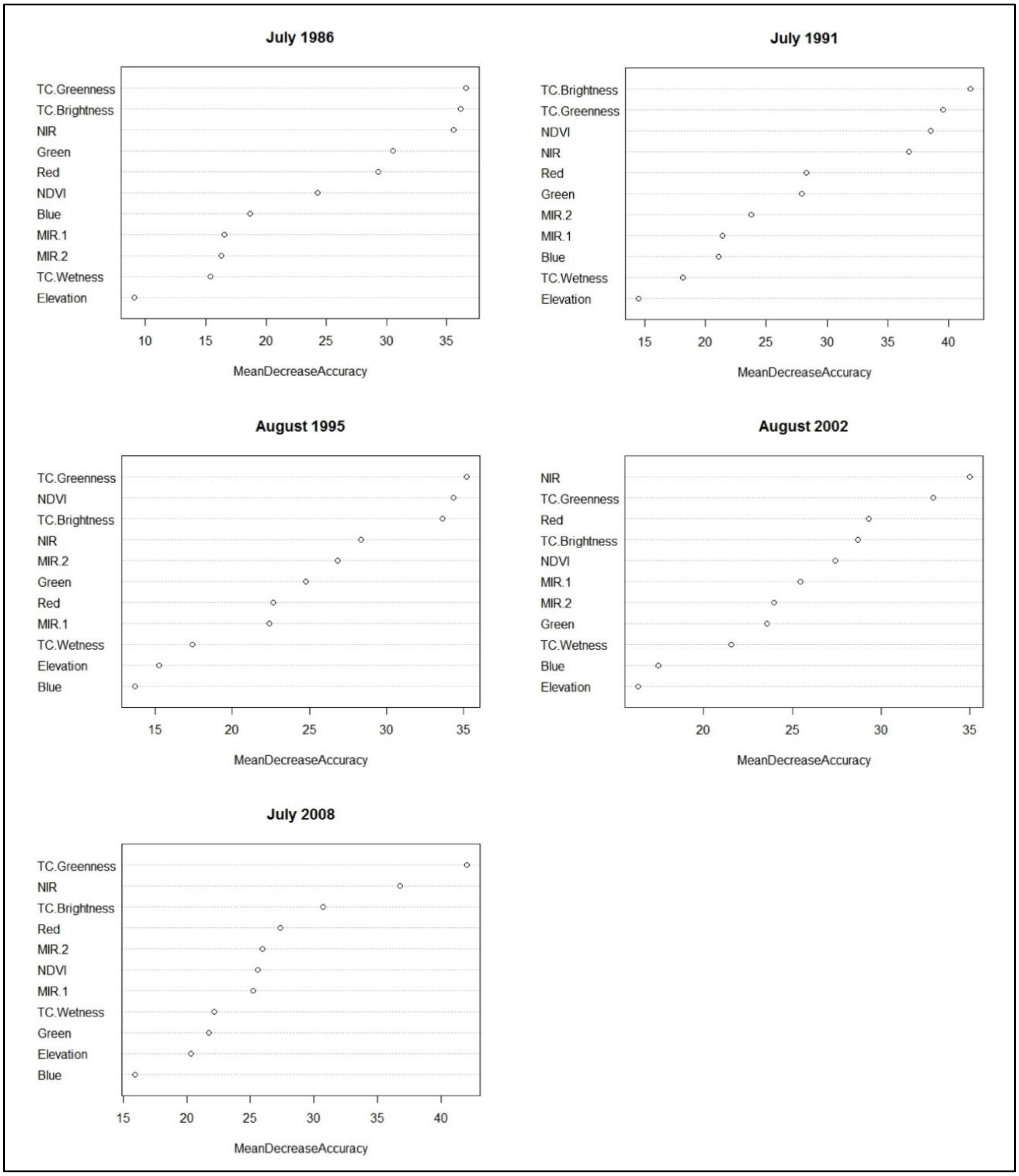

Figure 4.3 Variable importance of different input bands in terms of mean decrease in accuracy for 1986, 1991, 1995, 2002, and 2008

Random forest classification performed well in the complex landscape of Suzhou. The producer's accuracy, user's accuracy, overall accuracy, and Kappa coefficient for the 2008 image was summarized in Table 4.3. Producer's accuracy ranged from 70.5% to 87.4% and user's accuracy from 77.5% to 81.0% with an overall accuracy of 80.2% and a Kappa coefficient of 0.712. We could only assess classification accuracy of the 2008 image as reference data were not available for the other 4 years. However, with the consistency of our classification method, we believe that classification accuracies of the other four images should be within a reasonable range as that of the 2008 image.

4.4.2 Land Use and Land Cover Change Analysis

4.4.2.1 LULC change and urban expansion

The individual land class area and change statistics for all 5 years are summarized in Table 4.4. From 1986 to 2008, built-up area increased from 9.8% to 30.8% of the total landscape while vegetated land decreased from 70.2% to 30.1%. Specifically, built-up land, wetland, and water increased by approximately 380 sq. km, 123 sq. km, and 14 sq. km, respectively, while vegetated land decreased by 517 sq. km. Relatively, built-up land, wetland and water respectively increased by 214.6%, 350.2%, 4.3%, and vegetated land decreased by 40.6%. The extent of wetland may change from year to year due to varying

Table 4.3 Summary of land classification accuracy (%) for the 2008 image

Land cover class	Producer's accuracy	User's accuracy
Water	87.4	79.0
Wetland	70.5	77.5
Vegetated	81.4	81.0
Built-up	76.8	80.4
Overall accuracy	80.2	
Kappa coefficient	0.712	

Table 4.4 Summary of image classification area statistics for 1986, 1991, 1995, 2002, and 2008

Land cover class	1986		1991		1995		2002		2008		1986-2008 change	
	Area (sq. km)	%	Area (sq. km)	%	Area (sq. km)	%	Area (sq. km)	%	Area (sq. km)	%	Area (sq. km)	%
Water	327	18.1	348	19.2	348	19.2	338	18.6	341	18.8	14	4.3
Wetland	35	1.9	92	5.1	38	2.1	160	8.9	157	8.7	123	350.2
Vegetated	1272	70.2	1164	64.3	1153	63.7	868	47.9	755	41.7	-517	-40.6
Built-up	177	9.8	207	11.4	271	15.0	445	24.5	557	30.8	380	214.6

precipitation and temperature, but the significant fluctuations in wetland area might also be related to classification errors (Yuan et al., 2005). The most considerable increase was in the built-up area. For the four consecutive intervals between the 5 years, built-up land increased by 30 sq. km, 80 sq. km, 124 sq. km, and 94 sq. km with an annual growth rate of 6.05 sq. km/year, 16.03 sq. km/year, 24.72 sq. km/year, and 18.77 sq. km/year. For the entire study period from 1986 to 2008, the average annual growth rate of built-up land was 17.27 sq. km/year.

Spatial patterns of LULC change in Suzhou in the 5 years are shown in Figure 4.4. Between 1986 and 1991, urban expansion (referred to the expansion of built-up area) concentrated around the pregrowth urban core (the old city district); a few new built-up patches developed along major rivers at towns and townships far away from the city center. From 1991 to 1995, the development of the China-Singapore Suzhou Industrial Park to the east of the old city district and the Suzhou New & High-Tech District to the west significantly expanded the urban core. Between 1995 and 2002, urban expansion was more development-zone-oriented. The construction of transportation infrastructure (mainly highways and local roads), which aimed to improve the accessibility of development zones, was clearly reflected in the classified image. From 2002 to 2008, urban expansion took place in all directions at more distant locations.

4.4.2.2 Land class change matrices

To further analyze the results of land conversion and provide specific from-to information about LULC change, land class change matrices from 1986 to 1991, from 1991 to 1995, from 1995 to 2002, from 2002 to 2008, and from 1986 to 2008 were generated in Table 4.5. Unchanged pixels are located along the diagonal of each matrix.

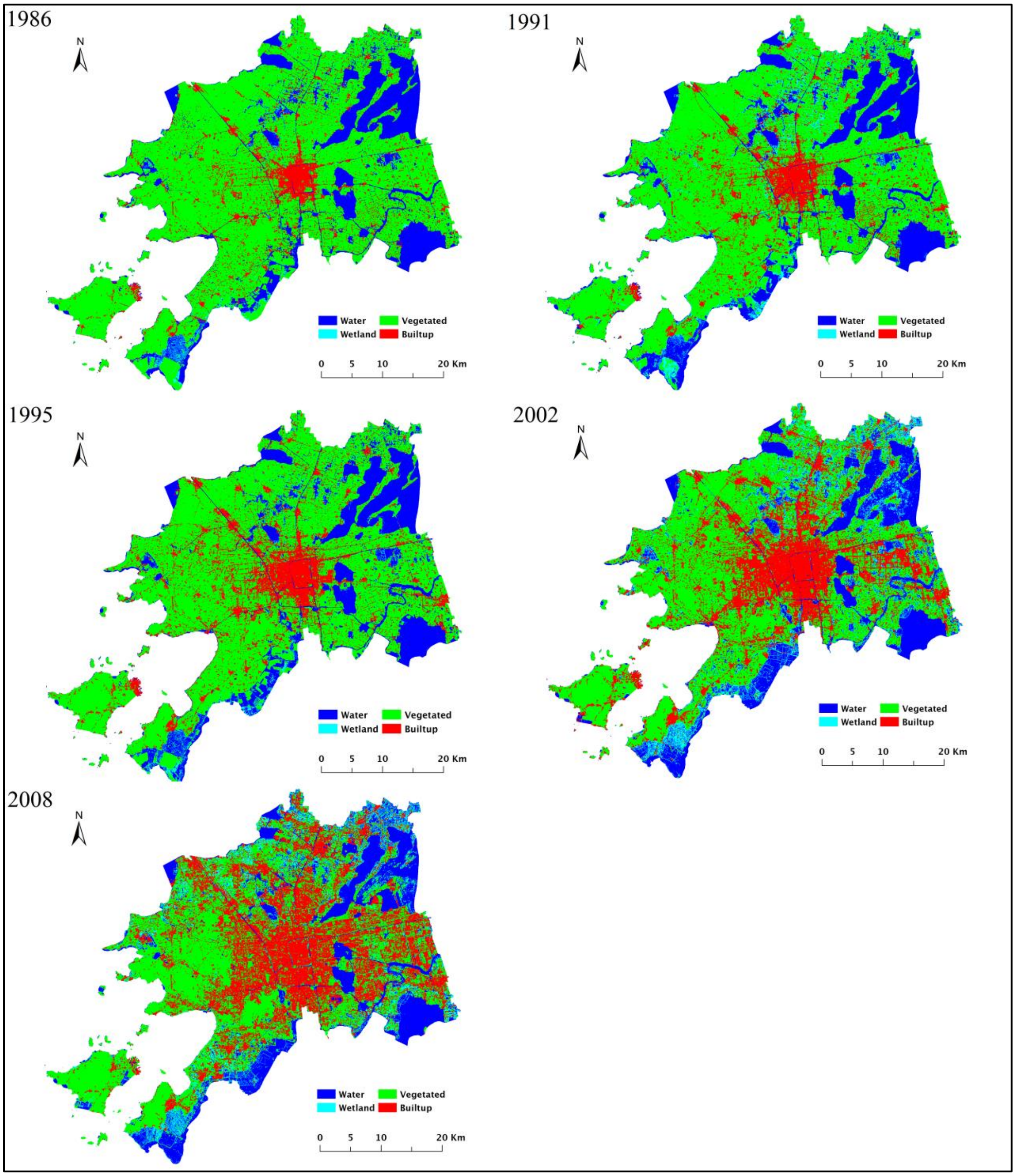

Figure 4.4 Classified land use/cover maps of Suzhou in 1986, 1991, 1995, 2002, and 2008

Table 4.5 Matrices of land class change (sq. km) from 1986 to 2008

(a)1986-1991					
1991	1986				1991 Total
	Water	Wetland	Vegetation	Built-up	
Water	296.7	15.0	30.0	6.4	348.2
Wetland	15.6	12.9	55.6	7.7	91.8
Vegetated	12.1	6.2	1107.6	37.7	1163.6
Built-up	2.7	0.9	78.4	125.3	207.3
1986 Total	327.1	35.0	1271.6	177.1	1810.9
(b)1991-1995					
1995	1991				1995 Total
	Water	Wetland	Vegetation	Built-up	
Water	304.8	20.1	19.2	4.0	348.0
Wetland	14.3	15.4	7.6	0.7	37.9
Vegetated	22.8	49.5	1041.0	40.2	1153.5
Built-up	6.3	6.7	95.9	162.5	271.5
1991 Total	348.2	91.8	1163.6	207.3	1810.9
(c)1995-2002					
2002	1995				2002 Total
	Water	Wetland	Vegetation	Built-up	
Water	268.8	9.9	55.5	3.4	337.6
Wetland	56.6	19.1	79.1	5.6	160.4
Vegetated	9.3	5.6	822.4	31.0	868.3
Built-up	13.2	3.4	196.5	231.5	444.5
1995 Total	348.0	37.9	1153.5	271.5	1810.9
(d)2002-2008					
2008	2002				2008 Total
	Water	Wetland	Vegetation	Built-up	
Water	264.6	48.4	20.8	7.2	341.1
Wetland	20.8	52.4	70.6	13.6	157.5
Vegetated	28.4	35.2	568.8	122.7	755.1
Built-up	23.8	24.4	208.0	301.0	557.2
2002 Total	337.6	160.4	868.3	444.5	1810.9
(e)1986-2008					
2008	1986				2008 Total
	Water	Wetland	Vegetation	Built-up	
Water	242.0	10.4	82.8	5.9	341.1
Wetland	28.4	11.6	107.7	9.7	157.5
Vegetated	32.6	7.6	671.6	43.3	755.1
Built-up	24.1	5.4	409.5	118.1	557.2
1986 Total	327.1	35.0	1271.6	177.1	1810.9

The results indicate that increase in built-up area mainly came from conversion of vegetated land. Of the 380 sq. km of total growth in built-up area from 1986 to 2008, 96.4% was converted from vegetated land.

Table 4.5(d) shows that 208 sq. km of vegetated land converted to built-up area from 2002 to 2008 and 122.7 sq. km of built-up area converted to vegetated land at the same time. These changes may seem to be the result of classification errors. In fact, this was partially the result of restoration of inefficiently-used or abandoned industrial land and rural residential land in Suzhou. Since 2003 the central government of China has implemented many policies to revoke and restore underused economic development zones, a major form of built-up land in industrialized Chinese cities. On the other hand, when urban tree canopies along the streets grow and expand, the associated pixels might be classified as forest while in reality, streets should be classified as built-up area (Yuan et al., 2005).

4.4.2.3 Driving forces of LULC change

Major driving forces of LULC change in Suzhou are a combination of economic reform, industrialization, and urbanization. Since the economic reform in 1978, China has gradually transformed to a market-oriented economy. From 1978 to the early 1990s, the economic development in Suzhou was characterized by the Sunan Model of rural industrialization and urbanization, in which township and village enterprises (TVEs) dominated the industrial sector (Wei, 2002). This bottom-up rural urbanization was characteristic of spontaneous growth of town and town economy and was slight and stable due to the small-scale of most TVEs (Cui & Ma, 1999; Ma & Fan, 1994). Therefore, from 1986 to 1991, LULC change in Suzhou was moderate, and most urban growth took place in towns and townships away from the city center. Since the early-1990s, Suzhou has gradually moved beyond the traditional Sunan Model through globalization and emerged as a hot manufacturing center and a major foreign direct investment (FDI) destination in China (Wei, Lu, & Chen, 2009). This city-based industrialization and urbanization created a rising demand for built-up land, mostly satisfied by converting agricultural land. As a result, LULC change in Suzhou began to accelerate from the mid-1990s, especially the increase of built-up land. Since then, urban expansion has been mainly stimulated by the FDI-driven industrialization. Foreign investment oriented economic development zones expanded rapidly and accounted for most of the new built-up area in Suzhou.

4.5 Discussion and Conclusion

This chapter demonstrates that the random forest method is able to effectively classify multitemporal Landsat TM imagery and analyze LULC change in a rapidly industrialized and urbanized landscape. As a relatively novel method, RF is easy to be implemented and fast in computation. In addition to spectral data, we incorporated spatial data such as elevation in the RF classification, although it was not ranked high in term of variable importance. Other spatial data such as slope, aspect, and texture features may be incorporated in future studies. Classification accuracy was high for the 2008 image, but could not be assessed for the other 4 years because of no reference data.

Using multitemporal Landsat TM images, this chapter identified and quantified LULC change in Suzhou for 1986, 1991, 1995, 2002, and 2008. Among the four land over classes, built-up and wetland increased substantially while vegetated land decreased dramatically and water was relatively stable. Change matrices confirmed that the majority of new built-up area came from the conversion of vegetated land. Spatiotemporal analysis indicated that urban expansion had accelerated since the mid-1990s in Suzhou. Relating to the transitions that Suzhou experienced in recent decades, we identified that China's economic reform, industrialization, and urbanization were the major driving forces of the LULC change.

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CHAPTER 5

SPATIOTEMPORAL DYNAMICS AND SPATIAL DETERMINANTS OF URBAN GROWTH IN SUZHOU, CHINA

5.1 Introduction

Since the economic reform and open-door policy launched in 1978, China has experienced unprecedented urbanization. Tremendous land use change and urban land expansion have taken place in many Chinese cities and regions (Long, Tang, Li, & Heilig, 2007; Seto, Woodcock, Song, Huang, & Kaufmann, 2002; Yeh & Li, 1999). At the end of 2011, for the first time in the history of China, more Chinese people lived in cities and towns than in the countryside (Page, Davis, & Areddy, 2012). However, the rapid urbanization in China is also accompanied by arable land loss, landscape fragmentation, and sustainability challenges (Wei, 2007; Xie, Yu, Bai, & Xing, 2006; Yeh & Li, 1999). Many efforts have been made to analyze the complex pattern of urban land expansion and understand the underlying factors (Cheng & Masser, 2003; Liao & Wei, 2014; Luo & Wei, 2009).

Urban growth in Chinese cities has been studied from many perspectives. Scholars have managed to understand the driving forces of urban land expansion in China from institutional and political economy perspectives (Deng & Huang, 2003; Lin & Ho, 2005; Lin & Wei, 2002; Wei, 2012, 2015). They find that urban growth in China is driven by economic reform and globalization and led by the state and transnational corporations. With the advances in spatial modeling, GIS, and remote sensing, various models have been developed to analyze urban growth patterns in Chinese cities. Among them, neural-network-based cellular automata models and agent-based models are usually used to predict/simulate land use change scenarios (Li & Yeah, 2000, 2002; Xie et al., 2007). Nevertheless, these models are often inadequate to incorporate socioeconomic factors and institutional analysis to explain underlying mechanism and diverse patterns of urban growth.

Most previous urban expansion models tend to reveal urban growth patterns from a global view, which assume the influence of various factors can be applied uniformly throughout the whole study area without consideration for spatial variation. However, urban growth is in fact a nonstationary process over space. The importance of spatial heterogeneity in the rules of landscape change should not be overlooked (McDonald & Urban, 2006). A few recent studies have taken account of the spatial nonstationary relationship between urban growth and explanatory factors and address this issue by using spatially explicit models such as geographical weighted regression (GWR) and spatial expansion method (Liao & Wei, 2014; Luo & Wei, 2009; Luo, Yu, & Xin, 2008).

Through a case study of Suzhou City in the Yangtze River Delta, this chapter aims to achieve the following research objectives. First, this study aims to examine the spatiotemporal dynamics of urban growth in Suzhou by using spatial analysis, GIS, and landscape metrics and incorporating institutional analysis. Second, by employing the logistic GWR model, this study investigates the spatially varying relationship between urban land conversion and underlying variables. Third, the case of Suzhou, a second-tier city different from the largest national centers, can help improve the understanding of diverse patterns and determinants of urban growth in China.

5.2 Data and Methodology

5.2.1 Study Area and Data

5.2.1.1 Study area

Suzhou has a history of more than 2500 years. It is one of the ancient capitals and historical cities of China. Suzhou is located in southern Jiangsu Province (Sunan) of East China (Figure 5.1). The city is situated on the eastern shore of Taihu Lake and the lower reaches of the Yangtze River Delta. Suzhou is well known for its beautiful scenery, especially its classic gardens, waters, and bridges, and dubbed as Venice of the East. It is crisscrossed with numerous rivers, canals, and lakes. The average elevation of Suzhou is only about 4 meters, but there are low mountains distributed in the west of the city. Suzhou has a long history of agricultural development with its advantages in water, climate, and soil, and was once a major rice production base.

Suzhou had been the economic and cultural core of the Yangtze River Delta since the Song Dynasty. It was the national center of manufacture and commerce in the Ming and Qing Dynasty (Wei, Lu, & Chen, 2009). However, in the mid-19th century, Suzhou began to stagnate because of the penetration of colonial forces and the devastating Taiping Rebellion. Its status was gradually replaced by the booming port-city Shanghai. Since the economic reform in 1978, Suzhou has experienced rapid economic development, boosting its GDP to 670 billion yuan in 2008 and ranked the fifth in the nation. During the 1980s, local state-directed township and village enterprises (TVEs) blossomed in *Sunan* and created a successful pathway of development known as the Sunan Model (Wei, 2002). In the early 1990s, Suzhou began to learn from the

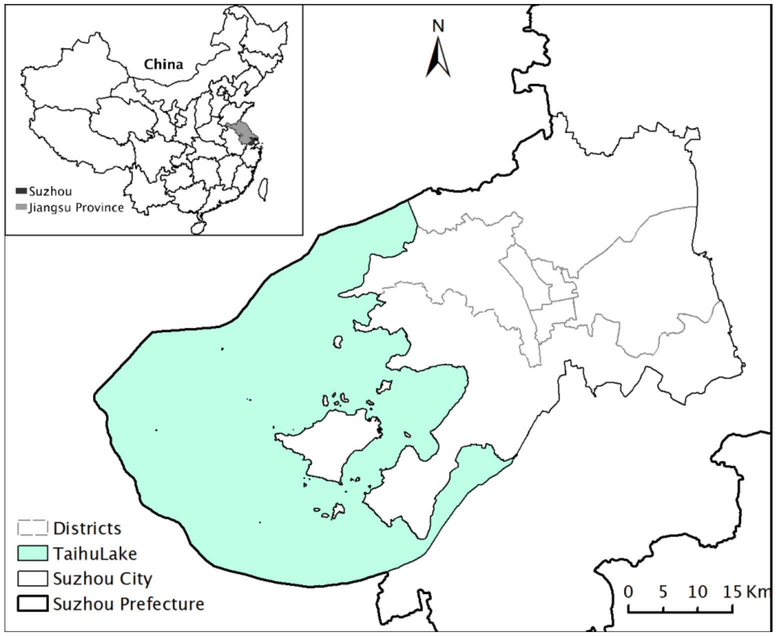

Figure 5.1 Location and administrative division of Suzhou City

experiences of successful development zones and their strategies of attracting foreign direct investment (FDI). Since the mid-1990s, Suzhou has moved away from the orthodox Sunan Model towards globalization and emerged as a hot manufacturing center and a major FDI destination in China (Wei et al., 2009).

Suzhou City is the prefectural seat of Suzhou Prefecture, which also includes five other county-level cities. The administrative division of this prefecture has been changing since the 1980s, and Suzhou City has been annexing land from neighboring cities. To maintain the consistency for analysis, we use the administrative division of Suzhou City in 2008, when it consisted of seven districts (Figure 5.1). At the end of 2010, this city covered an area of 1810 sq. km with a population of 4 million.

5.2.1.2 Data

Satellite remote sensing data can provide accurate and timely geospatial information for monitoring land use change patterns. We used five Landsat Thematic Mapper(TM) images (Path 119/ Row 38) from 1986, 1991, 1995, 2002, and 2008 for this research. These images were all downloaded from the website of USGS (U.S. Geological Survey, http://earthexplorer.usgs.gov/). We also used other spatial data such as digital elevation model (DEM), GIS files of the transportation network (2006) and administrative divisions (2008), and socioeconomic data from statistical yearbooks (1991-2009). These data were provided by Nanjing Institute of Geography and Limnology, Suzhou Statistic Bureau, and Suzhou Planning Bureau.

5.2.2 Methods

5.2.2.1 Land use data sampling

Land use data employed in this study were derived from the five Landsat TM images (30m x 30m resolution). The software package ENVI version 4.8 (Exelis Visual Information Solutions, Boulder, Colorado) and the public domain software R (R Foundation for Statistical Computing, Vienna, Austria) were used for image processing and land use classification. Specifically, we used a machine learning algorithm random forest, developed by Breiman (2001) and implemented in R by Liaw and Wiener (2002), to “train” the computer system to do supervised classification. Accuracy assessment indicated that the overall classification accuracies for the images were about 80 %. Four types of land use were classified: water, wetland, vegetated, and built-up. In this study, urban land is defined in a broad sense as the built-up area in the classified images.

To extract the nonurban to urban land use conversion area, a spatial overlay operation was performed between two classified images in 1991 and 2008. The image for urban land expansion has 2318 x 2059 pixels, a huge dataset that is very difficult to handle, and a proper sampling method is required. To reduce the spatial dependence and ensure the sample representing the population, we used a spatial sampling method combining systematical sampling and random sampling (Liu, Yue, & Fan, 2011; Luo & Wei, 2009). First, we extracted regularly spaced points with a 10-pixel (300 m) interval from the nonurban areas in the 1991 image. Then, from this result, we extracted all 2409 points with nonurban to urban land use conversion. Lastly, we randomly selected another 2409 points from those without urban land conversion and got a total of 4818 sample points. Such a sample size well represents the population and can be handled by most statistical software.

5.2.2.2 Selection of landscape metrics

Originally developed in the study of landscape ecology, landscape metrics have been recently applied to urban morphology (Herold, Scepan, & Clarke, 2002; Seto & Fragkias, 2005). Landscape metrics can be defined at the patch, class (patch type), and landscape level. A variety of landscape metrics have been developed to describe the proportion of landscape with a particular land cover class, the size, number, perimeter, and the complexity of shape of the patch in that class (McGarigal, Cushman, Neel, & Ene, 2002). Many empirical studies have employed these indices to assess the fragmentation of urban land use (Luck & Wu, 2002; Yue, Liu, & Fan, 2010). In this study, we selected the following landscape metrics, defined at the class level, to analyze the overall changes in urban land pattern: number of patches (NP), largest patch index (LPI), edge density (ED), mean patch size (MPS), area-weighted mean patch fractal dimension (AWMPFD), and area-weighted mean Euclidean nearest-neighbor distance (Table 5.1). All the indices were calculated with the public domain software FRAGSTATS version 4.2 (McGarigal et al., 2002).

5.2.2.3 Type of urban growth

For the convenience of implementation, we used a simple equation to distinguish three types of newly developed urban land patches, proposed by C. Xu et al. (2007).

$$S = \frac{Lc}{P} \tag{5.1}$$

where *Lc* is the length of the common boundary of a newly developed urban patch and the pregrowth urban patches, and *P* is the perimeter of the newly grown patch. Urban growth type is defined as infilling when $S \geq 0.5$, edge-expansion when $0 < S < 0.5$, and leapfrog growth when $S=0$, which indicates no common boundary (C. Xu et al., 2007).

5.2.2.4 Sector and concentric circle analyses

Sector and concentric circle analyses were employed to characterize the spatiotemporal dynamics of urban land expansion in Suzhou (Figure 5.2). The sector analysis was used to characterize the quantity and spatial distribution of urban land in terms of angular orientation relative to a predetermined urban center (Xu, Liao, Shen, Zhang, & Mei, 2007). We drew 16 directional axes from the urban center to form 16 sectors (fan-shaped areas), each having an angle of 22.5 degrees. Then we overlaid these fan-shaped sectors with land use data and calculated the area of urban land within each sector. These values were displayed on the corresponding directional axes to show the spatial distribution of urban land in the city. The concentric circle analysis was used for analyzing the relationship between the area of urban growth and the distance from the

Table 5.1 Landscape metrics used in this study

Metrics	Unit	Range	Description
NP	None	NP≥0	NP equals the number of patches of the corresponding patch type (class)
LPI	Percent	0<LPI≤100	LPI equals the area(m^2) of the largest patch of the corresponding patch type divided by total landscape area(m^2, multiplied by 100 (to convert to a percentage)
ED	Meters per hectare	ED≥0	ED equals the sum of the lengths(m) of all edge segments involving the corresponding patch type, divided by the total landscape area (m^2), multiplied by 10,000 (to convert to hectares)
MPS	Hectares	MPS>0	MPS equals the sum of areas(m^2) of all patches of the corresponding patch type, divided by the number of patches of the same type, divided by 10,000 (to convert to hectares)
AWMPFD	None	1<AWMPFD≤2	AWMPFD equals the sum, across all patches of the corresponding patch type, of 2 times the logarithm of 0.25 the times patch perimeter (m) divided by the logarithm of patch area(m^2), multiplied by the patch area (m^2) divided by total class area
AWMENND	Meters	AWMENND≥0	AWMENND equals the sum, across all patches of the corresponding patch type, of the nearest neighbor distance of each patch multiplied by the proportional abundance of the patch (i.e., patch area divided by the sum of patch areas)

Source: McGarigal et al., 2002

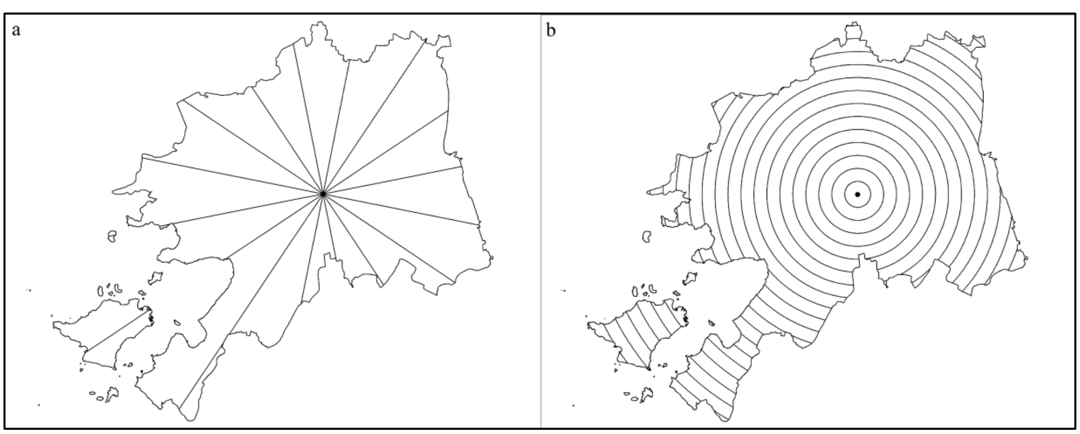

Figure 5.2 Sector and concentric circle analyses

urban center. A total of 15 concentric circles were created, each having a width of 2 km. Then we overlaid these concentric zones with newly grown urban land in each time period and calculated the percentage of urban growth area within each zone.

5.2.2.5 Logistic regression model

The logistic regression model has been widely used to analyze the determinants of urban land conversion. Applying the model to land use change in Guangzhou, Wu (1998) found that road accessibility and socioeconomic factors were the important determinants of urban land development in a transitional economy. Verburg, van Eck, de Nijs, Dijst, and Schot (2004) used this model to analyze land use change in Netherland and found that the expansions of residential, industrial/commercial, and recreational areas could be explained by a combination of accessibility measures, spatial policies, and neighborhood interaction.

In this research, we also adopted the logistic regression model to identify the determinants of urban growth in Suzhou. The dependent variable of the logistic regression was a presence or absence event when Y =1 means a pixel converted from nonurban to urban land and Y= 0 otherwise. P(Y =1) means the probability of nonurban to urban land conversion. The logistic regression model is described as (Liu et al., 2011; Luo & Wei, 2009)

$$\text{logit}\,(Y) = \beta_0 + \sum_{k=1}^{n} \beta_k X_k + \varepsilon \qquad (5.2)$$

where X_k are explanatory variables and logit(Y) is a linear combination function of the explanatory variables; β_0 is the constant; parameter β_k is the regression coefficient of explanatory variable X_k to be estimated. The logit(Y) can be transformed back to the probability that (Y =1)

$$P(\ =1) = \frac{\exp(_0 + \sum^{n}_{=1} \ X)}{1+\exp(_0 + \sum^{n}_{=1} X)} \tag{5.3}$$

5.2.2.6 Specification of dependent and explanatory variables

As mentioned above, the dependent variable was a presence or absence event when Y =1 means a pixel converted from nonurban to urban land and Y= 0 means the pixel remained as nonurban land. Many types of explanatory factors have been identified in land use conversion models, including accessibility to road infrastructure, attributes of neighborhoods of land use site, and spatial policies such as planning restrictions (Liu et al., 2011; Luo & Wei, 2009; Verburg et al., 2004; Wu, 1998). In this study, we used three groups of explanatory variables including proximity to transportation infrastructure, neighborhood physical conditions, and socioeconomic factors.

First, three explanatory variables distance to intercity highways, distance to local arterial roads, and distance to railways can be used to represent the proximity of a sample point to transportation network. To obtain the values of proximity variables for sample points, we used the Euclidean Distance tool in ArcGIS version 10.2.2 (Environmental Systems Research Institute, Redlands, California) to generate a set of distance raster surfaces (30m x 30m cell size) and then extracted variable values for each point from those surfaces.

Land use change is closely dependent on the neighborhood physical conditions (Cheng & Masser, 2003; Verburg et al., 2004). We selected two variables density of waters (water and wetland combined) and density of vegetated area to represent the physical land use conditions in the neighborhood. The neighborhood was defined as a circle of 480-meter radius with the consideration of the effect of distance decay and the practices adopted by other scholars (Cheng & Masser, 2003; Luo & Wei, 2009; Verburg et al., 2004). The neighborhood density variables were calculated using the Zonal Statistics tool in ArcGIS. We also extracted the slope information from a 30m x 30 m digital elevation model (DEM) for sample points to measure their topographical suitability for urban development.

Existing research on urban land conversion tended to emphasize more the accessibility and physical conditions. Scholars have recently recognized socioeconomic factors as important driving forces for urban growth (Seto & Kaufmann, 2003; Wei, 2015). We selected four variables to reflect the influence of socioeconomic factors: distance to the city center, distance to district centers, distance to industrial centers, and the density of built-up area in the neighborhood of a 480-meter radius from the central cell.

Furthermore, we performed a correlation analysis for the explanatory variables mentioned above. The result showed that density of water and density of vegetated area as well as distance to city center and distance to district centers were highly correlated. The land use type vegetated area was general and not specified to subclass such as forest land or agricultural land. Different vegetated land may have different influence on urban land conversion such as constrains (forest land) or availability (agricultural land). Therefore, the variable density of vegetated area was not included in the final model. We also dropped the variable distance to city center because its regression coefficient was not statistically significant if we included it in the model and excluded the variable of distance to district centers. Finally, all the variables used in the land use models are listed in Table 5.2. The spatial distributions of transportation network, important socioeconomic

Table 5.2 Variables used in the urban land use conversion models

Variables	Descriptions
Dependent Variable	
Change	Land conversion from nonurban to urban
Explanatory variables	
Proximity to transportation infrastructure	
Dis2Hwy	Distance to intercity highways
Dis2Lard	Distance to local arterial roads
Dis2Rail	Distance to railways
Neighborhood physical condition	
DenWater	Density of water and wetland
Slope	Slope of sample points measured by degree
Socioeconomic factors	
Dis2Dcen	Distance to district center
Dis2Indu	Distance to industrial center
DenBuilt	Density of built-up area

centers, water, and wetland as well as topographical conditions in Suzhou are shown in Figure 5.3.

5.2.2.7 Geographically weighted logistic regression

Although it is widely used to model urban land conversion, the above classic global logistic regression model may have problems when it is employed to model land use change at the local level. Conventional global statistical analysis of urban land conversion often implicitly assumes that relationships between explanatory variables and land use change are spatially stationary, which is not often tenable (Fotheringham, Brunsdon, & Charlton, 2002; Luo & Wei, 2009).

In addition to the classic logistic regression, this study used Geographically Weighted Regression (GWR) to model urban land expansion. GWR is a local regression technique for investigating the spatial nonstationarity (Fotheringham et al, 2002). It assumes the relationship obtained from conventional global regression model is an

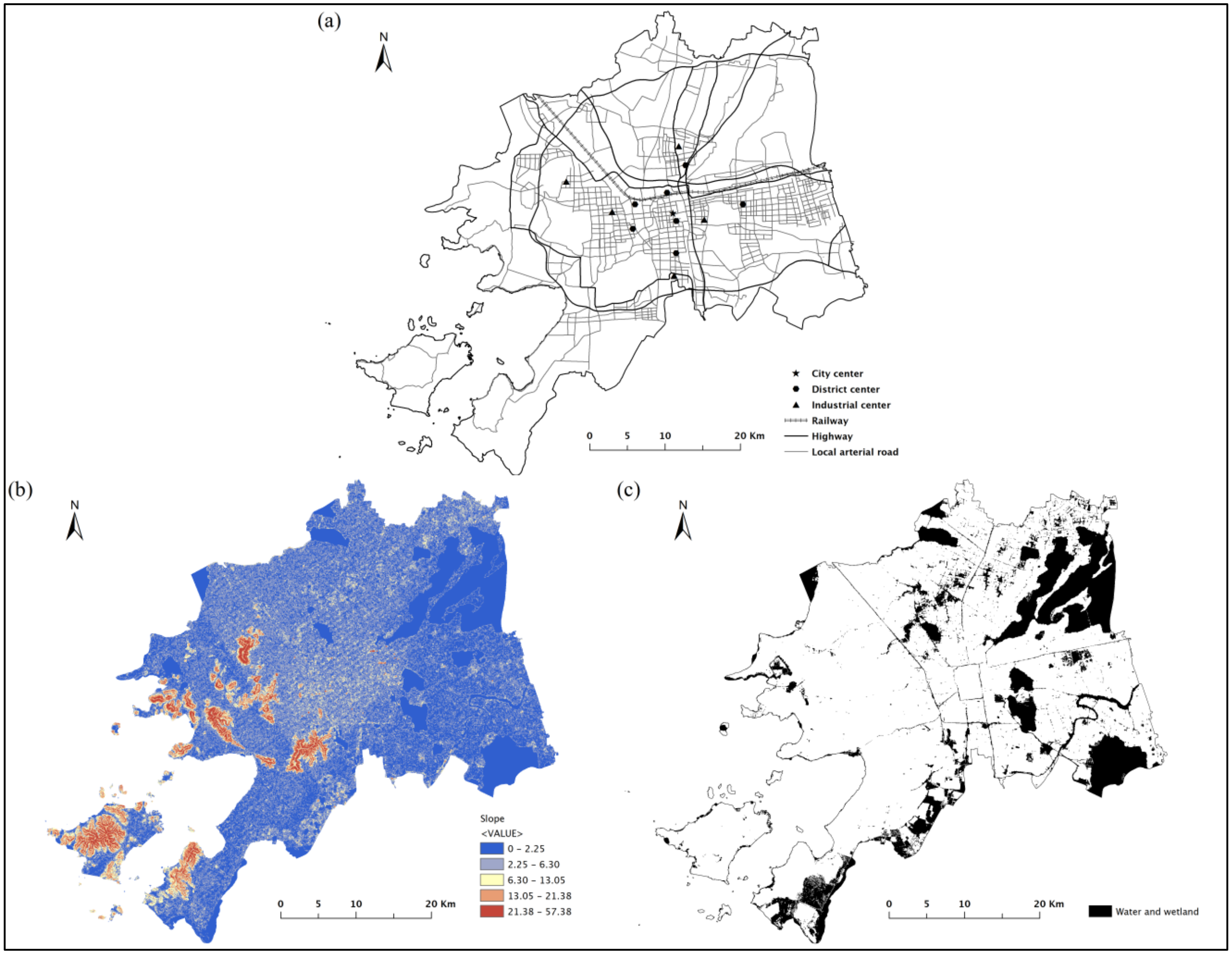

Figure 5.3 Spatial distribution of (a) roads, railways, and centers (b) slope (c) water and wetland in Suzhou city

"average" of varying local spatial process. Using the kernel functions, researchers can create local samples for a particular location from geographically weighting the neighboring data to simulate the local process. Therefore, GWR is suitable for modeling the complex local variation of regression parameters and has been recently used in various studies (Fotheringham, Charlton, & Brunsdon, 2001; Gilbert & Chakraborty, 2011; Luo & Wei, 2009). In its basic form, GWR model takes the following equation (Fotheringham et al., 2002):

$$Y_i = \beta_{0\mathrm{i}} + \sum_{k=1}^{n} \beta_{ki} X_{ki} + \varepsilon_i \tag{5.4}$$

where β_{0i} is the constant parameter specific to location i; β_{ki} is the parameter of explanatory variable X_k at location i. Based on Equations (2)-(3), (4) can be modified to the following forms, which represent the logistic GWR:

$$\mathrm{P}(Y \ =1) = \frac{\exp\left(\beta_{0i} + \sum_{k=1}^{n} \beta_{ki} X_{ki}\right)}{1+\exp\left(\beta_{0i} + \sum_{k=1}^{n} \beta_{ki} X_{ki}\right)} \tag{5.5}$$

GWR estimates the parameters for each observation at location i using a local sample generated through a nonparametric kernel weighting scheme to data at other locations according to their spatial proximity to location i (Fotheringham et al., 2002). Nearer locations get higher weights and farther ones get lower weights. Two types of kernel functions are usually used to obtain weights fixed kernel and adaptive kernel. The fixed kernel function is less computing-intensive but it may produce large local estimate variance in areas where data are sparse and mask subtle variations in areas where data are dense (Fotheringham et al., 2002). In our study, we used the adaptive kernel function, which can ensure a certain number of nearest neighbors as local samples and better represent the degree of spatial heterogeneity. This adaptive kernel function was based on a bi-square distance decay function as follows (Fotheringham et al., 2002; Luo & Wei, 2009):

$$w_{ij} = \left[1 - \left(\frac{d_{ij}}{b}\right)^2\right]^2 \quad \text{if} \quad j \in \{N \text{ nearest neighbor points}\}$$

$$d_{ij} \text{ is the distance from } j \text{ to } i \qquad (5.6)$$

$$b \text{ is the distance from the } N\text{th nearest neighbor to } i$$

$$= 0 \text{ otherwise}$$

We used the software package GWR4 (Nakaya, 2014) to calibrate the logistic GWR for urban land conversion in Suzhou, in which the number of nearest neighbor points, 648, was chosen by minimizing the corrected Akaike Information Criterion (Fotheringham et al., 2002).

5.3 Spatiotemporal Dynamics of Urban Growth

5.3.1 Changes in Landscape Characteristics

During the period from 1986 to 2008, the urban land increased rapidly and continuously in Suzhou city. In 1986, the built-up area was 168.84 sq. km (9.32% of the study area) while in 2008, the area expanded to 552.47 sq. km (30.85% of the study area), representing an increase of 327%. The average annual growth rate also increased greatly, which were 15.99, 26.66, 30.21, and 42.45sq.km/ year for the four periods of 1986-1991, 1991-1995, 1995-2002, and 2002-2008, respectively, which indicated that urbanization in Suzhou had been accelerated over the past 22 years.

The changes in selected landscape metrics are illustrated in Figure 5.4. The number of urban patches (NP) was 8016 in 1986; it decreased to 6263 in 1991 but increased to 6373 in 1995 and then decreased again to 5869 in 2002 and 5540 in 2008. The largest patch index (LPI) continuously increased from 2.21% in 1986 to 18.98% in

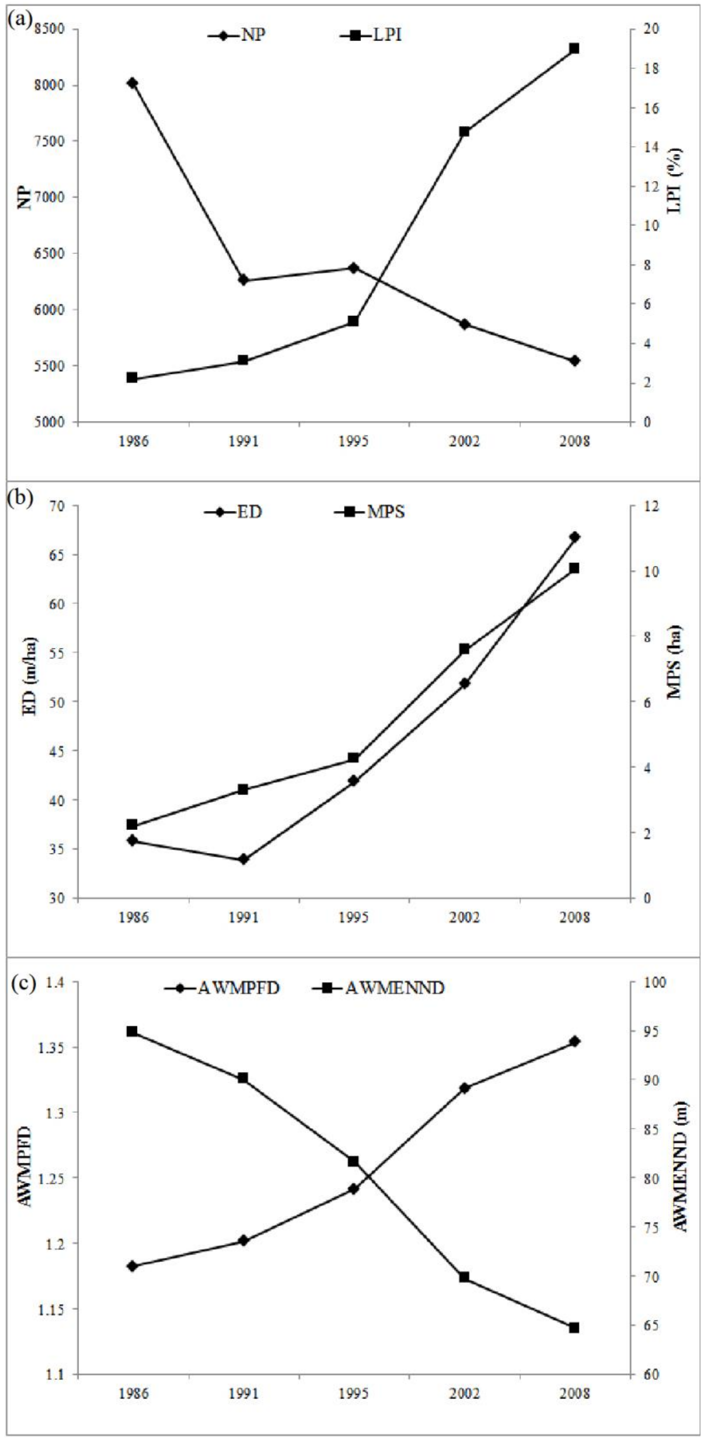

Figure 5.4 Changes in the landscape metrics during the period of 1986-2008: (a) number of patches (NP) and largest patch index (LPI) (b) edge density (ED) and mean patch size (MPS) (c) area-weighted mean patch fractal dimension (AWMPFD) and area-weighted mean Euclidean nearest-neighbor distance (AWMENND)

2008, indicating that the main urban patch (corresponding to the urban core) became more dominant in the landscape. The edge density (ED) and the mean patch size (MPS) both had an ascending tendency despite a slight descending of ED in 1991, which indicates that the average length and size of the urban patch type had increased. At the same time, the area-weighted mean patch fractal dimension (AWMPFD) also showed an upward tendency, indicating an increase in the urban patch shape complexity. The area-weighted mean Euclidean nearest-neighbor distance (AWMENND) continuously decreased from 95 meters in 1986 to 65 meters in 2008, which indicates urban patches became closer to each other. The changes in these landscape metrics suggested that many urban patches might have joined each other as they expanded in the process of urbanization. Therefore, their total number decreased and their average length and size increased.

5.3.2 Typology of Urban Growth

Three urban growth types were identified and the contribution of each type in the growth area was shown in Figure 5.5a. Obviously, the edge-expansion was the primary growth type throughout the 22-year period. In the first period (1986-1991), the infill growth accounted for 10.86% of total newly developed urban land while the edge-expansion growth took up 73.07% and the leapfrog type 16.07%. From 1991 to 2002, the percentage of the infill growth decreased to 5.15% and that of the leapfrog growth decreased to 7.14%. In contrast, the edged-expansion type increased to 87.70%. In the last period (2002-2008), the infill growth decreased to a negligible portion of 1% and the leapfrog type slightly higher than 5% while the edged-expansion type clearly dominated the new urban area with a percentage of 93.24%.

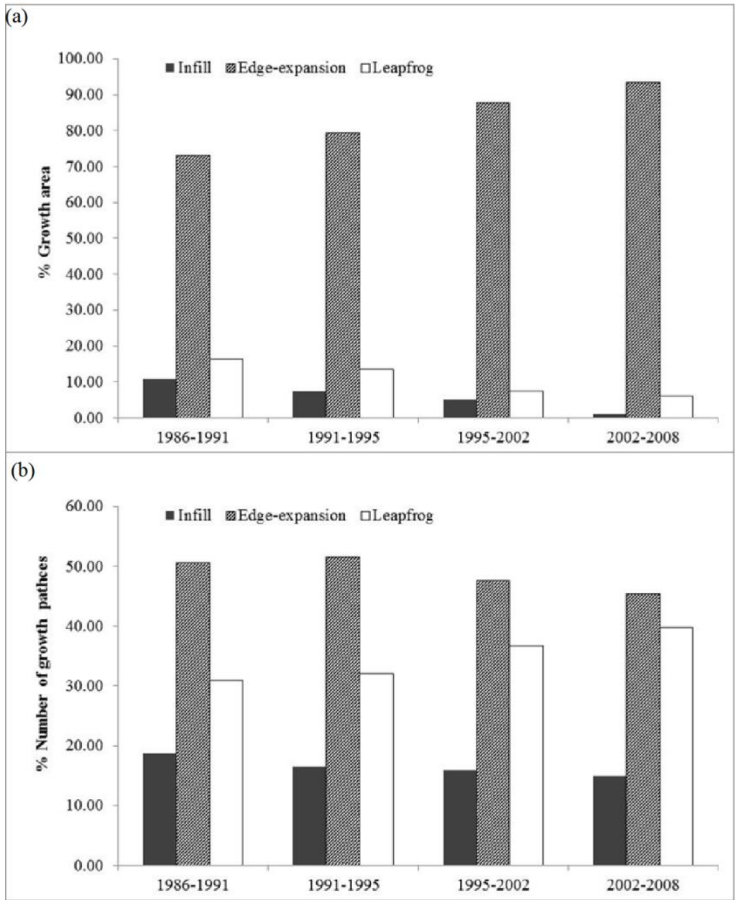

Figure 5.5 The proportion of (a) growth area and (b) patch number of the three urban land growth types in different periods

NP portion of the three growth types exhibited a different trend in the temporal pattern (Figure 5.5b). The edge-expansion growth had the largest percentage in patch number with a slight decrease from 50.46% in the first period to 45.31% in the last period. The infill type also decreased from 18.70% to 15.03% whereas the leapfrog growth gradually increased from 30.85% to 39.66%. Throughout the 22-year period, edge-expansion always had the largest portion, the leapfrog the second largest, and the infill the smallest one.

During the early stage of urban land expansion in Suzhou, there were gaps between those pregrowth urban patches; the leapfrog growth urban patches were isolated from the dominant urban core. As the urbanization process proceeded in Suzhou, those gaps were gradually filled by infilling growth patches, which also connected some of the pre-growth urban patches. At the same time, with the continuous edge-expansion the urban core expanded outwards and gradually approached and eventually joined those formerly isolated leapfrog urban patches.

5.3.3 Changing Urban Growth Patterns

Based on results from land use classification (Figure 5.6), the sector analysis (Figure 5.7), and concentric circle analysis (Figure 5.8), we can analyze the changing urban growth patterns in different periods in detail. During the first period (1986-1991), urban land increased almost at the same rate along the 16 directional axes; urban growth concentrated around the pregrowth urban core (the old city district); a few new built-up patches developed at some towns and townships away from the city center. The curve depicting percentage of new urban area by distance to city center had multiple peaks, which reflected hot-zones of urban growth in this period (Figure 5.8). The first peak occurred at the distance of 4-6 km with the single largest percentage of growth area. This corresponded to the new urban land developed around the urban core. At the distance of 10-20 km, there was the largest concentration (almost half) of growth area, which reflected the new built-up area in those towns and townships.

From 1991 to 1995, urban growth rate showed great variation along different directions. The highest growth rates took place along the E, SWW, NWW and NW directions (Figure 5.7). The land use classification image (Figure 5.6) also reflected this pattern. The development of the China-Singapore Suzhou Industrial Park (SIP) to the east

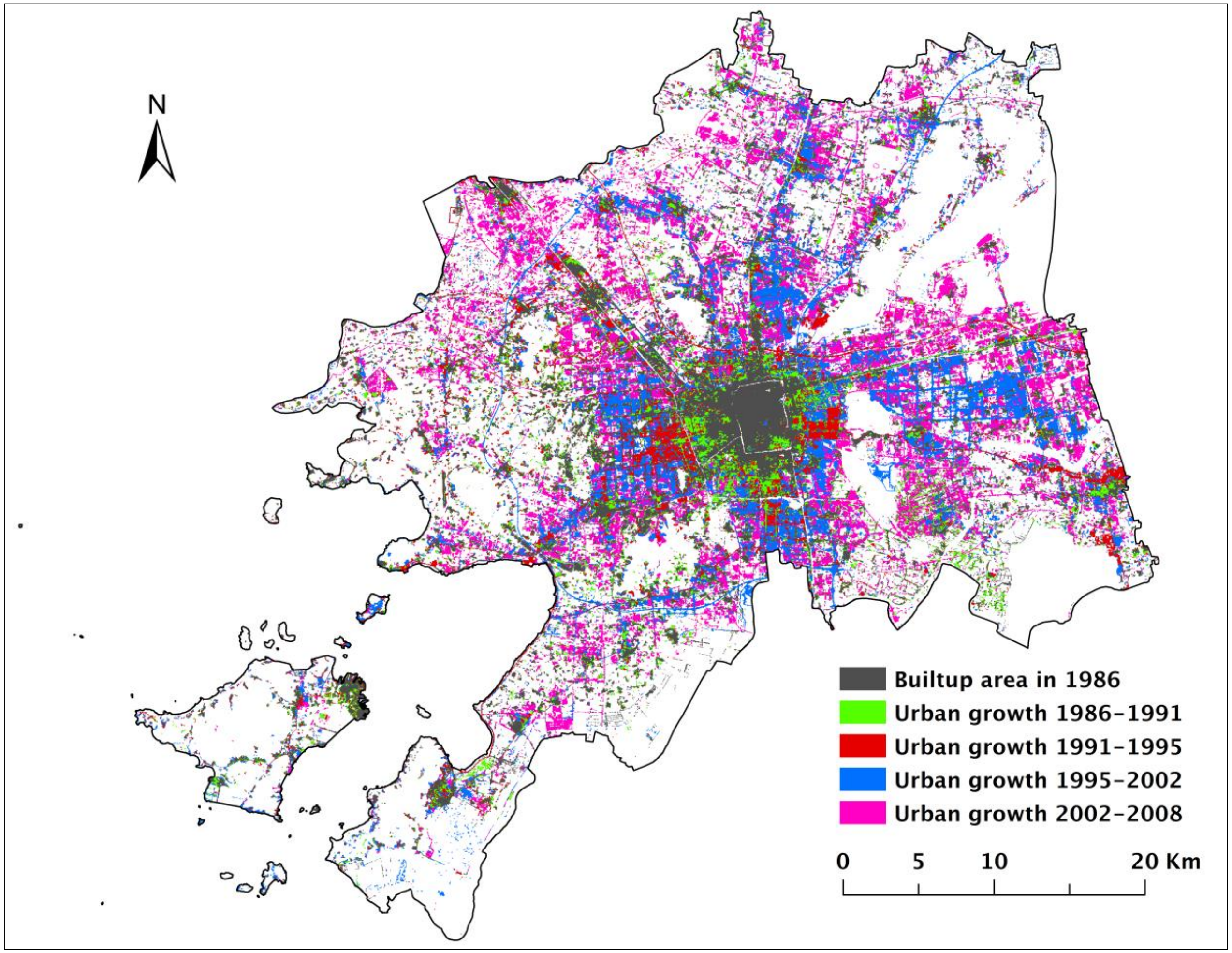

Figure 5.6 Urban growth in Suzhou City in four time periods

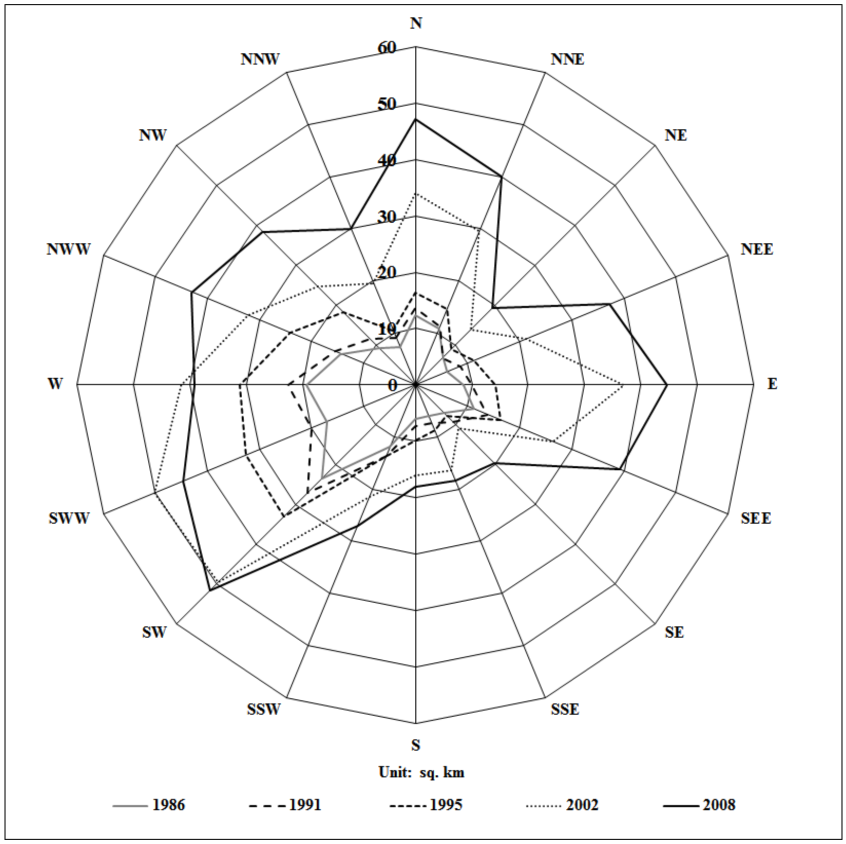

Figure 5.7 Spatial orientation of urban land expansion in Suzhou, 1986-2008

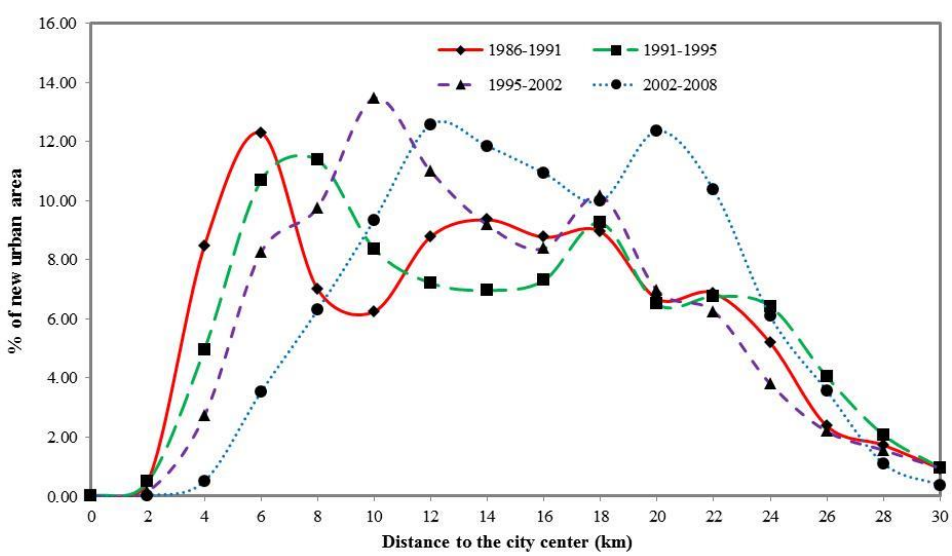

Figure 5.8 Percentage of new urban area by distance to city center, 1986-2008

of the old city district and the Suzhou New & High-Tech District (SND) to the west significantly expanded the urban core. The first peak with the largest percentage of growth area, which represented the urban fringe, outward moved to the distance of 6-8 km (Figure 5.8).

During the third period (1995-2002), the highest growth rates occurred along the N, NNE, E, SWW, SSE, and NNW directions (Figure 5.7). This reflected the rapid expansion of Xiangcheng Economic Development Zone, SIP, Chengyang Science and Technology Park, SND, and Xushuguan Economic Development Zone. Urban growth was obviously development-zone-oriented in this period. The construction of transportation infrastructure (highways and local arterial roads), which aimed to improve the accessibility of adjacent development zones, was clearly reflected in the classification image (Figure 5.6). The urban fringe further moved to the distance of 8-10 km (Figure 5.8).

From 2002 to 2008, the largest newly developed urban areas took place along the NEE and NW directions, which were closely related to further development of SIP and establishment of the Caohu Science and Technology Park. The urban fringe had moved to the distance of 10-12 km by 2008 (Figure 5.8). Percentages of new urban area at the zones within the distance of 10 km from the city center were much lower than those of previous period. Urban growth mostly occurred at the distance of 12-24 km, within which percentages of growth area were the highest among the four periods. Compared with previous three periods, urban expansion took place at more distant locations, especially at the concentric zones of 20-24 km distance. We noticed that built-up area decreased along the SWW and W directions during this period. This was partially the result of restoration of inefficiently used or abandoned industrial (manufacturing and mining) and rural residential land in this area (Chen, 2014).

5.3.4 Economic Transition and Urban Growth

Changing urban growth patterns from 1986 to 2008 in Suzhou were actually the result of economic transition during the past 3 decades. Urban growth changed from bottom-up rural urbanization to top-down urban expansion. The underlying mechanism for urbanization changed from TVEs-driven rural industrialization to FDI-driven development zone fever.

5.3.4.1 From bottom-up rural urbanization to top-down urban expansion

Suzhou is located in the heart of Sunan region, where the orthodox Sunan model attributed the early development (from 1978 to the early 1990s) of Sunan to the local state-directed TVEs (Wei, 2002). During this period, economic growth and urbanization mainly took place in the rural areas. Rural-dominated urbanization dispersed all over the countryside of Sunan region because rural industry was widely dispersed into small towns and villages (Ho & Lin, 2004). The growth of towns and townships created a new track of “urbanization from below” whose process and control mechanisms totally differed from those of the city-based track of “urbanization from above” (Cui & Ma, 1999; Ma & Fan, 1994). This bottom-up rural urbanization was characteristic of unplanned, spontaneous growth of town and town economy without significant investment from the central government (Ma & Fan, 1994). This type of urbanization was slight and stable due to the small-scale of most TVEs. Therefore, from 1986 to 1991, urban land increased modestly in Suzhou and almost half of the growth area took place in those towns and townships away from the city center.

Since the early-1990s, the combined effect of the influx of FDI and government support to urban economies had created a more competitive market where TVEs gradually lost their advantages. Suzhou gradually moved beyond the traditional Sunan Model through globalization and emerged as a hot manufacturing center and a major FDI destination in China (Wei, 2002; Wei et al., 2009). This top-down urban expansion created a rising demand for industrial land, which was mostly satisfied by converting agricultural land. The establishment of SND in 1992 and SIP in 1994 manifested the significant investment from above (the central government) and from outside (Singapore), which also modified the urbanization process from rural-dominated to city-based.

5.3.4.2 From TVE-driven urbanization to FDI driven development zone fever

The bottom-up rural urbanization was mainly driven by TVES. From 1978 to the early 1990s, TVEs dominated the economic and industrial structure of Suzhou. The widely dispersed rural industry could absorb rural surplus labors into TVEs, which allowed people to leave the field without leaving the village (*litu bu lixiang*). However, TVEs began to experience the slowdown in the early 1990s because of unclear property rights and inefficient management. While TVEs underwent restructuring and privatization, a large amount of foreign investment infused into the Suzhou shortly after the development of Pudong New Area in Shanghai in 1992. The 2000s witnessed an unprecedented increase of FDI in Suzhou (Figure 5.9). Many of the Fortune Global 500 Companies such as Siemens, Samsung, Fujitsu, and Philips have invested in Suzhou.

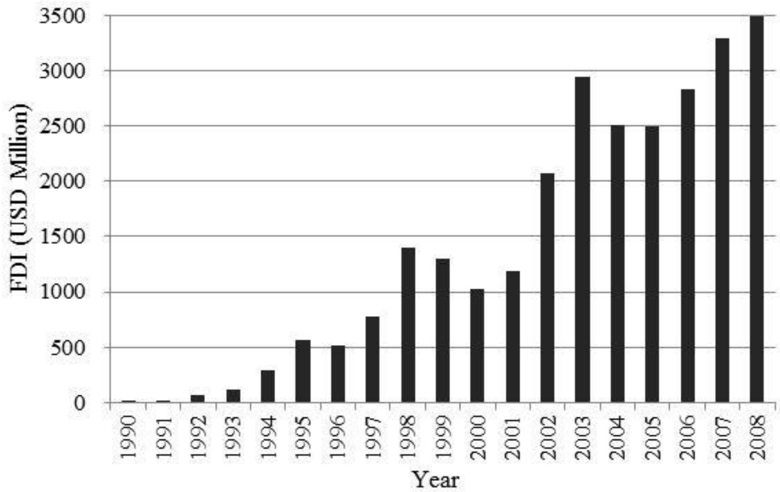

Figure 5.9 Actualized FDI in Suzhou City, 1990-2008

Since the mid-1990s, urban land expansion in Suzhou has been mainly stimulated by FDI-driven industrialization. Foreign investment oriented development zones expanded rapidly and accounted for most of the new urban area (Table 5.3). In addition to major national and provincial development zones, some town-level governments also entered the race for foreign capital by setting up their own development zones (so-called “one town, one zone”). In order to attract FDI to stimulate the local economy, almost every town planned its own industrial estate and preferential policies, one of which is the low-cost land use. As a result, a development zone fever emerged in the late 1990s (Cartier, 2000; Wei, 2015; Yang & Wang, 2008).

This tide of zone development without any rational plan swept coastal China and caused a dramatic urban land expansion. Lack of scientific plans for industrial development resulted in insufficient use of development zones and a waste of valuable agricultural land. In the summer of 2003, the central government released two decrees, stopped approving any new development zones, and urged local governments to clean up the existing zones (Deng & Huang, 2004). As a result, many unofficially approved

Table 5.3 Major development zones in Suzhou

Development Zones	Division	Year of Establishment	Level	Planned Area (sq. km.)
Suzhou New & Hi-Tech District		1992	National	52
	SND Export Processing Zone	2003		2.7
	Suzhou State Environmental Protection Hi-Tech Industrial Park	2003		0.4
	SND Bonded Logistics Center	2004		0.7
	Suzhou Science & Technology Town	2006		25
Suzhou Industrial Park		1994	National	80
Xushuguan Economic Development Zone		1992	Provincial	26
Wuzhong Economic Development Zone		1993	Provincial	
	Hedong New & High-Tech Industrial Park	2001		8
	Dongwu Industrial Park	2002		8
	Wangshan High-Tech Industrial Park	2002		14
	Suzhou Wuzhong Science & Technology Park	2004		3
	Jiangsu Wuzhong Export Processing Zone	2005		3
	Wusongjiang Science & Technology Park	2010		12
Xiangcheng Economic Development Zone		2002	Provincial	
	Chengyang Industrial Park	2002		12
	Caohu Industrial Park	2006		33

development zones were revoked and restored into agricultural use. This might partially explain the decrease of built-up area along SWW and W directions from 2002 to 2008.

5.4 Spatial Determinants of Urban Growth

5.4.1 Global Logistic Regression Model

As analyzed in the previous section, economic transition in Suzhou took place in the early 1990s. In addition, the administrative division and transportation network mostly formed in the 1990s. Therefore, we chose the year of 1991 as the starting year for the land conversion model. The results of the global logistic regression model are presented in Table 5.4. The percentage correctly predicted is 76.6%, which indicates

Table 5.4 Global logistic regression model results for urban land conversion

Explanatory variables	Coef.	Std. Err.	z value	Pr(>|z|)
Dis2Hwy	0.046	0.014	3.366	0.001
Dis2Lard	-0.873	0.079	-11.106	0.000
Dis2Rail	-0.048	0.008	-6.153	0.000
DenWater	-2.362	0.166	-14.215	0.000
Slope	-0.106	0.012	-8.762	0.000
DisDcen	-0.098	0.011	-8.997	0.000
Dis2Indu	0.021	0.011	1.911	0.056
DenBuilt	3.379	0.465	7.265	0.000
Constant	2.223	0.106	21.056	0.000
Sample size	4818			
-2 Log Likelihood	4645.499			
PCP[a]	76.6			

PCP[a]: percentage correctly predicted with cut-value 0.5.

moderate prediction accuracy. The explanatory variables are all significant: Dis2Indu at the 0.1 level and all the other variables at the 0.01 level.

Among the three proximity variables, distance to local arterial roads (Dis2Lard) had the strongest negative effect on land conversion, and distance to railways (Dis2Rail) had the second strongest. Contrary to our expectations, distance to highways (Dis2Hwy) had a minor positive effect. The significance of local arterial roads in land use conversion is similar to the findings of Cheng and Masser (2003) and Luo and Wei (2009). The findings suggest that urban growth in Suzhou was largely dependent on transportation infrastructure development and that local roads were a more important determinant.

The two variables representing neighborhood physical conditions, density of water (DenWater) and slope (Slope), both had negative effect on urban land conversion. This indicates that urban expansion is generally constrained by water density and topographical condition. Density of waters (DenWater) actually had the strongest negative effect among all variables. This was probably because major water bodies and wetland were highly protected in Suzhou. Among the socioeconomic variables, only distance to district center (DisDcen) had a negative effect on urban land conversion. Distance to industrial centers (Dis2Indu) had a positive effect on urban growth, which indicates that urban development was not dependent on existing industrial centers in Suzhou. Density of built-up area (DenBuilt) in the neighborhood had the strongest positive effect among all variables. It played a significant promotional role for urban land conversion.

Our global logistic regression model can explain the determinants of urban land conversion in Suzhou. However, the potential spatial nonstationarity of urban growth is still unknown. We further use logistic GWR for the detection of spatial nonstationarity, as it allows the regression parameters to vary across space and can therefore expose local spatial variations of urban growth patterns in Suzhou.

5.4.2 Spatial Variations of Urban Growth Patterns

We applied the geographically weighted logistic regression to the same dataset of 4818 sample points. Table 5.5 represents a comparison between the global logistic model and the logistic GWR model. The logistic GWR model shows a clear improvement over the global logistic model. First, the decreases of -2 Log likelihood, residual sum of squares and AICc, and the increase of Pseudo R squared indicate that the GWR model has a much better goodness-of- fit than the global model. Second, the increases of PCP and ROC suggest that the logistic GWR model has higher prediction accuracy. Third, the GWR model has remarkably reduced the spatial dependence of residuals, which can be measured by the decrease of Moran's *I* of residuals.

Table 5.5 Comparison between global logistic regression and logistic GWR

	Global logistic model	Logistic GWR
-2 Log Likelihood	4645.499	3942.417
PCP	76.6	80.2
Pseudo R squared	0.3045	0.4097
Residual sum of squares	763.9226	643.9371
Moran's *I* of residuals	0.0731	0.0197
ROC	0.847	0.890
AICc	4663.5371	4196.4052

Different from the global logistic model, the values of parameter estimates of logistic GWR model show significant variations. Table 5.6 represents the summary statistics of the GWR parameter estimates for the sample points. All the variables have both positive and negative parameter values although they have variations in the portions of both values. The parameter values of Dis2Hwy, Dis2Rail, slope, Dis2Dcen, and Dis2Indu have clear division of positive and negative results. Such significant spatial variations are ignored by the global logistic model, but can be detected by the GWR model. The parameter values of Dis2Lard, DenWater, and DenBuilt have relatively low level division of positive and negative results, which indicates that these variables have fewer spatial variations.

The software package GWR4 generated a set a parameter estimates for each sample point. In addition, pseudo *t*-statistics was also calculated to indicate the significance of the parameters. Based on the sample points with parameter estimates and *t*-statistics, a set of parameter and *t*-statistics surfaces were generated to reveal the spatial variation of urban la growth patterns. An inverse distance weighted (IDW) interpolation was employed to generate these surfaces. The IDW interpolation method assumes that the surface is driven by the local variations, which can be captured through the neighborhood (Luo & Wei,

Table 5.6 Summary statistics for GWR parameter estimates

Variable	Min	Max	Mean	STD	% positive	% negative
Dis2Hwy	-2.922	0.748	-0.008	0.433	60.46	39.54
Dis2Lard	-4.286	0.177	-1.275	0.882	3.94	96.06
Dis2Rail	-1.544	1.867	-0.044	0.476	33.96	66.04
DenWater	-5.627	16.877	-1.803	2.236	16.19	83.81
Slope	-0.369	0.241	-0.065	0.129	25.61	74.39
DisDcen	-2.020	2.573	-0.034	0.648	41.24	58.76
Dis2Indu	-1.515	1.491	-0.015	0.468	46.82	53.18
DenBuilt	-4.175	13.484	3.376	3.420	85.84	14.16

2009). Figures 5.10-5.12 represent the generated parameter and *t*-statistics surfaces with cell size of 30m x 30m. Different from the global logistic model in which the parameters are unified across space, it is clear from Figures 5.10-5.12 that all parameters vary across the study area. In terms of significance, all the parameters have certain parts in the study area where they are not statistically significant.

Mennis (2006) argued that mapping only the parameter estimates without associated *t*-values may visually emphasize areas of highest (or lowest) parameter values, regardless of significance, and give misleading impressions. He also pointed out that the color scheme assigning a series of class intervals with increasing shades of grey for choropleth mapping of parameter estimates and *t*-statistics was problematic in cases where the value was positive in some locations and negative in others (Mennis, 2006). Therefore, in this study, we employed a diverging color scheme, which indicates the magnitude of departure from a midpoint value (i.e., zero in the case for distinguishing positive from negative) for mapping the parameter estimates. In addition, the data classification for *t*-values should account for certain exogenous criteria that are important to the variable being mapped, which means the threshold values should distinguish parameter estimates

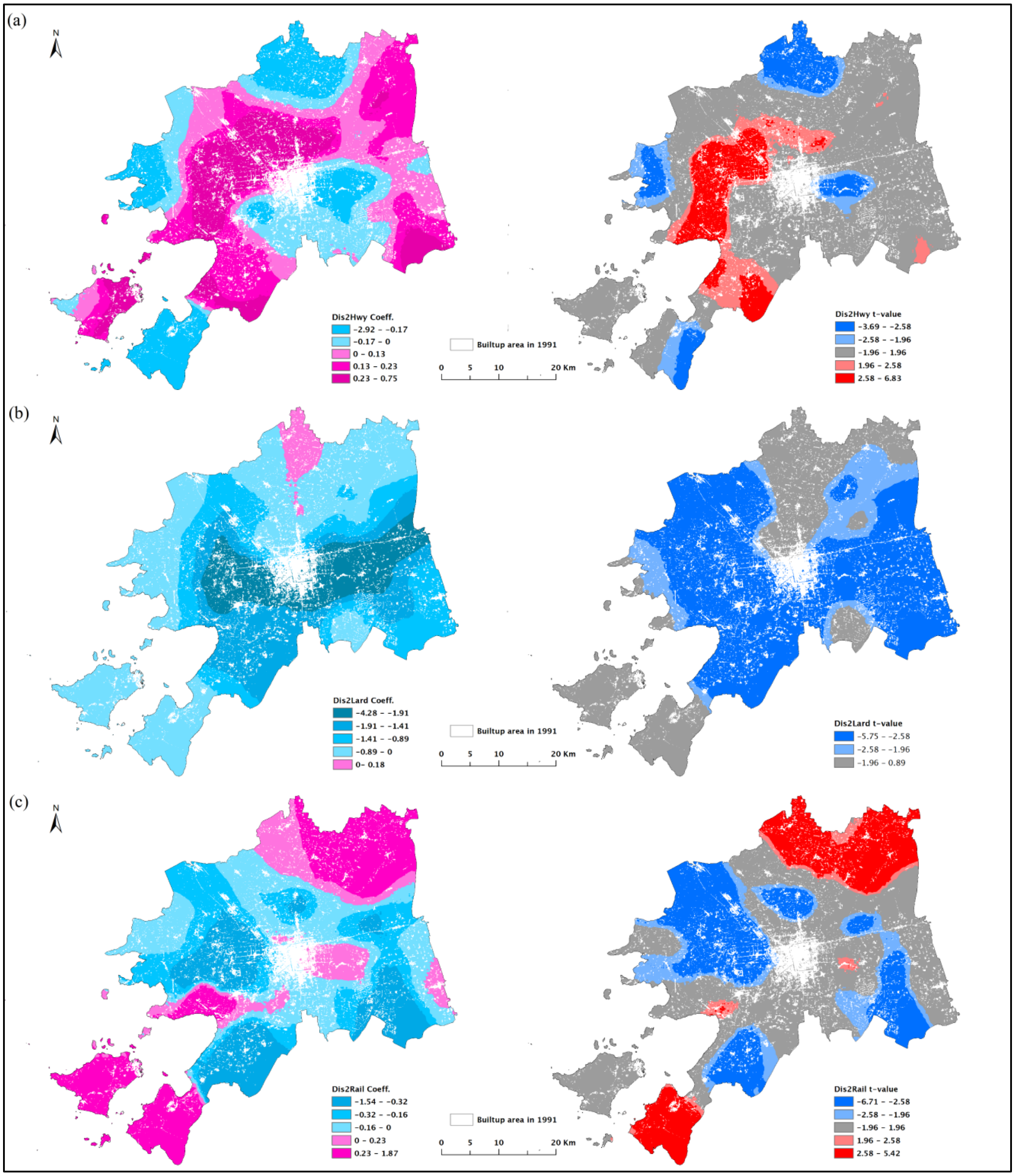

Figure 5.10 GWR coefficient and *t*-value surfaces of (a) distance to highways (b) distance to local arterial roads (c) distance to railways

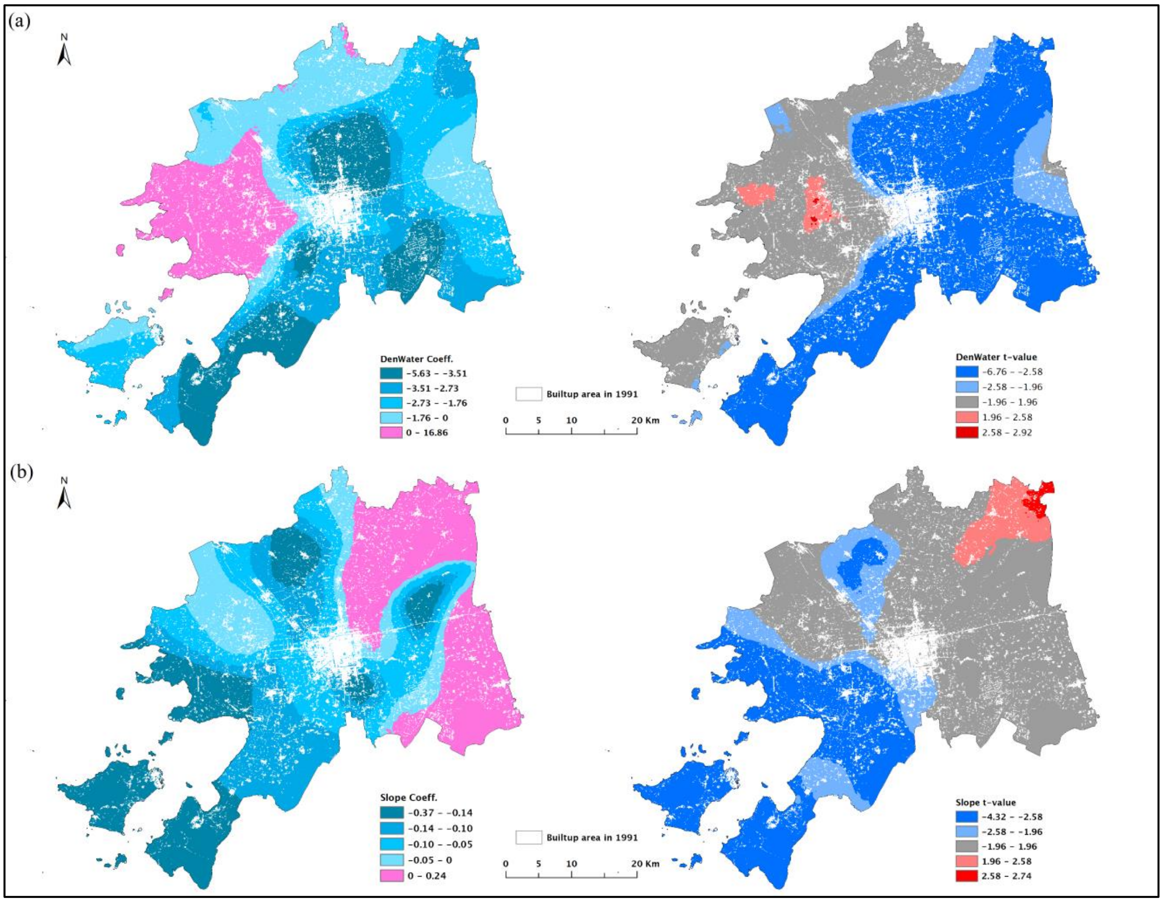

Figure 5.11 GWR coefficient and *t*-value surfaces of (a) density of water and wetland (b) slope

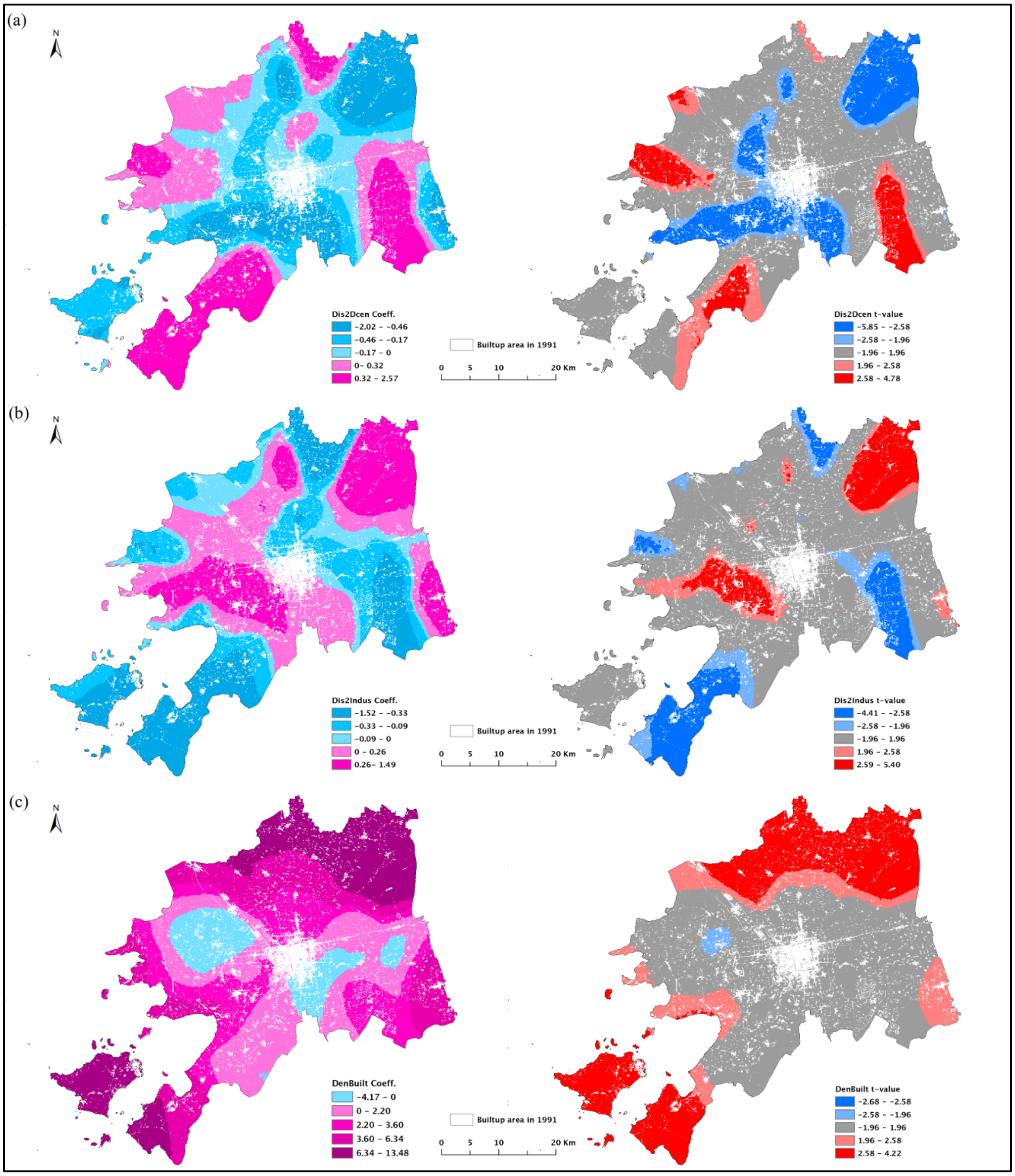

Figure 5.12 GWR coefficient and *t*-value surfaces of (a) distance to district centers (b) distance to industrial centers (c) density of built-up area

that are significant from those that are not (Evans, 1977).

Figure 5.10 presents the parameter and *t*-statistic surfaces of the three variables of proximity to transportation networks. While the global logistic regression model proved that the distance to highways (Dis2Hwy) had positive influence on urban land development, the parameter surface of Dis2Hwy suggests that there are portions in the northwestern, northern, central, southeastern, and southwestern of the study area where the distance to highways had negative effect on urban land conversion (Figure 5.10a). Negative coefficients of Dis2Hwy were significant in the north of the city (Caohu Industrial Park), to the east of the pregrowth urban core (Suzhou Industrial Park), in the south of the Dongshan Peninsula, and around the shoreline of Taihu Lake in the west of the city. This may indicate that the development of Suzhou Industrial Park and Caohu Industrial Park depended more on intercity highways than other areas. The distance to local arterial roads (Dis2Lard) had a dominantly negative influence on land conversion, except in a very small area in the north of the city (Figure 5.10b). This influence was strongest next to the original urban core along an east-west axis and decreased towards south and north. The parameter of Dis2Lard was significant for most of the study area, except in the two islands at the eastern shore of Taihu Lake and to the north of the pre-growth urban core. The global logistic regression model showed that the distance to railways (Dis2Rail) had a negative influence on urban land expansion. However, this was not true for the whole study area. Positive influence of Dis2Rail could be found in the northeastern part; east to the original urban core (Suzhou Industrial Park) and in the two islands, but the parameter was significant only in the northeast and in the Dongshan Peninsula (Figure 5.10c).

The logistic GWR model also revealed the spatial variation of parameter estimates of the two variables for neighborhood physical conditions. The density of water and wetland (DenWater) largely had a negative influence on land conversion in Suzhou except in the western area (Figure 5.11a). The parameter of DenWater was significant in most areas in the northeastern, eastern, southern, and southwestern of the study area. Representing the topographical conditions, slope generally exerted a negative impact on urban growth in Suzhou (Figure 5.11b). However, slope did have a positive influence in the northeastern and southeastern parts of the city, where two large inland lakes Yangcheng Lake and Cheng Lake are located. The coefficients of Slope were negatively significant in the western part of the study area, where some low mountains are located, and positively significant only at the northeastern corner of the city.

Figure 5.12 presents the parameter and *t*-statistic surfaces of the three socioeconomic variables. Although the distance to district centers (Dis2Dcen) had weaker negative influence in the global model, its parameter surface varied greatly across the space (Figure 5.12a). This variable had positive effect on urban land development in the northern, southeastern, southwestern, northwestern parts of the city. The coefficients of Dis2Dcen were negatively significant in the northeastern (Yangchenghu Lake) and southern (Wuzhong Economic Development Zone) of the study area, west and northwest to the original urban core (Suzhou New District and Xushuguang Development Zone) and positively significant only in a very small portion in the southeastern, southwestern, and northwestern of the study area. The global model demonstrated that urban development was not dependent on existing industrial centers. Logistic GWR found that this statement was oversimplified. Although the distance to industrial centers (Dis2Indu) had positive influence to the south, west, and northwest to the pregrowth urban center and the northeastern part of the city, the parameter of Dis2Indu was positively significant only to the west of original urban core and in the northeastern of the study area (Figure 5.12b). Coefficients of this variable were negatively significant only in a small portion of the southeastern and in the southwestern of the city. For the majority part of the city, the parameter of Dis2Indu was not statistically significant. Similarly, the density of built-up area (DenBuilt) had a dominantly positive influence on land conversion (Figure 5.12c), but its parameter was not statistically significant in most part of the city. Only in the north of the city and in the two islands were the coefficients of DenBuilt positively significant. These areas were less urbanized in the pregrowth period, and this may indicate that existing built-up area played a more important role in promoting urban development in less mature areas.

5.5 Conclusion

This chapter analyzes the spatiotemporal dynamics of urban growth and modeled its spatial determinants in urban China through a case study of Suzhou. We have contributed to the research on urban development in Chinese cities by investigating the unique transition from bottom-up rural urbanization to top-down urban expansion in Suzhou. We used landscape metrics, spatial analysis, and GIS to analyze land use data derived from remote sensing images, and developed global and local logistic regression models, which integrated a set of spatial variables to analyze patterns and underlying factors of urban growth in Suzhou. We found that from 1986 to 2008 built-up areas in Suzhou had increased from 9.32% to 30.85% of the study area and the average annual growth rate had accelerated.

Landscape metrics and spatial analysis have quantified the spatiotemporal dynamics of urban development in Suzhou. We distinguished three types of urban growth, of which the edge-expansion growth dominated the new urban area while infilling and leapfrog growth decreased over the study period. Sector and concentric circle analyses have identified the changing directions and hot-zones of urban growth in Suzhou, which mostly overlapped with the FDI-driven development zones.

In our global logistic regression model, all of the explanatory variables were statistically significant. Among the proximity variables, distance to the local arterial roads had the strongest negative influence on land conversion. Density of water and wetland as well as slope in the neighborhood also had negative effects. Among the socioeconomic variables, density of built-up area tended to promote urban growth while distance to district centers had a negative influence.

We found that the logistic GWR model improved over the global logistic regression model. Logistic GWR had a better overall goodness-of-fit and higher prediction accuracy than the global model. Therefore, it had better performance in exploring the relationships between the explanatory variables and urban growth patterns. In addition, logistic GWR remarkably reduced the spatial dependence of residuals measured by the decrease in Moran's *I* of residuals.

In addition, the logistic GWR model allowed the parameters to vary across space, which provided more insights to the spatial variations of urban growth pattern. Each variable had both negative and positive influence on urban growth in different parts of the study area. The distance to local arterial roads and the density of water had predominantly negative influence and their coefficients were significant in most parts of the city. The other variables tended to have very local influence and coefficients of them were statistically significant only in a very small area. Although logistic GWR could more effectively reveal spatial variations of the influence of explanatory variables, interpretation of these variations should be closely related to the specific context of the study area.

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CHAPTER 6

CONCLUSION

6.1 Findings

This dissertation focused on one aspect of China's economic transformation and one consequence of its rapid economic development: retail internationalization and urban spatial restructuring. Specifically, this research studied the expansion of foreign hypermarket retailers in China and urban growth in one Chinese city, Suzhou.

Chapter 2 analyzed the general spatial penetration pattern of foreign hypermarket retailers, how home and host economies impacted their local embeddedness in China, and how they resolved the structural paradox between enforcing standardization and conducting localization. Chapter 3 examined the spatial inequality and dynamics of foreign hypermarket retailers at different geographical levels from regional and provincial to intercity and intraurban and identified their location determinants. In both chapters, I explicitly investigated how state policies influenced their spatial and temporal expansion patterns.

This study found that foreign retailers have their own spatial strategies in penetrating the Chinese retail market. However, their spatial strategies have been largely dictated by the gradual liberalization policy of the Chinese government. Their major changes in market expansion often took place right after a retail deregulation policy was implemented. China's accession to the WTO in 2001 and the complete removal of restrictions in retailing in 2004 best exemplified how institutional factors influenced the spatial dynamics of foreign retailers.

Foreign retailers' local embeddedness in China has been impacted by both home and host economies. The home country effect greatly influences their initial strategies, but they are constantly changing to be better embedded in the Chinese market. Retail TNCs have to confront the structural paradox between standardization and localization when expanding in foreign markets. Three major foreign hypermarket retailers adopted different strategies in dealing with local embeddedness. Carrefour's initially localized strategy enabled it to quickly embed in the diverse Chinese market but also brought in problems as its store network expanded, and therefore, Carrefour was forced to centralize. Wal-Mart's centralized and standardized strategy was slow to accommodate the rapidly changing local market, so it had to add localized elements. RT-Mart did not bring much experience from its home market, but it took advantage of closer ethnic and cultural affinity to embed in mainland China

Foreign hypermarket retailers have remarkably expanded since the mid-1990s. Spatially, they have expanded along China's urban hierarchy from the first- and second-tier cities (large urban centers) to the third- and fourth-tier (small and medium sized) cities. Spatial inequality in foreign hypermarkets among three regions has changed dramatically. The relative gaps among them are narrowing while the absolute gaps are widening. Foreign retailers have favored the eastern region and located most of their stores there. At the provincial level, relative spatial inequality in foreign hypermarkets has decreased over the years. Since 2005, provincial foreign hypermarket distribution has shown statistically significant clustering in the Yangtze River Delta. At the intraurban level, foreign hypermarket retailers in Shanghai gradually expanded from the inner city to the suburb. Suburbanization of foreign hypermarkets has been a clear trend in recent years. Spatial distribution of foreign hypermarkets has changed from dispersion to clustering in 2004, and this spatial clustering has intensified since then.

Three leading retailers, Carrefour, Wal-Mart, and RT-Mart, had different location determinants at the intercity level. Although urban district population was a significant factor to them all, they had preferences for cities of different sizes. Carrefour preferred cites with an urban district population of two million or more (large, extra-large, and super-large cities) and concentrated the majority of its stores there. Wal-Mart had a more balanced distribution of stores in various city groups but also focused on medium, large, and extra-large cities. RT-Mart preferred to expand into small-medium and medium sized cities. Provincial expansion patterns confirmed that Carrefour was more interested in concentrating stores at the urban level while Wal-Mart and RT-Mart aimed to achieve internal economies of scale at the provincial level. Their first-city strategy during different time periods indicated that Carrefour had not changed its bigger city preference while Wal-Mart scaled down to small and medium cities and RT-Mart scaled up to larger cities.

Chapter 4 applied the random forest (RF) classification algorithm to multitemporal Landsat TM images and utilized postclassification comparison to analyze land use and land cover (LULC) change in Suzhou in 1985, 1991, 1995, 2002, and 2008. This study confirmed that RF could effectively classify the heterogeneous landscape in Suzhou and achieve high classification accuracies. Postclassification change detection identified that tremendous LULC change had taken place in this rapidly industrializing and urbanizing city. Built-up area and wetland increased substantially while vegetated land decreased dramatically.

Chapter 5 applied landscape metrics and GIS analysis to land use data produced in Chapter 4, and developed global and local logistic regression models to analyze patterns and determinants of urban growth in Suzhou. Landscape metrics identified that the average length and size of urban patches had increased while the average distance between them had decreased. Among the three urban growth types, the edge-expansion growth dominated the new urban area while infilling growth and leapfrog growth decreased over the study period. Sector and concentric circle analyses identified the changing directions and hot-zones of urban growth in Suzhou, which mostly overlapped with FDI-driven development zones. Institutional analysis revealed that the changing urban growth patterns were actually the result of economic transition in the past 3 decades. Urban growth in Suzhou changed from bottom-up rural urbanization to top-down urban expansion. The underlying mechanism changed from TVEs-driven rural industrialization to FDI-driven development zone fever. Although the global logistic regression model had moderate explanatory power, it could not reveal the spatial variation of location determinants. The logistic GWR model improved over the global model with better overall goodness-of-fit and higher prediction accuracy. The GWR model allowed the parameters to vary across space and provided more insights to the spatial variations of urban growth pattern. Each variable had both negative and positive influence on urban growth in different parts of the Suzhou.

6.2 Contributions

This dissertation has made contributions in several areas. First, this research has contributed to the largely neglected retail geographical studies in China by focusing on the development and expansion of foreign hypermarket retailers. The spatial and temporal expansion of retail TNCs has been largely dictated the state policies in China (Wang, 2009; Zhang & Wei, 2015). The case study of foreign hypermarket retailers substantiates the argument of mutual transformations of the host economies by the retail TNCs and reciprocally, of the retail TNCs themselves (Coe & Wrigley, 2007). Foreign retailers have transformed China's retail sector through introducing new retail formats, transferring advanced retail technology, and influencing Chinese customer's shopping behavior. Meanwhile, China's vast territories, unique culture, and highly fragmented retail markets have challenged retail TNCs' standardization strategy and forced them to localize and accommodate the local culture, and satisfy the preferences of Chinese customers (Zhang & Wei, 2015). In the early stage of opening retail sector, the discrepancy between the central and local governments in China made an inconsistent retail regulatory system that retail TNCs could take advantage of to rapidly expand their business (e.g., Carrefour). Retail transformation in China has also been driven by interplays of the state, foreign capital, and localities (Wei, 2000). Because of their distribution-based nature, retail TNCs adopted different expansion strategies from manufacturing TNCs. For example, foreign hypermarket retailers skipped most of the central region during their early stage of expansion and developed stores in the southwestern region instead, which was different from the gradual expansion strategy that manufacturing-oriented FDI adopted to expand from eastern to central and then to western region in China.

Second, this dissertation has contributed to study of LULC change and urban growth through a methodological framework that integrates spatial and statistical modeling, landscape metrics, remote sensing technique, and GIS analysis. By applying random forest classification to multitemporal Landsat TM images in Suzhou, this study has demonstrated the effectiveness of the RF algorithm in classifying heterogeneous urban landscape. This method can be extended to other cities and regions that have experienced rapid urban expansion. The logistic GWR model successfully revealed the local spatial variation of urban growth patterns, which had been ignored in previous studies that tended to view urban growth from a global view. In addition, through the case study of Suzhou, this research demonstrated how globalization through the influx of FDI has dramatically changed the magnitude and mechanism of urban growth in a city originally representative of the TVEs-driven Sunan Model. This helps to better understand how physical LULC changes are closely related to the socioeconomic transitions.

6.3 Limitations and Future Research

This dissertation has several limitations that might be addressed through future research. First, this research mainly used secondary data for the study of foreign hypermarket retailers. Little was known about retail TNCs' own ideas and opinions about their expansion in China. In the future, first-hand data from in-depth interviews and surveys with senior executives of retail TNCs would provide more insights from the perspective of foreign retailers. In addition, this study only examined foreign hypermarket retailers, who are large general merchandise retailers. The consideration of other types (e.g., clothing retailers) and sizes (e.g., small and medium) of retailers might tell a different story.

Second, reference data for the random forest classification were very limited. We only had high-resolution images in Google Earth as reference data for the 2008 TM land classification. In the future, if high-quality field data or more high-resolution images about ground truth become available, more detailed analysis of classification accuracy should be conducted. In addition, other spatial data such as slope, aspect, and texture features may be included for classification since random forest is capable of incorporating a variety of data.

Third, the GWR model is computationally intensive. When the data set becomes large, this model might not be a cost-effective method to reveal spatial variations of the influence of explanatory variables. Moreover, recent research has suggested that GWR may introduce potential correlation among locally estimated coefficients and generate spurious coefficient surfaces for statistical inferences and policy implications (Páez, Farber, & Wheeler, 2011; Wheeler & Tiefelsdorf, 2005). Therefore, interpretation of the spatial variation of GWR parameter estimates should be with caution and closely related to the specific context of the study area. Alternative methods such as the expansion model could be considered for modeling spatial variation of the influence of explanatory variables (Liao & Wei, 2014; Páez, Mercado, Farber, Morency, & Roorda, 2010).

6.4 References

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