GEOGRAPHIC INFORMATION SYSTEM SPATIAL ANALYSIS OF URBAN AND REGIONAL DEVELOPMENT IN CHINA: A CASE STUDY OF GUANGDONG PROVINCE

by

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ABSTRACT

This research focuses on the application of geographic information systems (GIS) and spatial analysis methods to urban and regional development studies. GIS-based spatial modeling approaches have recently been used in examining regional development disparities and urban growth. Through the cases of Guangdong province and the city of Dongguan, the study employs a spatial-temporal, multiscale, and multimethodology approach in analyzing geographically referenced socioeconomic and remote sensing data.

A general spatial data analysis framework is set through a study of regional development in China's Guangdong province and urban growth in the city of Dongguan. Three intensive spatial statistical analyses are carried out. First, the dissertation investigates the spatial dynamics of regional inequality through Markov chains and spatial Markov-chain analyses. In so doing, it addresses the effect of self-reinforcing agglomeration on regional disparities. Multilevel modeling is further employed to evaluate the relative importance of regional development mechanisms in Guangdong. Second, a spatial filtering perspective is employed for understanding the spatial effects on multiscalar characteristics of regional inequality in Guangdong. Spatial panel and space-time regression models are integrated to detail the spatial and temporal heterogeneity of underlying mechanisms behind regional inequality. Third, drawing upon a set of high-quality remote sensing data in the city of Dongguan, the dissertation analyzes the spatial-temporal dynamics and spatial determinants of urban growth in a rapid industrializing

area. Through the application of landscape metrics, three types of urban growth, including infill, spontaneous, and edge expansion, are distinguished, addressing the diverse spatial patterns at different stages of urban growth. A spatial logistic approach is further developed to model the spatial variations of urban growth determinants within the Dongguan city.

In short, the dissertation finds that regional inequality in the Guangdong province is sensitive to spatial scales, dependence, and the core-periphery structure therein. The evolution of inequality can hardly be simplified into either convergence or divergence trajectories. Furthermore, development mechanisms and urban growth determinants are apparently different in space and are sensitive to spatial hierarchies and regimes. Overall, through the application of GIS spatial modeling techniques, the dissertation has provided more valuable information about spatial effects on China’s urban and regional development under economic transition and highlights the importance of taking into consideration spatial dimensions in urban and regional development studies.

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CHAPTER 1

INTRODUCTION

Background

Geographers have long sought to unveil the process that shapes uneven geographical development and the reasons behind patterns of regional development that often persist for years. In the economic geography literature, regional inequality mainly refers to economic disparities among regions, focusing on the question of whether regional economic output follows the trajectory of divergence (inequality is persistent and the gap between rich and poor is widening) or convergence (the gap between rich and poor areas keeps narrowing, and inequality will decline in the long run; Barro & Sala-i-Martin, 1992; Hirschman, 1958). Spatially uneven development is only one aspect of imbalanced development. Concomitant to this uneven economic development are rapid changes of landscape in both urban and rural areas (United Nations, 2001).

From a policy perspective, governments tend to have strong incentives to devise policies toward more balanced spatial development, due to the fact that inequitable regional development may threaten national unity and social equity. Policies concerning urban growth have also become a hot topic given their relevance to environmental sustainability, sustainable urbanization, and livability of cities.

China has been experiencing rapid economic and urban growth over the past 3 decades. The unprecedented economic growth in the reform period has been driven by multiple transitions, including globalization, decentralization, marketization, and urbanization (Li & Wei, 2010; Wei, 2000). At the same time, China's regional development is spatially uneven. Although a number of different development programs, such as "Go West," have been implemented since the early 2000s, the salient coastal-inland divide has persisted for years (Hao & Wei, 2010; Li & Wei, 2011). In addition to inequalities between regions, there have been rising disparities between urban and rural areas due to the urban biased development policies (Chen et al., 2010). The overconcentration of development resources in cities has also contributed to unprecedented urban expansion and massive loss of cropland.

The research on China's urban and regional development has been widely supported by methodological advances in GIS and spatial modeling. Exploratory spatial data analysis (ESDA) and spatial modeling methods have been employed to analyze the restless transformation of China's urban and economic landscapes (Luo & Wei, 2009;Yu & Wei, 2008). Nevertheless, partly due to data issues, previous studies of China's regional development and urban growth mainly focus on general spatial patterns of regional development, mostly at the provincial level, and urban growth in the largest Chinese cities, such as Beijing (Zhao, 2011), Shanghai (Han et al., 2009; Yue et al., 2014), and Hangzhou (Yue et al., 2010, 2013).

Recent research on China's regional inequality has extended to the study of intraprovincial inequality by incorporating the developments in GIS and spatial analysis and emphasizing the issues of scales and spatial dependence (e.g., Wei & Ye, 2009; Ye & Wei, 2005). However, the relationship between spatial dependence and regional inequality or convergence/divergence in provincial China appears to be self-evident. The present dissertation aims to quantify to what extent spatial dependence can have an impact on regional disparities and convergence in China, and the ways in which economic transitions interact with local geographies to yield new forms of uneven development. On the other hand, scholars have made substantial efforts on modeling the urban growth determinants in China (e.g., Liu et al., 2011; Luo & Wei, 2009). The literature documents the limitation of the orthodox logistic regression model when addressing the local dimensions of urban development in China (e.g., Luo & Wei, 2009). The dissertation thus provides an alternative and computationally less expensive tool to model the spatially varying relationship between urban growth and its underlying factors, aiming to shed further light on urban development and land use policies in a rapidly industrializing area.

Literature Review and Research Objectives

The dissertation research draws upon two strands of literature, including contextual issues related to regional development and inequality in China and scholarly debate over urban development in Chinese cities.

Regional inequality is a central academic inquiry in the area of economic geography. The recent 2 decades have witnessed a resurgence of interdisciplinary interest in regional inequality and development, fueled by the theoretical advancements in economics and geography (Rey & Janikas, 2005). In general, there are two opposing theoretical views about the expected long-run trajectories of regional development. Following the neoclassical growth model, Barro and Sara-i-Martin and others claim that given the “diminishing return” in the high-income regions, economic endowments tend to evolve interregional mobility of capital and labor, leading to the overall decline of the dispersion of per capita income or outputs (Barro & Sara-i-Martin, 1991, 1992). In contrast to the neoclassical growth model, new endogenous growth theory predicts divergence and sees government policy as necessary to reduce inequality. As Martin and Sunley (1998) stated, economies of scale and agglomeration of human capital result in a self-reinforcing process of regional development, and thus there will be evident divergence among regions. Different from the convergence and divergence assumptions, new economic geography theory has proposed a more eclectic view toward the spatial structure of regional development (Krugman, 1991, 1995). It formulates an econometric model for analyzing how the centripetal forces pull economic activities together and the centrifugal forces push it apart. Given the declining transportation and communication costs, the NEG model predicts that resource flows agglomerate in the core region and the economic situation of the region will depend on interrelations with its neighborhoods. Based on the NEG models, economists have called for a "spatial turn" in economic growth policies (Martin, 2011). More significantly, the World Bank's 2009 Development Report, titled *Reshaping Economic Geography*, drew upon the NEG idea that spatial agglomeration of economic activity promotes economic growth, though in the short to medium term this may result in rising inequality. Although the NEG model has shared some similar thoughts of geographers by addressing the impact of self-reinforcing spatial agglomeration on economic growth and regional development, the spatial effect has been treated in a very rough manner in the literature. As Rey and Janikas (2005) suggested, much more has to be done to apply spatially explicit methods to the studies of regional inequality and economic convergence.

The literature on regional inequality in China follows mainstream theories of regional development and inequality, but it emphasizes China's unique political economy and economic transitions (Long & Ng, 2001; Wei, 2007). As Wei (2002) argued, both convergence and divergence theories have limited ability to explain the evolution of regional inequality in China. By employing a multimechanism and multiscale framework, recent studies suggest that China's regional inequality is sensitive to geographical scales, and its underlying factors can be better conceptualized into a triple-process transition (i.e., decentralization, marketization, and globalization; Wei, 1999, 2000, 2002).

Methodological advances are of particular importance in recent studies of regional development and inequality in China. Scholars are thrilled by new evidence derived from exploratory spatial data analysis (ESDA; Wei & Ye, 2009; Yu & Wei, 2003), spatial-temporal modeling (Li & Wei, 2010), and finer-scale analyses at the intra-provincial level (e.g., Liao & Wei, 2012; Wei & Ye, 2009). Through the applications of rigorous spatial econometric models such as Geographically Weighted Regression (GWR; Yu, 2006, 2014) and spatial regressoin models (Yu & Wei, 2008), recent works reveal the importance of accounting for spatial dependence in analyzing regional inequality and development mechanisms in China. Nevertheless, to what extent spatial dependence can have an impact on regional inequality or convergence speed remains unexplored thoroughly and quantitatively.

On the other hand, there is a plethora of literature on urban growth in China (e.g., Wei & Ye, 2014). Scholars have debated about the extent, process, and consequences of urban expansion and land change in Chinese cities. Researchers have documented the extent and spatial forms of urban growth (Yue et al., 2010) and employed GIS and remote sensing techniques to explore the underlying drivers of urban land expansion (Luo

& Wei, 2009). Specifically, globalization and rapid economic growth have become major driving forces of China's urban growth. As He et al. (2013) stated, land urbanization and regional development are mutually reinforcing, and urban land is both the driving force and consequence of economic growth.

Urban land expansion in Chinese cities is also a geographically uneven process led by coastal cities. Within coastal areas, there are a variety of spatial forms of urban land expansion. Besides spatial patterns or urban forms, some scholars are more interested in underlying factors behind urban expansion in China, following a political economy perspective. They emphasize the notion of "land-centered development" as a consequence of land market forms in China and the decentralization of decision-making power from the central government to local states (e.g., Lin, 2009). By contrast, taking advantage of the more reliable satellite and aerial photo images, others are concerned about the modeling techniques and localized statistics of the spatial determinants behind urban growth in Chinese cities (Luo & Wei, 2009). In general, research on urban growth has dealt with the largest Chinese cities and regions such as the Yangtze River Delta and the Pearl River Delta (Seto & Kaufmann, 2003). The spatial-temporal dynamics and driving forces of urban growth in second-tier cities are largely understudied.

As mentioned, this study intends to fulfill two primary objectives. The first objective is to investigate the role of "space" in shaping regional inequality and convergence dynamics in China, and Guangdong in particular. This objective is achieved by drawing upon more detailed space-time data collected from China's Guangdong province at the county level, the most disaggregated administrative units in China. Specifically, temporally sensitive methods, including Markov chain analysis and stochastic Kernel density, were coupled with ESDA and spatial filtering to derive such new and detailed space-time empirics. In addition, multilevel modeling, spatial panel, and space-time models were integrated to evaluate the relative importance of development mechanisms in Guangdong over space and time.

Second, the research turns its focus on urban growth in Chinese cities through a case study of Dongguan city in Guangdong. A spatially and temporally sensitive landscape analysis was conducted to differentiate the three types of urban growth patterns including infill, edge-growth, and leapfrog, following a "diffusion-coalescence" model. Furthermore, the study developed a novel spatial expansion model to furnish a spatial logistic regression analysis of influential factors behind temporal changes in urban land use. Lastly, previous studies have investigated Chinese cities' urban expansion and urban-rural migration (Shen et al., 2002), polycentric urban development (Yue et al., 2010), and suburbanization (Feng et al., 2008), mostly through cases of the largest Chinese cities or regions. The study of Dongguan city will add to the literature an examination of a unique township-based urban growth pattern in a second-tier city.

Data and Methodology

Study area

The study area includes the 21 municipalities and 81 counties or cities in China's Guangdong province and the city of Dongguan in Guangdong. Guangdong is selected as a case for the analysis of regional development and inequalities for the following reasons. First, Guangdong's economic size ranks first in China, accounting for 11% of China's GDP in 2013 (CSB, 2014), and its size is approximately the same as California in the US in terms of purchasing power parity. Moreover, the spatial pattern of regional development is characterized by a salient uneven pattern, making Guangdong an ideal laboratory to examine theories of regional development and inequality.

Second, Guangdong's regional development disparities have been a central issue in the agenda of the provincial government since the late 1990s. The provincial government in Guangdong has put in tremendous efforts, trying to minimize the spatial inequality in regional development (see Chapter 2 for a detailed review of these policies). It is argued that Guangdong may move "one step ahead" in China, given the efforts toward a more spatially balanced regional development (World Bank, 2011).

Third, with the rapid increase of city populations, urban growth in Guangdong has drawn considerable scholarly attention. The urban growth in Guangdong is considered as a typical case of urbanization driven by globalization and industrialization (Lu et al., 2013). Within Guangdong, Dongguan is considered as a typical case in which unprecedented urban growth has given rise to a massive loss of agricultural land (Yeh & Li, 1999).

Data and data sources

The first set of data are the socioeconomic statistics at the county level in Guangdong and GIS spatial data files (shapefiles). Socioeconomic data include the following six variables: constant price GDP per capita (GDPPC), per capita fixed asset investment (FIXPC), share of non-state-owned enterprises in employment (NSOEPT), foreign direct investment per capita (FDIPC), share of urban population in the total population (URBAN), and mountain dummy (mountainous area = 1, others = 0). GIS shape files refer to boundary files of Guangdong. These data are from two sources: the first source is the Guangdong statistical yearbook, which provides county-level socioeconomic data from 1988 to 2012. The second source is the China Data Center, where GIS boundary files are stored. The second set of data is collected in the city of Dongguan, including detailed classified TM/ETM+ satellite images at particular time points (1988, 1993, 1999, and 2006). In addition, transportation network data are obtained from the GIS division in the municipality government.

Analysis methods

In order to explore the spatial-temporal dynamics of regional inequality in Guangdong and urban growth in Guangdong's Dongguan city during the postreform period, statistical and spatial modeling techniques are applied in the study.

First, three statistical indices, including population-weighted CV (coefficient of variation), Gini coefficient, and Theil index, are employed to examine the temporal variation of inequalities to minimize potential misinterpretation. Population-weighted CV (WCV), taking into account the share of population in a region, is more reliable as opposed to traditional CV index (Petrakos et al., 2005). The Gini coefficient and Theil indexes are used since they are readily decomposable (Fan & Sun, 2008). The above three inequality measures only reveal overall inequality, but have limited ability to detect spatial dependence (Yu & Wei, 2003). Moran's *I* is employed to analyze spatial autocorrelation and spatial relationships among counties in Guangdong. Furthermore, from a spatial filtering perspective, we quantify the relationship between spatial dependence and the inequality (details about this method are discussed in Chapter 3).

Second, following Quah (1993, 1996), a distribution dynamics approach, including Markov chain analysis and (stochastic) kernel density estimation, is employed to quantify the dynamics of regional convergence (whether poor regions tend to grow faster than rich ones). Spatial-temporal dynamics are also analyzed by using spatial Markov-chain analysis and comparing actual and spatially filtered data.

Third, a set of spatial-temporal regression models are furnished for understanding the space-time hierarchy and heterogeneity of development mechanisms. The dissertation starts with a multilevel model to investigate the spatial-temporal hierarchy of underlying factors behind regional development in Guangdong. This is followed by three spatial panel regression models (spatial filtering panel, spatial lag, and error panel regression models). In addition, space-time and space-time regime models are used to probe the spatially and temporally varying development mechanisms in Guangdong.

Fourth, a landscape metrics-based analysis is carried out to analyze the temporally sensitive remote sensing data in Dongguan. In doing so, the three types of urban growth (i.e., infill, leapfrog, and edge-expansion) are differentiated. Concentric analysis is also employed to understand the unique township based urban growth pattern in Dongguan. Moreover, a spatial logistic approach is developed to model the spatial variations of temporal changes in land use in the city.

Organization of the Dissertation

This dissertation is organized into five chapters. Following this introductory chapter, Chapter 2 applies (spatial) Markov-chain approaches to quantify dynamics of regional inequality in Guangdong using county level data. Choosing constant-price GDP per capita as the indicator of regional development, the chapter analyzes the multiscalar patterns of regional inequality and points out the evident effect of spatial agglomeration on regional inequality. Multilevel modeling is used to examine the spatial-temporal hierarchy of regional development mechanisms.

Using a spatial filtering approach, Chapter 3 quantifies the relationship between agglomeration and inequality. The chapter also explores the space-time heterogeneity of different development mechanisms through the applications and development of a set of spatial panel and space-time models.

Chapter 4 furthers the debate over the urban growth resulting from spatially uneven economic growth in Guangdong, using Dongguan as a case. A landscape metrics-based method is used to quantify the urban growth type and the fragmentation of urban land in Dongguan. This is followed by a spatial logistic model to illustrate the spatial heterogeneity of growth drivers.

Chapter 5 summarizes major findings presented in the previous chapters and highlights the directions of future studies.

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CHAPTER 2

DYNAMICS, SPACE, AND REGIONAL INEQUALITY IN PROVINCIAL CHINA: A CASE STUDY OF GUANGDONG PROVINCE [1]

Abstract

This chapter investigates the regional inequality in one of the most developed provinces in China, Guangdong, from 1979 to 2009 and follows the multiscale and multimechanism framework. We have found a new round of intensifying inequality in Guangdong since the early 2000s, which is attributed to the widening gap between the core region of the Pearl River Delta (PRD) and the rest of the province (periphery) and between the urban and rural areas. We also apply a distribution dynamics approach and spatial Markov chains to identify the spatial-temporal dynamics of regional disparities in Guangdong. The results show that there has been a progressive bias towards a poverty trap in the province, and the effect of self-reinforcing agglomeration is evident. Using a multilevel model, the study further reveals that the regional inequality in Guangdong is sensitive to the core-periphery hierarchy of multimechanisms and reveals the relative influence of decentralization, marketization, and globalization. We argue that the policies towards inequality-reduction in Guangdong have been constrained by the geographical barriers and the effect of self-reinforcing agglomeration in the Pearl River Delta (PRD),

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while marketization has potential to mediate the uneven development driven by the spatial concentration of foreign investment.

Introduction

Over the past 3 decades, China's gradual transition towards a market-oriented globalizing economy has generated a spectacular economic growth with an annual growth rate at 9.9 % (CSB, 2011). However, behind the economic success in China, the country also faces serious challenges arising from distinctive regional development trajectories, imbalanced growth, and intensifying social injustice (Wei, 2002; World Bank, 2005). Since regional inequality may threaten national unity and social stability, it has become a burning issue in China, attracting considerable attention from policy makers and scholars (e.g., Fan et al., 2011; Fan & Sun, 2008; Wei, 2002). Research has revealed an intensifying regional inequality in China and found the significance of globalization, institutional reforms, and local agents in regional development (Hao & Wei, 2010; Wei, 2002).

As China is characterized by vastness in size, regional inequalities not only exist among provinces or groups of provinces but are even more evident within provinces, triggering the research front of China's regional inequality to "scale down" to a finer-scale analysis at the intraprovincial level (e.g., Gu et al., 2001; Wei et al., 2011; Wei & Fan, 2000;). With the aid of the more rigorous GIS and spatial analysis methods, this strand of literature has found rich details of the dynamics, patterns, and mechanisms of the uneven economic landscape in Chinese provinces (Wei & Ye, 2009; Wei et al., 2011; Yu & Wei, 2008).

Being China's leading powerhouse and a pioneer in the reform for the past 3 decades, Guangdong province is a representative of regional inequality in provincial China (Gu et al., 2001; Lu & Wei, 2007). The development within the province has been heavily focused on the core region of the Pearl River Delta (PRD) near Hong Kong while the rest of the province (periphery) has lagged far behind (Gu et al., 2001; Lu & Wei, 2007). The research on the regional inequality in Guangdong, however, has mainly dealt with the situation in the 1980s and the 1990s (e.g., Fan, 1995; Gu et al., 2001), while the changes in the 2000s have rarely been investigated.

Notably, in response to problems of economic polarization, since the early 1990s, the provincial government of Guangdong has shifted its development strategy from stressing the development of the PRD to promoting regional integration between the PRD and the periphery, coined as “the Mountain Area Development Program” in the late 1990s and the “Anti-Poverty Development for Rural Guangdong” in the early 2000s. The provincial government also invested heavily in the construction of the intercity highways connecting the PRD and the peripheral areas (Lu & Wei, 2007). Specifically, since 2005, under the administration of the new governor in Guangdong, the provincial government has initiated a “dual-track transformation” policy and built up a number of “industrial relocation parks” to foster the upgrading of the PRD and promote more equitable development through the relocation of low-end manufacturing from the PRD to the peripheral areas (Liao & Chan, 2011; Yang, 2012). The substantial efforts towards inequality reduction in Guangdong has also attracted attention from the World Bank, who forecasted that Guangdong province has the potential to lead the nation again for a more balanced and sustainable development in China (World Bank, 2011). Therefore, a timely assessment of the regional inequality in Guangdong also sheds light on the recent efforts working towards reducing inequality in the frontier of the Chinese economy.

Drawing upon a multiscale and multimechanism framework (Wei, 2002), this chapter attempts to update our understanding of the regional inequality in Guangdong. Employing the advanced GIS and statistical modeling methods, it particularly addresses the space-time complexity of regional inequality and the persistent core-periphery structure in Guangdong in the context of intensifying globalization. On the one hand, following a distribution dynamics model proposed by Quah (1993a, 1993b, 1996) and the spatial Markov chains developed by Rey (2001), we move beyond the traditional convergence analyses to recognize the temporal and spatial dimensions of regional inequality in Guangdong. On the other hand, the underlying mechanisms of the uneven regional development in Guangdong are analyzed based on the triple-process conceptualization of China's transition, namely, globalization, decentralization, and marketization (multimechanism); with a spatially explicit multilevel model, the analyses reveal the relative importance of such a triple process over space and time. This chapter is organized as follows. The next section presents a brief review of the literature and the analytical framework. Then, we start with analyzing patterns of regional inequality at regional, municipality, and county levels. This is followed by a detailed investigation of the distributional dynamics of regional inequality among 82 counties and cities in Guangdong with both traditional and spatial Markov chains. In association with Markov chains, the spatial-temporal hierarchy of the underlying mechanisms is further analyzed in a multilevel model. The chapter concludes with major findings and policy implications.

Theoretical and Contextual Issues

Regional inequality is undoubtedly a central topic for economic geographers. The longstanding concerns with spatial inequality and the causative process of economic growth have generated a variety of schools, such as convergence (the gaps between rich and poor keep narrowing, and inequality will decline in the long run), divergence (inequality is persistent and the gap between rich and poor is widening), and evolutionary (the degree of inequality is contingent upon the development stages of the economy; Barro & Sala-I-Martin, 1992; Kuznets, 1955; Smith, 1984). Represented by the neoclassical growth model of Solow-Swan, neoclassical economists maintain that regional inequality is a temporary phenomenon (Solow, 1956). Similar to the neoclassical thought of convergence, inverted-U theory holds that regional inequality is likely to rise during the early stages of development and tends to decline when the economy matures (Kuznets, 1955; Williamson, 1965). In contrast to the view of convergence, the empirical work in the 1960s and 1970s found a lack of convergence and regarded the persistence of poverty and inequality as an inevitable consequence of capitalism (Smith, 1984). Different from the neoclassical approaches, some scholars also focus on the role of government intervention and policies in the evolution of regional inequality. This strand of literature is represented by the top-down development and the growth pole policies advocated by Hirschman and Perroux in the 1950s and 1960s.

In the early 1990s, Barro and Sala-i-Martin (1991) put forward two important concepts, β-convergence and σ-convergence, to elaborate the regional development differentials in the U.S. and Europe. The β-convergence indicates that poorer regions will grow faster than richer regions at the initial stage, and the σ-convergence assumes that due to the β-convergence, the overall degree of dispersion tends to decline in the long run. However, like the other economic growth and regional inequality theories, the new convergence theory based on the notions of β- and σ- convergences has been challenged for its overlooking scales, space, and time (e.g., Martin & Sunley, 1998; Petrakos et al., 2005; Wei & Ye, 2009). Specifically, the new economic geography theory has provided strong evidence for the importance of geography in economic and regional development (Krugman, 1999). It posits that when the degree of trade openness increases, production factors are more likely to flow toward the advanced region where the returns are higher, which encourages the formation of a core-periphery economy (Krugman, 1991, 2011). Empirically, overwhelming evidence has also been found that the core-periphery structure has strong geographical foundations and is hard to change. In many transitional and developing economies, such core-periphery structures, such as the dominance of Moscow and the Siberian dilemma, are often maintained or even strengthened through new spatial division of labor, political struggle, and the integration of the core regions into the global economy (Bradshaw & Vartapetov, 2003; Carluer, 2005; Wei & Fang, 2006). In Asia, the core-periphery structure is still maintained and even intensified, although the degree of regional inequality has declined in some nations (Akita, 2003; Hill, 2002; Silva, 2005).

China's rapid economic growth and tremendous transitions in the past 3 decades have provided a good laboratory to deepen our understanding of the evolution of regional inequality in a transitional economy under globalization. First, the research on China's regional inequality has reached a consensus that there has been a rising gap between coastal and interior provinces, mainly because the coastal provinces have experienced a more rapid growth under globalization and liberalization (Chen & Fleisher, 1996; Hao & Wei, 2010; Sakamo & Islam, 2008; Yu & Wei, 2003). Scholars also questioned the effectiveness of governmental policies such as the "Go West" program and argue that interior provinces are facing more challenges in regional development under globalization (Hao & Wei, 2010; Wei & Fang, 2006). Second, since China adopts a gradual and experimental approach to the reform, the evolution and magnitude of regional inequality are found to be sensitive to structural shocks in reforms such as China's accession into WTO in the early 2000s (Sakamo & Islam, 2008). Third, with more rigorous spatial analysis techniques, geographers have demonstrated that space or geography does matter in shaping the uneven economic landscape in China. Spatial dependence, scale, and hierarchy are all important for a better understanding of the complexity of regional inequality in China (Li & Wei, 2010; Ke, 2010; Ying, 2000; Yu & Wei, 2003). They have found that the evolution of regional inequality in China is sensitive to scales (between provinces and between regions), which cannot be simplified into divergence or convergence, and the relative importance of underlying factors are also contingent upon the spatial hierarchy of regional inequality. Fourth, although the intensification of coastal (core) inland (periphery) inequality in China shares some common characteristics with other transitional economies such as Russia (Carluer, 2005), the mechanisms underlying the uneven development in China are complicated, which can hardly be explained by either market openness or governmental intervention (Wei, 2007). Wei (1999, 2002) conceptualized China's transition into a triple process of globalization, marketization, and decentralization, which has provided a more ground-based conceptual tool to synthesize the multiple stakeholders including global, state, and local forces in

China's regional development.

Lastly, in addition to a plethora of literature on the interprovincial inequality, given its diversity, dynamics, and scale, provincial China has become a new frontier of research on regional inequality in China. Researchers also focus on the inequalities in China's most dynamic economic powerhouses including Jiangsu (e.g., Wei & Fan, 2000), Zhejiang (Wei & Ye, 2009; Ye & Wei, 2005) and to a less extent Guangdong (Gu et al., 2001; Lu & Wei, 2007; Weng, 1998) and Beijing (Yu & Wei, 2008). Similar to the coastal-inland divide at the national level, researchers have found rising core-periphery inequalities within many Chinese provinces. For example, in Jiangsu, the development is centered on the core region of *Sunan* (South Jiangsu) in the south close to Shanghai and the inequality between *Subei* (North Jiangsu), *Suzhong* (Central Jiangsu) and *Sunan* has continued to worsen (Wei et al., 2011). Evidence has also been found that the traditional north-south divide in Zhejiang has been transformed towards the coastal-inland divide in the reform era (Wei & Ye, 2009). The research on regional inequality in provincial China also provides rich details for the diverse development models in those thriving regions, which are represented by the *Wenzhou* model in Zhejiang (Ye & Wei, 2005), the PRD model in Guangdong (Lin, 1997; Lu & Wei, 2007), and the *Sunan* model in Jiangsu (Wei, 2002).

The research on Guangdong, a province known for being "one-step ahead" in China's reform (Vogel, 1989), has identified a salient core-periphery economy centered on the PRD. However, given different scales of analyses and time spans, the findings about the evolution of regional inequality in Guangdong tend to be mixed. Studies focusing on the rural industrialization and market reform in the 1980s and 1990s have found a more balanced growth within the PRD, mainly because of the decline of the original core city of Guangzhou (Lin, 2001; Weng, 1998). In contrast, others found the evidence of the widening gap between the core region of the PRD and the periphery areas in the 1980s and 1990s, which was driven by the socialist market reform and the “local state corporatism” (Gu et al., 2001). With few exceptions (Fan, 1995), the regional inequalities at different spatial scales in Guangdong have rarely been analyzed. More importantly, the literature has analyzed the inequality in Guangdong during the 1980s and 1990s, while its changes in the 2000s have not been updated.

In order to explore the regional inequality in Guangdong with an emphasis on the changes in the 2000s, this chapter draws on a multiscale and multimechanism analytical framework proposed by Wei (2002) to address the space-time complexity of regional inequality in provincial China and synthesize its multiple driving forces. On the one hand, as displayed in Figure 2.1, the regional inequality in China is sensitive to spatial scales and can be analyzed at the provincial, regional, and the intraprovincial levels. Within a province, the patterns of regional inequality are manifested by the interregional inequality (in a province), intermunicipality, and the intercounty inequalities. Specifically, the intercounty inequalities are also multifaceted including the interrural county, the interurban and urban-rural disparities (the urban areas refer to the urban districts [city] and the others are rural counties or equivalent level cities [county-level cities]).

On the other hand, China’s reform can be understood as a triple transitional process of decentralization, marketization, and globalization. First, the political economic context in China has shifted from idealistic egalitarianism to pragmatist uneven regional

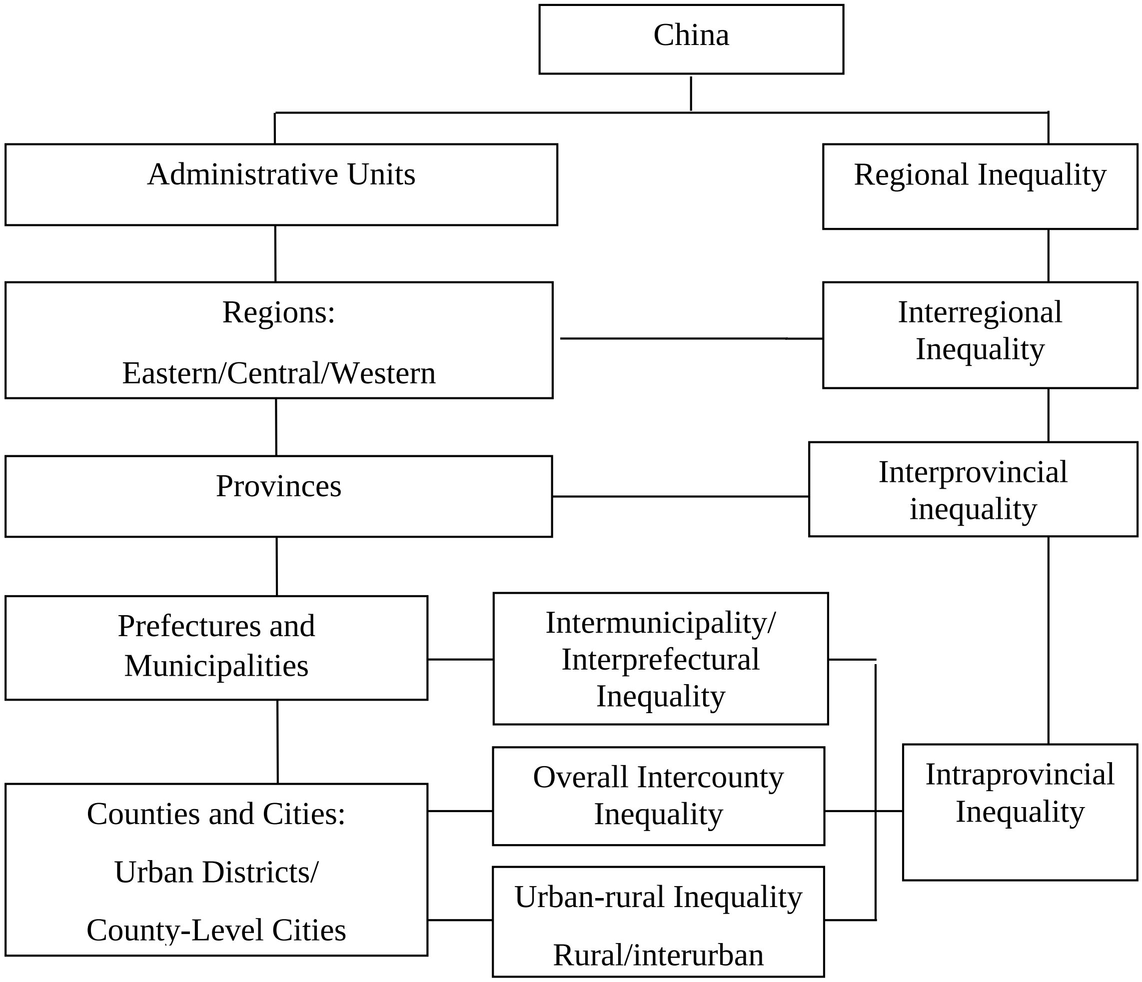

Figure 2.1 A typology of multiscalar regional inequalities in China
Adapted from Wei & Ye, 2009

development with an emphasis on efficiency and output (Long & Ng, 2001). Local governments have been granted more power in revenue collection and local spending (decentralization), and they have had more incentives to promote local economic development (Wang, 2010). At the same time, the market system is introduced in the original socialist planned economy, and the state-owned sector is exerting much less control over the economy (marketization; Wei, 2002). Together with marketization and decentralization, globalization, manifested by market openness and China's integration into the global economy, has triggered a huge inflow of foreign direct investment (FDI), making China the most popular destination of FDI in developing countries (UNCTAD, 2011). These three broad processes—a triple process of regional development in China—also have profound influences on regional inequality (Hao & Wei, 2010; Wei, 2002). Coastal localities where local governments have more resources and the investment environment is favored by investors have emerged as the biggest winners in the reform. At the same time, those traditional industrial bases dominated by state-owned enterprises have fallen behind (Wei & Ye, 2009). Based on the multiscale and multimechanism framework, we hypothesize that regional inequality in Guangdong is sensitive to scales; the core-periphery inequality between the PRD and the periphery is intensified due to the triple process of China's transition from a socialist planned economy to a market-based capitalist economy.

Research Setting and Methods

Research Setting: Guangdong Province

As shown in Table 2.1, many Chinese provinces and in particular Jiangsu and Guangdong in the coastal area and Gansu in the inland area have encountered severe challenges arising from the intensifying regional inequalities in the postreform period (Table 2.1) and Guangdong is also one of the most imbalanced provinces in China.

Table 2.1 Regional inequalities in selected provinces in China (CV), 1990–2009

	1990	1995	2000	2005	2009	Total numbers of counties
Guangdong	0.71	0.70	0.72	0.84	0.82	82
Zhejiang	0.45	0.54	0.56	0.56	0.51	67
Jiangsu	0.63	0.75	0.78	0.91	0.92	65
Henan	-	0.62	0.60	0.58	0.56	127
Gansu	-	0.94	1.04	1.11	1.23	86

Adapted from GSB, 1991-2009, 2010a; ZSB, 2010; JSB, 2010; HSB, 1996-2010; GaSB, 1996-2010. Notes: the calculation in this table is based on current prices. CV = coefficient of variation

As shown in Figure 2.2, Guangdong province is located in Southeastern China and neighbors Hong Kong. With a population of 95.44 million in 2009, the province covers 179,800 square kilometers, occupying 1.9% of China's territory. Guangdong province is one of the most developed provinces in China, and the size of Guangdong's economy measured by GDP surpassed Taiwan in 2007 (GSB, 2008). In 2009, Guangdong produced 3,948 billion yuan of GDP, ranking first in China's 31 provinces (CSB, 2010). Its GDP per capita also increased from 410 yuan (65 USD) in 1979 to 41,166 yuan (6,534 USD) in 2009 with an annual growth rate of 11.2% (GSB, 2010a). According to the administrative structure in Guangdong, in 2009, there were 21 municipalities and 82 county-level spatial units including 21 urban districts (city) and 61 counties (rural counties and county-level cities) in the province (Figure 2.2).

Geographically, Guangdong is divided into two distinct regions including the core region of the PRD, the peripheral region including the North Guangdong (or mountain

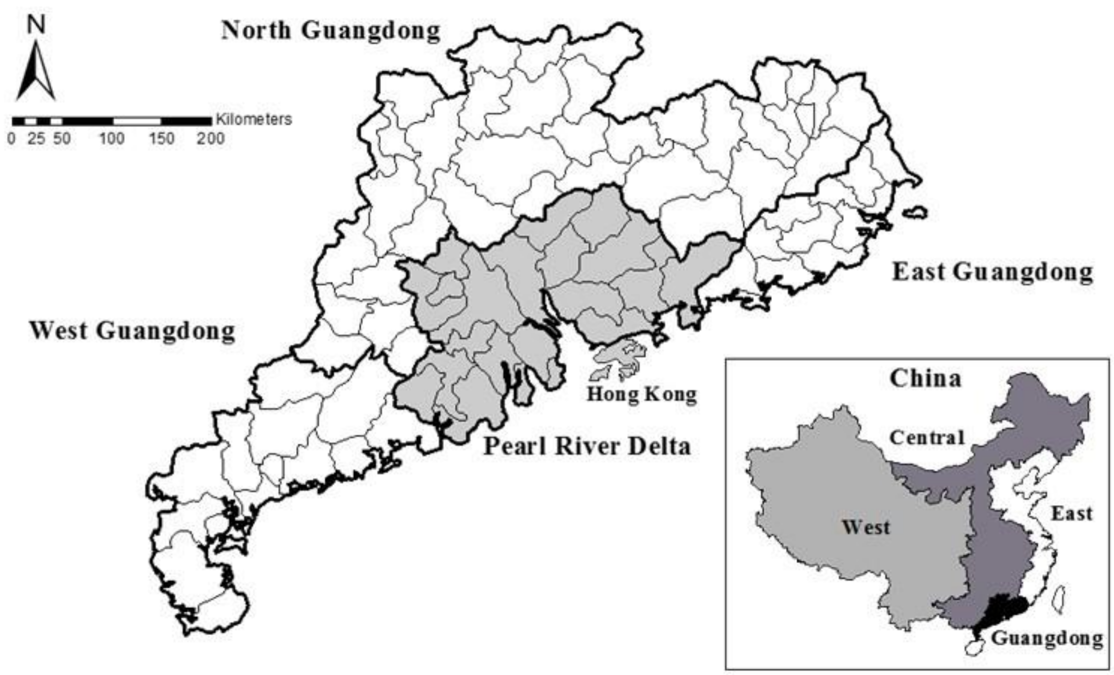

Figure 2.2 Location of Guangdong and regional divisions

area), the East Guangdong, and the West Guangdong (Figure 2.2).

In general, the economic development in Guangdong follows a core-periphery gradient with the PRD being the most developed area (Table 2.2). With the rise of the PRD, the peripheral areas have lagged far behind, which intensified the regional inequality in the province. The ratio of GDP per capita in the PRD compared to that in the rest of Guangdong (periphery) doubled from 2.2:1.0 in 1979 to 4.4:1.0 in 2009 (GSB, 2010b).

In this study, the major indicator of the regional development status is the most commonly used per capita GDP (GDPPC). The municipality-level (21 municipalities) GDPPC data from 1979 to 2009 and county-level GDPPC data from 1988 to 2009 are obtained from a report entitled "GDP Data in Guangdong, 1952–2005" and the statistical yearbooks of Guangdong (various issues from 1988 to 2010). Both are published by the Guangdong Statistical Bureau.

In terms of the calculation of GDP per capita, due to the unique *hukou* (household registration) system in China, the population data in coastal provinces tend to be

Table 2.2 Development indicators of Guangdong Province, 2009

	GD	% of China	PRD	% of GD	Periphery	% of GD
Population (million)	95.4	7.2	47.9	50.2	47.6	49.9
Land Area (sq. km)	179800	1.9	54733	30.4	125067	69.6
GDP (billion yuan)	3948.3	11.8	3214.7	81.4	733.6	18.6
Investment in fixed assets (billion yuan)	1335.3	5.9	960.4	71.9	375.0	28.1
Exports (US $billion)	359.0	29.9	341.8	95.2	17.2	4.8
FDI (US $billion)	19.5	21.7	17.5	89.6	2.0	10.4
Local Fiscal Expenditure (billion yuan)	433.4	7.2	288.2	66.5	145.2	33.5
Local Fiscal Revenue (billion yuan)	365.0	11.2	252.2	69.1	112.8	30.9

Adapted from GSB, 2010a. Note: GD = Guangdong.

underestimated since the temporal migrant population without *hukou* is often excluded in the population statistics (Chan & Wang, 2008).

In Guangdong, this problem is more challenging due to the massive inflow of migrant workers in specific cities such as Shenzhen and Dongguan. In order to get more accurate population data, we used a report entitled “Guangdong’s Development in the Reform Era” published by the Guangdong Statistical Bureau in 2010, which released the municipality level migrant population from 1979 to 2009. Since the county-level *de facto* population (population including migrants without *hukou*) is still unavailable, according to the municipality-level data, we adjusted the numbers of total population in the county-level units within specific municipalities, including Shenzhen, Dongguan, Zhongshan, Foshan, Zhuhai, and Guangzhou where the total population is more likely to be underestimated. Then, we computed the ratios of de jure population (population not including migrants without hukou) to *de facto* population (population including temporally migrants) for the other 15 municipalities. We found that the resulting ratios ranged from 0.85 to 1.1, indicating that the biases in the total population of the counties within these 15 municipalities can be acceptable for the following analyses, given the data limitation.

Besides the data of population and GDP, in order to measure the underlying factors of the uneven economic development in Guangdong, a set of county-level socioeconomic data were also collected, which included foreign direct investment (FDI), local fiscal expenditure, fixed assets investment, and employment data. The GDP data were converted into the constant price in 1980 based on the provincial implicit GDP deflator. The GIS maps (shape files), referring to boundary files of the Guangdong province down to the county level, were downloaded from the China Data Center (http://chinadatacenter.org).

Methods

As Fan and Sun (2008) summarized, in comparison with other indexes such as CV and Gini coefficient, a major advantage of the entropy indexes such as the Theil index (Mean logarithmic deviation) is that they are readily decomposable.[2] In this research, Theil index is used to investigate the evolution and the sources of regional inequality in Guangdong. This study also adopts a distribution dynamics model (Fotopoulos, 2008; Quah 1993a, 1993b, 1996) to identify the dynamics of regional inequality among counties in Guangdong.

To begin with, Kernel density estimation is applied to estimate the changes in the distributions of relative GDPPC (the ratio of GDPPC in each county compared to the mean value in the province). In comparison with the traditional histogram, Kernel density

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[2] The Theil index is defined as

$$I(y:x) = \sum_{i=1}^{N} y_i \log(y_i/x_i)$$

where x_i is the share of population of county *i* in the province and y_i is the share of GDP of county *i* in the province. $I(y:x)$ can be decomposed into

$$I(y:x) = I_0(y:x) + \sum_{g=1}^{G} Y_g I_g(y:x)$$

where the first term on the right $I_0(y:x)$ measures interregional inequality, and the second term is a weighted sum of intraregional inequalities within *G* groups where $I_g(y:x)$ measures the inequality within the g^{th} region.

estimation can smooth the data but retain the overall structure.[3] However, although the Kernel density estimation allows characterizing the evolution of the distribution shape, it does not offer any information about the movements of the counties within the distribution. A possible way to remedy this inadequacy is to track the evolution of each county's position in the distribution shapes and examine the transition probability matrices in a Markov-chain like process (Le Gallo, 2004). The specific advantages of the Markov-chain method are twofold.

First, the Markov transition matrix enables us to characterize such spatial-economic asymmetries and highlights the performance of each region, as well as the nature of its mobility (both upward and downward) in detecting the trend of convergence, divergence, and polarization (Carluer, 2005; Fingleton, 1997). Second, the Markov-chain method is also realistic since it can identify the long-run properties towards some form of poverty-trap or convergence club (Fingleton, 1997, pp. 399–400), which cannot be deciphered by the β convergence analysis that relies on smooth time-trends approximation and suffers from the Galton's fallacy of regression toward mean (Fingleton, 1997; Quah, 1993a, 1993b).

The basic approach of the Markov chains is to classify different spatial units (counties) into various subcategories based on the relative GDPPC and examine their transition probabilities for a given period (Quah, 1993a, 1993b, 1996). First, a matrix F_t is constructed to store the cross-sectional distribution of county-level relative GDPPC at time point t. A set of K different GDPPC classes are defined. Therefore, a transition probability matrix M can be established, which has a dimension of K by K, where K is the

[3] Similar to Le Gallo (2004), the densities are calculated nonparametrically using a Gaussian kernel, and the bandwidth is selected as suggested by Silverman (1986, section 3.4.2).

number of subcategories. A typical element of a transition probability matrix $m_{(i, j, t)}$ indicates the probability that a county that is in the class i at time t ends up in class j in the following period. Formally, the (K, 1) vector R_t indicates the frequency of the counties in each class j at time t, following the equation below:

$$R_{t+1} = M^*R_t \tag{2.1}$$

where M is the (K, K) transition probability matrix representing the transitions between the two distributions. If transition probabilities are stationary, that is, if the probabilities between the two classes are time-invariant, then

$$R_{t+P} = M^{p*}R_t \tag{2.2}$$

Under the assumption of time-invariant matrix (t→∞), the properties of this Matrix can be further examined to determine the Ergodic distribution (or the long-term distribution) of R_t to indicate if the regional system is converging or diverging.

By adopting the Markov chains, researchers also attempt to incorporate the spatial dependence or autocorrelation in determining the transition probability matrices. Quah (1996) used spatial conditioning, and Rey (2001) proposed a more explicit spatial Markov-chain to examine the magnitude of spatial dependence in the Markov-chain framework. The transition matrix is expanded, and the transition probabilities of a region are conditioned on the GDPPC class of its spatial lag for the beginning of the year. In doing so, we can obtain a spatial transition matrix and expand the traditional K by K matrix into K conditional matrices of dimension *(K, K)*. In other words, we categorized the spatial lags into the same number of groups as GDPPC. Therefore, a K by K by K three-dimensional transitional matrix is constructed. The element of such a matrix, $m_{ijt}(k)$, represents the probability that a region in category i at the time point t will converge to category j at the next time point if the region's spatial lag falls in category k at time point t ($k = 1, \ldots\ldots, K$; $t = 1, \ldots\ldots, T$).

In this study, the GDPPC data are categorized into four groups (rich, developed, less developed, and poor) using the quartile method, and the cutoff values are selected so that the overall distribution in the entire sample of the relative GDPPC prove to be close to being uniform. This discretion based on the gridlines in uniform distribution generally follows the previous empirical studies using Markov chains (Quah, 1993a; Sakamoto & Islam, 2008), and it also better corresponds to the core-periphery structure in Guangdong in line with the geographical notions of core, semicore, semiperiphery, and periphery (Wei et al., 2011). The time interval of the Markov-chain transition matrix is 1 year, and the spatial lags are defined by the queen contiguity matrix. The Markov chain-based analysis was carried out in a software called PySAL (Open Source Python Library for Spatial Analytical Functions) developed by the GeoDa center at Arizona State University (Rey & Anselin, 2010).

To further understand the regional inequality in Guangdong, multilevel regression modeling is applied to examine the mechanisms behind the uneven regional development. As argued by Li and Wei (2010a), most studies of regional inequality neglect the hierarchical characteristics in the dataset. A possible consequence of neglecting the hierarchical structure is the underestimation of standard errors of regression coefficients, resulting in an overestimation of statistical significance (Subramanian et al., 2001). Multilevel modeling, however, overcomes the limitation by allowing for residual components at each level in a hierarchy (individual, group, subgroups, etc.; Mercado &

Páez, 2009). Despite the wide usage of multilevel modeling in the fields of public health, demographic, and transportation geography (Li & Wei, 2010b; Mercado & Páez, 2009; Subramanian et al., 2001), the application of multilevel modeling in the study of regional inequality is still limited (Li & Wei, 2010a). In this research, we coupled the Markov chains with the multilevel modeling to test the spatial-temporal hierarchy of development mechanisms down to the county level in Guangdong. In doing so, we attempted to better understand the relative importance of the triple-process in Guangdong's regional development. The multilevel regression analysis was performed using MLwiN 2.24 software (Rasbash et al., 2009).

Our model has three levels. The one-level model is a pooled regression using county-level data regardless of the core-periphery and temporal hierarchies. The two-level model adds the core-periphery continuum as suggested in the Markov chains, which allows us to control for the geographical and structural effects within the four groups (core, semicore, semiperiphery, and periphery). The three-level model further controls for the time points (1988, 1993, 1998, 2003, 2008), which takes the between-year variations into account. Such time points were selected based on the data availability.

$$y_{ijt} = \beta_0 + \beta_1 x_{ijt} + v_{0t} + \mu_{0jt} + e_{ijt} \tag{2.3}$$

As shown in equation (2.3), the y_{ijt} refers to the dependent variable (GDPPC) in county *i* that belongs to the core-periphery continuum *j* defined by the Markov chains at year *t*, and x_{ijt} is the independent variables in county *j* at year *t*; v_{0t} is the error term at year *t*; μ_{0jt} is the error term of core-periphery continuum *j* at year *t*; e_{ijt} is the error term of *i* county in core-periphery continuum *j* at year *t*.

We selected a number of exploratory variables based on the multimechanism that conceptualizes Guangdong's regional development as an aforementioned triple-process of globalization, marketization, and decentralization.

1. Globalization (FDIPC): Guangdong's development over the past 3 decades has been fueled by the export-oriented economy and inflow of FDI. So the per capita FDI (FDIPC) is the most commonly used indicator to measure the extent of globalization (Gu et al., 2001).
2. Marketization (NSOE): Guangdong's development is also based on the establishment of the socialist market system and the retreat of the state owned enterprises (SOE) in the economy (Gu et al., 2001). The share of non-SOE in the total employment (NSOE) is employed to describe the influence of marketization.
3. Decentralization (DECEN): The decentralization process is captured by the ratio of local budgetary spending per capita to the provincial government's budgetary spending per capita. It mainly reflects the degree of fiscal decentralization and the shift of power from upper level governments to local governments (Hao & Wei, 2010; Wang, 2010).
4. Investment (FIXPC): It has been widely acknowledged that socialist economies are traditionally investment driven, and the per capita fixed asset investment (FIXPC) is selected to represent whether the development is driven by the investments particularly from the central government (Yu & Wei, 2008).
5. Urban-rural divide (URBAN): China's regional development policy is also biased toward the urban area, which has intensified the urban-rural inequality (Chen et al., 2010; Long et al., 2011). A dummy variable URBAN is employed to reflect the

impact of urban-biased development. If the spatial unit at the county level is an urban district, it is coded by 1; otherwise it is a 0.

6. Topography (MOUNTAIN): In Guangdong, most of the plain area is located in the PRD, while mountain counties are mostly located in the periphery. A dummy variable (MOUNTAIN) is used to investigate the impact of physical topographical conditions on the economic development in Guangdong.

Findings and Interpretation

The multiscalar regional inequality in Guangdong

In this section, a multiscale decomposition analysis is undertaken to portray a holistic scenario about the evolution of regional inequality in Guangdong over the past 3 decades. Figure 2.3 shows that the regional inequality in Guangdong is sensitive to the geographical scales. The average numbers of the intercounty inequality, the intermunicipality inequality, and the interregional inequality are 0.25, 0.21, and 0.14, respectively. The regional inequality is more significant at finer spatial units. Figure 2.3 also reflects a general trend of rising inequalities at the three geographical scales in Guangdong during the study period. Both of the intermunicipality inequality and intercounty inequality showed a U-shape pattern since the early 1990s. By contrast, the interregional inequality displays a more consistently upward trend despite a slightly decrease in the early 1990s. Therefore, the regional inequality has not shown persistent divergence or convergence trajectories while these changes are responsible to the different stages of reforms. First, a more dramatic rising trend of intermunicipality inequality in the 1980s can be observed, which is consistent with Fan’s (1995) study using per capita gross value of industrial and agricultural output (PCGVIAO).

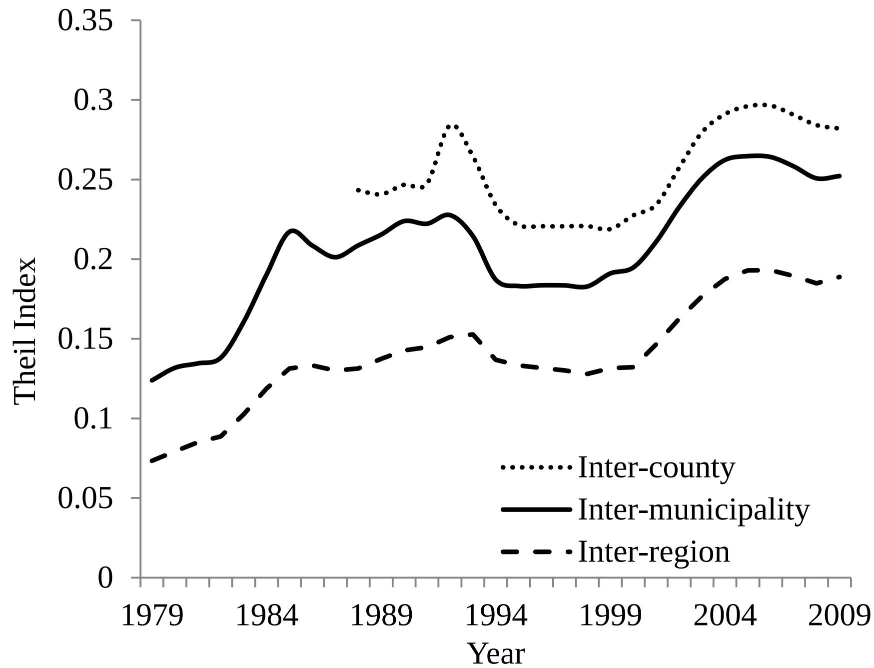

Figure 2.3 Regional inequalities at different scales in Guangdong, 1979–2009

The rise of regional inequality in this period was driven by the development of Shenzhen and Zhuhai, two special economic zones (SEZ) located at the border between Guangdong and Hong Kong or Macau (Figure 2.2).

Second, in the early 1990s, Dengxiaoping's South China tour in Guangdong had stimulated a new round of "Socialist Marketization" reform in the province that was ceased after the 1989 Tiananmen incident. Since then, the implementation of open door policies and market reform had been expanded to the whole province while the influence of the SEZ policies in the 1980s gradually faded, which narrowed the gap between other municipalities in the province and the SEZ municipalities. In particular, since the early 1990s, the municipality of Zhuhai, a SEZ municipality located in the western part of the PRD, has been in a backward status. In comparison with other municipalities in the eastern part of the PRD (Figure 2.2), the municipality of Zhuhai is relatively far from Hong Kong, which is the motor of the economic development in this area. Its development was also constrained by the heavy burden of debt as a result of unwise infrastructure investments such as the airport construction in the early 1990s (Yang, 2006b).

Third, since the early 2000s, the regional development in Guangdong has been driven by a new round of inflowing FDI after China's entry into WTO (Yang, 2006a). At the same time, the development of a knowledge-based economy in the PRD has also been accelerated (Lu & Wei, 2007). Such a transformation has provided more resources in favor of the specific municipalities in the PRD and intensified the regional inequality in the province. Fourth, there has been a slightly declining inequality since 2006. This is greatly attributed to the relative slow-down of economic growth in Shenzhen. In recent years, Shenzhen has encountered more challenges in its development due to the limited resources such as land (the land area of Shenzhen is one-third of Guangzhou, which is another largest municipality in Guangdong and the capital of the province), and its economy was more significantly influenced by the global financial crisis (Sina News, 2006).

In order to unfold the relationship between multiscalar inequalities in Guangdong, we decompose the overall intercounty inequality into the inequality between the PRD and the rest of the province (the periphery) and the inequalities within the PRD and the peripheral region, which resembles the core-periphery structure in Guangdong (Figures 2.4 and 2.5).

As illustrated in Figure 2.4, the contribution of the core-periphery inequality between the PRD and the rest of the province increased from 56.81% in 1990 to 66.02% in 2009.

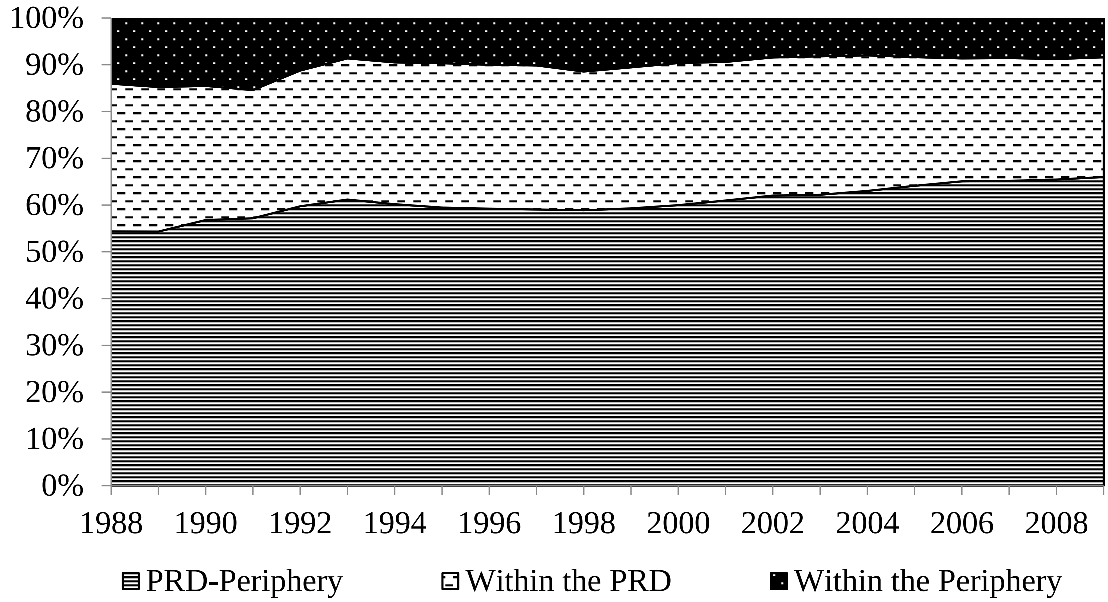

Figure 2.4 Theil decomposition of overall intercounty inequality in Guangdong (core-periphery), 1988–2009

Another important source of regional inequalities in Guangdong is the urban-rural divide. Figure 2.5 shows that the urban-rural inequality has consistently accounted for over 50% of the overall intercounty inequality in Guangdong. The persistent rural-urban disparity is also related to the core-periphery inequality since most of the rural counties in Guangdong (46 out of 61, or 75%) are located in the periphery, while nearly half of the urban districts are in the PRD.

In short, the proceeding analysis finds that the uneven economic development in Guangdong is sensitive to the time dimension and geographical scales. It is also related to changing policies such as the SEZ policies in the 1980s and the early 1990s as well as China's entry into World Trade Organization (WTO) in the early 2000s. However, the provincial level inequality-reducing policies initiated since the late 1990s could barely achieve their goal, and Guangdong has experienced a new round of economic polarization in the 2000s in the context of further globalization.

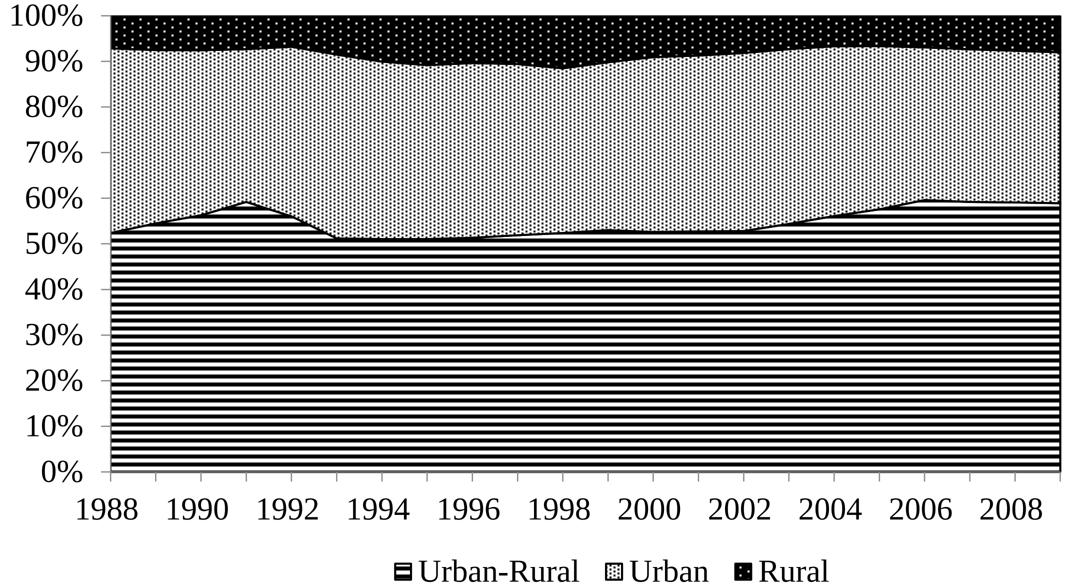

Figure 2.5 Theil decomposition of overall intercounty inequality in Guangdong (urban-rural), 1988–2009

Distributional dynamics of regional disparities

In this section, the dynamics that underline regional inequality or the "long-run" properties of convergence or divergence across 82 counties and cities in Guangdong are analyzed with a distribution dynamics model and in particular the Kernel density estimation and Markov chains (Quah, 1993a, 1993b, 1996).

As illustrated in Figure 2.6, the shape of the distribution for the county-level GDPPC has changed considerably over time. The density plots clearly suggest a skewed distribution shape of the relative GDPPC in Guangdong. In comparison with the years of 1988 and 2000, more counties reported below half of the average GDPPC in 2009, and only a small subset of counties transited towards above average. This result may reflect that a substantial proportion of counties near the average GDPPC have become relatively poorer since the early 2000s.

Table 2.3 contains the transition probability matrices over the period between

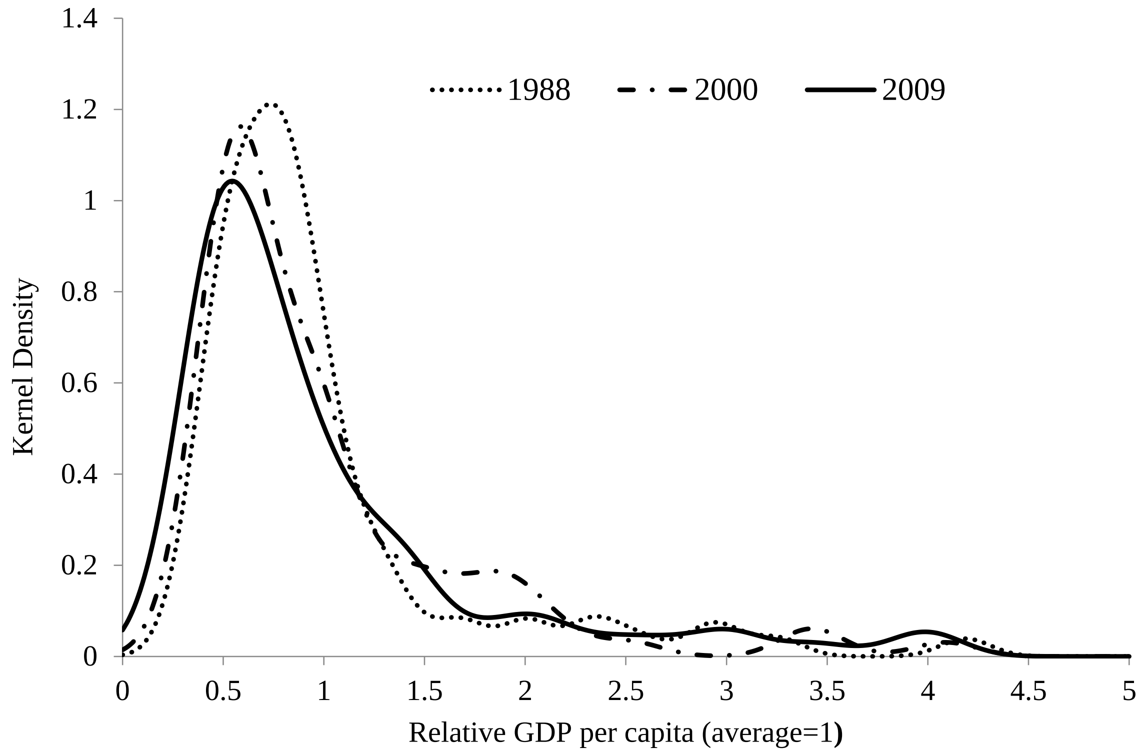

Figure 2.6 Kernel densities of relative per capita GDP at the county level, 1988, 2000, 2009

1988 and 2009 as well as in the two subperiods—the 1990s (socialist market system reform) and the 2000s (China's accession into WTO).The results of the Markov chains analyses more clearly point out the system dynamics in Guangdong's regional development, which are sensitive to the different stages in the course of the reform. In general, the transition probabilities along the dialog are high. In other words, if a county falls into the specific class (rich, developed, less-developed, and poor), the probability of its being in the same group is at least 82.1%. The transition frequency between different groups is low, and the highest transition frequency is only 12.6% (Table 2.3). The results also show that it is very difficult for a county to leapfrog from poor to rich or from less developed to rich and vice versa, indicating the stable structure in Guangdong's regional development and the persistence of core-periphery inequality.

Table 2.3 Markov-chain transitional matrices for county-level GDP per capita, 1988–2009

	P [<=58.4]	L[58.5–79.3]	D[79.4–102.5]	R[>=102.6]
1988-2009				
P (422)	0.924	0.076	0.000	0.000
L (434)	0.108	0.834	0.058	0.000
D (436)	0.000	0.085	0.878	0.037
R (430)	0.000	0.000	0.030	0.970
Ergodic distribution	36.33%	25.44%	17.27%	20.96%
1988-2000				
P (198)	0.874	0.126	0.000	0.000
L (283)	0.099	0.841	0.060	0.000
D (255)	0.000	0.090	0.863	0.047
R (248)	0.000	0.000	0.040	0.960
Ergodic distribution	24.28%	30.99%	20.64%	24.08%
2001-2009				
P (224)	0.969	0.031	0.000	0.000
L (151)	0.126	0.821	0.053	0.000
D (181)	0.000	0.077	0.901	0.022
R (182)	0.000	0.000	0.016	0.984
Ergodic distribution	60.73%	15.08%	10.33%	13.85%

Notes: P = poor (periphery); L = less developed (semiperiphery); D = developed (semicore); R= rich (core); the numbers in the parentheses are total numbers of transitions.

Changing spatial patterns of development

and spatial dependence of dynamics

The analysis of the evolving spatial patterns of regional development and spatial Markov chains provides more details for the economic geography of inequality dynamics in Guangdong. Figure 2.7 shows that the core-periphery pattern of regional development based on the divide between the PRD and the rest of Guangdong is salient: most of the counties in the rich category are the counties in the PRD; as the distance to the PRD increases, counties are more likely to become poor. In comparison with the map in 1988, the 2009 map has shown that the statuses of many counties in the periphery have declined. Moreover, the boundary of the richest counties has changed slightly: the originally less developed counties in the eastern part of the PRD such as the counties in

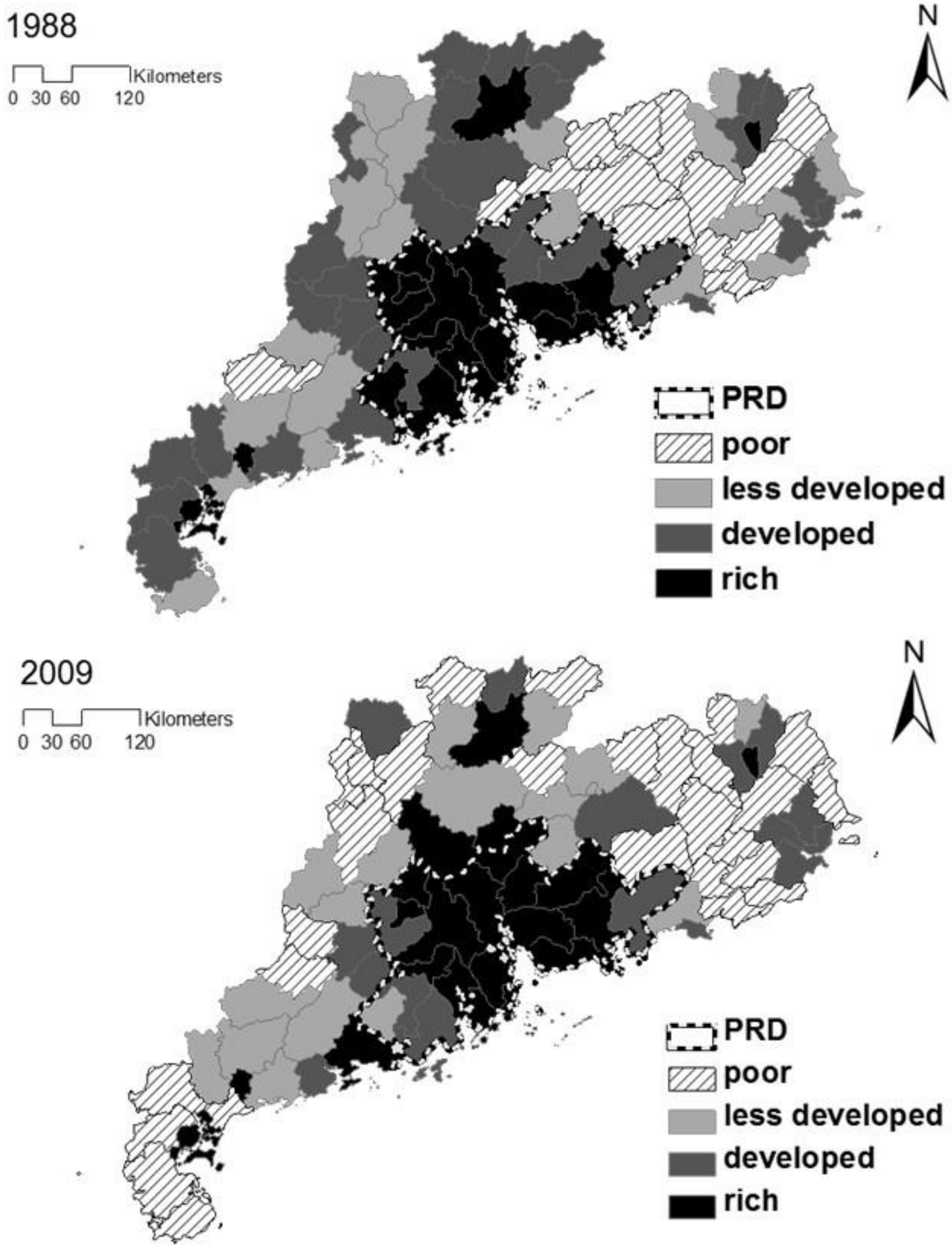

Figure 2.7 Spatial patterns of regional development in Guangdong, 1988, 2009

Huizhou municipality moved upward while the counties in the Zhaoqing and Jiangmen municipalities in the western part of the PRD deteriorated into backward statuses (Figures 2.2 and 2.7). The revealing fact that the eastern PRD located closer to Hong Kong develops faster implies that the core-periphery structure of development in Guangdong is also attributed to the globalization forces channeled through the external core of Hong Kong (Ng & Tuan, 2003; Weng, 1998; Yeung, 2006). With respect to the periphery area, our results echo Gu, Shen, Wong, and Zhen's (2001) study that many counties in the originally developed industrial municipalities driven by state-owned sectors in the peripheral regions, such as the counties in Shaoguan in the North Guangdong and Zhanjiang in the West Guangdong, have declined in the postreform period. In contrast, as found in a recent report from the World Bank, a small subset of counties or districts in the periphery area, particularly in the Qingyuan municipality neighboring the northern part of the PRD (Figures 2.2 and 2.7), have moved upward (World Bank, 2011). The development in these specific counties is greatly fueled by their abundant land resource and lower cost of labor as well as the recently surging cost of production in the PRD (Liao & Chan, 2011; Yang, 2012). We also computed the global Moran's I to capture the overall tendency of geographical concentration of regional development in Guangdong (Figure 2.8). Different from the U-shape trajectory of the intercounty inequality measured by the Theil index, the resulting global Moran's I increased from 0.469 in 1988 to 0.551 in 2009, and all are significant at the 0.01 level. This result implies that when the spatial dependence is taken into account, the inequality measured by Moran's I is less sensitive to the fluctuations at specific time points and provides a holistic picture of the increased regional inequality in Guangdong.

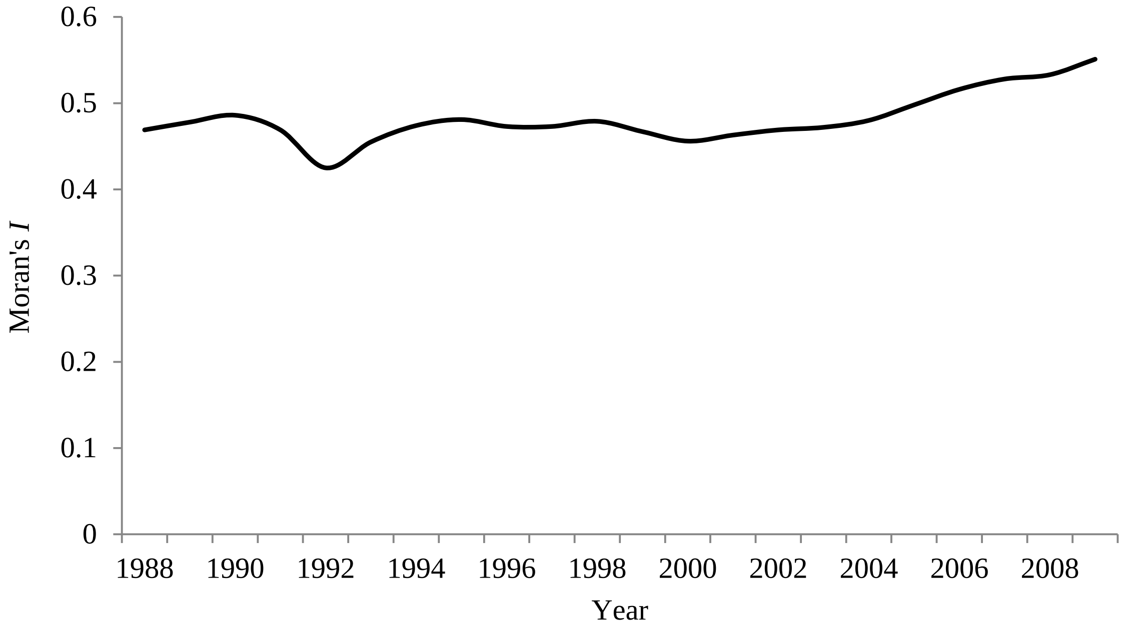

Figure 2.8 Global Moran’s *I* of county level GDP per capita in Guangdong, 1988–2009

The results of the spatial Markov chain analysis are shown in Table 2.4. They provide more details about the possible association between the direction and probability of transitions and the neighborhood context. For example, for the richest counties, the probability of a downward transition is affected by the economic development of nearby counties. As shown in Table 2.3, the richest counties in general have a 3.0% tendency of moving downward. However, if a rich county is surrounded by other richest counties, the tendency of moving downward drops to 2.3%. Meanwhile, if the neighbors are relatively poorer counties, such as the developed counties, the tendency of moving downward increases to 5.6% (Table 2.4). This neighborhood effect is also evident for the upward transitions of poor counties. The chance of a poor county moving out of the bottom averages 7.6% (Table 2.3). However, if its neighbor is poor, it has a lower probability of moving upward (6.5%). In contrast, those poor counties surrounded by relatively richer

Table 2.4 Spatial Markov-chain transition matrix for county-level GDP per capita in Guangdong, 1988–2009

			2009			
Spatial lag	1988	N	P	L	D	R
P	P	124	0.935	0.065	0.000	0.000
	L	38	0.237	0.737	0.026	0.000
	D	11	0.000	0.091	0.909	0.000
	R	10	0.000	0.000	0.000	1.000
L	P	162	0.914	0.086	0.000	0.000
	L	127	0.142	0.819	0.039	0.000
	D	96	0.000	0.052	0.917	0.031
	R	45	0.000	0.000	0.044	0.956
D	P	123	0.919	0.081	0.000	0.000
	L	245	0.078	0.853	0.069	0.000
	D	195	0.000	0.123	0.846	0.031
	R	72	0.000	0.000	0.056	0.944
R	P	13	1.000	0.000	0.000	0.000
	L	24	0.042	0.875	0.083	0.000
	D	134	0.000	0.052	0.896	0.052
	R	303	0.000	0.000	0.023	0.977

Note: P = poor (periphery); L = less developed (semiperiphery); D = developed (semicore); R = rich (core); N refers to the numbers of transitions.

counties, such as the less developed counties, are more likely to be richer (8.6%). We also find that the transitions in the intermediate groups are also influenced by the neighbourhood context. For instance, for a developed county, the probability of moving upward towards a rich county is 3.7%. But if its neighbour is a rich county, it has a higher chance (5.2%) of becoming a rich economy. At the same time, if a less developed county is surrounded by poor counties, the tendency of moving downward doubles from 10.8% regardless of its neighbourhood status (Table 2.3) to 23.7% (Table 2.4).

The core-periphery hierarchy of underlying mechanisms of regional inequality

In association with the Markov chains, the underlying mechanisms of the uneven regional development are examined in a multilevel model with a consideration of the core-periphery structure of regional development in Guangdong. The multicollinearity test based on the one-level model (or pooled regression) shows no variables reported a VIF higher than 2.5, indicating the explanatory variables do not suffer from the problem of multicollinearity (Yu and Wei, 2003).

The results of one-level, two-level, and three-level regression models are reported in Table 2.5 and discussed as follows. First, based on the results of likelihood ratio tests, the one-level model can explain 82.9% of the total variances of the county level GDPPC, and there is a significant reduction in deviances from both the one-level model to the two-level model ($p < 0.001$) and from the two-level model to the three-level model ($p < 0.001$; Table 2.5). This result indicates that the core-periphery hierarchy of regional inequality as suggested by the Markov chains exists and regional inequality is also sensitive to different time points. Second, the results differ from Li and Wei (2010a), who also used multilevel modeling and found that the FDI is a singular factor that causes regional disparities at the provincial level in China. The model shows that local governments, foreign investors, and the state collectively affect the local economic development in Guangdong. Many development agents in China's regional development are actually operating at the lower levels (city or county) under provinces, and their roles are likely masked by the analysis of large spatial entities such as provinces (Wei & Fan, 2000).

Third, the influence of marketization is significant in the one-level model but insignificant and marginally significant ($p = 0.12$ and $p = 0.06$) in the two-level and three-level models. In other words, the multilevel modeling avoids exaggerating the effect of marketization on the regional inequality in Guangdong. It implies that, among

Table 2.5 Results of the multilevel regressions

	One-level (county)		Two-level (county & core-periphery)		Three-level (county & core-periphery & time)	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
FDIPC	8.472	0.0253	8.106	0.0053	7.305	0.0113
DECEN	213.062	0.6687	1678.574	0.0001	1716.451	0.0001
NSOE	13425.501	0.0001	4548.353	0.1170	5646.382	0.0593
FIXPC	1.725	0.0001	0.380	0.0001	0.370	0.0001
URBAN	1640.425	0.1065	1934.463	0.0062	2097.407	0.0027
MOUNTAIN	-655.637	0.4149	-555.074	0.3290	-330.837	0.5569
-2loglikelihood	8361.751		8110.889		8096.617	
R square	0.829		Likelihood ratio test	<0.001	Likelihood ratio test	<0.001

the triple processes, globalization coupled with decentralization has become the most important mechanism that causes regional disparities between counties and between the core and the peripheral areas as well as between different time points in Guangdong (Table 2.5). However, our results contradict Gu, Shen, Wong, and Zhen’s (2001) study based on the data before the mid-1990s, which suggested that the FDI was an auxiliary factor underlying the regional inequality in Guangdong. In fact, as an indicator of globalization, FDI has been increasingly important in the economic development in Guangdong, especially after China’s accession into the WTO in the early 2000s. Notably, FDI has strong policy and geographical preferences and is characterized by path dependence (Ng & Tuan, 2003). As shown in Table 2.1, the peripheral area only accounted for 10% of the FDI in Guangdong while most of the FDI was concentrated in the PRD. The uneven distribution of FDI has become an important, rather than auxiliary, factor causing the regional disparities in Guangdong. On the other hand, our findings confirm the positive relationship between fiscal decentralization and the uneven development in Guangdong. The fiscal decentralization in the reform era has encouraged local governments in Guangdong to actively engage in local economic development (Lin, 1997). With the changes of fiscal capacity, local governments can finance infrastructure development and public goods to promote economic growth and attract investors. This process, however, often results in the greater development in the already affluent regions and the detriment in the poor areas (Wang, 2010). Fiscal decentralization also reinforces the local governments' reliance on local revenue, which encourages the local protectionism and has weakened the capability of the regional-level government to redistribute resources for an equity objective. Therefore, fiscal decentralization, despite its effectiveness in creating a growth-oriented environment in Guangdong, tends to have a negative impact on the equitable development and indirectly aggravates regional inequality. Multilevel modeling also deepens our understanding of the impact of marketization on the regional inequality in Guangdong. In comparison with globalization and decentralization, marketization has no longer been a significant factor accounting for the uneven economic development in Guangdong where the socialist market reform was initiated earlier than the other provinces in China (Gu et al., 2001). In addition, the domestic private enterprises have experienced remarkable growth in Guangdong, and their distribution tends to be more balanced in comparison with the overly concentrated foreign invested enterprises (Lin & Hu, 2011). Therefore, development of the non-state-owned sector or domestic private enterprises has potential to mediate the uneven development in Guangdong driven by the unevenness of FDI.

Fourth, the results also show that fixed asset investments have exerted strong influences on the regional development in Guangdong, and it is consistently significant in the multilevel model (Table 2.5). These results demonstrate that the economic development in Guangdong relies greatly on investments, while the distribution of fixed-asset investments is imbalanced and focused on the PRD (Table 2.1), exerting significant influences on the rising regional disparities. Fifth, the resulting multilevel model indicates that the urban-rural variable is marginally significant in the one-level model; however, when the core-periphery hierarchy is taken into account, the urban-rural divide significantly affects the regional inequality in Guangdong. In this sense, the application of multilevel modeling provides a more nuanced understanding that the rural industrialization in the PRD is still far from alleviating the overall economic inequality in the whole province. Lastly, the topography variable (MOUNTAIN) is insignificant in the multilevel model, and its coefficient is negative. Therefore, the economic developments in these counties are constrained by their physical and topographical conditions, which also intensify the regional inequality in the province.

Discussion and Conclusion

The chapter has analyzed the regional inequality in one of China's most developed provinces, Guangdong, in the postreform period and confirms the applicability of a multiscale and multimechanism framework in the empirical research on China's regional inequality at the intraprovincial level. We find that regional inequality in Guangdong is sensitive to geographical scales and such structural changes in the postreform period as China's accession into the WTO. By emphasizing the distinctive distributional dynamics in different stages of economic reform, this study also corresponds to the increasing interests of economic geographers in the transformation of economic landscape from an evolutionary perspective (Martin & Sunley, 2007).

Overall, Guangdong has experienced a new round of polarized development since the early 2000s under further globalization, which is greatly attributed to the widening gap between the PRD and the periphery as well as the urban and rural areas. It is worth noting that only a small subset of counties or cities in the periphery have benefited from the spillover from the PRD, while a large number of the counties or cities in the semicore and semiperiphery areas have experienced a progressive bias towards a "poverty trap" in the 2000s. With global Moran's *I* and spatial Markov chains, we have demonstrated the significance of spatial dependence and self-reinforcing agglomeration in Guangdong's regional development, which is consistent with the findings in the recent studies of regional development in Zhejiang (Ye & Wei, 2005) and Jiangsu (Wei et al., 2011).

The results of multilevel modeling are capable of better explaining the factors underlying the regional inequality in Guangdong over space and time. We have found that many development agents such as the local governments, foreign investors, and the central state are functioning at the low levels under provinces, which are likely to be concealed in the analysis of large spatial aggregates such as provinces and groups of provinces (Wei & Fan, 2000). More importantly, in the case of Guangdong, the uneven distribution of foreign investment, coupled with decentralization, has become the most crucial driving force behind the uneven regional development.

The above findings thus contribute to the literature and suggest meaningful theoretical and policy implications. First, as suggested by the new economic geography literature (Krugman, 1991, 2011), the importance of space revealed in these intraprovincial studies reiterate the pervasive evidence of agglomeration toward a core-periphery model operating at local scales. The persistence of core-periphery inequality also challenges the neoclassical growth theory, which emphasizes free mobility of capital and celebrates the long-term convergence. As found in this study, given the geographical and political preferences of the global capital, the uneven development in Guangdong has been intensified in the context of globalization. Second, the results of this study clearly point out that the efficacy of inequality-reducing policies in Guangdong has been constrained by the geographical barriers and the effect of self-reinforcing agglomeration. The recent efforts towards inequality reduction have also not achieved the expected effects because these policies such as the construction of “industrial relocation parks” were biased towards the specific localities in the periphery, especially the urban districts, which had a limited impact on the reduction of overall inequality in Guangdong and worsened the urban-rural inequality. Given the results of multilevel modeling, institutional reform is needed to strengthen the role of provincial government and foster cooperative relationships among local governments so as to minimize the negative impact of decentralization on regional disparities. The resulting multilevel model further provides a basis for the regional development policy to promote the spontaneous development of domestic private enterprises, which are spatially more balanced and locally embed and which have the potential to play a role in mediating the polarized development in Guangdong that is driven by the overly uneven distribution of the globalization force.

From a methodological perspective, this study underscores the promising aspects of employing GIS and spatial analysis techniques such as spatial Markov chains and multilevel modeling in understanding regional development processes. Besides spatial Markov chains, other techniques such as geovisualization have been developed to investigate the dynamics of regional inequality in the U.S. (Rey et al., 2011). Applying these rigorous GIS and spatial analysis methods is of great potential in the future research. Recent advances in spatial statistical techniques such as geographically and temporally weighted regression (GTWR; Huang & Barry, 2010) and spatial panel models (Elhost, 2003) have also tried to incorporate the time dimension in spatial econometric models. The applications of these space-time modeling techniques might also generate more insights in the triple process of regional development in China and Guangdong. Our empirical analysis of Guangdong also demonstrates that the multiscale and multimechanism framework is an appropriate ground-based conceptual tool for analyzing regional inequality in China and Chinese provinces by addressing its spatial-temporal complexity and the underlying triple process (globalization, decentralization, and marketization). We believe that this framework is not only relevant to specific coastal provinces like Guangdong. Applying this framework to the regional inequalities in inland provinces is also of great significance for a more comprehensive understanding of the varied patterns, dynamics, and mechanisms of regional inequality in China. Finally, besides the economic inequality, other aspects of inequality such as education, health, and social inequalities should deserve attention from policy makers and scholars in future research.

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CHAPTER 3

REGIONAL DEVELOPMENT AND INEQUALITY IN PROVINCIAL CHINA: A SPATIAL FILTERING PERSPECTIVE

Abstract

Through the case of Guangdong province, this chapter investigates the spatial dependence of regional development and inequality in China. Departing from previous studies assuming that the relationship between spatial dependence and regional inequality is self-evident, we apply a spatial filtering method that eliminates the spatial dependence of the data and allows for quantifying the extent to which spatial dependence contributes to inequalities at different spatial scales. The results suggest that the multiscalar nature of regional inequality is robust regardless of spatial dependence. Findings also reveal that the relationship between spatial dependence and the extent of inequality is apparently sensitive to spatial scales. In the case of Guangdong, the divide between the Pearl River Delta and the rest of the province has been strengthened by the effect of self-reinforcing agglomeration. We further investigate spatial effects on the dynamics of regional inequality and employ spatial panel and space-time regression models to reveal the space-time and core-periphery heterogeneities of development mechanisms in Guangdong.

Introduction

The past 25 years have witnessed renewed interdisciplinary interests in regional inequality and convergence (Barro & Sala-i-Martin, 1991), fueled by recent theoretical advances in new economic geography, endogenous growth and new convergence literature (Barro & Sala-I-Martin, 1997; Martin & Sunley, 1998; Scott & Storper, 2003). Scholars have also debated over the spatial impacts of globalization, decentralization, and economic liberalization, while retesting divergence, convergence, or inverted-U hypotheses (Ezcurra & Pascual, 2008; Ezcurra & Rodríguez-Pose, 2013; Lessmann, 2014). Updated cross-country analysis of regional inequality at the global level have found that globalization and trade liberalization may reduce regional inequalities and bring wealth to poor regions in developed countries (Ezcurra & Rodríguez-Pose, 2013). However, evidence has shown that inequalities in developing countries tend to persist. In many Asian countries, there have been new forms of spatially uneven growth (e.g., Akita, 2003).

China's regional development is essentially uneven in space, and regional inequality is undoubtedly a burning issue in China since inequality may threaten political stability and national unity. Intensive inequality may also cause the rise of social unrest. Researchers have found that the evolution of regional inequality in China can hardly be simplified into a convergence (the gap between rich and poor keeps narrowing) or divergence (the disparity between rich and poor increases over time) trajectory (Li & Wei, 2010). The complexity of regional inequality and uneven economic landscape can be better understood by a multiscale and multimechanism framework (Wei, 2002). At the same time, a triple-process of economic transition (i.e., marketization, decentralization, and globalization) is found to be a fundamental cause behind China's regional inequality (Hao & Wei, 2010; Li & Fang, 2013; Wei, 2002;).

Given its significance, patterns, and scales, more efforts have been made to investigate China's regional development and inequality within specific coastal provinces using finer-scale data. Case studies of Zhejiang, Jiangsu, Greater Beijing, and Guangdong have provided more detailed evidence about the space-time complexity of regional inequality in China (Wei et al., 2011). Notably, the works on regional development and inequality in provincial China, particularly using more rigorous GIS-spatial modeling methods, have allowed for a more detailed analysis of the role of space in understanding development disparities and mechanisms (Wei et al., 2011; Ye & Wei, 2005). Nevertheless, the relationship between spatial dependence and inequalities has rarely been clarified in a quantitative manner. In addition, the work on the triple process of transition was focused on the spatial heterogeneity of these mechanisms using GWR (Wei & Ye 2004, 2009), a more informative analysis of the temporal heterogeneity and core-periphery heterogeneity of these multiple mechanisms in China is needed.

Drawing upon more recent data in the Guangdong province, the present chapter attempts to "revisit" the role of space in the analysis of regional inequality and development mechanisms in China. The chapter has two objectives. First, departing from the previous studies in which the relationship between spatial dependence and inequality appears to be self-evident, the study applies a spatial filtering method to quantitatively investigate the relationship between spatial dependence and the scales as well as dynamics of regional inequality. The application of spatial filtering thus sheds light on the new economic geography theory (Krugman, 2011; Martin, 2013) and has provided detailed empirics about how economic transitions and local geographies in Guangdong interact to yield new spatial forms of development. Second, by incorporating spatial filters in a set of panel regression and space-time modeling frameworks, we further address the space-time and core-periphery heterogeneity of multimechanisms in China's regional development.

The empirical case of Guangdong was chosen for the following reasons. First, Guangdong ranks first among 31 provincial units in China in terms of the size of its economy, roughly the same size as the Netherlands in Europe. Guangdong's rapid economic growth has been greatly driven by economic globalization and market reform. Second, the province has been known for its evident regional disparities, characterized by the divide between the core region of Pearl River Delta (PRD) and the rest of the province and spatial agglomeration in the PRD (He & Wang, 2012; Lu & Wei, 2007). Therefore, Guangdong is an ideal laboratory to investigate the role of space in shaping regional inequality at different scales. Third, the literature on regional development in Guangdong has paid more attention to the period of 1978–1990; with few exceptions (Liao & Wei, 2012; Lu & Wei, 2007), regional development in Guangdong since the early 1990s has rarely been studied.

This chapter employs the recent developments in spatial analysis methodologies, particularly a spatial filtering approach, to investigate regional inequality and development in Guangdong using county-level data. We first review the development process and patterns of regional development in Guangdong. This is followed by a discussion on relevant conceptual issues and details about the spatial filtering method. The empirical results consist of the investigation of spatial dependence of regional development and its impact on regional inequalities and convergence/divergence dynamics. We further incorporate spatial filters in a set of panel and space-time model specifications, aiming to achieve a more reliable estimation of multimechanisms over space and time. The conclusion section summarizes the findings and discusses methodological and policy implications.

Research Setting and Conceptual Framework

Geographically, Guangdong is located in southeastern China and consists of four subregions, including the core region of PRD, North Guangdong, West Guangdong, and East Guangdong (Figure 2.2). There were 21 municipalities as well as 81 counties and cities in Guangdong as of 2012. The province has a land area of 179,612 square kilometers (approximately 2% of China's territory), and a total population of 105.9 million in 2012. The core region is called the Pearl River Delta or PRD, which is adjacent to Hong Kong (Figure 2.2). On par with the Yangtze River Delta (YRD), the PRD is known as an economic powerhouse in China, driven by the development of export oriented manufacturing and a huge flow of investment from Hong Kong and Taiwan (Lin, 2009; Sit & Yang, 1997).

Regional development in Guangdong has benefited from the reform policy launched in 1978 in China. It should be noted that Guangdong's geographic location is distant from the political and economic center of the country to the north (Lin, 2009). In the period of state socialism under Mao, Guangdong had never been a favorable destination of state capital. Historically, the province has been known for its globally ethnic connections with Chinese diaspora in North America, Europe, and South East Asia. As Lin (2009) summarized, the geographical proximity to Hong Kong and kinship ties with overseas Chinese investors have allowed Guangdong to move "one step ahead" in China's reform and become a favorable laboratory to experience reforms and opening up (*gaige kaifang*). The leading role of Guangdong in China's economy can be manifested by its rapid economic growth over the past 3 decades with an annual growth rate of 13.3% as compared to 9.2% at the national level (GSB, 2013). In terms of the size of the economy, the rank of Guangdong rose from 5 in 1978 to 1 in 1990 among 31 provincial units in China and has continuously ranked the first since then. This makes Guangdong's economy the same size as the Netherlands in Europe and one-third of the economy of California in the US in 2012.

While Guangdong has achieved a massive economic growth in the reform era, regional development in the province is clearly characterized by a spatially uneven pattern. The PRD region accounts for 30.5% of the land area in the province, but it has dominated the province's foreign direct investment (FDI) and exports (Table 3.1). In 2012, the PRD produced 76.6% of Guangdong's GDP, as compared to 55.5% in 1990.

The present research draws upon Wei's (2002) multiscale and multimechanism framework of regional development and inequality in China. On the one hand, regional inequality in Guangdong is sensitive to a variety of geographical scales. Under provinces, regional inequalities can be further analyzed on interregional, intermunicipality, and intercounty scales (Liao & Wei, 2012).

Table 3.1 Core-periphery structure in Guangdong

	Guangdong		As percentage of Guangdong			
			Pearl River Delta		Periphery	
	1990	2012	1990	2012	1990	2012
Population (million)	63.5	105.9	30.4	53.3	69.6	46.7
Land area (sq km^2)	179,612	179,612	30.5	30.5	69.5	69.5
GDP (billion yuan)	155.9	5706.8	55.5	76.6	44.5	23.4
Investments in fixed assets (billion yuan)	38.1	1930.8	69.3	64.1	30.7	35.9
Exports (US$ billion)	22.2	574.1	100.0	88.2	0.0	11.8
FDI (US $billion)	1.5	23.5	84.7	82.8	15.3	17.2

Adapted from GSB, 2014

On the other hand, major drivers of Guangdong's regional development are consistent with China's triple process of economic process. First, regional development in Guangdong has been fueled by the globalization process. Guangdong is among several coastal provinces that have benefited considerably from the preferential open door policy. For instance, three out of the four designated special economic zones (SEZ) in China were located in Guangdong. For years, Guangdong has succeeded in attracting FDI, and its exports have accounted for nearly one-third of the total exports in China in the 1990s. Second, economic growth in Guangdong is motivated by the decentralization of decision-making power to the local government. Prefecture- and county-level governments have actively participated in local economic development, coined as "local state corporatism" (Oi, 1995; Xu & Yeh, 2005). Third, under market reform, the development of private enterprises has become another major agent of Guangdong's regional development (Lin & Hu, 2011; Liu & Yang, 2013). The original PRD model is recently modified given the rise of domestic Chinese private enterprises and the development of knowledge-based economy (Liu & Yang, 2013; Lu & Wei, 2007).

Based on this multiscale and multimechanism framework, the following sections will analyze the spatial dependence of regional development in Guangdong and further investigate the spatial effects on multiscalar patterns and distributional dynamics of regional inequality. Most of the data used in this study are compiled from the Guangdong statistical yearbook, and the GDP data have been adjusted to the constant price in 1990. The population data in noncensus years was interpolated using census data in 1990, 1995, 2000, 2005, and 2010 since population with residence registration tends to exaggerate the extent of inequality in China (Chan & Wang, 2008; Li & Gibson, 2013). The interpretation of the findings are aided by years of fieldwork since 2005.

Methodology: A Spatial Filtering Perspective

Spatial filtering is a specific technique that is able to remove the spatial dependence in the data. In this study, we employ Griffith's spatial filtering approach to eliminate spatial autocorrelation (Getis & Griffith, 2002). The main advantage of these filtering procedures is that the studied variables (which are initially spatially correlated) are divided into spatial and nonspatial components. This approach is also preferred because it can be easily incorporated in other regression model specifications, such as panel data framework (Patuelli et al., 2011), and can also be used to furnish a space-time model while controlling for spatial autocorrelation in residuals (Griffith, 2008).

The selection of spatial filters is based on the computational formula of Moran's *I (MI)* statistic. This methodology uses eigenvector decomposition techniques, which extract the orthogonal and uncorrelated numerical components from a $N\times N$ modified spatial weight matrix:

$$w = \left(\mathbf{I} - \frac{II^T}{n}\right) C (\mathbf{I} - \frac{II^T}{n}) \qquad (3.1)$$

where C is an indentity matrix of dimension $n\times n$ binary 0–1 geographic connectivity matrix, and I is an $n\times 1$ vector containing 1s. The eigenvectors of the modified matrix are calculated to maximize the sequential *MI* values. The first computed eigenvector, E1, is the one that results in the largest *MI* value among all eigenvectors of the modified matrix. This is followed by the second eigenvector, E2, which is a set of numbers that aimed to maximize the *MI* value while being orthogonal and uncorrelated with E1. The process continues until *N* eigenvectors have been computed. The final set of these eigenvectors includes all possible mutually orthogonal and uncorrelated map patterns (Getis & Griffith, 2002; Thayn & Simanis, 2013). When employed as regressors, these eigenvectors could be treated as proxies for missing explanatory variables that capture the underlying geographical structure (Patuelli et al., 2011). It should be noted that employing all *N* eigenvectors in a regression framework is not desirable due to issues related to model parsimony and statistical significance, and is often impossible to add other covariates. Therefore, a smaller subset of candidate eigenvectors can be selected from the *N* eigenvectors on the basis of their *MI* values. In this analysis, we follow the spatial filtering method suggested by Chun and Griffith (2013). The spatial weight matrix is based on the rook's contiguity definition (i.e., on border-sharing schemes) and coded according to the C-coding scheme, which yields a symmetric matrix *W* (Tiefelsdorf & Griffith, 2007).

Spatial Dependence of Regional Development

Before presenting the results of spatial filtering based analysis, this section generally applies an exploratory spatial data analysis (ESDA) approach to investigate the spatial dependence of regional development in Guangdong. In calculating the Moran's *I*, the spatial weight matrix is of particular concern (Anselin, 1988) because it represents the particular spatial linkage between spatial units. It is appropriate to investigate the alternative weighting strategy due to the complexity of spatial interactions. Following Yu and Wei (2008) and Li and Fang (2013), five spatial weight metrics are employed to reveal the significance of Moran's *I*. As shown in Table 3.2, the resulting Moran's *I* over the study period are all higher than 0 and significant at a level of 0.001, indicating the significance of spatial dependence in Guangdong's regional development.

Table 3.2 Z-scores of Moran's *I*

Year	Contiguity	Inverse distance	Inverse distance square	Fixed distance band	Zone of indifference
1988	6.278	4.296	2.550	4.769	4.771
1990	6.066	4.053	2.370	4.508	4.510
1995	6.251	4.894	2.913	5.472	5.475
2000	6.205	4.848	2.913	5.440	5.442
2001	6.238	4.798	2.871	5.397	5.399
2002	6.237	4.697	2.804	5.279	5.281
2003	6.177	4.583	2.741	5.134	5.137
2004	6.257	4.659	2.817	5.187	5.189
2005	6.468	4.744	2.834	5.294	5.296
2006	6.629	4.828	2.855	5.402	5.404
2007	6.958	4.871	2.848	5.467	5.468
2008	7.228	4.943	2.888	5.572	5.574
2009	7.539	5.127	3.004	5.775	5.776
2010	7.390	4.848	3.110	5.897	5.898
2011	7.502	4.798	3.115	5.906	5.908
2012	7.509	4.697	3.129	5.893	5.895

Table 3.3 presents changes of Moran's *I* values in Guangdong. The Moran's *I* indicator, under the border-sharing strategy, rose consistently from 0.44 in 1988 to 0.53 in 2012, revealing the existence of statistically significant positive spatial autocorrelation and a rapid increasing trend of spatial autocorrelation or agglomeration since the early 1990s. As Yu and Wei (2008) stated, there are two possible scenarios when an upward Moran's *I* is observed. First, there may be new clusters. Second, more areas become similar. In this regard, LISA Moran's *I* can supplement the global Moran's *I* index in detecting the sources of global spatial autocorrelation. As demonstrated in Figure 3.1, LISA Maps, both in 1988 and 2012, reflect the agglomeration of development in the PRD. So the rise of global Moran's *I* is largely driven by the clustering of regional development rather than the formation of new clusters out of the PRD. It also implies that the spatial dependence should be considered in our analysis.

Table 3.3 Moran's *I* of actual and spatially filtered GDP per capita, 1988–2012

	Nonfiltered data			Filtered data		
Year	Moran's *I*	z-value	p-value	Moran's *I*	z-value	p-value
1988	0.457	6.466	0.000	-0.053	-0.559	0.576
1990	0.449	6.327	0.000	-0.096	-1.131	0.258
1995	0.461	6.593	0.000	-0.105	-1.281	0.200
2000	0.461	6.500	0.000	-0.093	-1.096	0.273
2001	0.468	6.589	0.000	-0.149	-1.857	0.063
2002	0.469	6.639	0.000	-0.131	-1.622	0.105
2003	0.466	6.608	0.000	-0.136	-1.687	0.092
2004	0.472	6.679	0.000	-0.148	-1.843	0.065
2005	0.485	6.832	0.000	-0.144	-1.788	0.074
2006	0.492	6.918	0.000	-0.132	-1.617	0.106
2007	0.508	7.101	0.000	-0.123	-1.485	0.137
2008	0.515	7.182	0.000	-0.101	-1.186	0.236
2009	0.526	7.324	0.000	-0.108	-1.280	0.201
2010	0.527	7.321	0.000	-0.117	-1.401	0.161
2011	0.535	7.420	0.000	-0.112	-1.338	0.181
2012	0.536	7.433	0.000	-0.118	-1.415	0.157

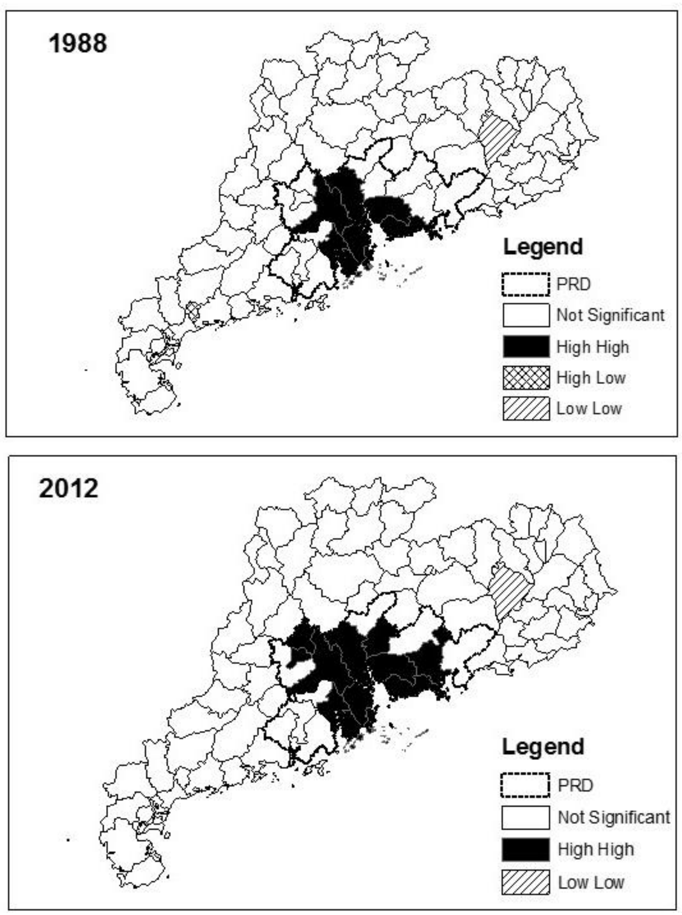


Figure 3.1 Local Moran's *I* of GDP per capita in Guangdong, 1988, 2012

The present research uses the spatial filtering approach proposed by Griffith. The first step in the construction of a spatial filter to be applied to the county-level GDP per capita is the eigenvectors of the spatial weight matrix, followed by the choice of a subset of "candidate" eigenvectors from which the selection is made. Candidate eigenvectors are selected based on their MI values and their correlations with the geo-referenced GDP per capita data, using a minimum threshold of 0.5 for the statistic MI/max (MI). Once a set of "candidate" eigenvectors has been selected, its statistical significance as explanatory variables for Guangdong's GDP per capita data has to be established.

The results of spatial filtering show that the spatial correlation between counties in Guangdong has been effectively removed (see the columns of filtered data in Table 3.3). In fact, the significant high positive Moran's *I* statistics obtained with actual data are not only reduced dramatically, but they also become negative and are statistically insignificant. Thus, we have two sample series, one with actual data and the other with filtered data. In the rest of the chapter, we examine the multiscalar characteristics and distribution dynamics of regional inequality with two sample series; therefore, the only differences between them are attributed to spatial effects.

Scales and Dynamics of Regional Inequality

This section is devoted to the analysis of regional inequalities at different scales, including intercounty, intermunicipality, and interregion scales and the distribution dynamics, with a particular focus on spatial effects.

Regional inequality can be measured by a variety of indexes such as GINI, Theil, and Coefficient of Variation (or CV). Starting with Figure 3.2, we estimate regional inequalities in Guangdong using a population-weighted coefficient of variation (WCV).

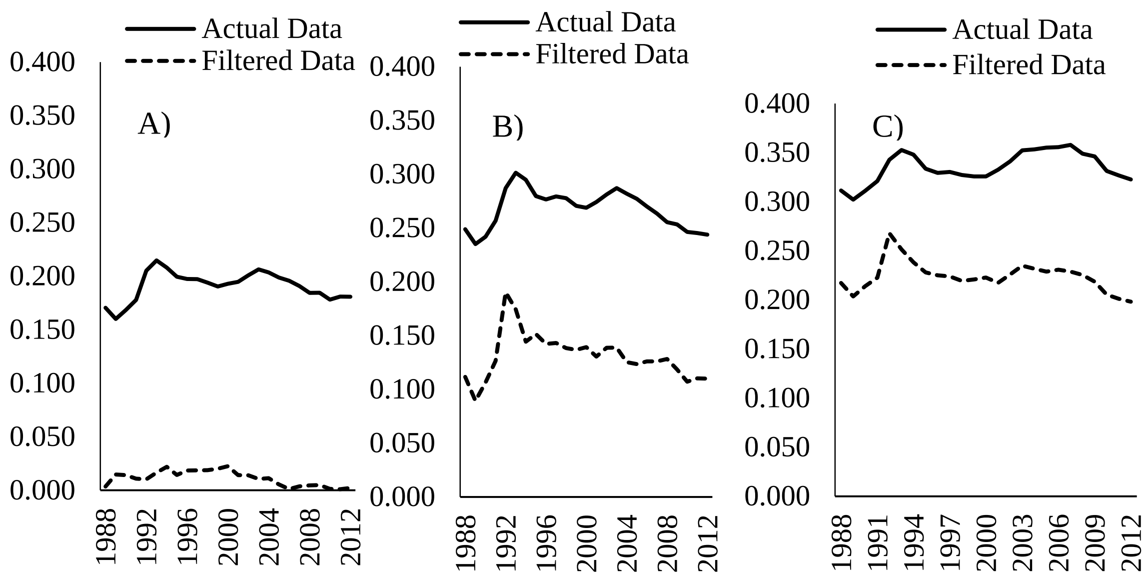


Figure 3.2 Multiscale inequalities with/without spatial filters in Guangdong: A) Interregional inequalities; B) Intermunicipality inequalities; C) Intercounty inequalities

Figure 3.2 leads to some interesting findings: first, the regional inequality is sensitive to spatial scales (Liao & Wei, 2012). We have also found that regional inequality at three scales tended to increase in the early 1990s and then became stable until the end of 1990. The inequality rose again in the early 2000s and declined afterwards, although the decrease of intercounty inequalities occurred later in the study period. In other words, the evolution of regional inequality can hardly be simplified into convergence and divergence. Third, Figure 3.2 also shows that at more disaggregated geographical scales, there are more intensive disparities. Notably, this finding holds when taking into account spatial effects. Fourth, the impact of spatial agglomeration on regional inequality is significant, whereas the relationship is contingent upon geographical scales.

Table 3.4 further illustrates that spatial dependence accounts for over 90% of the inequality at the regional level, while the influence declines to around 60% at the

Table 3.4 Spatial inequality with and without spatial filers

Year	Theil Nonfiltered	Filtered	% of spatial dependence	GINI Nonfiltered	Filtered	% of spatial dependence
Interregional						
1988	0.064	0.000	99.95	0.170	0.004	97.93
1995	0.087	0.000	99.94	0.199	0.014	92.85
2000	0.082	0.001	98.52	0.193	0.023	88.28
2005	0.087	0.001	99.92	0.199	0.006	97.22
2010	0.070	0.000	99.99	0.178	0.001	99.27
Intercity						
1988	0.124	0.034	72.88	0.249	0.112	55.19
1995	0.158	0.056	64.45	0.280	0.151	45.85
2000	0.138	0.046	66.94	0.269	0.139	48.22
2005	0.159	0.037	76.62	0.277	0.123	55.47
2010	0.125	0.027	78.61	0.246	0.107	56.50
Intercounty						
1988	0.176	0.088	49.99	0.311	0.217	30.24
1995	0.199	0.098	50.54	0.334	0.228	31.66
2000	0.184	0.089	51.52	0.326	0.223	31.59
2005	0.222	0.094	57.82	0.355	0.229	36.05
2010	0.187	0.070	62.53	0.331	0.205	38.01

municipality level and approximately 40% at the county level. Therefore, by using a spatial filtering approach, we have been able to quantify these relationships.

In order to shed further light on the regional inequalities across counties in Guangdong, we apply two methods, including a cross-profile dynamics and stochastic Kernel approach, to capture the distribution dynamics of regional inequality and intradistribution mobility of spatial units. We start with Figure 3.3 showing cross-profile dynamics. The vertical axis is the relative per capita incomes. Two curves in the figure point to the situations in 1988 and 2012. The most striking feature of Figure 3.3 is not this comparative stability through time. It is the change in choppiness through time in the cross-profile plots indicated by local peaks. The curve of 2012 suggests that the relative declines are more likely to occur in counties in the periphery region. However, the upward mobility of counties in the periphery region is also evident, partly explaining the

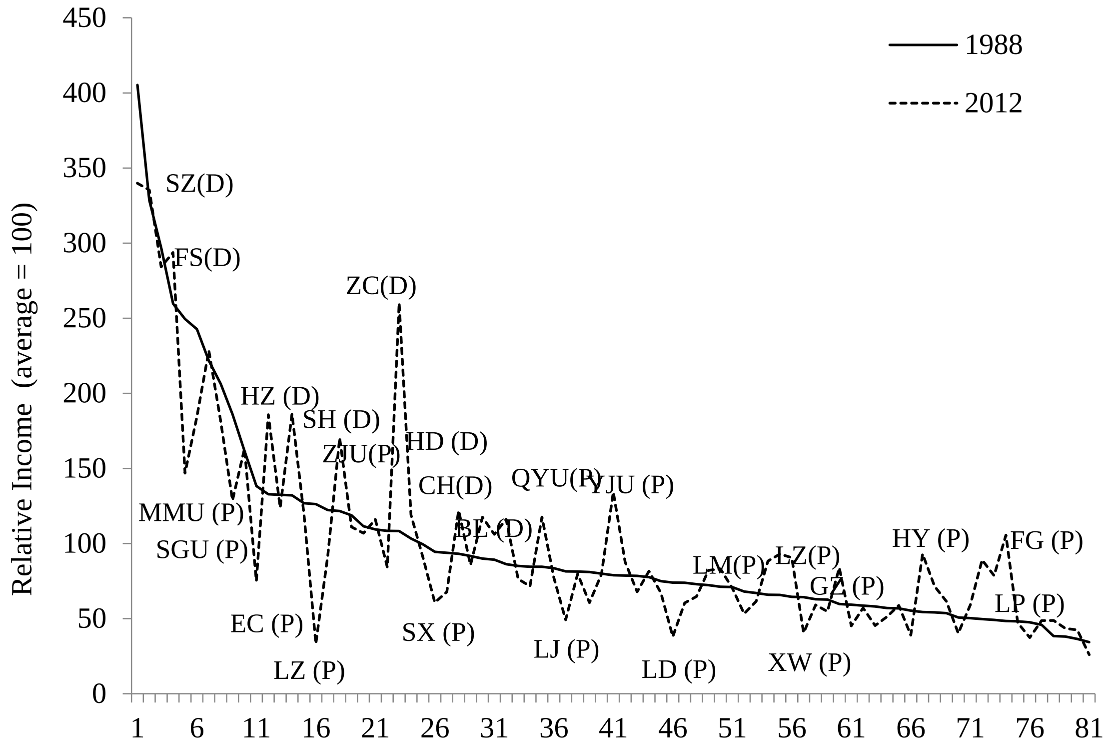


Figure 3.3 Cross profile dynamics (D = PRD, P = Periphery)

recent decline of regional inequality in Guangdong. Figure 3.3 also shows that a set of counties or cities in the PRD including Foshan, Guangzhou, Zhongshan, and Zhuhai have moved upward in the distribution, while a number of counties in the periphery area converged towards the average at the same time.

Consistent with the cross-profile dynamics shown in Figure 3.3, many counties that are distant to the PRD in the periphery area have been diverging from below (Figure 3.4). Counties moving upward are those areas geographically closer to the PRD. In addition, the spatial effect on the cross-profile dynamics is evident (Figure 3.5). Figure 3.5 highlights that if spatial effect is removed, the gap between richest and poorest is narrowed. There are more counties moving upward in the poor region while more counties are declining in the rich region.

Although the cross-profile dynamics are informative, they do not identify

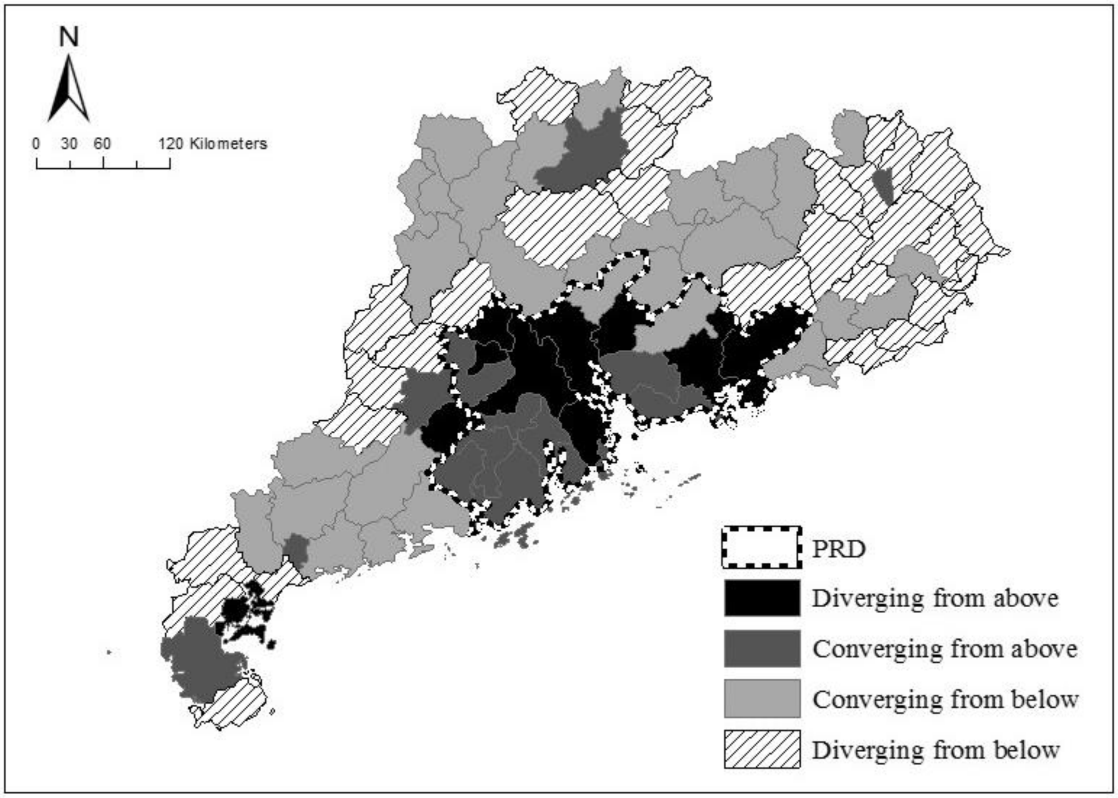


Figure 3.4 Changing GDP per capita in Guangdong, 1988–2012

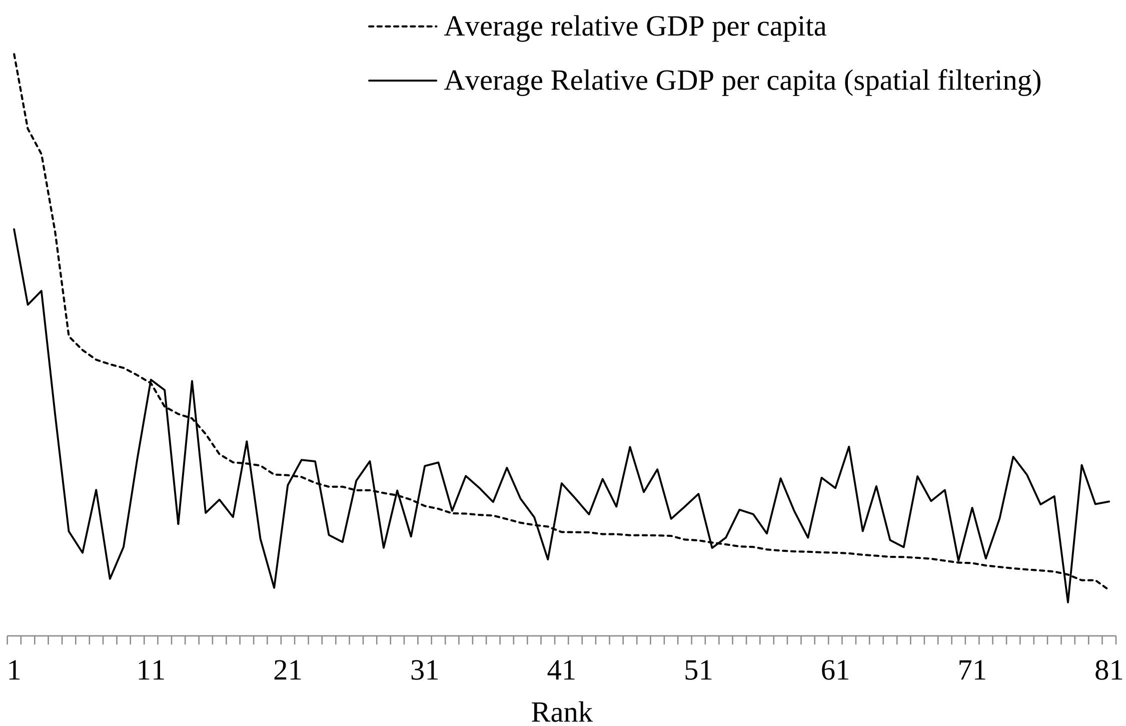
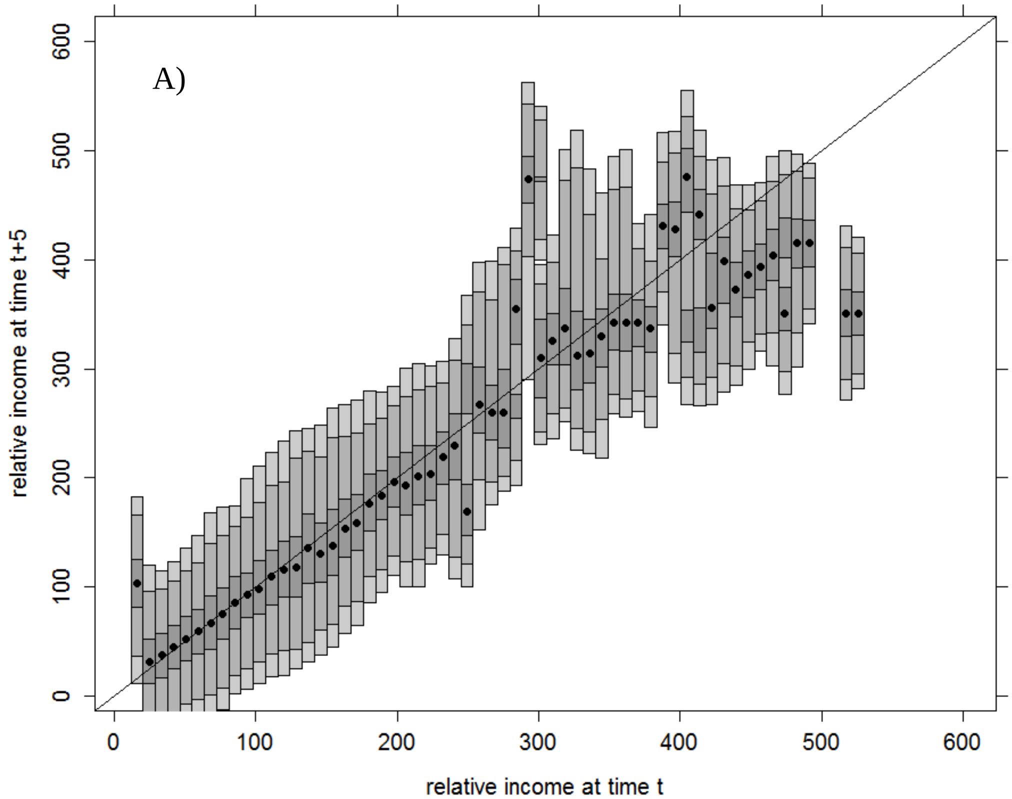


Figure 3.5 Intradistribution mobility in Guangdong, 1988–2012

underlying dynamic regularities in the data. We thus turn to the stochastic kernel representation of intradistribution dynamics. Similar to a Markov chain, stochastic kernel densities are the continuous version of the model of distribution dynamics. Let F_t denote the cross-section distribution of GDP per capita at time *t*, then the distribution evolves according to:

$$F_{t+1} = MF_t \tag{3.2}$$

where M denotes the distribution from time *t* to time $t + 1$, and tracks where points in F_t end up in F_{t+1} , and it can also be viewed as a stochastic kernel or transition function that describes the (time-invariant) evolution of the cross-section distribution in time. Following Hyndman et al. (1996), we employ the stochastic kernel approach and estimate the highest density plots using a 5-year transition period. The highest density plot is defined as “the smallest region of the sample space containing a given probability” (Maza & Villaverde, 2009). Thus, each vertical strip in Figure 3.6 denotes the conditional density of a per capita income level in time *t*. For any point y on the period *t* axis, looking in the direction parallel to the *t* + 5 time axis traces out a conditional probability density. In particular, Figure 3.6 shows the highest density regions for probabilities of 25, 50, 75, and 99% (as it passes from a darker to a less darker area). In addition, it illustrates, as a bullet, the mode (value of per capita GDP in time *t* + 5 where the density function takes on its maximum value) for each conditional density for each per capita GDP in time *t*. Just as a transition matrix based on Markov-chain approaches, the 45-degree diagonal in the graph indicates persistence properties. Therefore, most of the densities are concentrated along this diagonal, and the elements in the cross-section distribution remain where they started.



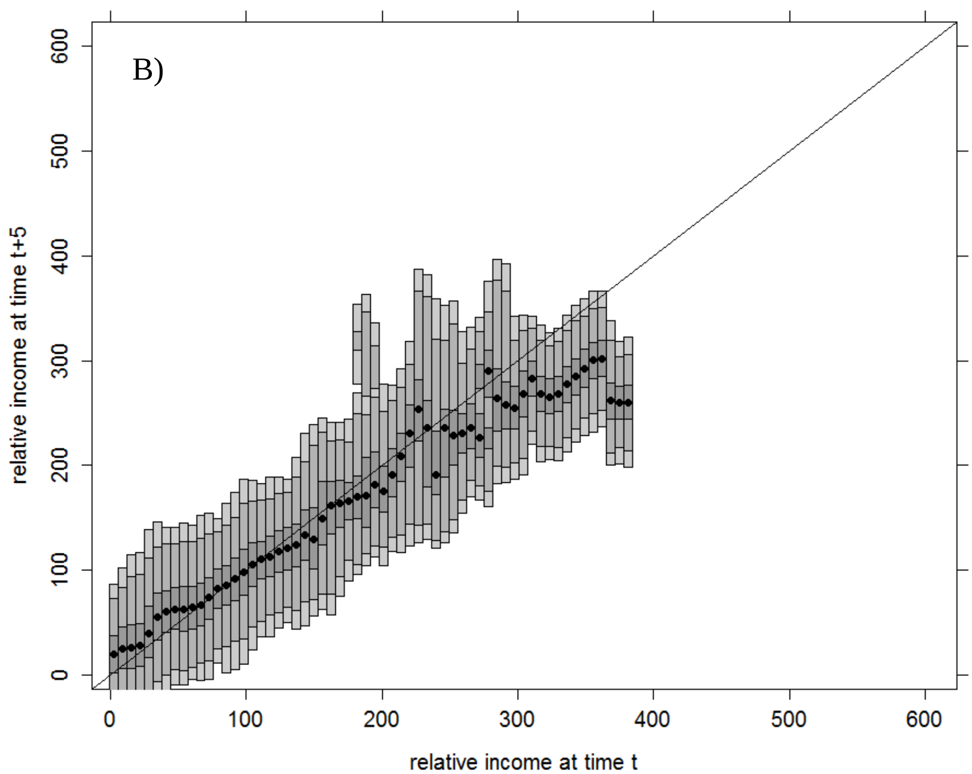


Figure 3.6 Stochastic kernel density of per capita GDP in Guangdong, 1988–2012: A) Actual Data (average=100); B) Filtered Data (average=100)

As evident from Figure 3.6A, a large proportion of the probability mass tends to remain agglomerated along the main diagonal over the 5-year horizon, and it is clear that the poorest counties have been facing more challenges to move upward. On the other hand, we find that some counties well above average decline in the intradistribution shape, which is consistent with recent decline in regional inequalities among counties. The plot based on spatial filter data reveals an evident spatial effect on regional mobility in Guangdong (Figure 3.6B). It mainly suggests that if spatial autocorrelation is eliminated, the upward mobility of these most affluent counties is constrained, and the gap between the rich and poor tends to shrink. In short, our results indicate that spatial effects have been more influential on the mobility of wealthiest counties within the distribution of county level GDP per capita.

Spatial-temporal Models of Multimechanism of Regional Inequality

The above sections compare spatially filtered and actual data to investigate spatial effects on regional inequalities and distribution dynamics. To better understand the underlying mechanisms, this section employs a set of spatial filter-based panel and space-time models to investigate the space-time and core-periphery heterogeneity of development dynamics.

Underlying mechanisms of regional inequality

Following the production function and considering the lack of reliable growth rates, we treated the individual year's per capita GDP as dependent variables (Li & Fang, 2013; Yu & Wei, 2008). The independent variables selected in this study are broadly similar to those used to analyze Zhejiang (Wei & Ye, 2009), Jiangsu (Wei & Kim, 2002) and Guangdong (Liao & Wei, 2012). They are also based on the conceptualization of China's development as a triple process of marketization, globalization, and decentralization.

1. The foreign direct investment per capita (FDIPC) is selected as a proxy of the effect of globalization. It reflects the effect of globalization and is assumed to positively contribute to regional development in Guangdong.

2. The importance of socialist institutions and the infusion of market mechanisms can be represented by the share of non-SOE in employment (NSOEPCT).

3. The decentralization process is represented by the ratio of local governmental expenditure per capita to the provincial government's budgetary spending per capita (GOVPC). It is a proxy of the degree of fiscal decentralization and the shift of power from upper level governments to local governments (Hao & Wei, 2010).

4. Fixed asset investment per capita (FIXPC) is selected as the primary factor of input in regional development. In China, fixed investment is also considered as a key instrument in the process of industrialization and economic growth. FIXPC is expected to positively contribute to regional development.

5. Agglomeration economies such as urbanization economies are widely acknowledged as a key driver of economic growth (Jacobs, 1969). As noticed by scholars (Chen & Partridge, 2013), China's regional development policy leans toward the urban area, and urbanization has been considered as an engine of regional development. We employ the percentage of urban population in the total population (URB) to investigate the effect of urbanization on regional development.

6. In Guangdong, most of the plain area is located in the PRD, while mountain

counties are mostly located in the periphery. A dummy variable (MOUNTAIN) is used to represent the impact of physical topographical conditions on the regional development (Li & Fang, 2013). In addition, since the early 2000s, the provincial government in Guangdong has put in more efforts to promote local economic growth in these mountainous counties (Liao & Wei, 2012). Therefore, the variable also denotes the impact of these policies on regional development in Guangdong.

Model specifications

We build our model based on the production function, which formally expresses the output of an economic system (per capita GDP) as the product of basic input factors: FDIPC, GOVPC, NSOEPCT, FIXINV, URB, and all the input factors are hypothesized to be exogenous input. Therefore, a production function-like regional development mechanism model can be specified as

$$GDPPC=A*FDIPC^{\beta1}*GOVPC^{\beta2}*NSOEPCT^{\beta3}*FIXINV^{\beta4}*URB^{\beta5}*Mountain^{\beta6} \quad (3.3)$$

The exponential form can be transformed into a linear form through logarithm transformation, which results in the familiar linear model:

$$y_{it} = \beta_{it} X_{it} + \varepsilon_{it} \quad (3.4)$$

where y_{it} is the logarithm transformed GDPPC in county *i* in the year of *t*, X_{it} is the matrix containing the five independent variables in their logarithm transformed forms and a constant term, β_{it} is the vector of model coefficients, and ε_{it} is the error term. After the transformation, all the variables are asymptotically normally distributed. Equation 3.4 is an orthodox panel data model. Serial correlation is difficult to assess. Nevertheless, the additional structure in the space-time dataset can be accounted for with a geographically and temporally varying random variable, which in part acts as a surrogate for missing variables. This random effects intercept also supports inferences beyond the employed spatial partitioning and set of points in time. Following Griffith (2008), we further incorporate spatial filters in equation 3.2 to construct a spatially structured random effect panel data model. Therefore, equation 3.4 becomes

$$y_{it} = \beta_{it} X_{it} + sf_{it} + \varepsilon_{it} \tag{3.5}$$

where sf_{it} is the linear combination for a county *i* in time *t* of the selected spatial filter components, assuming that spatial autocorrelation is specific to individual year *t*. As mentioned above, a subset of "candidate" eigenvectors have been selected and treated as regressors in equation 3.5. An AIC-based stepwise regression approach is employed to further investigate between explanatory variables and county-level GDP per capita data in Guangdong.

Spatial panel regression models

We first estimate both OLS and spatial filter panel regression models using county level socioeconomic data in 1990, 1995, 2000, 2005, and 2010. Table 3.5 reports the overall pseudo-R2 and *MI* of residuals as well as year-specific filters that can account for spatial autocorrelation in the data. The spatial filtering panel regression model removes all of the residual spatial autocorrelation and further increases pseudo-R2 values. We also compare the spatial filter panel data model to the selected benchmark spatial panel regression models, including spatial lag panel and spatial error panel (Elhorst, 2003; Patuelli et al., 2011). A spatial lag and error panel model are expressed as

Table 3.5 Spatial filter regression and selected eigenvectors, 1990–2010

Year	OLS		Spatial filtering		
	Pesudo R^2	MC for residuals	Selected Eigenvectors	Pesudo R^2	MI for residuals
1990	0.662	0.462	E1, E2, E3, E4, E7, E9, E10, E11, E12, E19, E21	0.910	-0.145
1995	0.794	0.057	E3, E4, E7, E8, E9, E10, E11, E12, E15, E16, E17	0.958	-0.183
2000	0.730	0.153	E3, E4, E5, E7, E8, E9, E10, E11, E12, E13	0.959	-0.195
2005	0.706	0.188	E3, E4, E7, E8, E9, E10, E11, E12,E13, E15	0.962	-0.046
2010	0.761	0.160	E3, E7, E8, E10, E11, E12, E13, E15, E20, E21	0.958	-0.164

$$y_{it} = \delta \sum_{j=1}^{N} (w_{ij} y_{it}) + x_{it}\beta + u_i + \varepsilon_{it} \qquad (3.6)$$

where δ is the spatial autoregressive coefficient and w_{ij} is an element of spatial weight matrix W, describing the spatial arrangements of the units in the sample. u_i denotes a spatial specific effect, and ε_{it} is an independently and identically distributed error term.

The spatial error model is computed as follows:

$$y_{it} = x_{it}\beta + u_i + \varphi_{it} \qquad (3.7a)$$

$$\varphi_{it} = p \sum_{j=1}^{N} (w_{ij} \varphi_{it}) + \varepsilon_{it} \qquad (3.7b)$$

where φ_{it} is the spatially auto-correlated error term and p is the spatial autocorrelation coefficient. Table 3.6 presents results based on four model specifications including simple pooled OLS regression, spatial filter panel regression (equation 3.5), spatial lag panel regression (equation 3.6) and spatial error panel regression (equation 3.7a and equation 3.7b). Multicollinearity is not a problem as VIF estimates are all lower than 2.5. Based on the results (Table 3.6), four interesting findings emerge. First, measured by

Table 3.6 Results of spatial filter mixed effect and spatial panel models

	pooled OLS				spatial filter panel			spatial lag panel			spatial error panel		
	Coef.	Sig.	T-value	VIF	Coef.	Sig.	T-value	Coef.	Sig.	T-value	Coef.	Sig.	T-value
FDIPC	0.014		0.876	2.116	0.061	***	5.313	0.029	**	2.417	0.063	***	5.193
NSOEPT	1.103	***	7.778	1.758	0.528	***	5.616	0.039	***	4.688	0.089	***	6.565
GOVPC	0.102	***	4.010	1.518	0.078	***	3.479	0.118	***	4.432	0.095	***	3.915
FIXPC	0.147	***	11.906	2.211	0.061	***	3.924	0.716	***	6.491	0.590	***	5.854
Urban	0.996	***	6.568	2.432	0.565	***	4.423	0.616	***	5.727	0.770	***	6.298
Mountain	-0.146	***	-3.710	1.263	-0.077		-1.550	-0.291	***	-4.069	-0.238	***	-4.157
W*y_{it}								0.593	***	15.381			
W*φ_{it}											0.758	***	20.665
Constant	6.042	***	82.409		6.674	***	85.490	2.399	***	31.562	6.586	***	58.888
BIC	349.347				104.034			155.617			121.774		
Adjust R2	0.772		Log likelihood ratio test			<0.001		<0.001			<0.001		

BIC, the three spatial panel regression model specifications report better fitting statistics in comparison with the simple pooled OLS model, which explains 77.2% of the total variance of the county-level GDPPC. Results of likelihood ratio tests also identified that there is a significant reduction in deviance. Second, consistent with Patuelli's study (2011), the fitting of the spatial-filter random-effect panel model, based on BIC, is superior to the spatial-lag and error-model specifications, mostly because its random effects term is a surrogate for various model deficiencies. Third, Table 3.6 shows that variables representing decentralization, marketization, and globalization are significant drivers of regional development in Guangdong (Table 3.6). Nevertheless, in comparison with the pooled OLS model, the *t* values of coefficients for GOVPC and NSOEPT decrease. More importantly, FDIPC, reflecting globalization, is significant in explaining regional development, and its coefficients are positive in spatial regression models. However, the pooled OLS model shows that the coefficient of FDIPC is insignificant. The result that the globalization effect has been declining is contrary to the basic nature of regional development in Guangdong. Therefore, spatial panel models, while taking into consideration spatial autocorrelation, result in more reliable estimation of the development mechanisms. In addition, urbanization is a key driver of regional development, and physical conditions matter given the fact that the coefficient of MOUNTAIN is significantly negative. The results also suggest that the effect of provincial government's policies aiming to reducing the gap between mountainous counties and those richest ones in the PRD has been constrained by these geographical conditions.

Space-time models

Results of spatial panel models are mainly concerned about the time-invariant coefficients. However, as Li and Wei (2010) argued, many factors of regional development are characterized by temporal heterogeneity/hierarchy. Following Griffith's space-time model (2008), five time dummies and time-specific terms are added in the equation 3.5 to detail the temporal heterogeneity of the underlying factors while taking into account spatial autocorrelation. The space-time model is expressed as follows:

$$y_{it} = \beta_{0,t} I_{it} + \beta_{1,t} x_{it} + sf_{it} + \varepsilon_{it} \quad (3.8)$$

where

y_{it} denotes the GDPPC of county *i* in time *t*;

I_{it} denotes the binary 0/1 indicator variable to time *t* for county *I*;

x_{it} denotes the triple process of economic transition, including FDIPC, GOVPC and NSOEPT; and β_{0t} denotes the regression coefficients for the temporal dummies.

$\beta_{1,t}$ denotes the regression coefficients for covariates of FDIPC, GOVPC, and NSOEPT in time *t*. Figure 3.7 shows the time-varying coefficients of the three variables of FDIPC, GOVPC, and NSOEPT. The simple pool OLS regression reveals a conspicuous decrease in the coefficient of FDIPC through the period of 1990–2010. However, the spatial lag/error models and spatial filtering models all confirm the fact that coefficients of FDI increased especially in the early 2000s right after China's entry into WTO. Spatial filter and spatial lag models reduce standard errors of these coefficients as compared to the results of OLS regression. Furthermore, the impact of marketization and decentralization on regional development is sensitive to different time points (Figure 3.7).

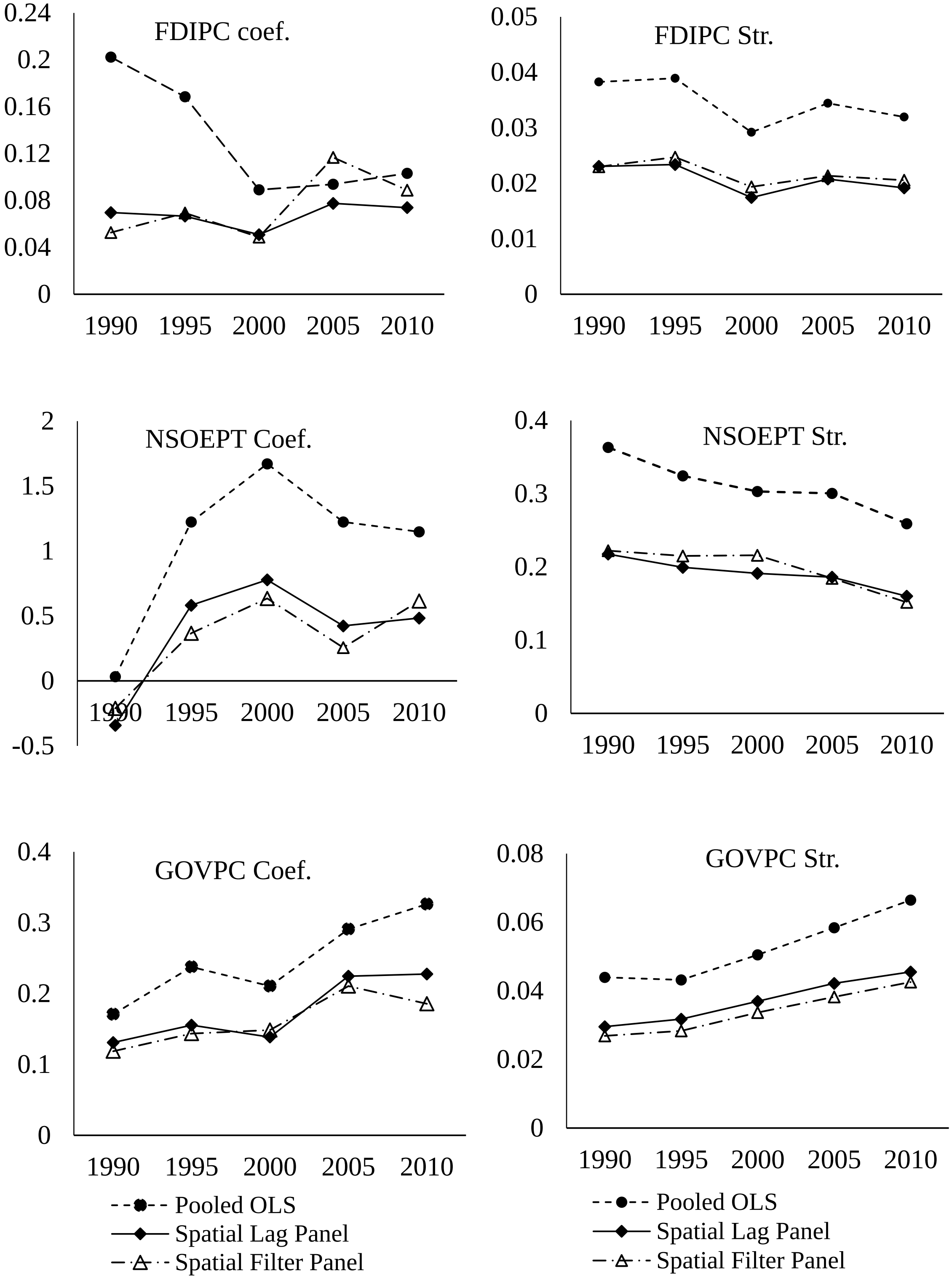


Figure 3.7 Temporally varying coefficients in three spatial panel specifications

Consistent with the finding from Li and Wei (2010) and Liao and Wei (2012), the influence of market reform has been declining. By contrast, the influence of government and public spending increased consistently, indicating the more important role of local governments' expenditure in Guangdong's development under decentralization.

The model based on equation 3.7 can be further expanded by taking into account the core-periphery structure in Guangdong. We borrow the idea of spatial regime model and add two regimes in the model (equation 3.9). Core region refers to the PRD, and the periphery region is those counties in the areas out of PRD.

$$\begin{bmatrix} y_{it,c} \\ y_{it,p} \end{bmatrix} = \begin{bmatrix} x_{t,c} & y_{t,c} & & \\ & & x_{t,p} & y_{t,p} \end{bmatrix} \begin{bmatrix} \beta_{it,c} \\ \beta_{it,p} \end{bmatrix} + sf_{it} + \varepsilon_{it} \qquad (3.9)$$

where $\beta_{it,c/p}$denotes the specific coefficients of covariates for counties in the core/periphery region in time *t*.

Figure 3.8 presents spatially and temporally varying coefficients in the core and periphery regions. Clearly, the impact of the triple process of economic transition on regional development in the core region of the PRD is significantly more intensive than their counterparts in the periphery region. These results suggest that regional development in the PRD is more intensively driven by the triple process of economic transition. We also find that these coefficients differ from each other in their evolution. Coefficients of FDIPC, reflecting globalization effect, tend to decline in the PRD region recently. As Lu and Wei (2007) described, the original PRD model has been modified while other factors, such as the public spending, have become another agent of the development. The coefficients reflecting marketization are declining in the PRD while being increasing in the periphery. This finding substantiates the previous analysis using a

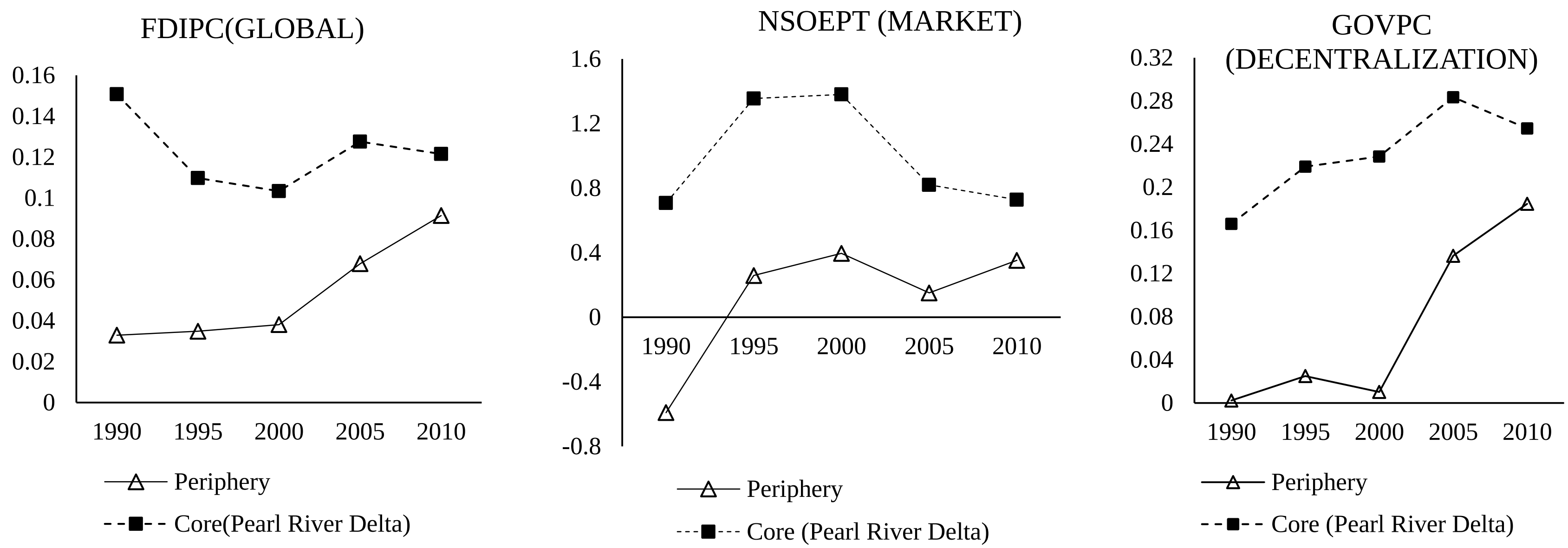


Figure 3.8 Spatially and temporally varying coefficients derived from two-regime spatial filtering mixed effect model

multilevel model (Liao & Wei, 2012), suggesting that the market reform tends to be less influential in the PRD, where socialist market reform has been initiated earlier than the periphery.

Discussion and Conclusion

Drawing upon Wei (2002)'s multiscale and multimechanism framework, this chapter "reinvestigates" the scales, dynamics, and mechanisms of regional inequality in provincial China from a spatial filtering perspective. The chapter contributes to the literature by examining two issues: 1) the relationship between spatial dependence and the scales and dynamics of regional inequality and 2) the spatially and temporally variations of underlying factors of regional development and inequality. These contributions are made through comparing spatially filtered and actual data and adding spatial filters in a set of panel data and space-time modeling frameworks.

In general, the empirical case of Guangdong confirms the applicability of a multiscale and multimechanism framework when analyzing regional disparities in China. Specifically, taking into consideration spatial effects as well as space-time heterogeneity is valuable to achieve a deeper understanding of the relationship between agglomeration, scales, dynamics, and inequality. First, we demonstrate that spatial dependence has reinforced regional inequalities at different spatial scales while the multiscalar nature of regional inequality is robust regardless of spatial autocorrelation. In the case of Guangdong, spatial effects have accounted for more than 90% of the core-periphery divide between the core region of the PRD, and the rest of the province and its contribution to intermunicipality and intercounty inequalities decline to 60% and 40%, respectively. Therefore, the theory of new economic geography is validated (Krugman, 1999). Furthermore, geography or spatial effects also matter for the mobility of regions within the distribution of county-level GDP per capita. We have found that spatial effects have constrained the mobility of poorest counties well below average, while they tend to better explain the mobility of wealthiest counties in the GDP per capita distribution. This polarization effect has contributed to the emerging “poverty trap” in the periphery region distant to the core region of the PRD.

Another aim of the chapter was to examine the space-time heterogeneity of these triple processes of economic transition while taking into account spatial autocorrelation and the core-periphery structure in Guangdong. Our models using spatial filters lead to better model performance and a substantial reduction of standard errors associated with independent variables’ coefficients. The spatially sensitive and temporally varying coefficients imply that the influences of globalization, marketization, and decentralization are sensitive to different stage of economic development in Guangdong. In addition, the triple processes of economic transition have stronger influences on regional development in the PRD. They also become increasingly important for the development in the periphery in recent years. These results imply that the triple processes of economic transition are one of the fundamental causes underlying the core-periphery divide in Guangdong, a finding consistent with Hao and Wei (2010)’s research using provincial-level data and a gap model.

Given the results in this work, the spatial policy in Guangdong should place emphasis on the spatial spillover from the PRD to the periphery region and more efforts should be made to foster new clusters of development in the periphery. Development policies that emphasize the rebalance between export and domestic oriented development have potential to help reduce regional development in Guangdong in the future, given the spatial concentration of the export-oriented development and FDI in the PRD.

From a methodology perspective, removing the spatial autocorrelation in the original data allows for comparisons between spatially filtered data and the actual data. In doing so, the spatial effects can be, to some extent, quantified in a highly flexible manner (Thayn & Simanis, 2013). More specifically, spatial filters can be added to many statistical packages and in different model specifications. Recent research has shown that spatial and temporal autocorrelation can be considered simultaneously by using space-time filters (Griffith, 2008). Future improvements could be focused on two aspects: 1) incorporating spatial filters in a geographically and temporally weighted regression framework to address the issues related to continuous spatial-temporal heterogeneity and 2) comparing the effectiveness of spatial filters in different regression models to support the application of spatial filtering models in different research domains.

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CHAPTER 4

SPATIAL-TEMPORAL DYNAMICS AND SPATIAL DETERMINANTS OF URBAN GROWTH IN DONGGUAN, CHINA [4]

Abstract

This chapter examines spatial and temporal dynamics and spatial variations of urban growth patterns in Chinese cities through a case study of Dongguan, a rapidly industrializing city characterized by a bottom-up pattern of development based on townships. To better understand the spatial-temporal dynamics of urban growth, we conducted a series of spatial analyses using temporally sensitive remote sensing data. Three growth types including infill, edge-expansion, and leapfrog growth were distinguished. Furthermore, we have employed both nonspatial and spatial logistic regression models to analyze urban land conversion. The nonspatial logistic regression has found the significance of accessibility, neighborhood conditions, and socioeconomic factors for urban development. The logistic regression with spatially expanded coefficients significantly improves the orthodox logistic regression with better prediction accuracy. More importantly, the spatial logistic model reveals the spatially varying relationship between urban growth and its underlying factors, particularly the local

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influence of environment protection and urban development policies. The results of the spatial logistic model also provide clear clues for assessing environmental risks to take the rich local contexts into account.

Introduction

By 2012, over half of the population (51.3%) in China lived in urban areas (Page et al. 2012). This is the first time that more people lived in cities than in rural areas in this country. The unprecedented urbanization in China, however, has given rise to the enormous loss of agricultural land (Yeh & Li, 1998) and landscape fragmentation (Sui & Zeng, 2001). Urban expansion also imposes challenges for environmental sustainability, such as water pollution and degeneration of land ecological security (Hu et al., 2005; Su et al., 2011). With the advances of spatial analysis, GIS, and remote sensing techniques, extensive efforts have been made to analyze the complex spatial patterns of urban landscape changes and to understand the underlying factors with spatially explicit models (Gao & Li, 2011; Luo & Wei, 2009; Su et al., 2012). Evidence has shown that applying spatial analysis and spatially sensitive statistical models to urban expansion not only contributes to the understanding of the complex urbanization process (Luo & Wei, 2009), but also offers more valuable information for environmental risk assessment, mainly by taking into account the spatially nonstationary relationship between urban landscape transformation and its neighborhood ecological environment (Gao & Li, 2011).

A wide range of factors underlying the urban growth in Chinese cities have been identified and studied. On the one hand, social scientists attempted to explore the driving forces of urban growth from institutional and political economic perspectives (Ding & Lichtenberg, 2011; Yang & Wang, 2008). They have found that urban development in

China has been shaped by a triple-process transformation of globalization, decentralization, and marketization (Wei, 2005). Scholars also argue that the growth of Chinese cities is a path-dependent trajectory influenced by the legacy of socialist political and planning systems (Lin, 2006; Wei, 2012). On the other hand, GIS scientists and landscape ecologists have improved our understanding of urban growth in China through landscape ecology methods, GIS modeling, and simulation techniques (Li & Yeh, 2002; Yu & Ng, 2007; Yue et al., 2010). Specifically, some GIS specialists have applied simulation techniques, represented by multiagent model and cellular automata (CA), to predict urban development patterns (Li & Yeh, 2002; Xie et al., 2007). However, most of these models deemphasize the socioeconomic factors and institutional and political contexts of China's urban development; the models also tend to focus on the prediction of urban growth in the future and technological methods. As argued by Luo and Wei (2009), these models have limited ability to explain the mechanisms and the diverse patterns of urban development in Chinese cities.

Through a case study of Dongguan city in South China, the chapter aims to achieve three research objectives. First, by applying landscape metrics-based approaches, it aims to investigate the spatial-temporal dynamics of urban growth. Second, using the spatial expansion method, this chapter provides an efficient and computationally less expensive way to model the spatially varying relationship between urban growth and its underlying factors (Luo & Wei, 2009; Su et al., 2012). We also argue that revealing the spatially nonstationary process of urban growth would provide more nuanced evidence for environmental risk assessment. Third, as the recent research on China mainly focuses on the largest cities, the case study of Dongguan, a second-tier city, also aims to emphasize the diverse urban growth patterns in a different regional setting. More importantly, the analysis of the results, supported by in-depth knowledge of local institutions and fieldworks, attempts to highlight that integrating remotely sensing data with socioeconomic factors and local institutions (policies) is necessary for a better understanding of the complex urbanization process in China.

In addition, since the late 1990s, in response to challenges arising from environmental degradation, the city government in Dongguan has also put more efforts to better protect the environment and promote a compact and sustainable urban development (Hu et al., 2005; Lin, 2006). This research also intends to assess the efficacy of these new urban development policies based on a spatially explicit model and recent remote sensing and GIS data. The chapter is organized as follows: after a brief introduction of the study area and data, we will introduce a landscape metrics-based method to differentiate urban growth type and analyze spatial-temporal dynamics of urban growth in Dongguan. This is followed by a discussion of a spatial logistic regression model; we then apply both nonspatial and spatial logistic regression methods to model urban growth in Dongguan from 1988 to 2006; the last section presents our conclusion and discussion.

Study Area and Data

Study area

As shown in Figure 4.1, Dongguan, located between 22’39N to 23’9N and 113’43E to 114’15E, borders Guangzhou, the capital of Guangdong province, in the north, and Shenzhen, China’s largest special economic zone, in the south, and is close to Hong Kong. The city covers approximately 2,465 km^2 with a population of 8 million at the end of 2010. The city consists of 32 towns and districts, characterized by a river-distributed plain in the north of the city and by low mountains and hills in the southern part (Figure 4.1).

Before the reform, most towns in Dongguan county were agricultural towns, and there was a small city center in the north. Agriculture, especially planting fruit and vegetable, and fishing were two important activities in these towns (Yeh & Li, 1999). The city is also home to more than a half million compatriots from Hong Kong, Macau, and Taiwan. Since the late 1970s, the urban landscape in Dongguan has experienced a dramatic transformation mainly driven by the inflow of migrant workers and foreign investment from Hong Kong and Taiwan, making this city a typical case of so-called exo-urbanization (Sit & Yang, 1997). Rapid growth and urbanization prompted the

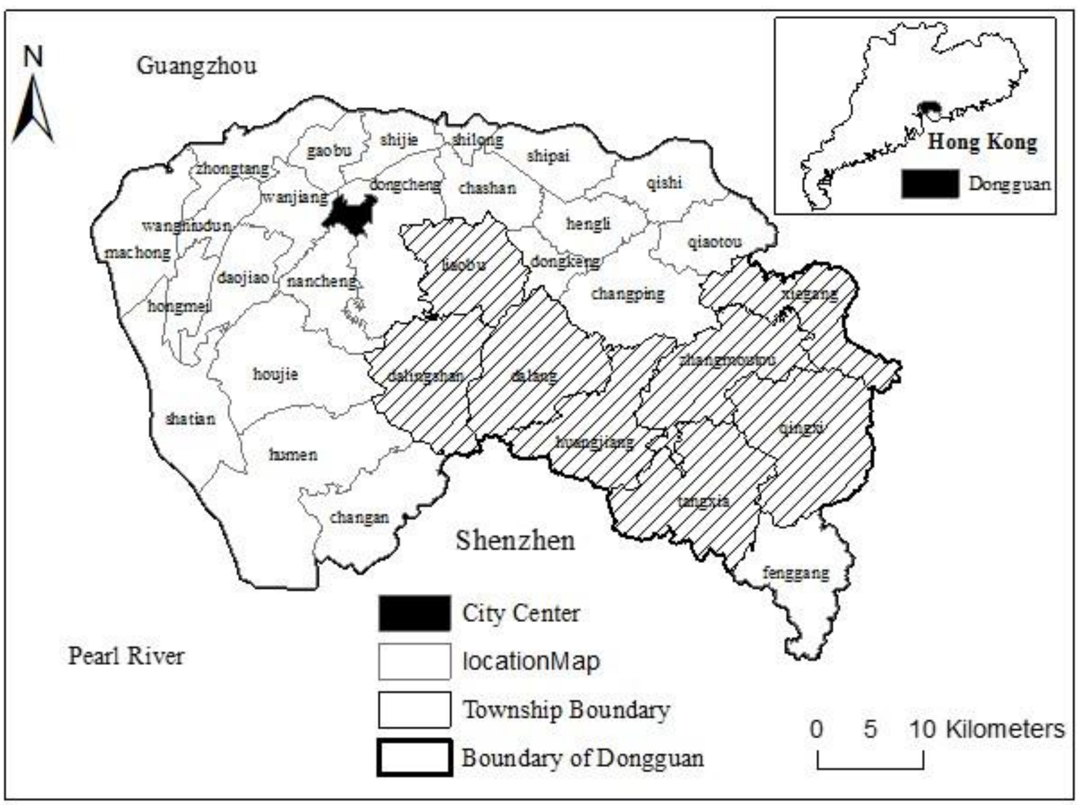


Figure 4.1. Location of Dongguan

upgrading of Dongguan county to Dongguan city in 1985 and to a prefecture-level city in 1988. However, rapid economic development and unprecedented urbanization result in a profound change of ecological environment in the city. There have been substantial challenges facing the city due to the massive loss of agricultural land and the serious impact of environmental pollution (Hu et al., 2005; Yeh & Li, 1998).

Data and land use sampling

This research analyzes space-time dynamics and models the spatial variations of urban growth in the city of Dongguan. The data used in this research include both land use and GIS data. First, land-use data was derived from TM remote sensing imageries in 1988, 1993, 1999, and 2006 (30m×30m resolution, 2,693×1,864 pixels). The geometric correction was done using evenly distributed ground control points. The object-based classification software, eCognition, was employed to perform the supervised classification. Accuracy assessment based on the ground truth data indicated that the classification accuracy was 92.0% for these images.

As illustrated in Figure 4.2, the TM remote-sensing images were classified into six types: built-up area, development zones or construction sites, farmland, orchard, forest, and water body. Second, we did fieldwork in Dongguan in the summers during the period from 2009 to 2011. Specifically, mainly in the summer of 2011, we interviewed a number of urban planners from the municipality-level planning bureau and town-level urban planning divisions. These interviews did not only enhance the error verification of the classified images but also gained more knowledge about the rural-urban land conversion in Dongguan.

We also collected the most updated and reliable GIS map files of the

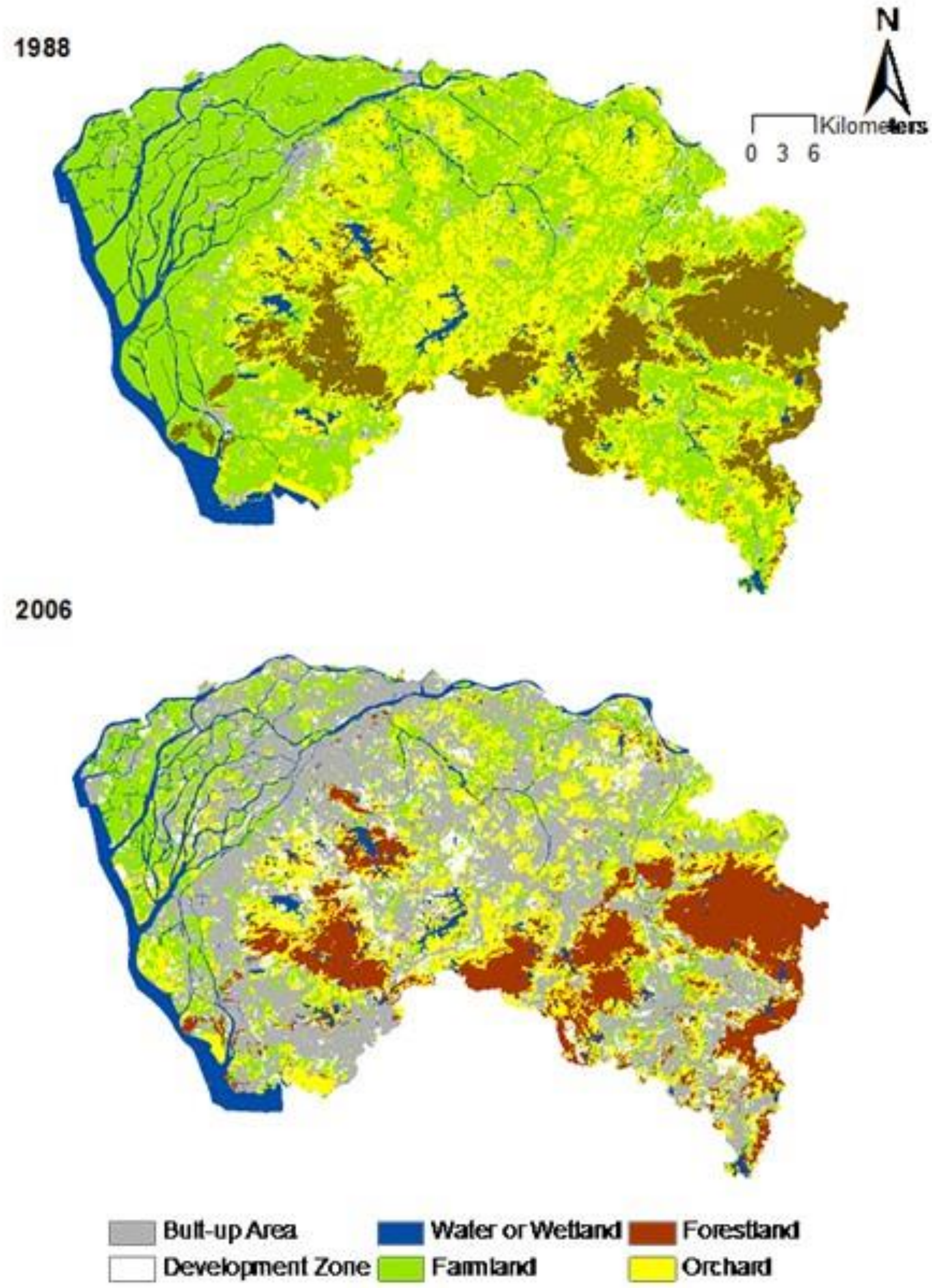


Figure 4.2 Land use in Dongguan, 1988, 2006

transportation network, urban centers, and administrative boundaries from the Bureau of Urban Planning of Dongguan in 2011 (Figure 4.3). Since our focus in this research is urban growth dynamics and determinants, the urban area is defined as the built-up area in both classified images in 1988 and 2006. A spatial overlay operation was performed between the two classified images to extract the conversion between nonurban to urban land uses. The size of the original data is large (5,019,752 pixels, 2693 rows, 1864 columns), which cannot be handled by most statistical software packages. In order to reduce the size of the data set, a spatial sampling method combining the systematic and random sampling was used (Luo and Wei, 2009). The first subset of pixels was obtained through the systematic sampling. We sampled the pixels based on the 300 m or10-pixel

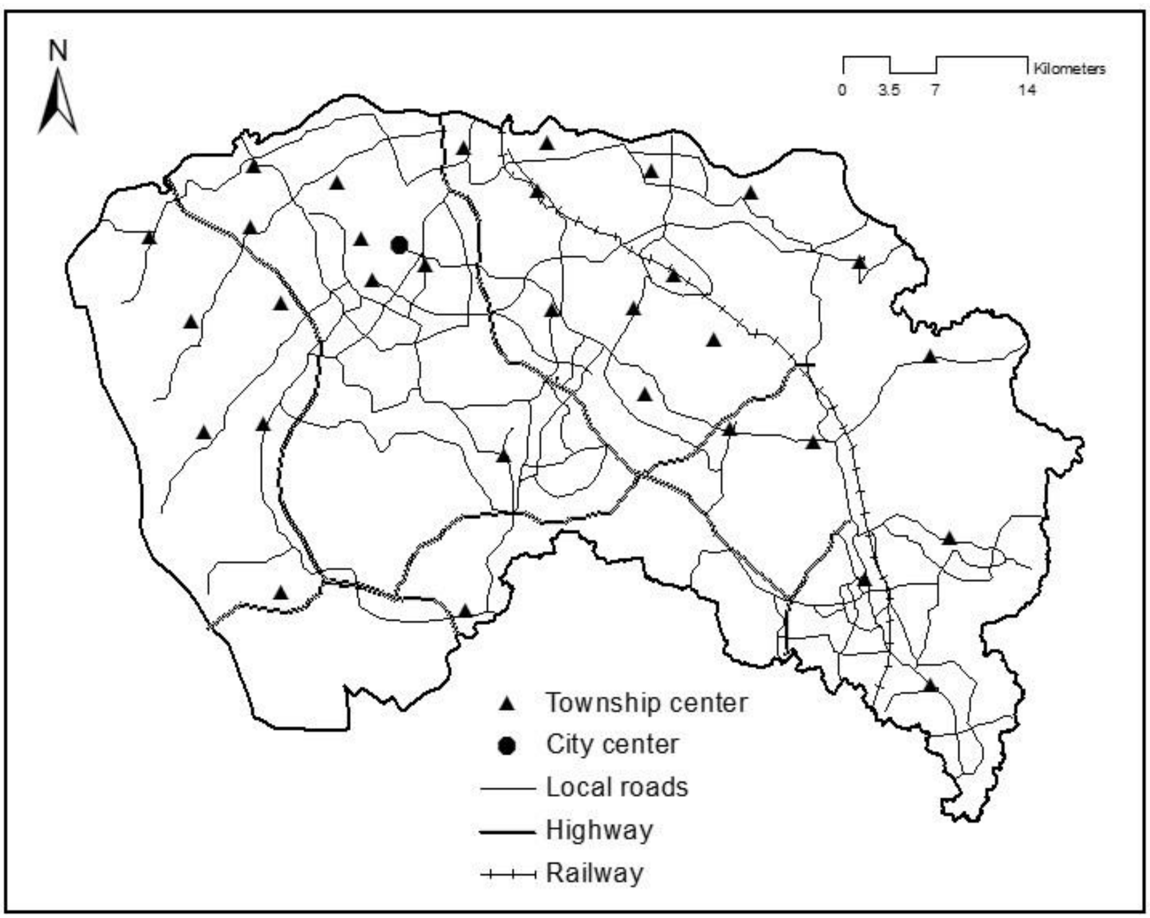


Figure 4.3 Spatial distribution of roads, railways, and centers in Dongguan, 2011

interval and got 27,503 pixels. And then, all pixels with nonurban-urban land conversion (8,776 pixels) were used in the following logistic regressions. We also randomly selected another 8,776 pixels from those pixels without urban land conversion in the study period (Luo & Wei, 2009). Therefore, the total number of pixels employed in the final logistic regression models is 17,552. Such a sample size well represents the population and can be handled by such commonly used statistical software packages as STATA 11.0 (http://www.stata.com/).

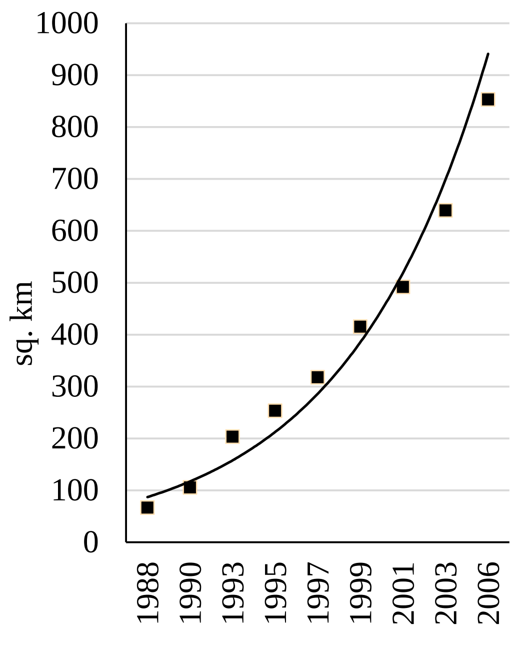
Spatial-temporal Dynamics of Urban Growth

Changes in landscape characteristics

The fast economic development in Dongguan has resulted in dramatic urban expansion and massive loss of agricultural land in the city. Figure 4.4A shows that the urban area increased by 1181% from 67 sq km^2 in 1988 to 853 sq km^2 in 2006. Farmland and orchard land are two dominating sources of newly developed urban areas. Until 2006, nearly half of the farmland (46.74%) and one third of the orchard land (31.63%) in 1988 were converted into urban areas. This suggests that the urban land development in Dongguan has caused the substantial loss of agricultural land and resulted in more challenges for environmental sustainability (Yeh & Li, 1999).

The mean growth rate also increased greatly (Figure 4.4 B), which were 22.46, 28.96, 45.98, and 57.82 sq km2/year for the periods of 1988–1993, 1993–1999, 1999–2003, and 2003–2006, respectively, indicating that the urban growth in Dongguan has been accelerated continuously.

Three landscape indexes were employed to reflect the landscape fragmentation in the course of urban expansion in Dongguan (Figure 4.5).



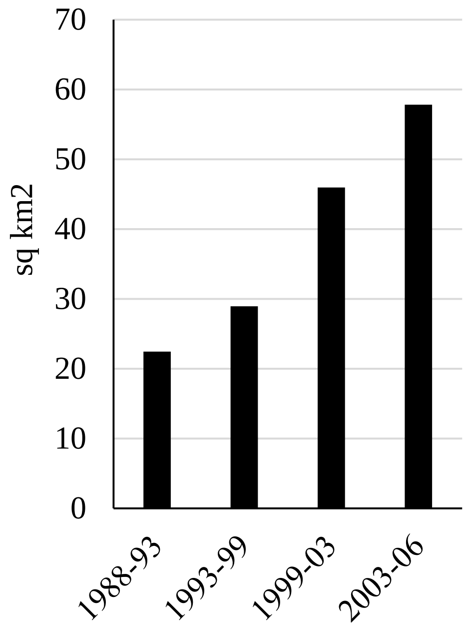


Figure 4.4 Urban area (A) and growth rate (B) in the different periods from 1988 to 2006

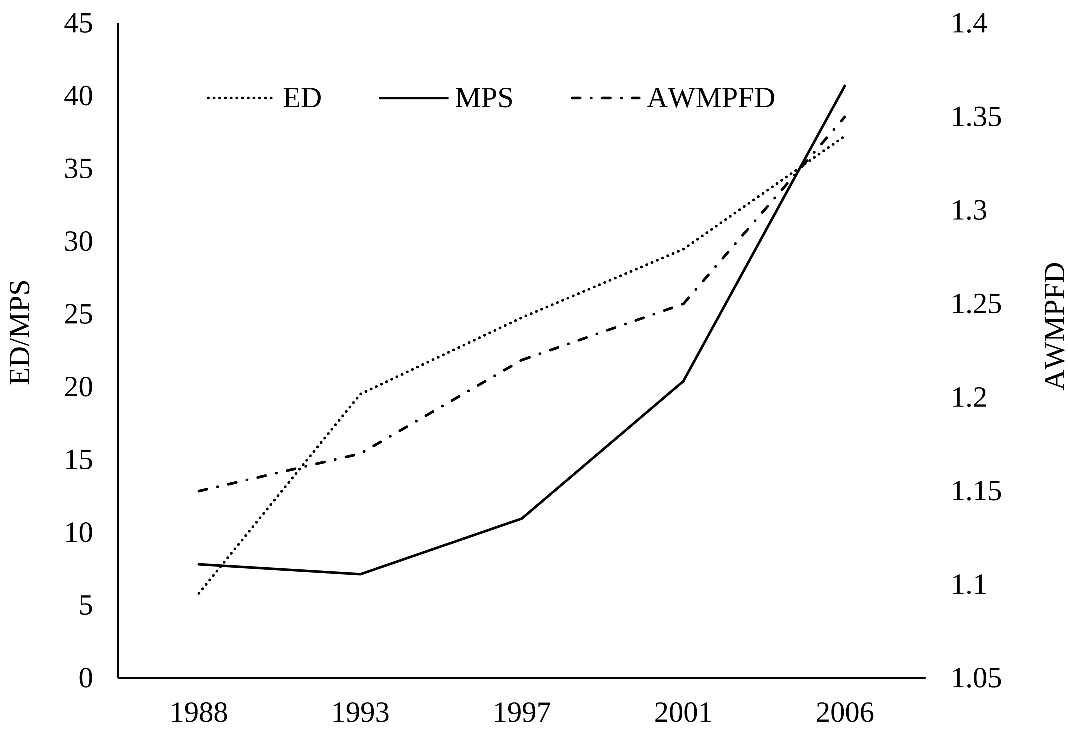


Figure 4.5 Changes in the landscape indices during the period of 1988–2006

The area-weighted mean fractal dimension index (AWMFDI) equals the sum, across all patches, of two times the logarithm of patch perimeter divided by the logarithm of patch area, multiplied by the patch area divided by total landscape area.

$$\text{AWMPFD} = \sum_{i=1}^{m}\sum_{j=1}^{n}\left[\left(\frac{2\ln\left(0.25p_{ij}\right)}{ln a_{ij}}\right)\left(\frac{a_{ij}}{TA}\right)\right] \tag{4.1}$$

The range of AWMPFD is given as $1 \leq$ AWMPFD $\leq$ 2 and has no unit of measurement.

The edge density (ED) index measures the sum of lengths (m) of all edge segments in the landscape, divided by the total landscape area (m^2) and multiplied by 10,000.

$$\text{ED} = \frac{E}{A} * 10000 \tag{4.2}$$

MPS (Mean patch size) measures the average size of urban patch.

$$\text{MPS} = \frac{A}{N}\ \ 10^6 \tag{4.3}$$

where A is the total landscape area (m^2), and N is the number of patches of the corresponding patch-type class.

Based on the three landscape metrics, the changes of landscape indexes are illustrated in Figure 4.5. The numbers of ED and MPS increased consistently, indicating that the average size and length of urban patch increased. At the same time, the AWMPFD showed an upward trend, highlighting there has been an increasingly fragmented landscape in Dongguan.

Figure 4.6 shows the spatial pattern of urban growth in Dongguan by comparing

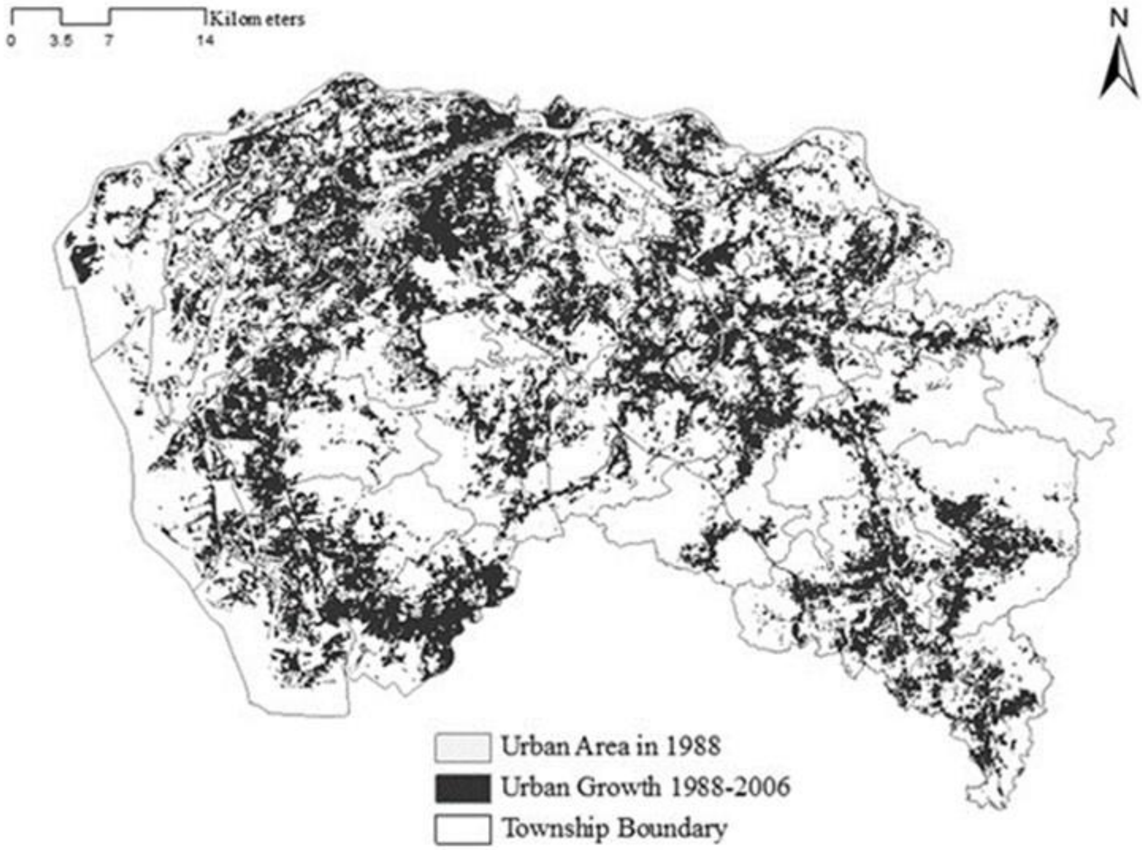


Figure 4.6 Spatial pattern of urban growth in Dongguan, 1988–2006

urban areas in 1988 and 2006. Four specific areas of growth can be identified: the areas near the city center, the areas in the southeastern part near the Guangzhou-Shenzhen highway, the areas in the southwest close to the city of Shenzhen (Figure 4.1), and some areas in the northeast near the railway station located in Changping township. However, besides these four hotspots, the urban growth areas spread over the whole city; the urbanization process is more likely driven by the bottom-up rural industrialization or township-based economies (Yang & Liao, 2010; Yeh & Li, 1999).

Concentric analysis is used to distinguish between the monocentric form and polycentric form of urban growth. The land-development intensity is computed based on the total amount of urban land conversion in concentric ring *i* with rings at an interval of

2 km around the city center (i = 1, 2, 3…).

$$I_{dev,i} = \left(\frac{c_i}{c_i + a_i}\right)\frac{1}{t}100\% \tag{4.4}$$

where $I_{dev,i}$ is the development intensity in the concentric rings i (i = 1, 2, …), c_i is the total amount of urban land-use conversion in zone i; a_i is the total amount of available land in zone i; t is the number of years in the study period (Liu et al., 2011).

Figure 4.7 indicates a conspicuous multicenter pattern of urban growth, corresponding to the spatial pattern in Figure 4.6. Although recent years have witnessed more urban patches centered on the city center, there have been more localities closer to Shenzhen that experienced significant urban expansion (Figure 4.7).

Notably, this bottom-up and township based urban expansion in Dongguan is interestingly in contrast with those in the largest Chinese cities or provincial capitals,

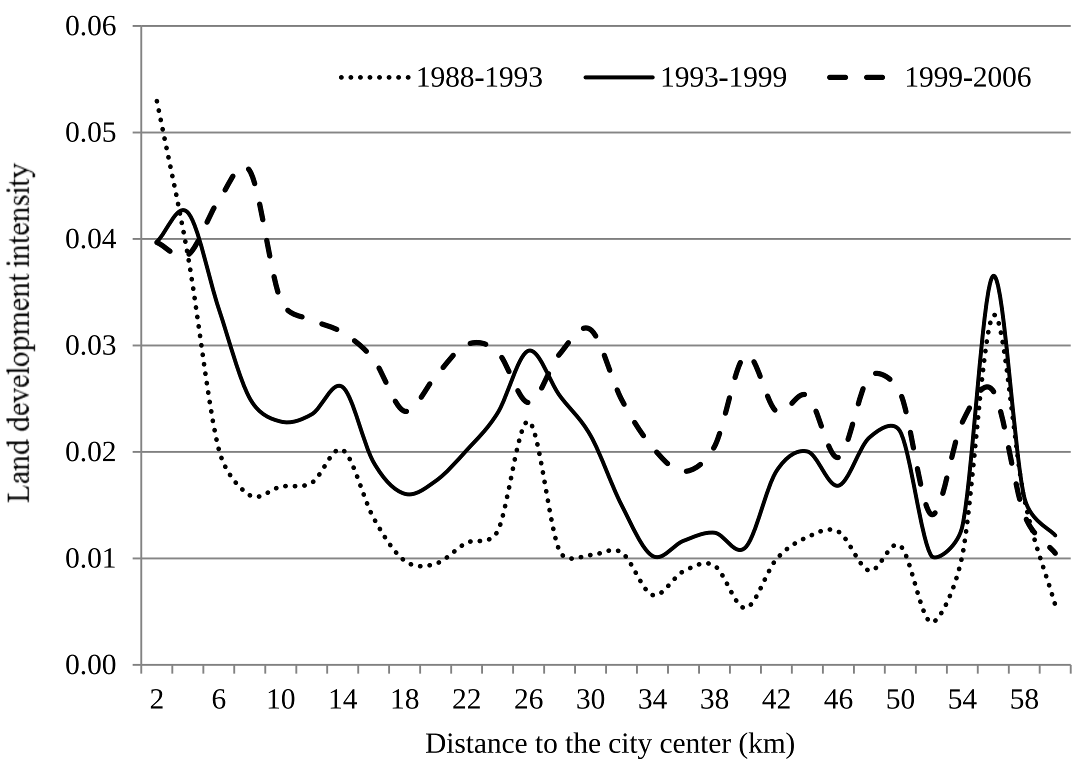


Figure 4.7 Land development intensity and the distance to the city center

such as Guangzhou, Hangzhou, and Nanjing, where urban development is centered on a small number of new centers or the traditional urban core (Luo & Wei, 2009; Wu, 1998; Yue et al., 2010).

Urban growth types

To better understand the spatial-temporal dynamics of urban growth, the newly developed urban patches were classified into three growth types: infill growth, spontaneous or leapfrog growth, and edge growth. Equation 4.5 is applied to distinguish three growth types, proposed by Xu et al (2007):

$$S = \frac{L_C}{\mathrm{P}} \tag{4.5}$$

where L_C is the length of the common boundary of a newly developed urban patch and the pregrowth urban patches, and P is the perimeter of this newly developed patch. Urban-growth type is identified as “infill growth” when S is larger than 0.5. The spontaneous or leapfrog growth is defined as S = 0, indicating no common boundary, and edge growth when 0 < S < 0.5 (Xu et al, 2007).

Figure 4.8 shows the results regarding three urban patch growth types. Several interesting findings can be summarized. First, in the early stage of urban expansion, the leapfrog-type or spontaneous growth occupied nearly 40% of the growth area and urban patches. However, the percentage of leapfrog growth declined as urban area expanded. Second, the share of edge expansion tends to be stable and accounted for 50%–60% of the total new urban area and 20–30% of the new urban patches. Third, infill growth was responsible for roughly 20% of the urban growth throughout the study period. The share of this type increased from 10% in the period of 1988–1993 to 30% in the period of

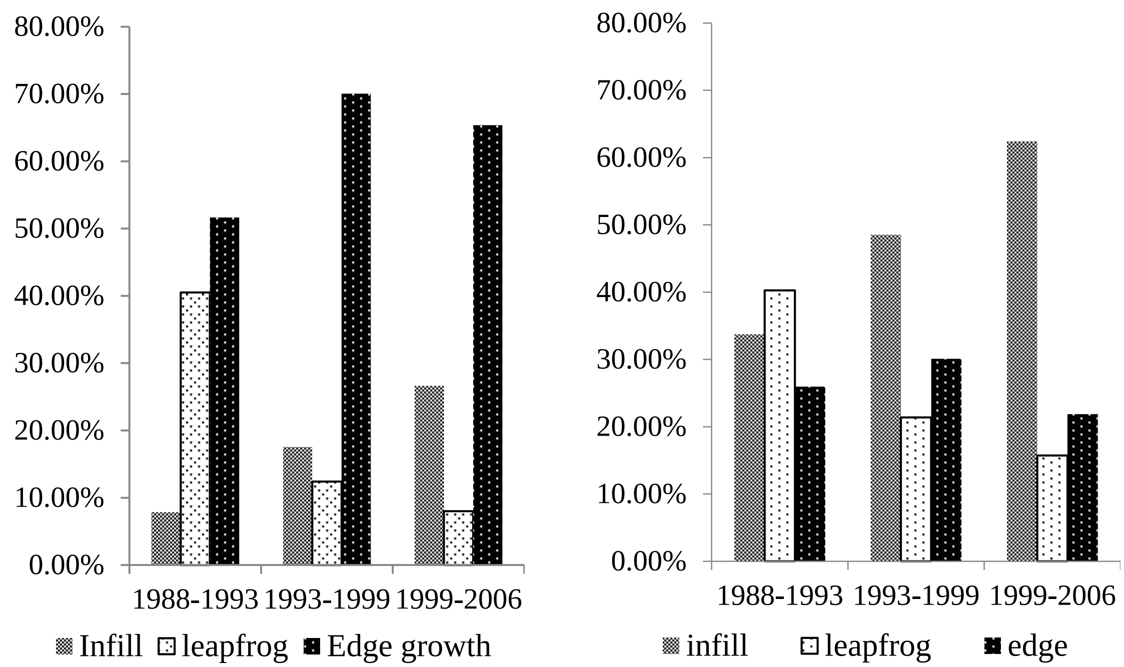


Figure 4.8 The proportion of growth area (a) and patch number (b) of the three growth types in the different periods

1999–2006.

Overall, the spatiotemporal dynamics of urban expansion in Dongguan can be conceptualized as a “diffusion-coalescence” model (Dietzel et al 2005). In other words, the urban growth process could be described as a general temporal oscillation between stages of diffusion and coalescence. Leapfrog or spontaneous urban growth patches are more likely to dominate in the early stage of urban growth or the phase of diffusion while proximate urban growth patches tend to increasingly connect. As depicted in Figure 4.8, in the period of 1988–1993, Dongguan has experienced a diffusion phase. It is consistent with the earlier urban growth pattern in Dongguan when small-medium size manufacturing firms from Hong Kong entered the city. As the growth continued, the infill growth type played a more important role, indicating that coalescence has become the major characteristic of the changes in urban pattern since the mid-1990s. The enhancement of coalescence in the process of urban growth is also particularly related to the development of large-size development zones and scaling up urban development in the city, aiming to attract investments from large-size foreign manufacturing firms from Taiwan, Europe, and other developed economies (Lin, 2009; Yang, 2009; Yang & Liao, 2010).

Spatial Determinants of Urban Growth

Dependent and explanatory variables

Logistic regression has been widely used to analyze the determinants of urban growth. Applying this model to cities in the Netherlands, Verburg et al. (2004) found that accessibility, spatial policies, and neighborhood conditions are major factors accounting for land use changes (Verburg et al., 2004). Wu (1998) applied a logistic regression model to the land use change in Guangzhou and found that socioeconomic and spatial factors have significant impacts on urban development in a transitional economy. Using logistic regression, Liu et al. (2011) demonstrated the spatial policies, especially polycentric development policy, played an important role in Hangzhou's urban land conversion. In this research, we also employed logistic regression to model the probability of urban land conversion from nonurban to urban. The dependent variable is a dummy variable with values of 0 (no conversion) and 1 (with conversion). Following Luo and Wei (2009), three groups of explanatory variables were used, including the proximity to transportation infrastructure, physical land suitability, and socioeconomic factors (Table 4.1).

Table 4.1 Variables used in urban land conversion models

Variables	Types	Descriptions
Dependent variable		
Change	Dummy	Land use conversion from nonurban to urban
Explanatory variable		
Proximity to transportation infrastructure		
Dis2Hwy	Continuous	Distance to highway
Dis2Rail	Continuous	Distance to railway
Dis2Road	Continuous	Distance to roads
Physical conditions		
DenFarm	Continuous	Density of farm land
DenOrchard	Continuous	Density of orchard land
DenForest	Continuous	Density of forest
DenWater	Continuous	Density of water land
Slope	Continuous	Slope of sampled pixels measured by degree
Socioeconomic factors		
Dis2CBD	Continuous	Distance to city center
Dis2TC	Continuous	Distance to township center
DenDevZone	Continuous	Density of development zones/construction sites
DenUrban	Continuous	Density of built-up area

Proximity to transportation infrastructure

Transportation is one of the most important mechanisms behind the urban development and exerts great influences on urban development. Road construction in the city of Dongguan has been strongly intensified in the past 30 years (Yeh and Li 1999). Highways have been constructed in the region to connect nearby large cities including Hong Kong, Shenzhen, and Guangzhou. In this study, three variables including distance to local artery roads (Dis2Road), distance to intercity highways (Dis2Hwy) and distance to the Hong Kong-Guangzhou railway (Dis2Rail) were used to denote the accessibility of a sample point. To obtain values of proximity variables for each sampled pixel, the Euclidean Distance tool in ArcGIS 10.0 was used to generate the distance raster surfaces, and then these pixel values were extracted to sample points.

Physical conditions

As land-use land-cover change is also closely related to the neighborhood physical land-use conditions (Cheng and Masser 2003; Luo and Wei 2009), we employed several neighborhood variables encompassing density of farm land (DenFarm), density of water body (DenWater), density of forest (DenForest), and density of orchard land (DenOrchard) as the proxy of land-use conditions. They can indicate the availability of land or neighbor environmental conditions. The neighborhood was defined as a circle of a 480-m radius. This discretion was based on the consideration of distance decay effect and drew upon the experience of other scholars (Cheng & Masser, 2003; Luo & Wei, 2009; Verburg et al., 2004). We calculated the neighbor densities using the zonal statistics tool in ArcGIS 10.0. We also extracted slope information (Slope) from a 90m×90m digital elevation model (DEM) for all sample points so as to measure the topographical suitability for urban development.

Socioeconomic factors

Research on urban growth places more emphasis on accessibility and physical conditions, which are necessary conditions. Scholars have increasingly recognized socioeconomic factors as sufficient drivers underlying urban expansion (Seto & Kaufmann, 2003). Our selection of socioeconomic factors was guided by the theoretical development in economic geography and urban economics, especially agglomeration, network, and institution (policy; Luo & Wei, 2009; Wei & Gu, 2010). We selected four variables to represent the influence of socioeconomic factors on urban growth. We measured the urban agglomeration effect by the distance to the city center and the distance to the subcenters (or the centers of townships; Jacobs, 1969). We selected the density of built-up area and the density of development zones/construction sites in the neighborhood to measure the effects of industrial agglomeration economies (Krugman, 1991) and policies. In particular, in China, the construction of development zones, noted as “development zone fever,” is one of the most important policies to promote urban expansion (Yang & Wang, 2008). We computed the neighborhood indices, DenDevZone and DenUrban, by measuring the densities of urban built-up area and development zone land within a distance of 480 m from the central cell. Last, we performed a correlation analysis for the explanatory variables. The results show no pair of variables has a significant linear correlation, which ensure the afterwards regression analysis would not have the problem of multicollinearity.

Logistic regression and expansion method

As mentioned above, we applied the logistic regression to model the urban land transition. This method is widely employed to examine the determinants of rural-urban land conversion in Chinese cities (e.g., Liu et al., 2011; Luo & Wei, 2009; Wu, 1998). The logistic regression takes the following form:

$$\text{logit}\,(Y) = \beta_0 + \sum_{i=1}^{n} \beta_i\, x_i \tag{4.6}$$

where x_i are explanatory variables, and logit (Y) is a linear combination function of the explanatory variables. Parameters β_i are the regression coefficients to be estimated. The logit (Y) can be transformed back to the probability that (Y = 1):

$$\text{P}(Y = 1) = \frac{\exp(\beta_0 + \sum_{i=1}^{n} \beta_i x_i)}{1 + \exp(\beta_0 + \sum_{i=1}^{n} \beta_i x_i)} \tag{4.7}$$

The above typical logistic model could effectively explain the determinants of urban land conversion. However, the potential spatially nonstationary process of urban growth still remains unknown. A few methods have been applied to model a spatially nonstationary process, which mainly includes multilevel modeling (Duncan & Jones, 2000) and geographical weighted regression (GWR; Fotheringham et al., 2002).

The multilevel modeling approach particularly deals with the so-called discrete spatial heterogeneity of geographical phenomenon (Anselin, 1988). This approach is constrained by the arbitrary discretion of spatial hierarchy. It is more applicable when the spatial hierarchy of the data is known. However, in this research, we have limited information about the hierarchical structure of the probability of urban land conversion. Therefore, a multilevel approach was not applied.

A second alternative, GWR, focuses on the continuous spatial heterogeneity (Fotheringham et al., 2002). It has also been used to model the rural-urban land conversion in Chinese cities (Luo & Wei, 2009; Su et al., 2012). For example, Luo and Wei (2009) employed a logistic GWR to model land development in the city of Nanjing. Su et al. (2012) employed GWR to model the spatially varying relationship between urbanization and agricultural landscape patterns. However the method of GWR is less applicable in this research for a number of reasons. First, the logistic GWR is computationally expensive (Luo & Wei, 2009). The normal process of such a huge sample (17,000 observations) has a high computation demand for normal desktop computers and made the logistic GWR hard to use in this research. Second, the results of the GWR approach are highly sensitive to kernel bandwidth of weight determination. Different bandwidths may result in different coefficient surfaces (Su et al., 2012).

Adaptive bandwidth was an important improvement, but it made the logistic GWR more computationally demanding. Third and more importantly, recent research efforts have pointed out that GWR is suggested as a tool that performs well for interpolation and prediction (Harris et al., 2011) but may generate spurious coefficient surfaces for statistical inferences and policy implications (Páez et al. 2011; Wheeler, 2009; Wheeler & Tiefelsdorf, 2005). Given the controversy about whether the GWR approach is appropriated for making inference about the spatially nonstationary process (Páez et al., 2011), we elect to use the spatial expansion method to provide a computationally less expensive and more efficient way to explore spatially varying relationships in the context of large sample size.

The spatial expansion method was proposed by Casetti (Casetti, 1972). The expansion method is a spatial analytical tool attempting to integrate contextual variations (Páez et al., 2010). The model reflects variations over space as an expansion of deterministic coefficients. The initial model is based on the original logistic regression:

$$\text{logit}\ (Y) = \mathrm{C} + \sum_{i=1}^{n} \beta_i\, x_i \tag{4.8}$$

However, in the orthodox logistic regression model, the relationship between dependent and independent variables is based on an underlying assumption that the β_i coefficients are the same for all the observations involved; in other words, the model is stable across space (Casetti, 2010; Fan, 1994). This assumption is problematic because of spatial heterogeneity (Anselin, 1988). A simple way to model spatially varying relationships is to transform the vector β_i in equation 4.8 into a set of expansion coefficients in relation to contextual variations. For example, the parameters of the initial model can be further developed by means of a polynomial expansion of a suitable degree, using the coordinates (μ, v) of each location to take the effect of local context into account. Suppose the spatial trend in the relationship between urban land conversion and its explanatory variables in the initial model with respect to the coordinates (μ_k, v_{ik}) take the following forms:

$$\beta_i^k = \gamma_i^0 + \gamma_i^1 \mu_k + \gamma_i^2 v_k \tag{4.9}$$

where k is the location subindex defined by the μ_k and v_k. The component of the location-specific coefficient is a combination of a region-wide (i.e. spatially constant) coefficient γ_i^0 and other coefficients associated with the coordinates μ_k(easting) and v_k(northing) in a polynomial equation (see equation 4.10). Therefore, the model incorporates both spatially constant coefficients and the coefficients that represent a spatially varying relationship specific to each location (Roorda et al., 2010). In this research, the expansion was based on the employment of the coordinates using a cubic trend (Fan, 1994). The spatially varying coefficients were expanded in the following way to produce a spatial drift of a cubic function of coordinates (see equation 4.10).

$$\beta_i^k = (\gamma_i^0 + \gamma_i^1 \mu_k + \gamma_i^2 \mu_k^2 + \gamma_i^3 \mu_k^3 + \gamma_i^4 v_k + \gamma^5 \mu_k v_k + \gamma^6 \mu_k^2 v_k + \gamma^7 \mu_k^3 v_k + \gamma^8 v_k^2 + \gamma^9 \mu_k v_k^2 + \gamma^{10} \mu_k^2 v_k^2 + \gamma^{11} v_k^3 + \gamma^{12} \mu_k v_k^3 + \gamma^{14} \mu_k^2 v_k^3 + \gamma^{15} \mu_k^3 v_k^3) \tag{4.10}$$

It is noted that all coordinates have been adjusted to a one unit rectangle (see equations 4.11 and 4.12). We took the maximum extent of the coordinates of sample points and divided the difference of every coordinate and the minimum coordinate value in the corresponding axis by this extent (Páez et al., 2010).

$$\mu_i^* = \frac{\mu_i - \min(\mu_i)}{\max(\mu) - \min(\mu)} \quad (4.11)$$

$$v_i^* = \frac{v_i - \min(v_i)}{\max(v) - \min(v)} \quad (4.12)$$

Nonspatial logistic regression model

The results of nonspatial logistic regression model are presented in Table 4.2. Variables with low statistical significance coefficients ($p > 0.05$) have been removed from the model to make sure that model efficiency is not sacrificed (Roorda et al. 2010). The model is significant at the 0.01 level. The -2 Log likelihood value and the relative operating characteristic (ROC) are 19649.71 and 77%. In other words, the logistic regression is appropriate to model the determinants of urban growth in Dongguan with a moderate level of prediction accuracy.

Except for the distance to railway (Dis2Rail), all explanatory variables are significant for the urban land conversion, which is consistent with Luo and Wei's (2009) result. Among the proximity variables, the importance of accessibility to the transportation network for urban land conversion is evident. Dis2Road (distance to local artery roads) and Dis2Hwy (distance to highway) have a negative effect on rural-urban land conversion. The finding also confirms that the urban growth in many Chinese cities and Dongguan in particular is driven by the road infrastructure development. With respect to the physical condition variables, the model reveals that the urban growth in Dongguan is associated with the density of agricultural land (farmland and orchard land). In contrast, the urban expansion is, in general, constrained by the densities of forest land and water bodies. It is also conditioned upon the topographical condition (Slope). This result suggests the loss of agricultural land in Dongguan is more challenging than other

Table 4.2 Results of nonspatial logistic regression

Explanatory variables	Coef.	Std. Err.	z	P>z
Dis2Roads	-0.198	0.0163	-12.17	0.000
Dis2Hwy	-0.076	0.0050	-15.32	0.000
Dis2Rail	-	-	-	-
DenFarm	0.002	0.0004	5.78	0.000
DenOrchard	0.002	0.0004	4.20	0.000
Slope	-0.011	0.0011	-10.20	0.000
DenForest	-0.002	0.0004	-4.66	0.000
DenWater	-0.002	0.0004	-4.16	0.000
Dis2TC	-0.129	0.0100	-12.90	0.000
Dis2CBD	0.015	0.0016	9.67	0.000
DenUrban	0.002	0.0005	4.32	0.000
DenDevZones	0.006	0.0006	8.97	0.000
Constant	-0.457	0.362	-1.26	0.207
Observations	17552			
-2 log likelyhood	19649.71			
ROC	0.766			

Note: ROC is an indicator of prediction accuracy and it measures the area beneath the curve relating the true-positive proportion and the false-positive proportion for a range of cutoff values in classifying the probability (Verburg et al, 2004).

larger Chinese cities such as Nanjing, where the agricultural land is more efficiently protected (Luo & Wei, 2009). However, urban development in Dongguan also shares some common characteristics with other Chinese cities where urban land development is largely restricted by forests, water bodies, or rivers and is influenced by the land suitability measured by slope.

Some interesting findings emerge based on the coefficients of four socioeconomic variables. First, the distance to city center (Dis2CBD) has a positive effect on urban land conversion, while the distance to township center (Dis2TC) has a stronger negative influence on rural-urban land conversion. This finding is contradictory with what Luo and Wei (2009) found, which was that the distance to the city center has a negative influence on the probability of urban development. This finding is also surprisingly contradictory to the study conducted by Li and Yeh (2002) focusing on the urban development in the early 1990s. It suggests that the bottom-up or township-based urban development in Dongguan has become more evident since the mid-1990s. In addition, consistent with the theory of urban agglomeration economies, the density of built-up areas in the neighborhood encourages urban land development and so does the density of development zones/construction sites. The density of development zones, in particular, has exerted more significant influences on the rural-urban land conversion, indicating that the land development in Chinese cities and Dongguan is also influenced by government's institutions and urban development policies.

Logistic regression model with spatially expanded coefficients

We applied the logistic regression with spatially expanded coefficients to the same set of 17,552 sample point data so as to model the spatially nonstationary process of urban growth in Dongguan. Table 4.3 presents a comparison between the nonspatial logistic model and the model with spatial expansion using three indicators. First, the overall goodness of fit of the model assessed by pseudo-R-squared statistics shows that the model with spatial expansion improves over the nonspatial logistic regression model. A likelihood ratio test can be computed using the deviance. The information gains of the spatial versus nonspatial models are determined by the following way: 19649.71 – 17962.94 = 1686.77. This is the value of the likelihood ratio test and it can be compared with the chi-square distribution with 151 – 11 = 141 degrees of freedom (the difference in the number of explanatory variables between the spatial and nonspatial models). The likelihood test is significant at the $p < 0.0001$ level. Second, the increase of ROC from 76.6% to 81.9% suggests the model with spatial expansion has much better prediction

Table 4.3 Comparison between nonspatial logistic regression and the logistic regression with spatially expanded coefficients

	Nonspatial Logistic regression	Spatial logistic model
-2*Log likelihood	19649.71	17962.94***
Pseudo R square	0.1924	0.2618
ROC	0.766	0.819
Moran's *I* of residuals	0.2112**	0.1234**

Note: *** Significant at 0.001 level; ** Significant at 0.01 level

accuracy if compared with the nonspatial model.Third, we also computed Moran's *I* indexes to estimate the spatial dependence of residuals. The Moran's *I* index in the spatial model drops from 0.21 in the nonspatial model to 0.12 in the spatial model. In other words, the model with spatial expansion has remarkably reduced the spatial dependence of residuals and generated less spatially correlated errors (Luo et al., 2008). As shown in Table 4.4, in the spatial expansion model, the coefficient of each explanatory variable is expanded into a polynomial function of the coordinates (μ, v) and can be evaluated at various locations to generate spatially varying coefficients. For example, the coefficient of Dis2Hwy in the nonspatial logistic model is -0.076 while in the spatial model, the coefficient is a function of the adjusted coordinates(μ, v), taking the following form:

$$d_{Dis2Hwy} = -18.20 * \mu + 47.34 * \mu^2 + (-30.88) * \mu^3 + (-12.91) * v + 166.06 * uv + (-357.38) * u^2v + 213.80 * u^3v + 30.16 * v^2 + (-324.53) * v^2u + 661.79 * v^2u^2 + (-378.95) * v^2u^3 + (-16.90) * v^3 + 178.15 * v^3u + (-357.48) * v^3u^2 + 200.65 * v^3u^3 \tag{4.13}$$

Different from the constant coefficients across space in the orthodox logistic model, the values of coefficients derived from the spatial logistic model show significant variations.

Table 4.4 Results of spatially expanded coefficients

	Constant	μ	μ^2	μ^3	v	μv	$\mu^2 v$	$\mu^3 v$	v^2	$v^2\mu$	$v^2\mu^2$
Dis2Hwy	-	-18.20	47.34	-30.88	-12.91	166.06	-357.38	213.80	30.16	-324.53	661.79
p value	-	0.000	0.001	0.004	0.000	0.000	0.000	0.004	0.000	0.000	0.002
Dis2Rail	-9.09	53.06	-91.87	48.31	52.96	-300.36	503.70	-251.51	-95.62	540.76	-896.25
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Dis2Road	13.44	-50.65	42.62	-	-67.24	238.28	-205.90	-	105.74	-376.09	357.19
p value	0.000	0.000	0.000	-	0.000	0.000	0.000	-	0.000	0.001	0.000
Dis2CBD	0.10	-	-	-	-0.31	0.22	-	-	-	-	-
p value	0.013	-	-	-	0.001	0.036	-	-	-	-	-
Dis2TC	14.53	-98.45	183.31	-101.82	-73.14	500.26	-927.01	508.31	115.80	-797.25	1471.03
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
DenUrban	0.08	-0.34	0.29	-	-0.39	1.13	-	-1.02	0.70	-1.87	-
p value	0.000	0.000	0.000	-	0.000	0.000	-	0.000	0.000	0.000	-
DenDevZone	-	0.28	-0.25	-	-0.13	-	-2.70	2.96	0.23	-0.82	7.66
p value	-	0.000	0.006	-	0.000	-	0.000	0.000	0.000	0.000	0.000
DenFarm	0.08	-0.29	0.24		-0.59	2.42	-2.56	0.60	1.27	-5.70	7.41
p value	0.000	0.000	0.000		0.000	0.000	0.000	0.024	0.000	0.000	0.000
DenForest	-0.01	-	-	-	0.07	-0.40	0.80	-0.50	-	-	-
p value	0.0120	-	-	-	0.0030	0.0020	0.0010	0.0000	-	-	-
DenOrchard	0.04	-	-0.37	0.36	-0.30	-	2.57	-2.56	0.57	-	-4.89
p value	0.000	-	0.000	0.000	0.000	-	0.000	0.000	0.000	-	0.000
DenWater	0.07	-0.25	0.19	1.13	1.29	-0.56	-2.96	2.42	-6.37	-	9.68
p value	0.001	0.006	0.018	0.019	0.000	0.000	0.000	0.000	0.000	-	0.000
Slope	-0.82	5.58	-9.71	5.02	4.12	-26.93	44.02	-21.34	-5.71	34.01	-48.30
p value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 4.5 summarizes the spatially varying coefficients for 17,552 sample points. All of the twelve explanatory variables have both positive and negative coefficient values. This suggests that the constant coefficient estimates in the nonspatial logistic regression tend to mask the spatially nonstationary process of urban growth. DenFarm, DenOrchard, and DenDevZone report over 80% of positive coefficients, and Dis2Road and Den2TC have over 80% negative coefficients. This indicates that influences of these variables have fewer spatial variations. In contrast, Dis2Hwy, Dis2Rail, DenForest, Dis2CBD, DenUrban, DenWater, and Slope have apparent divisions of positive and negative results, suggesting that these variables are characterized by significant spatial variations. However, such spatially varying coefficients cannot be identified in the orthodox logistic regression.

The proceeding analysis explains in detail the spatially nonstationary process of urban growth. Employing the sample points with coefficient estimates, we generated a set of coefficient surfaces to reveal the spatially nonstationary relationship between urban land conversion and its underlying factors. An inverse distance weighted (IDW)

Table 4.5 Summary of spatially varying coefficients

Variable	Mean	Std. Dev.	Min	Max	% positive	% negative
Dis2Hwy	0.0047	0.2422	-1.1611	0.7173	59.09	40.91
Dis2Rail	-0.0429	0.1391	-0.7023	0.3513	37.97	62.03
Dis2Road	-0.3512	0.3319	-1.0893	2.0436	8.58	91.42
DenFarm	0.0040	0.0024	-0.0060	0.0135	93.51	6.49
DenOrchard	0.0032	0.0030	-0.0052	0.0106	82.65	17.35
DenForest	-0.0044	0.0102	-0.0765	0.0049	30.21	69.79
DenWater	-0.0011	0.0035	-0.0180	0.0139	26.18	73.82
Slope	-0.0081	0.0163	-0.0445	0.0650	23.64	76.36
Dis2CBD	-0.0147	0.0592	-0.1553	0.1024	45.20	54.80
Dis2TC	-0.1066	0.1402	-0.5612	0.8374	17.24	82.76
DenDevZone	0.0080	0.0078	-0.0137	0.0531	88.38	11.62
DenUrban	0.0029	0.0042	-0.0099	0.0207	75.11	24.89

interpolation was performed to generate coefficient surfaces. IDW assumes that the surface is being driven by the local variation, which can be captured through the neighborhood.

Figures 4.9–4.11 present the resulting coefficient surfaces with a cell size of 30 m × 30 m. Figure 4.9 illustrates the coefficient surfaces for three variables of accessibility to transportation networks. Dis2Hwy has a stronger negative impact on urban development in the western part than the eastern part. This finding interestingly echoes the spatial distribution of urban land development along the Guangzhou-Shenzhen highway in the western part of Dongguan (see Figure 4.9).

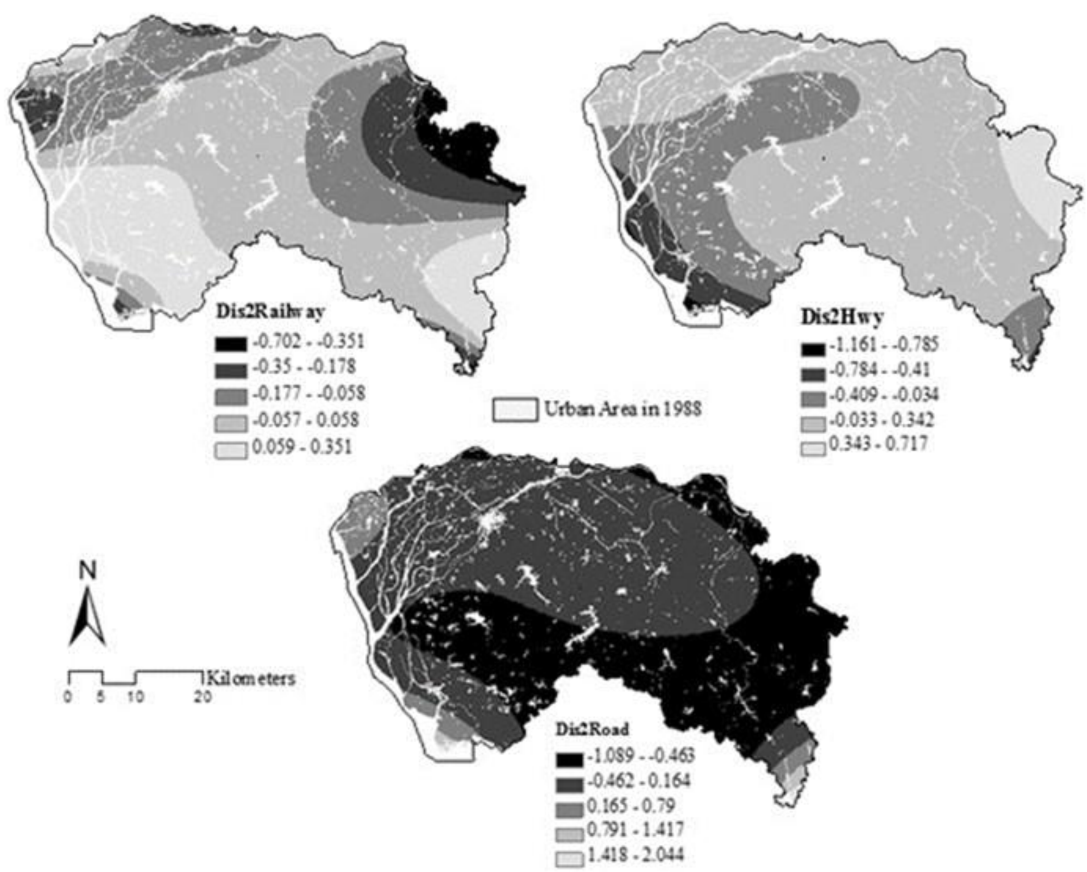


Figure 4.9 Coefficient surfaces of proximity to transportation infrastructure
Notes: Dis2Railway = distance to railway; Dis2Hwy = distance to highways, Dis2Road = distance to local roads

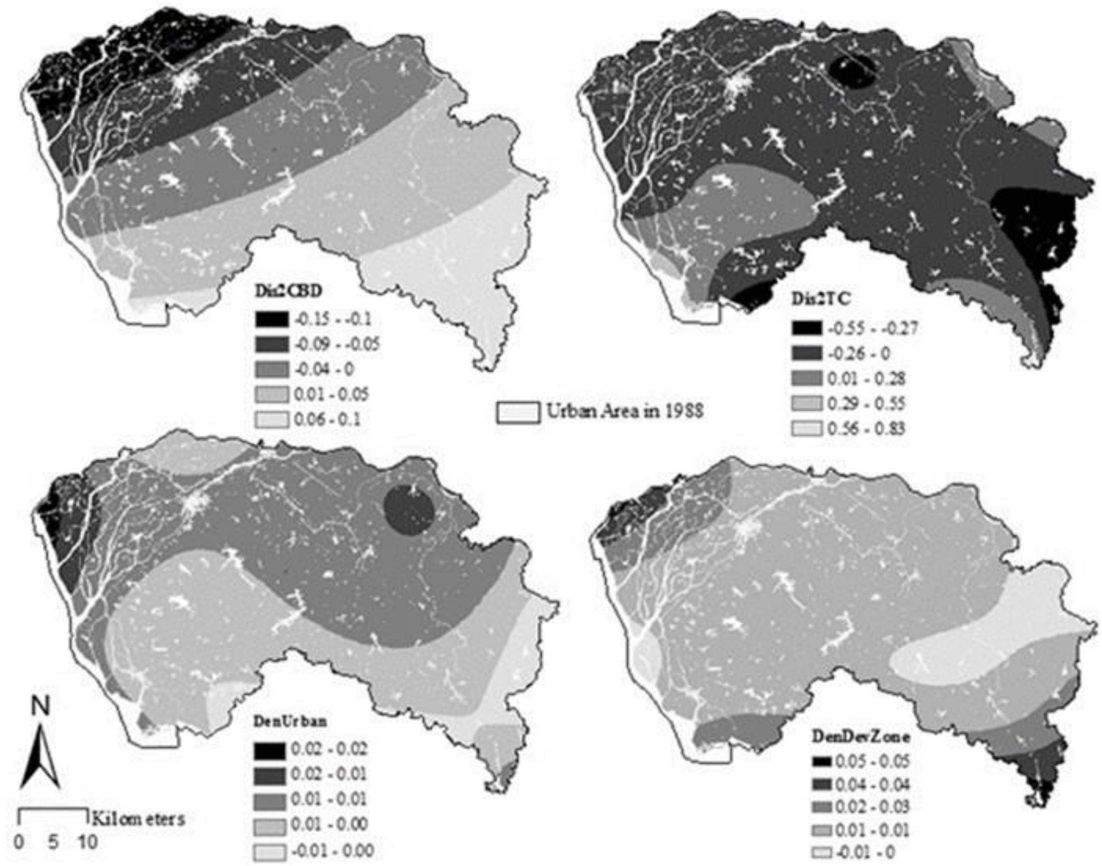


Figure 4.10 Coefficient surfaces of socioeconomic factors

Notes: Dis2CBD = distance to city center; Dis2TC = distance to township/sub centers, DenUrban= density of urban land; DenDevZone = density of development zones

The highway was constructed in the late 1980s, and it has become a major transportation corridor in the whole area. Other highways in the city such as the Dongguan-Shenzhen highway in the central and eastern parts have less influence since they were constructed later in the 2000s and are located in the mountainous areas. The spatial logistic regression model also improves our understanding about the spatially varying influence of distance to railway (Dis2Rail), while the variable is not significant in the nonspatial logistic model. As demonstrated in Figure 4.9, Dis2Rail has greater negative influence in those areas near the railway stations in the Changping township in the western part and the Shilong township in the northern part. In comparison with the surfaces of Dis2Hwy and

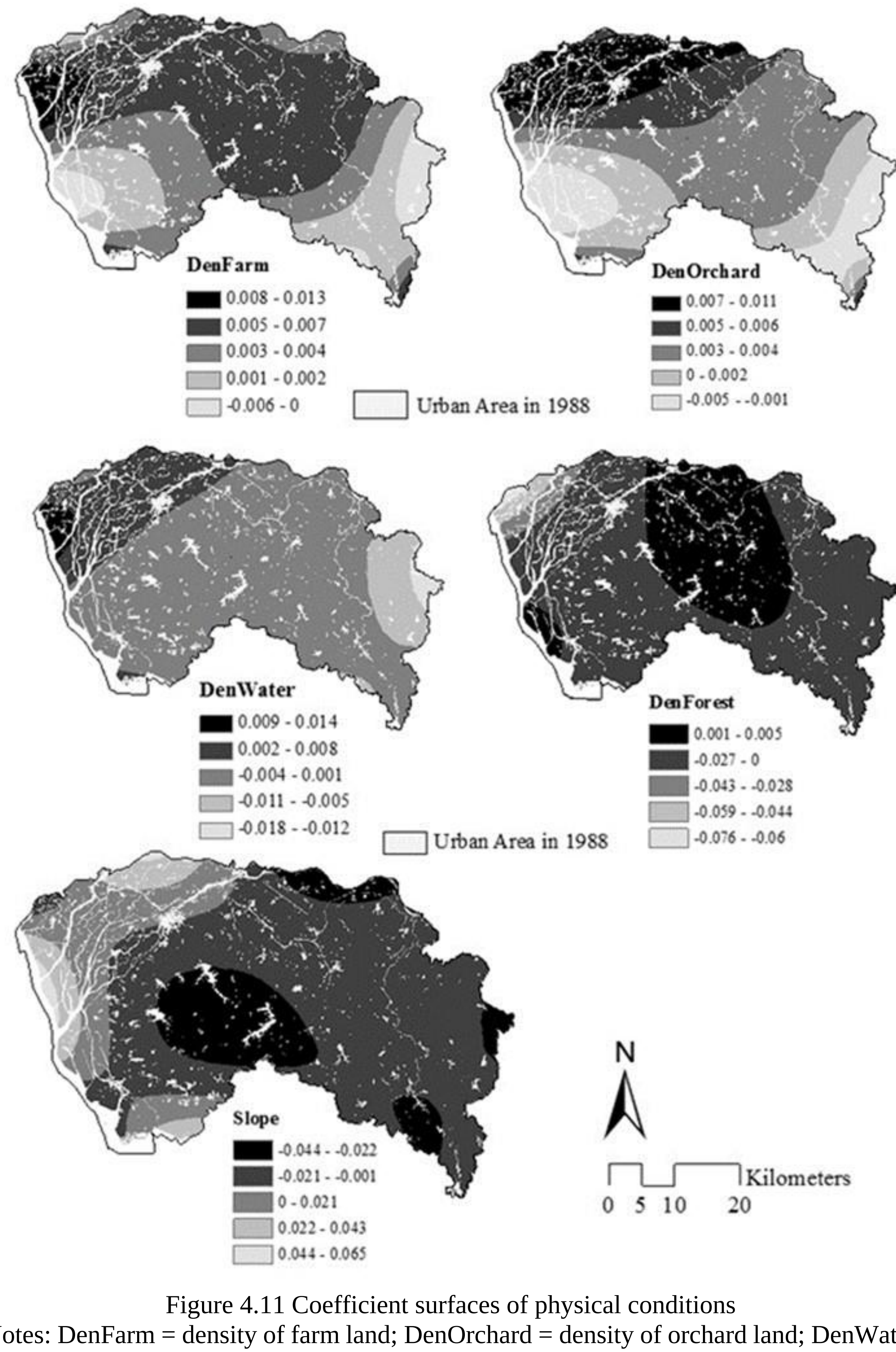


Figure 4.11 Coefficient surfaces of physical conditions
Notes: DenFarm = density of farm land; DenOrchard = density of orchard land; DenWater = density of water land; DenForest = density of forest land

Dis2Rail, one can see that the coefficients of Dis2Raod are mostly negative across the entire study area. However, it also varies across the city with stronger influences in the southern part, which is located in the north of Hong Kong and Shenzhen but further away from the city center.

The local logistic regression model also reflects spatially varying effects of the four socioeconomic variables (Figure 4.10). The nonspatial model demonstrates that the distance to city center (Dis2CBD) has a positive effect on land development. However, this does not hold true for all portions of the city. From a local view, the distance to city center has a stronger negative influence in the north of the city center than the south (Figure 4.10). In fact, the city master plan of Dongguan, which was implemented in 1999, proposed the strategy of building up a modern urban district and a new city center in the north of the original downtown. In the early 2000s, three towns including Nancheng, Dongcheng, and Wanjiang were transformed into new urban districts in order to provide more land for the construction of the new city center. A number of new urban projects have been built, including a new city hall, an international convention center, and a modern sports stadium, etc. (Lin, 2006). Therefore, the spatial logistic model is able to present more nuanced evidence of urban development in relation to specific urban planning policies at the local level. In contrast with Dis2CBD, we also find that the distance to township center (Dis2TC) has stronger influences across the entire study area, especially in the south. This is understandable since the land development in the southern part is relatively independent, which is more influenced by the nearby Shenzhen city. In short, we find that the roles of city center and subcenters in Dongguan's urban development is inconsistent with Luo and Wei (2009) in Nanjing and Liu et al (2011) in

Hangzhou, where the distance to the city center tends to have a strong influence across the entire city, but subcenters are more influential at the local level. This further confirms the previous observation that township centers have more significant influence on urban land development in Dongguan. In addition, the spatial logistic regression model also demonstrates the spatial variations of effects for the two variables—the density of urban land and the density of development zones. We find that the density of urban area in 1988 has much stronger influence in the north, while the impact of the density of development zones tends to be insensitive to particular areas. This is due to the fact that most urban areas in Dongguan in 1988 were concentrated in the north near the city center (Figure 4.10). Furthermore, different from other cities such as Suzhou in the Yangtze River Delta where development zones were constructed by the central and municipality level governments (Wei et al., 2009), development zones in Dongguan were mostly built up by township and village level governments. As a result, the spatial distribution of development zones in Dongguan is more disperse and relatively small in size (Yang, 2009), giving rise to a less apparent spatially varying influence across the study area.

For the five variables of physical conditions, the nonspatial logistic regression model shows that the density of farm land (DenFarm) and the density of orchard land (DenOrchard) have positive influence, while slope, the density of forest (DenForest), and the density of water bodies (DenWater) have negative influence. Based on the logistic regression with spatial expansion, we see that the impact of the density of farmland (DenFarm) is more evident across the entire study area (Figure 4.11). By contrast, slope has stronger local influence in the mountain areas, which indicates that the land development in the mountain areas is more likely restricted by the topographical condition. More importantly, although the nonspatial logistic model shows that the density of forest (DenForest) and the density of water body (DenWater) have negative influence on urban growth, this does not hold true for the entire study area. This, in particular, provides us with more reliable information for environmental risk assessment. In more detail, in the central part and some areas in the south of the city, the density of forest has positive influence on urban land conversion (Figure 4.11). It highlights the challenges for the protection of forest land in this area, although the orthodox logistic model reveals that DenForest has a negative influence. In fact, based on our fieldwork and interviews in Dongguan, in recent years, many towns in Dongguan have faced the problem of land supply due to the massive loss of agricultural land. Forest land has become an important new source of urban land. Another problem facing the urban planners in Dongguan is that the existing agricultural land has been more fragmented due to the unregulated urban development over the past 3 decades. This is particularly relevant for some large-scale development projects such as *Songsanhu* industrial park in the central part of the city and the "ecological industrial park" in the northeastern part. In order to provide sufficient land for these projects, many forests that are not as fragmented as the existing agricultural land and are more suitable for large-size industrial parks have been converted into urban areas.

Similarly, as indicated in the nonspatial logistic model, urban development is constrained by water bodies. However, drawing upon the spatial logistic model, this inference is problematic. DenWater only shows a strong negative impact on the urban growth in areas near the Dongjian River mainly because the Dongjian River is the source of drinking water for Hong Kong and Shenzhen and therefore more strictly protected (Hu et al., 2005). In contrast, for rivers and lakes close to the city center in the north, DenWater has strong positive influence, indicating water bodies in these areas are not strictly protected. This finding is consistent with Hu et al. (2005) on the spatial pattern of water pollution in Dongguan. They found that rivers and lakes in the northeastern part of Dongguan have been heavily polluted due to the concentration of polluting industries in nearby towns such as Macong and Zhongtang (Yang & Liao, 2010). In summary, some challenges of environmental sustainability are more likely masked by the nonspatial model, while the spatial logistic model is able to provide a valuable reference for the purpose of environment risk assessment, mainly by identifying spatially varying relationships between urban land development and neighborhood ecological environment.

Conclusion

The chapter has investigated the spatial-temporal dynamics of urban growth and its underlying factors in the city of Dongguan, China. We have contributed to the research on urban development in Chinese cities by analyzing the unique bottom-up township-based urban growth pattern in Dongguan. We have found that the city of Dongguan has faced substantial challenges of environmental sustainability arising from the loss of agricultural land. Recent years have witnessed more governmental efforts towards a compact and sustainable urban development (Lin, 2006). However, as evidenced in this research, the effect of these policies is very limited.

Results of landscape metrics and spatial analyses have quantified the spatial-temporal dynamics of urban growth, which is consistent with a “diffusion-coalesce” model. Nevertheless, different from the urban growth patterns in largest Chinese cities, we have identified that leapfrog or spontaneous urban growth was more evident at the early stage of urban growth in Dongguan city. This finding highlights a unique transforming landscape driven by a bottom-up urbanization in Dongguan.

We also developed a spatial logistic regression model to explore spatially varying relationships between urban development and its underlying factors in Dongguan from 1988 to 2006. We have confirmed the importance of the spatially nonstationary process in determining land use changes. Furthermore, our model incorporates both physical and socioeconomic factors in analyzing urban land expansion, guided by theoretical development in economic geography and urban economics. The analysis of results is further supported by the fieldworks and is associated with the local institutional contexts and urban development as well as environment protection policies. This approach, as shown in this research, is of particular importance for the research on urban development in China where the urban land development is being hosted in a transitional economy and thus characterized by instability, diversity, and dynamic spatial variety (Wei, 2012).

Using the orthodox logistic regression model, we have demonstrated that distances to local roads and township centers have the strongest negative effects on rural-urban land conversion in Dongguan. However, the distance to the city center has a positive influence. The case study of Dongguan indicates the bottom-up process of development where small towns play a significant role. Our study therefore suggests the complexity of urban development in different contexts and the diversity of urban growth patterns in Chinese cities.

The logistic model with spatially expanded coefficients has significantly improved the nonspatial logistic regression model with better prediction accuracy and the overall goodness of fit. It also reduced the spatial dependence of residuals. More importantly, the spatial logistic model allows the coefficients of explanatory variables to vary across space and clearly highlights the impact of underlying factors at the local level. On the one hand, we have found that the spatial variation of urban growth in Dongguan is highly sensitive to urban development policies and regional setting. The distance to the city center has a strong local impact on urban development in the north of the city where a new city center is being built. In contrast, the distance to township centers is more influential across the entire study area following the path-dependent bottom-up urbanization pattern. On the other hand, we also revealed that the spatial logistic regression approach not only contributes to the understanding of urban growth process but also provides more nuanced evidence for assessing environmental risks arising from urban expansion. For example, in the nonspatial logistic model, densities of water bodies and forest land have negative influences on rural-urban land conversion. However, drawing upon the spatial logistic model, their effects are contingent upon local conditions and environment protection policies—in the northwestern and central portions, more water bodies and forests have danger of being converted into urban land.

Finally, from a technical perspective, spatial expansion, if compared with other methods such as GWR, provides a computationally less expensive and more efficient way to model the spatially varying relationship in the context of large sample size. This is particularly relevant to some rapidly industrializing Chinese cities such as Dongguan, where urban development is not compact and urban expansion is broader in scope. In addition, recent literature has pointed out the limitation of GWR and the problematic coefficient surfaces resulting from the routine GWR algorithm (Páez et al., 2011;

Wheeler & Tiefelsdorf, 2005). There is a need to further compare GWR and the spatial expansion model as well as other spatially varying coefficient models (Waller et al., 2007), which can help us to learn more about the advantages and disadvantages of different spatial statistical methods.

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CHAPTER 5

CONCLUSION

China has experienced rapid economic and urban growth over the past 3 decades, attracting considerable scholarly attention. Researchers are keen to understand the patterns, processes and mechanisms of China's regional development and urban land use changes (Lin, 2009; Wei, 2007). On the one hand, empirical studies in China have enriched theoretical debates over regional inequality and economic convergence (e.g., Li & Wei, 2010; Liao & Wei, 2012; Wei, 2007). On the other hand, restless transformations in both economic and urban landscapes of China have provided the best laboratory in which GIS spatial modeling techniques are found to be applicable (Duque et al., 2013). However, due largely to limitations of research methods, development and implementation environment, data availability, and the willingness of local governments' collaboration, there is still a lot of room in this research domain.

First, although the importance of spatial dependence in shaping regional development and inequality has been identified (e.g., Wei & Ye, 2009; Yu & Wei, 2008), the relationship between spatial dependence and regional inequality appears to be self-evident. The extent to which they interact to yield uneven regional development remain poorly understood. In addition, the transformation of the economic system and globalization has triggered the articulation of states, foreign investors, and local institutions and geographies in China's regional development (Wei, 2007). Scholars have also identified that the triple process of decentralization, marketization, and globalization results in restructuring of the Chinese states (Wei, 2007). Researchers have identified a variety of development models in China, represented by the Pearl River Delta (PRD) model centered on foreign direct investment (FDI), the Wenzhou model driven by private enterprises, and the Sunan model based on the development of Township and Village Owned Enterprises (TVEs). Given the massive scale of the region and its tremendous diversity, more work is needed on the spatial variations of China's development mechanisms in relation to economic transitions.

Second, few efforts have been made to investigate the spatial-temporal dynamics of urban expansion in second-tier Chinese cities where urban expansion could be more conspicuous under a rapid economic growth. Methodologically, previous urban growth models, such as cellular automata (CA) or logistics regression model (e.g., Li & Yeh, 2000; Lin et al., 2011), have limited ability to fully reveal the spatial varying urban growth determinants in Chinese cities (Luo & Wei, 2009). The geographically weighted regression (GWR) is a major advancement in modeling spatial variations of urban growth determinants (Luo & Wei, 2009), but this method has been challenged (Paez et al., 2011), and GWR is also computationally expensive when analyzing remote sensing data.

To this end, this research initiates the task of studying regional development and disparities in China's Guangdong province and urban growth in Dongguan city within a GIS and spatial-temporal data analysis framework. A few key conclusions could be drawn from the analyses presented in previous chapters.

First, the application of Markov chains and spatial Markov-chain analysis techniques yields several interesting findings. The results reveal that there has been a "poverty trap" in the remote area in Guangdong. Spatial Markov-chain analysis further identifies that the persistence of core-periphery divide in Guangdong is greatly driven by the self-reinforcing effect of spatial agglomeration in the core region of PRD. The finding is different from those in Zhejiang and the Greater Beijing Area where more intensive spatial agglomeration is attributed to the emergence of new clusters (Wei & Ye, 2009; Yu & Wei, 2008). More importantly, the application of Markov chains and spatial Markov chains using county-level data has provided more detailed quantitative evidence about the spatial effects on regional convergence. By applying a spatial filtering approach, the project also generated interesting empirical findings about the relationship between multiscalar patterns of regional inequalities and spatial dependence. It highlights that the multiscalar nature of regional inequality is robust regardless of spatial effects. Therefore, consistent with the ideas of new economic geography (Krugman, 1995), peculiar agglomeration economies do have an impact on the core-periphery divide in Guangdong.

Second, modeling space-time heterogeneity of the multiple mechanisms helps to derive more reliable and in-depth understanding of these mechanisms. Spatial panel regression and multilevel modeling result in a substantial reduction of BIC statistics and standard errors associated with coefficients. The spatial regime model has revealed that the core-periphery divide in Guangdong is mainly caused by the triple processes of economic transition, including globalization, marketization, and decentralization. In addition, these processes are characterized by spatial and temporal heterogeneities. The functioning of these mechanisms has been strengthened in the periphery area, while globalization forces are increasingly domesticated in the core region of the PRD.

Third, the study on urban growth in Dongguan, China from 1988–2006 has used a multimethodology approach integrating GIS, remote sensing, and advanced landscape metrics as well as spatial modeling. Results of landscape metrics and spatial analyses have uncovered the spatial-temporal dynamics of urban growth, which is consistent with a "diffusion-coalesce" model. The bottom-up and multicenter pattern of urban growth in Dongguan is also closely related to the political economy of land use in China and driven by the decentralization of decision-making power from the upper level governments to lower level (township and village levels) governments.

Global logistics and spatial logistics regression models were set up and compared. Spatial variables were chosen as influential factors of urban land expansion. Findings demonstrate that spatial logistic regression has a much better goodness-of-fit than the global logistic regression model and has better performance in predicting urban land use change than the global logistic model. Furthermore, the use of spatial logistic approaches based on spatial expansion has verified that the influences of urban growth determinants have significant spatial variations. Such variations obviously demonstrate the challenges of environmental sustainability facing Dongguan in the course of rapid urban expansion.

The above findings have both theoretical and policy implications. From a theoretical perspective, the case of Guangdong substantiates the debate over the new economic geography (NEG) model (Krugman, 2011; Martin, 2013) while analyzing the self-reinforcing spatial agglomeration and the core-periphery model in greater detail. Specifically, we have incorporated the multiscalar nature of agglomeration and inequality in these GIS spatial analyses. In addition, in the case of Guangdong, the globalization force has strengthened the core-periphery divide between the PRD and the periphery, which is interestingly in contrast to many developed countries in which globalization and investments from outside have reduced regional inequalities (Ezcurra & Rodriguez-Pose, 2013). Therefore, the integration of western theories and the ground-specific context in China is a better approach to analyzing China's regional development and disparities under economic transition.

From a policy perspective, the dissertation suggests several issues that may challenge policy makers in Guangdong. The new strategies for reducing inequality in Guangdong may not be able to gain the expected effect due to the self-reinforcing agglomeration in the core region. The provincial government needs to recognize the core-periphery structure in Guangdong while promoting spillover from the PRD to the rest of the province. More attention may be paid to the comparative advantages of the periphery and the core region. Fostering new clusters in the remote area of Guangdong may help boost the development in these areas. A finer scale investigation in Dongguan reveals that the uneven regional development and overconcentration of resources have resulted in a deteriorating environment and a massive loss of agricultural land. Therefore, the provincial and municipality governments also need to coordinate for a sustainable development in Guangdong.

In addition, the dissertation contributes to the GIS spatial analysis methodology by incorporating a variety of spatial econometric and exploratory spatial data analysis (ESDA) techniques. Specifically, the application of a spatial regime model and spatial logistic regression has revealed evident spatial variations of development mechanisms and urban growth determinants in the core and periphery regions and within a city. In doing so, the dissertation has provided a solid empirical foundation for the cross-fertilization between exploratory spatial data analysis and economics theories (Ye & Rey, 2013).

The study could be improved through five aspects: (1) the study mainly emphasizes the influences of economic transitions on inequalities. Recent literature has been more interested in the relationship between sectoral transition and regional development disparities (Gardiner et al., 2011). The research on the spatial impact of sectoral transformation in China is promising. (2) In addition to a top-down approach to regional development in Guangdong, future work is needed by employing a bottom-up perspective and conducting more in-depth case studies of most influential municipalities behind Guangdong's uneven development. For example, in-depth studies of Guangzhou and Shenzhen are of great research significance. (3) Scaling-up the findings in Guangdong and comparing intraprovincial inequalities in different Chinese provinces is promising in future research. For example, regional development in the Greater Beijing Area is more policy driven giving the subsidy from the central government (Yu & Wei, 2008). Future comparative case studies could shed more light on the applicability of a multiscale and multimechanism framework in different geographical environments and institutional settings. (4) In addition, beyond economic inequality, research on inequalities in different forms (e.g., urban-rural inequality) and in different sectors (e.g., health and technology) is of particularly importance. (5) Applications of more rigorous GIS-spatial modeling approaches, such as spatial-filtering geographically weighted panel regression, are also likely to deepen our understanding of spatially varying drivers of urban growth in China. A spatial-temporal analysis could be more informative if it used some techniques that can trace the structural break and policy shocks in a GIS environment (Duque et al., 2013; Guo et al., 2013).

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- Fall 2013 Methods in GIS (GEOG5140, Instructor Evaluation: 5.14/6)
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- 2012 Ashok K. Dutt Best Graduate Student Paper Award. Regional Development and Planning Specialty Group (RDPSG), AAG: *Distribution dynamics and the core-periphery hierarchy of regional inequality in provincial China: a case study of Guangdong*.
- 2012-2013 Outstanding Student Research Award, Department of Geography, University of Utah.
- 2012 Travel Award, U.S. Foreign Policy Colloquium, National Committee for U.S.-China Relations, Washington. D.C.
- 2012-2013 TA Scholar (ten were selected campus-wide), Center for Teaching and Learning Excellence, University of Utah; project: *GIS pedagogy, flipping teaching, and student achievements*
- 2011 Third Place Prize, College of Social and Behavioral Science (CSBS) Graduate Student Research Day Paper Competition, University of Utah: *Multi-scalar regional inequality in Guangdong, China.*
- 2010, 2011, 2012 Graduate School Travel Award, University of Utah
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