

**MODELLING AND SIMULATING LAND DEVELOPMENT PROCESSES IN
SHANGHAI**

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Abstract

This thesis groups four papers to investigate the growth and evolution mechanisms behind urban land use change through multiple computer-based modelling and simulation approaches. The first paper theorizes land development in Shanghai into five modes and then delineates the location and estimates the magnitude of each of the land development modes in Shanghai. This paper lays down the groundwork for the following papers on land use change modelling and simulation in Shanghai. The second paper develops the Population-Driven Urban Land Development (PDULD) to simulate the land development and population dynamics of Jiading New City, one of the suburban districts in Shanghai. The third paper develops the Location-based Firm Profit (LbFP) model to delineate how urban land use growth may lead to the spatial structural transformation of industries. The fourth paper then furthers the industrial land use study and proposes the Industrial and Residential Land Use Competition Model (IRLUCM) to simulate the dynamic spatial transformation of industrial land use in Shanghai.

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Statement of Co-authorship

Chapters 3-6 of this dissertation were prepared as standalone manuscripts for submission to peer-reviewed journals. Chapter 3 has been submitted, Chapter 5 has been submitted and published (citation below). Chapter 4 and 6 are in manuscript preparing for submission. I was the first author of all four of these chapters and was responsible for their conceptualizations and associated study-designs, data collection, data analyses, model development and writing. All of these efforts were conducted under the guidance of my supervisor, Dr. Wei Xu. Specific contributions of Dr. Wei Xu and other co-authors are described below.

Chapter 3

This chapter was accepted by the Land Use Policy with Dr. Wei Xu as co-author. He made invaluable contributions to the field study design, literature and data analyses guidance, and manuscript editorial advice during the writing stage.

Chapter 4

This chapter will be submitted with Dr. Wei Xu, Dr. John Zhang, and Dr. Karl Staenz as co-authors. Dr. Wei Xu provided important guidance on model design, simulation results analysis, and made manuscript editorial contributions. Dr. John Zhang provided important guidance on the evolutionary algorithm design and efficiency improvements. Dr. John Zhang and Dr. Karl Staenz provided many manuscript editorial advice during the writing stage.

Chapter 5

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Chapter 6

This chapter will be submitted with Dr. Wei Xu, Dr. John Zhang, and Dr. Karl Staenz as co-authors. Dr. Wei Xu provided model design, simulation results analyses, and conceptual and editorial contributions. Dr. John Zhang provided model critics, method guidance, and editorial advice. Dr. Karl Staenz provided many manuscript editorial advices during the writing stage.

Chapter 1 Introduction

1.1 Background and motivation

Urbanization is a global issue in both developed and developing countries. As early as the 1950s, only 30% of the world's population lived in urban areas. This number increased to 80% in developed countries and 40% in developing countries around 2010. It is estimated that urban population in developing countries is going to be doubled to four billions in the middle of the 21st century (Bettencourt et al., 2007). At the same time, cities are emerging as humanity's engines of creativity, wealth creation and economic growth (Bettencourt & West, 2010). Despite the increasing importance of cities in human society, our ability to understand them scientifically and manage them scientifically is still limited.

Even though a variety of qualitative and quantitative methods have been adopted by urban planners and administrators to generate plans and policies for urban resource allocation, gaps still exist, because of the lack of behavioral and dynamics realism in most of the urban models (Batty, 2008b; Moreno et al., 2010; Heppenstall et al., 2016). The difficulties and challenges to any scientific approach to urban system researches have resulted from the numerous interdependent facets of cities, such as social, economic, political, infrastructural, and temporal-spatial processes. The problems associated with urban research and management lie in the treatments of those facets as independent issues. This frequently results in ineffective policies and leads to unfortunate and sometimes disastrous unintended consequences. For instance, the policies meant to reverse urban decay, or to control population movements and the spread of slums in some countries have been proven ineffective or counterproductive, despite huge expenditure (Bettencourt & West, 2010). In

order to eliminate this gap, during the past 50 years, urban geographers, computer scientists, and interdisciplinary researchers have made great efforts to understand the dynamic mechanisms behind urban growth and evolution through the construction of various urban models.

Urban models are those that provide well represented scientific thinking and theories of cities while perceiving them as spatial systems (Berry, 1964). They are essential for the analysis and prediction of the dynamics of urban land use growth (Al-shalabi et al., 2012). They can be used to forecast future changes or trends of land development of a city and to describe and assess the potential impacts of future development (Al-shalabi et al., 2012). The well-known urban models include von Thünen's concentric rings of agriculture and city theory (Sasaki & Box, 2003); Christaller and Losch's central location theory (Wilson, 2000); Auerbach's hierarchical distribution of city sizes theory (Portugali, 2011); Gibrat's lognormal distribution theory (Eeckhout, 2004); Alonso's mono-centric spatial growth model (Alonso, 1964); and Wilson's spatial interaction model (Wilson, 1970). These models established foundational knowledge for understanding urban growth and urban simulation, which are essential to help urban planning and management. However, it did not take long time for researchers, urban planners and city managers to realize that it is hard to apply these models in reality (Batty, 2007), because most of them are static and discrete. They cannot describe the variations of economic and social activities in urban areas.

From the middle of 20th century, with the fast development of computer science, researchers found that dynamic simulation models are good at delineating the process of structure evolution (Batty, 1971). Spatial simulation modelling techniques, such as Cellular Automata (CA) and Agent-based Modelling (ABM) were introduced into urban land use growth and evolution studies. The

advantages of these methods exist at their abilities to incorporate nonlinear, unorganized processes, cross-scale environment that can exhibit emergent properties, dynamic local interactions with spatial references, and indirect impacts and pattern-process linkages (Parker et al., 2003; Moreno et al., 2008). Treating a city as a complex system, a majority of researchers treat urban land use growth as a self-organized process (White & Engelen, 1993; Batty & Xie, 1994; Clarke et al., 1997; Clarke & Gaydos, 1998; Batty, 2008a). They adhere to the bottom-up theories and regard the suitability of land or factional spatial structure pattern which determines the growth and expansion of urban land. For instance, Dietzel et al. (2005) built a CA model on the basis of Clarke's work to test diffusion and coalescence theory of urban evolution. Sasaki and Box (2003) developed an agent-based model to verify Thünen's location theory. Filatova et al. (2009) designed a bilateral agent-based land market model on the land-market and land price theory to test Alonso's model. Wang and Marceau (2013) proposed a CA model by adopting the Rough Set Theory and Weight of Evidence method to simulate the transition of land patches. These models provide computational and visualizational frameworks upon which significant spatial and temporal information on the mechanisms of urban landscape evolution can be revealed (Berry, 1964; Moreno et al., 2010).

To date, however, the majority of the land use modelling and simulation studies root in a context of market economy. They have largely treated urban land development as a singular and uniform process, often neglecting place-based decision-making processes and multiple trajectories along which urban land could be developed. In market economies, land development in cities is mainly executed by private developers under a competitive environment. The process of land development follows a market principle of utility maximization, and urban land is assessed for its suitability and potential profitability. Land with greater suitability and profitability is normally developed first,

followed by development of less suitable and profitable land. Such market logic forms the theoretical foundation of most studies on land development modelling and simulation in recent decades (Batty, 1991; Deadman et al., 1993; White & Engelen, 1993; Wu, 1998). However, these models have some limitations when they are applied in the context of non-market or socialist market economies where the role of market is limited and government agencies frequently intervene in the land development process. For instance, the planned development of the ‘polycentric city’ and ‘special economic zones’ often defeats the market logic and causes leapfrog developments in the suburbs of metropolitan areas (Gordon & Richardson, 1997; Bae & Jun, 2003). The existence of non-market forces in land development undermines the utility of market-based models that often treat land development as a self-organizing process. This problem is particularly acute in China because China’s urbanization processes have been heavily shaped by distinctive institutional factors, including ambiguous land property rights, land development administration policies and socialist planning systems in the course of the transition to a market-oriented economy (Gaubatz, 1999). Therefore, it is imperative to understand various forms and processes of land development in different geographic contexts, before developing valid urban land development models and simulation procedures.

Toward this, the first objective this study was set to identify the specific modes of local land development and investigates how government agencies, regulatory policies, and various actors are involved in the land development and decision-making process. Meanwhile, the study is going to assess the spatial effects of different modes of land development in the city. Using Shanghai as a case, this study provides a theoretical basis for future land development modelling in China.

In addition to government policies, urban residents and their location-relocation activities also shape the land development process in a city. It is well recognized that varying housing preferences by individuals can give rise to an uneven spatial distribution in housing demand across a city space. Experimental studies found that there is a clear match between the stated housing preference and residential location choice (Levine et al., 2005). To interpret residential choice effects on land development, Waddell developed the UrbanSim model (Waddell, 2002; Waddell et al., 2003) to simulate the land-market interactions of households, firms, developers and public actors. Xie et al. (2007) constructed a dynamic household model to simulate the process of local household development leading to global urban landscape transformation. White et al. (2012) used historic population and land use data to evaluate neighbourhood influences on urban land. These models seek to investigate the relationships among individual residents' behavioral mechanisms and land developments at a broad level. However, dynamic social and economic characteristics and decision mechanisms of neighbourhoods and households are rarely considered, making the models fail to delineate the co-evolutionary processes of demographic transformation and land use change.

Upon the theoretical and experimental findings in the literature and fieldwork, the second objective of this study was set to develop a new theoretic urban land use growth simulation model that couples CA, ABM and Spatial Genetic Algorithm (SGA) methods. In the model, citizen agents make their location and allocation decisions based on their social-economic status. This will lead to the shift of social, economic, and environment status of neighbourhoods and urban region. Government agents will make development strategies and policies to balance citizens' needs and local sustainable development goals based on the social, economic, and environmental status of the region. The development strategies are then paraphrased into multi-objective planning problems that need to use optimization methods to solve. The Spatial Genetic Algorithm is used

to optimize those development strategies spatially, which determine the development or redevelopment of city land use. Jiading New City, planned as a satellite city for the metropolitan area of Shanghai, is selected to implement the model.

Moreover, in the built-up models described in literature, residential, commercial, industrial, and other land uses are often lumped together as non-agricultural uses. There is no differentiation among them and industrial land use transformation is likely ignored in the mainstream studies. The omission of industrial land use can bring major risks for credible modelling and simulation results facilitating urban administration policy-making, especially in the industrializing nations. Generally, industrial growth and agglomeration are the major driving forces of urban land use change and expansion (Walker, 2001). The start-up and concentration of industrial firms lead to the spatial clustering of residential, economic and social activities due to agglomeration effects. Meanwhile, spatial structure of industrial distribution in cities reconfigures urban spatial morphology, linked with land use, transportation, economic activities, housing, etc. (Anas et al., 1998). Appropriate and balanced urban industrial spatial structure is essential to the steady urban growth (Anas et al., 1998; Fischer & Nijkamp, 2012; Fujita & Thisse, 2013). Understanding the relationship between land use change and industrial spatial distribution and their co-transforming processes can help urban planners and decision makers achieve the goal of developing sustainable and livable cities. Therefore, modelling and simulation work may fail to reflect the actual situation without considering industrial land use activities.

To solve this problem, the third objective of this study was set to develop a dynamic simulation method for simulating the spatial transformation process of urban industries. A novel model, called Location-based Firm Profit (LbFP), is proposed. Taking Shanghai as a case study, it attempts to

demonstrate how urban land use growth may lead to the spatial structural transformation of industries. Different from the mainstream researches on industrial spatial redistribution, which delineate the de-concentration or suburbanization process of manufacturing industry among mega cities (Viehe, 1981; Henley, 1994; Walker, 2001; Hudalah et al., 2013), this research simulates the dynamic industrial de-concentration quantitatively. However, the model developed here is a one-dimension of computer simulation model. One of the main simulation results is the optimum distance of an industrial firm location from city center under the given land price. It does not show how the industrial production activities and their land uses in the city evolve spatially.

While the classic and neoclassic urban industrial land use theories established foundational knowledge for the study of urban industrial activities (Weber & Friedrich, 1962; Pellenbarg et al., 2002), however, they tend to neglect the historical, path-dependency, and evolutionary perspectives of urban industrial land changes. The evolutionary economic geography explains the spatial evolution of firms, industries, networks, and cities from elementary processes of the entry, growth, location, and relocation sequences (Ning & Yan, 1995; Walker, 2001; Boschma & Frenken, 2006). The current models and theories on urban industrial land use are largely based on neoclassic theories and often tend to be static and discrete. Few studies have incorporated dynamic theories in land development modelling and simulation. There is a lack of useful models to delineate dynamically the spatial structuring and restructuring processes of urban industrial land use.

Moreover, urban land is developed in a competitive manner. Because of the declining developable land, the value of land parcels in the central city proper increases continuously. More competitive land use types dominate others in an open-market competition process (Alonso, 1964;

Mieszkowski & Mills, 1993; Harvey & Jowsey, 2004). Generally, industrial use outcompetes agricultural use in suburban and rural areas, and therefore, the land is converted to industrial use. Commercial and residential uses in the inner city outcompete and displace agricultural or industrial land concentrically from inner city outward (Walker, 2001). In a market economy, the urban land development process in a city is largely regulated by this market competition mechanism. Any study on urban land use transformation is inconvincible without a delineation of land use competition theory.

Therefore, the fourth objective of this study was set to develop a CA-based dynamic industrial land development model to simulate the spatial transformation process of urban industries. In the model, industrial and residential land development activities coexist and co-evolve during the course of urban land redevelopment processes. To delineate the competition relationship between industrial and residential use, an integrated logit model, the Industrial and Residential Land Use Competition Model (IRLUCM), is developed. Through integrating with classic land use and industrial activity location-relocation theories, the model delineates the competition relationships among agricultural, industrial, and residential land uses. Focusing on the industrial landscape transformation in Shanghai, this study seeks to demonstrate how urban land use growth may lead to new spatial configuration of industrial land uses over time. Taking historic land use data as a benchmark, this study invents a new method to calibrate computer simulation model by deploying Genetic Algorithms.

1.2 Structure of the dissertation

The dissertation is divided into five chapters.

Chapter 1 gives an introduction of the background and motivation of this study.

Chapter 2 introduces study area and remote sensing land use data.

Chapter 3 theorizes land development in Shanghai into five modes, then delineates the location, and estimates the magnitude, of each of the land development modes in the city.

Chapter 4 develops the Population-Driven Urban Land Development (PDULD) to simulate the land development and population dynamics of Jiading New City.

Chapter 5 develops a dynamic simulation method for simulating the spatial transformation process of urban industries. A novel model called Location-based Firm Profit (LbFP) model is proposed.

Chapter 6 proposes the Industrial and Residential Land use Competition Model (IRLUCM) to simulate the dynamic spatial transformation of industrial land use in Shanghai.

Chapter 2 Study area and remote sensing data processing

2.1 Study area

Located at the tip of the Yangtze River Delta, the city of Shanghai covers a land area of 6,396 km² (Figure 2-1 and Figure 2-2). It is the largest city in China with a population of about 24 million according to 2010 census. Since 1978 when economic reforms were initiated, Shanghai has been one of the fastest developing cities around the world. It has experienced a rapid rate of economic growth and change, with an annual growth rate of 14% in GDP. Its urban landscape, particularly the spatial distribution of urban land use, has shifted greatly. From remote sensing data, the construction land area of Shanghai in 2013 (4033 km²) is more than four times as much as that in 1993 (968 km²).



Figure 2-1. The location of Shanghai, China.

Therefore, more and more researchers regard Shanghai as a window to understand China. Nevertheless, much of the literature on the land development process of Shanghai so far merely

focused on the transformation of land use policies of the city or particular cases from outside (Han, 2000; Wu, 2005; Han et al., 2009; Liao & Wong, 2015). Very few of them have tried to understand the decision-making processes behind the land development procedure internally and systematically. Although the city government, urban planners, and land use administrators have been using international urban land management theories and planning practices, their efforts were often blocked off by ill-defined local development strategies and complicated administrative power structure and systems (Gaubatz, 1999). The information resulted from this study can be adopted for better urban development policy and urban plan making.

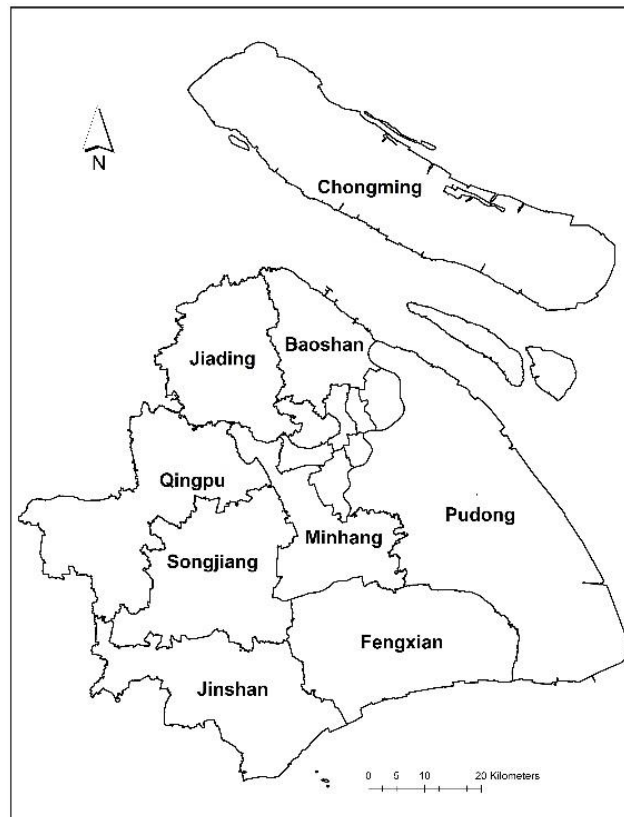


Figure 2-2. Administrative districts of Shanghai.

2.2 Urban land use classification

Remote sensing has been successfully used to monitor land use change and assess its environmental impacts. Remote sensing data, especially high-spatial resolution images, are capable to detect and measure the amount, shape, texture and spread of urban areas (Webster, 1993). The advantage of using remote sensing data to monitor urban land use change is also reflected in its timeliness. It can cover the same area again and again, which is very important for dynamic modelling. Another main reason that remote sensing has been broadly used for land use cover and land use change monitoring is that it can capture and manage huge amount of data. Obtaining and analysing the remote sensing images of Shanghai provide fundamental data for land development process modelling and simulation.

The data used for the study of Shanghai was acquired from three different satellites, SPOT5, LANDSAT5 TM, and LANDSAT7 ETM+. The data spanned two decades, from 1987 to 2010. Dates for the SPOT data are from April 22, 2009, January 12, 2010, March 10, 2010 and March 16, 2010. Data from the LANDSAT5 satellite are from May 18, 1987 and June 3, 1993. All the LANDSAT data were obtained from the USGS (<http://landstat.usgs.gov>) organization and the SPOT5 data were obtained from commercial purchase. Data from the LANDSAT7 satellite are all from November 6, 1999. The LANDSAT datasets are at a 30-m spatial resolution with the exception of band 6, which is the thermal band with a spatial resolution of 60 m. Primary classification was done on bands two to four to create a false-colour composite to clearly illustrate the difference between vegetation and urban areas. All data from the SPOT satellite are in supermode format, which is a processing technique applying the panchromatic band to the existing bands in order to increase spatial resolution of the resultant imagery. The imagery data used in

this analysis were originally of 10-m spatial resolution. As part of the processing package, the band number was decreased from four to three bands spanning a wavelength range of 500 nm to 800 nm.

For this research, the Random Forest (RF) classification technique was used in the processing of the imagery data due to its better off performance than other methods such as SVMs, bayes, and logistic remission (Caruana & Niculescu-Mizil, 2006). A platform-independent, free-of-charge software EnMap Box was used to classify the remote sensing images (van der Linden et al., 2015). Default settings for the RF classifier in ENVI were used for each run of classifying (Number of Trees: 100, Number of Features: square root of all features, Impurity Function: Gini Coefficient). A common method of change detection is post-classification change detection, where each image is classified individually before the change detection is calculated. A benefit of this method is its simplicity and flexibility in choosing of classification technique, allowing for a high level of specificity for each analysis.

Following the workflow shown in Figure 2-3, the image was first subset to the size of the study area before the data of Shanghai were processed. The known urban areas of Shanghai were manually digitized and masked out, using a high-resolution atlas from 1980 as a reference for the main urban areas, selecting the border of each urban area as it grew between each time period. Classes include: agriculture, which encompasses fallow and planted agricultural land; fish ponds; urban, which includes high-density urban and low-density urban; villages; and water, which includes river and lake areas. The individual results were then mosaicked together, and the study area was re-masked, and the complete classifications were converted into vector files. They were

converted to ESRI shapefiles, which were then intersected with county boundary shapefiles containing area information for each class and census data.

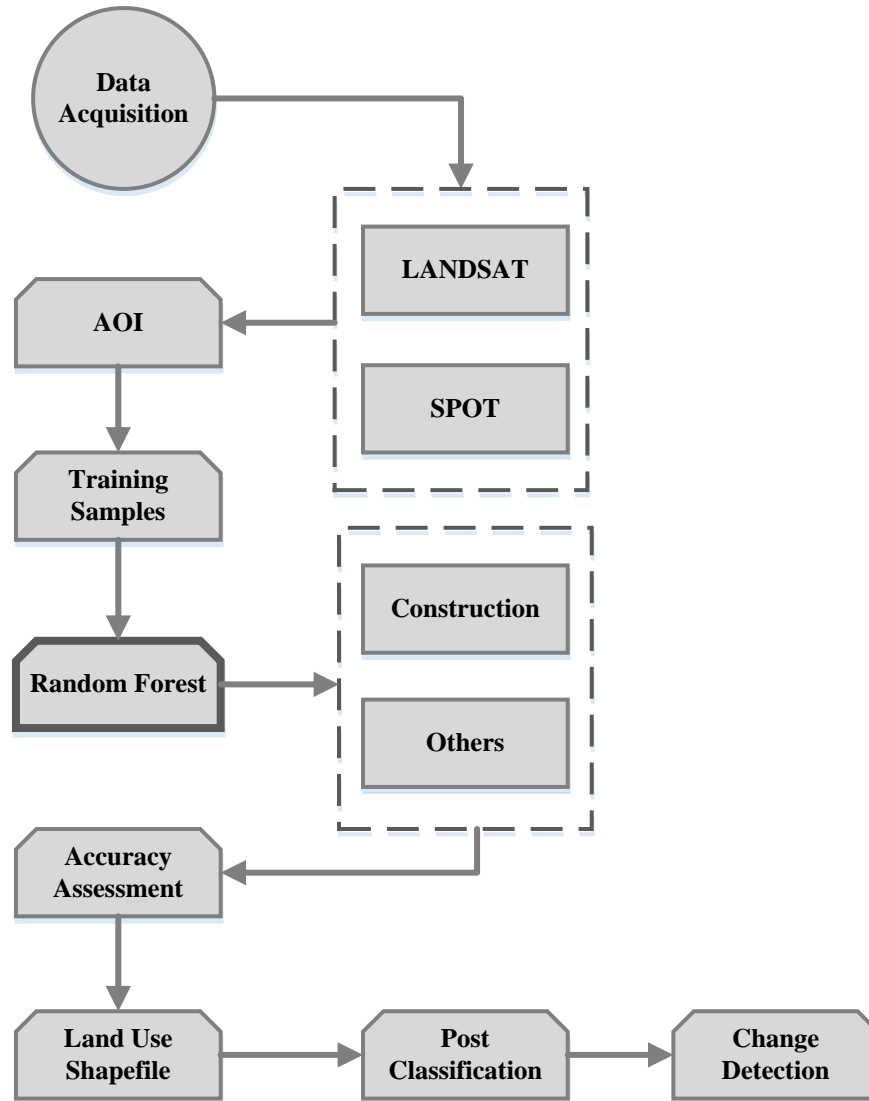


Figure 2-3. Remote sensing data process flow chart.

The SPOT data, which only cover the study area for 2010, required multiple runs of the RF classifier. The preliminary run was done on the study area less the urban area, with a mask built based on the known classified areas: agriculture, river, and rural villages. Once those known areas were removed, the remainder of each image was classified. The urban area, similar to the

LANDSAT imagery, was classified separately, resulting in 4 classes: green space, which includes ecological protection belt, urban parks, and public green spaces; urban, including high-density urban, low-density urban; industrial land; and water, which includes the river, lakes, canals, and fish-pond water bodies. All classified images were mosaicked together to make up the entire study area and converted to a 30-m resolution. For post classification, the images were vectorized and converted to an ESRI shapefile. Industrial land was then merged to urban land and took them as urban use. Thereafter, we subtracted the green spaces inside the city construction boundary was subtracted from the classified results by using 1980 vectorized atlas data, and 2002, 2006 land survey data and converted them into urban uses. Finally, we intersected the three classified land uses were intersected with the full information county boundary and statistics in their urban areas (Figure 2-4, Figure 2-5, Figure 2-6, Figure 2-7).

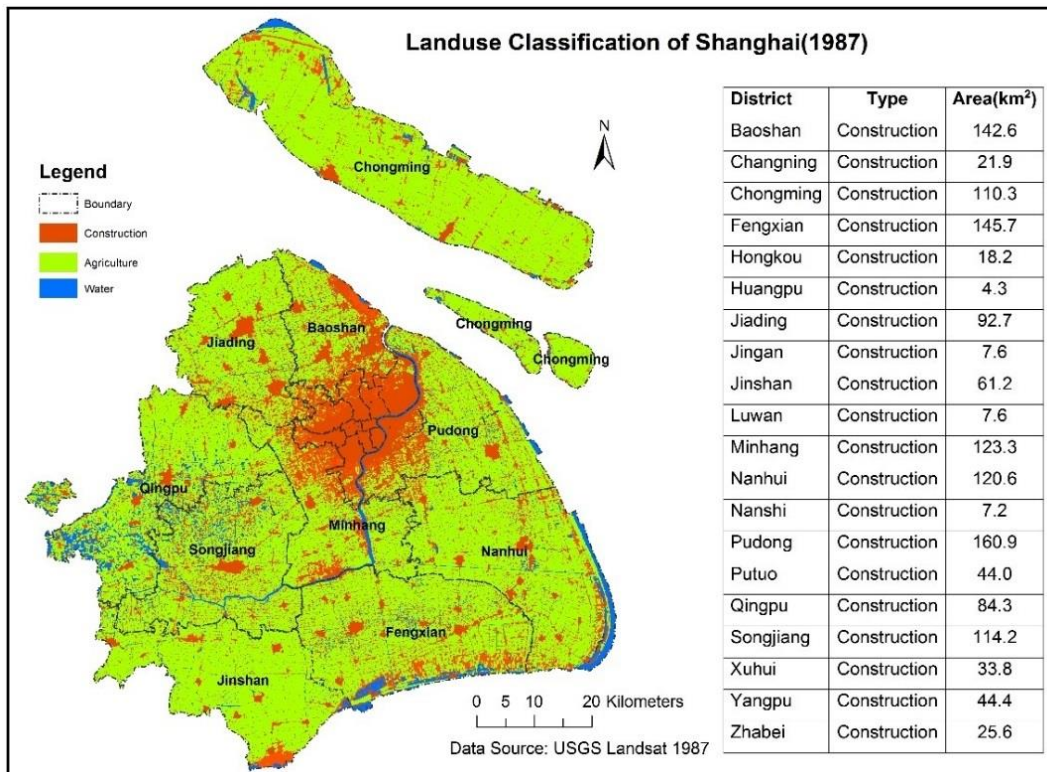


Figure 2-4. Land use classification: 1987.

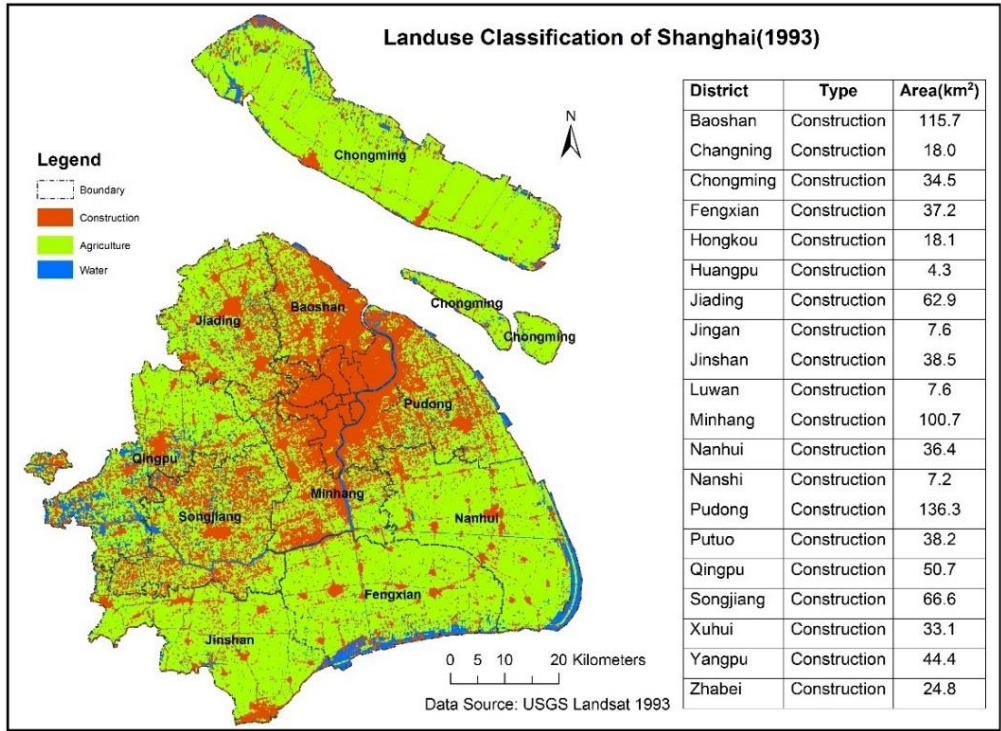


Figure 2-5. Land use classification: 1993.

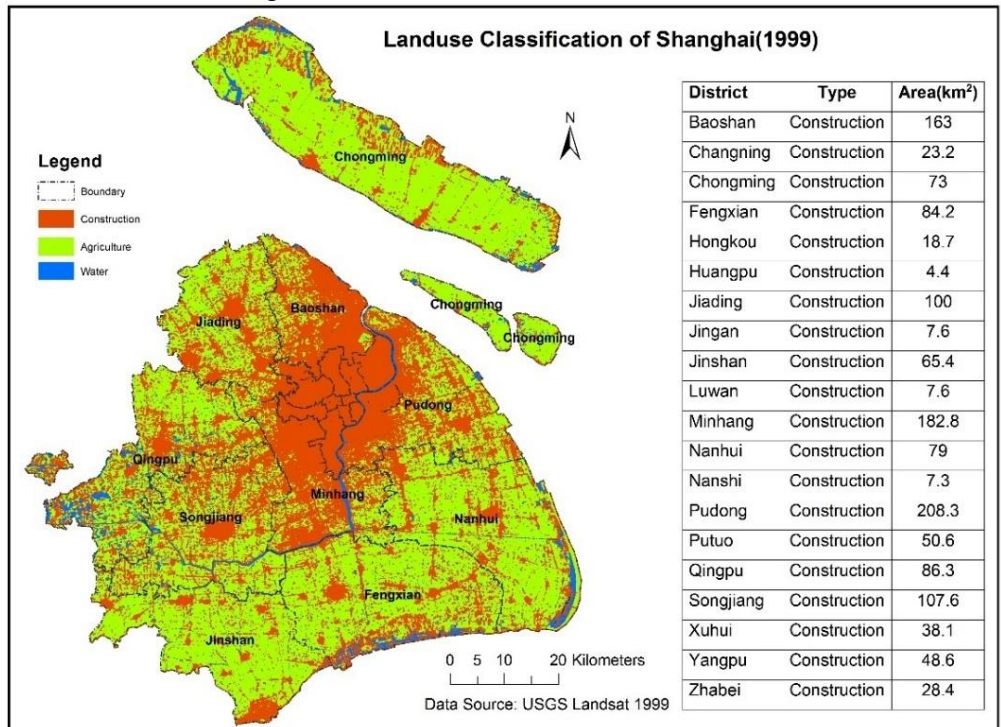


Figure 2-6. Land use classification: 1999.

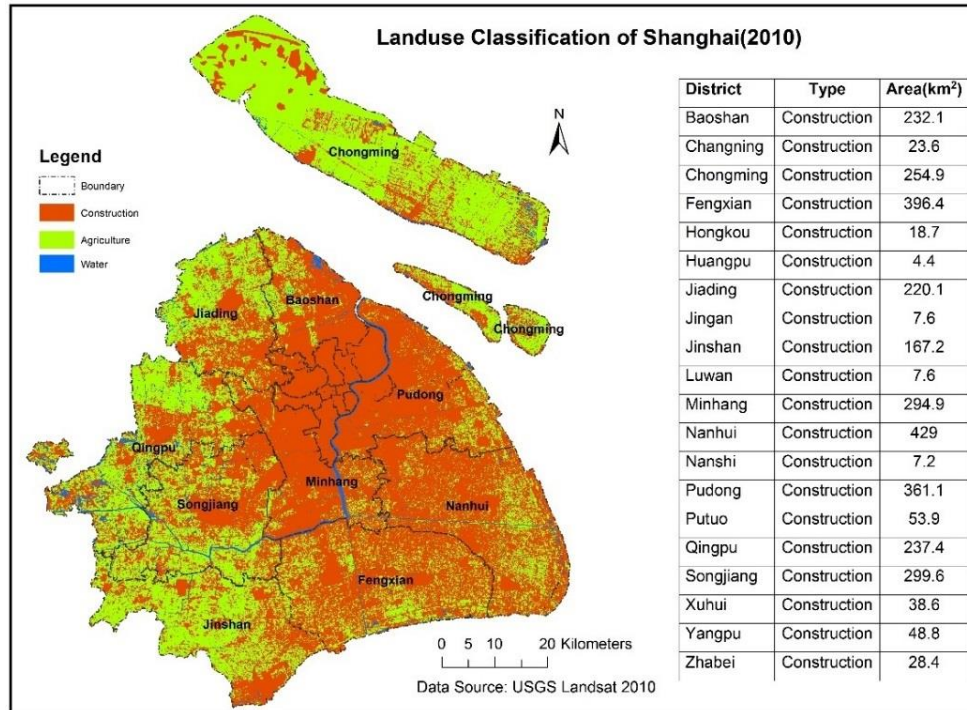


Figure 2-7. Land use classification: 2010.

Table 2-1. Accuracy and kappa coefficients of classified imagery of Shanghai

Year	Overall Accuracy	Kappa Coefficient
1987	97.0%	0.964
1993	96.5%	0.959
1999	95.8%	0.951
2010	85.7%	0.835

For each full-scene image of Shanghai at a 30-m resolution, an accuracy assessment was run (Table 2-1). Training areas were chosen with reference data from a high-resolution atlas from 1980 for the LANDSAT data, and from 2002, 2006 land survey data and visual inspection of the 2.5 m resolution data for SPOT. Confusion matrixes were generated for each year of analysis. Change detection statistics were generated for the four time periods of 1987-1993, 1987-2010, 1993-1999, and 1999-2010 (Figure 2-8, Figure 2-9, Figure 2-10).

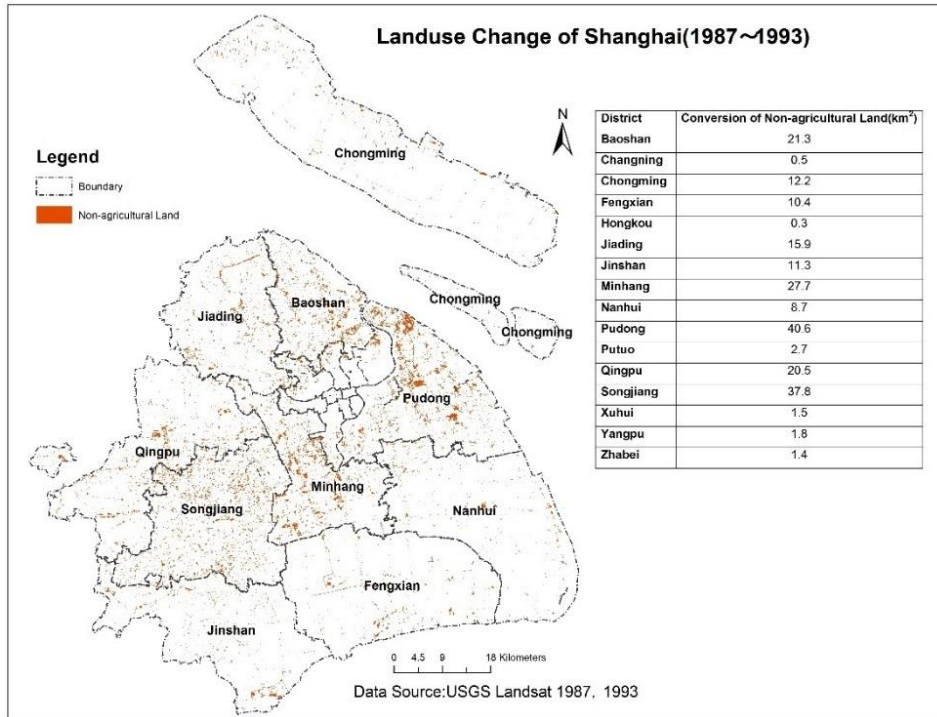


Figure 2-8. Urban land use change in Shanghai 1987-1993.

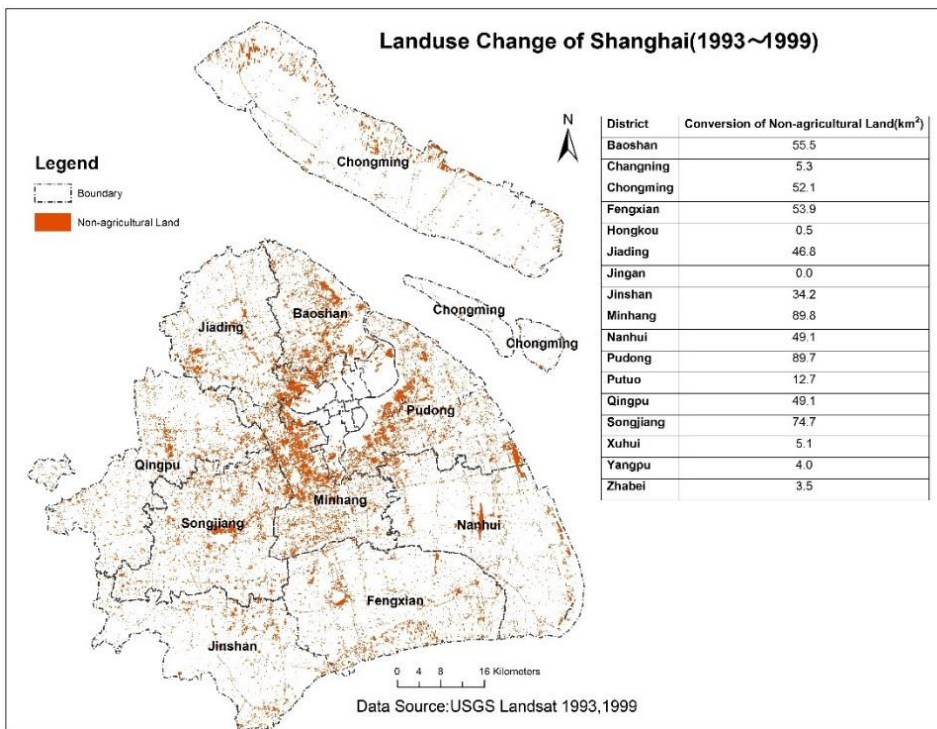


Figure 2-9. Urban land use change in Shanghai 1993-1999.

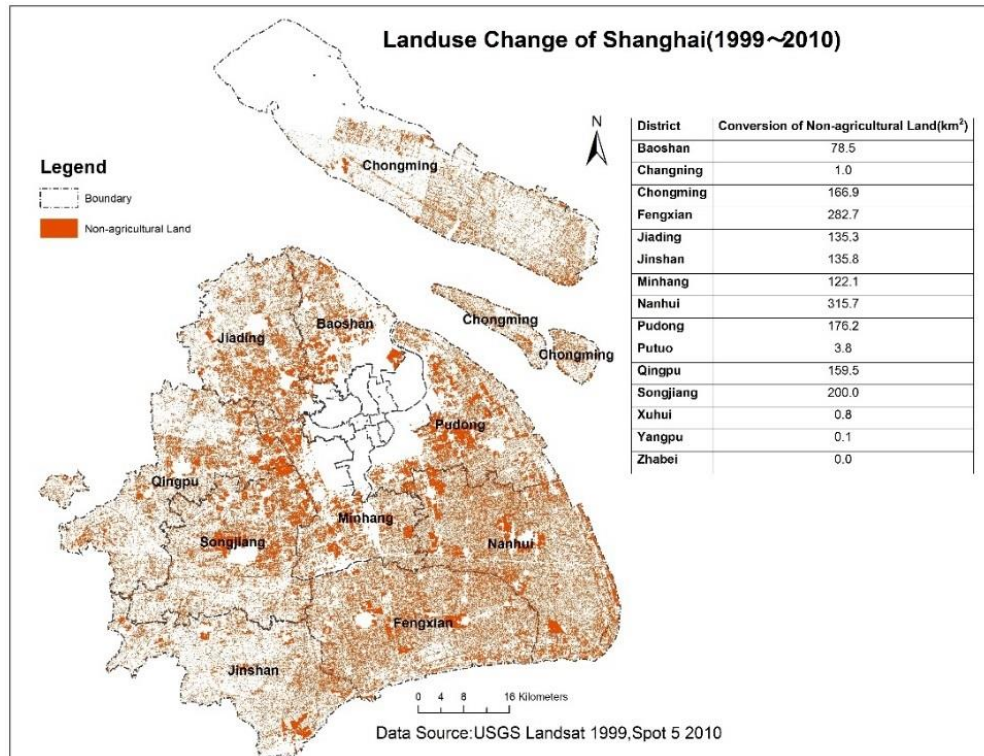


Figure 2-10. Urban land use change in Shanghai 1999-2010.

Chapter 3 Modes of land development in Shanghai

3.1 Introduction

Land development modelling and simulation becomes increasingly a tool for policy making in modern urban management (Alfeld & Graham, 1976). It provides a computational and visualizational framework upon which significant spatial and temporal information on mechanisms of landscape evolution can be revealed (Berry, 1964). To date, modelling and simulation studies have largely treated urban land development as a singular and uniform process and often neglected place-based decision-making processes and multiple trajectories that urban land could be developed (Batty, 1997; Dragicevic & Marceau, 1999; Wu & Martin, 2002; Parker et al., 2003; Xie et al., 2007; White et al., 2012; Wang & Marceau, 2013; Feng et al., 2015).

In market economies, land development in cities is mainly executed by private developers under a competitive environment. The process of land development follows a market principle of utility maximization and urban land is assessed for its suitability and potential profitability. Land with greater suitability and profitability is normally developed first and then the development of less suitable and profitable land is followed. Such market logic forms the theoretic foundation of most studies on land development modelling and simulation in recent decades (Batty, 1991; Deadman et al., 1993; White & Engelen, 1993; Wu, 1998). However, these models show some limitations when they are applied in the context of non-market or socialist market economies where the role of market is limited and government agencies intervene land development process frequently. For instance, the planned development of ‘polycentric city’ and ‘special economic zones’ often defeats the market logic and causes leapfrog developments in the suburbs of metropolitan areas (Gordon & Richardson, 1997; Bae & Jun, 2003). The existence of non-market forces in land development

undermines the utility of market-based models that often treat land development as a self-organization process. This problem is particularly acute in China because Chinese urbanization processes have been heavily shaped by distinctive institutional factors including ambiguous land property rights, land development administration policies and socialist planning systems in the course of transition to market-oriented economy (Gaubatz, 1999; Qiu et al., 2015). It is therefore imperative understand various forms and processes of land development in different geographic contexts in order to develop valid urban land development models and simulation procedures.

This study is going to identify the specific modes of local land development and investigate how government agencies, regulatory policies, and various actors are involved in the land development and decision-making process. Furthermore, the study is going to assess the spatial effects of different modes of land development in the city. Using Shanghai as a case, this study provides a theoretical basis for future land development modelling in China. We collected data from our in-depth interviews with urban developers, urban planners, and urban land use administrators and various government policies and planning documents and synthesize them to induce five modes of land development in Shanghai. By comparing the planned and actual land use changes, we mapped the spatial extent of these land development modes and assess the effect of each land development during the study period. The findings of this study lay the groundwork for future land use growth modelling and simulation in Shanghai.

The next section reviews land development theories pertaining to urban land growth and evolution simulation. This is followed by a discussion of research approaches. The empirical results are then presented. The paper is concluded with a discussion of the findings in relation to the relevant literature.

3.2 Theorizing land development

Since the late 1960s, with the rapid development of computer technology, urban growth and evolution simulations have mushroomed in urban and land use studies (Crecine, 1968; Forrester, 1969; Batty, 1971). Backing up the flourishing urban simulation models are two of the main land development theories: market-based and government-led land development models (as summarized in Appendix 1).

3.2.1 Market-based Land Development (MbLD)

In a market economy, land is owned privately. Land functions primarily as a commodity and its site attributes and situation characteristics determine how the land is used and its use is changed in a city. According to the neo-classic theory, urban land is developed in a competitive and efficient manner by those who are most competitive to bid for the rent of any land parcel. The spatial consequence of the market competition for urban land use is a concentric pattern of land use following a land value gradient descending away from city center to outskirts (Alonso, 1964; Mieszkowski & Mills, 1993; Harvey & Jowsey, 2004). The market-based land development process is rooted in a free and competitive market in which production and trading of land are regulated by land supply and demand. In such competitive markets, private property rights are protected, juridical individualism dominates, and an established legal and institutional system guarantees the operation of the market (Lin, 2009).

3.2.2 Government-led Land Development (GILD)

While most developed countries adopt a competitive market system, land development is not exclusively determined by the market forces of demand and supply. Landowners, capital investors,

real estate developers, land use planning specialists, politicians, stakeholders, and social, political, and economic organizations all influence the decision-making process of land development directly or indirectly (Healey & Barrett, 1990). Many attempts have been made to theorize and model the effects of non-market forces on urban land development. Two strands of theorizations can be found in the literature: one is on the government-led growth theories, especially Growth Machine Model (GMM) and the other on the government-led balanced land development theories, of which Urban Regime Model (URM) is influential.

Focusing on the economic attribute of urban land, GMM indicates that urban land growth is predominantly driven by the land-based elites who primarily aim to capture land exchange surplus values (Logan et al., 1987; Pfeffer & Lapping, 1994; Smith & Floyd, 2013). The land development process in a city is identified as economic growth seeking activity. Land developers, financial investors, and government agencies will collaborate with each other for the boom of economy and self-benefits. One of the key assertions behind GMM is the possibility to direct/redirect social, economic resources into specific urban locations to stimulate urban growth (Smith & Floyd, 2013). This is also known as place-based and place-making procedures (Bohl & Schwanke, 2002). Dockland development projects in London and La Défense project in Paris characterize this approach (Hoyle et al., 1988; Drozd & Appert, 2012).

Different from the coalitions formed among stakeholders to promote economic growth, the URM stipulates that governmental and non-governmental actors collaborate with each other for the achievement of assorted social and economic interests (Stone, 1989; Mossberger & Stoker, 2001). The theory asserts that stability and sustainability of urban development can only be achieved through an effective urban governance. For instance, many of European countries have been

endeavoring to carry out social housing projects to eliminate housing inequality and achieve mixed sustainable communities (Whitehead & Scanlon, 2007).

The existence of these government-led land use development processes shows that the utility of the prevalent market-based simulation models is limited. Under the assumption of a market-led land development process, it is often believed that urban land development process follows a bottom-up self-organization mechanism and accordingly it is possible to model and simulate the dynamic process of urban land development in a market economy based upon the urban complexity system theory (Batty, 2007). However, the actions of utilitarianism governmental and non-governmental agencies break the bottom-up and self-organization presumptions originated from a unitary market economic system. Instead of a bottom-up, self-organized procedure, government interventions and the place-based decision-making procedure among involved agencies bring about multiple possible trajectories of urban land development processes. This phenomenon is particularly evident in China, where distinctive land property rights, land development administration policies, socialist planning system and transition to market-oriented economy characterize conspicuous land development procedures. Therefore, it is imperative to differentiate various land development modes before a sound computer modelling and simulation procedure can be developed to model urban land use changes among cities in China (Guy & Hanneberry, 2008).

3.2.3 Land development process in China

From 1949 to 1978, under the socialist command economy, most of the land in China was owned by either the state or rural collectives (Zhang, 1997; Xu & Tang, 2014). The state allocates land for residential or industrial uses (Yeh & Wu, 1996). This land allocation system has been gradually

replaced with the “land-use rights system” (tudi shiyongquan) during the course of economic transition after 1978 (Ding, 2003). In 1988, the amendment to the Constitution of the People’s Republic of China made it official that land use right can be transferred with compensation in accordance to relevant legislation. Under this new regulation, the property rights of land was effectively de-bundled into land ownership rights and land use rights (LURs) (Lin, 2010). While the land ownership rights remain unchanged, the state and collective landowners were allowed to transfer their LURs in land markets. The introduction of land market helps to increase land use efficiency and leads to the involvement of multi-stakeholders in urban land development processes (Lin et al., 2014). This hybrid system of mixing state and collective land ownerships, market transfer of LURs, and previous path-dependent land allocation system is further coupled with the state administrative and planning system that is contingent upon local geographic and social conditions. Accordingly, in post-reform China, the land system produces various possible tracks of land development.

3.2.3.1 City-based Land Development (CbLD)

The City-based Land Development (CbLD) is referred to a city-centered land development process that the city government plays a leading role in transferring LURs and converting land use types from rural to urban. Economic reforms and spreading globalisation accelerate industrialisation and urbanization in major Chinese city-regions (Lin, 2007). Coupled with population growth and agglomeration of economic activities in the large coastal cities, the speedup of industrialization and urbanization has led to an increasing demand of land for capital accumulation. However, the state has a tight control of cultivated land for the reason of national food security (Ding, 2004; Tian & Ma, 2009). Consequently, the price differentials between urban and rural land have been

significantly elevated (Ding, 2004; Lin & Ho, 2005; Zhou, 2007; Tian & Ma, 2009). Meanwhile, the reform of social and commercial urban housing system, the upgrading of urban transportation infrastructures, and the continuously booming industrialization result in a growing demand for urban land development activities around the suburban areas of large Chinese cities (Lin, 2007). The heightened land value differentiations provide a great economic incentive for local government agencies and state-owned institutions to be actively involved in land transfer transactions in land markets as these land transactions provide the needed capital for coping with the rapid pace of urban growth. The CbLD processes surely lead to fast urban land use expansion and elevate urban land use intensity among major cities in China, particularly in the coastal provinces (Lin, 2009).

3.2.3.2 In-situ Land Development (IsLD)

The second model that explains land development process is the so-called In-situ Land Development (IsLD) (Zhu, 2000), which is also referred as rural-based land development in the literature (Xu, 2004; Lin, 2009). Contrary to the process of city-centered land use expansion, the IsLD theory explains the land use change in and around rural areas. It is often referred to spontaneous growth of urbanity in rural countryside, a phenomenon often called “urbanization from below” (Ma & Fan, 1994). Instead of a direct state involvement, local collectives initiate the process of land construction for non-agricultural uses. The primary cause for IsLD is the rapid growth of rural economy during the economic reform period. In 1980s, the spontaneous growth of township and village enterprises can be seen in numerous sites in coastal provinces (Yeh & Li, 1999; Zhu, 2000; Xu & Tan, 2001; Wei, 2002; Xu & Tan, 2002; Lin, 2009). After years of the primitive capital accumulation, local villagers all eager to improve housing conditions and rural

infrastructure (Zhu, 2002; Xu, 2004; Lin, 2009). Such amenity could not be provided by the state given these areas classified as rural. Rural collectives, especially those better-off villages start to plan and develop housing development projects and allocate the complete housing subdivision to the villagers. In the process, agricultural land is converted in-situ to factories and housing subdivisions without direct state land expropriation and the land ownership remains in the hand of rural collectives (Brown, 1995; Xu, 2004; Ding & Lichtenberg, 2011).

3.2.3.3 Zone-based Land Development (ZbLD)

Zone-based land development (ZbLD) explains the planned land development to create special industrial and technology zones. Such development is carried out by the government for achieving its economic growth targets. Using government power, the development projects are implemented by removing all the existing land users, agriculturalists or others, demolishing built-up buildings, and creating a brand new city zone. Similar to the CbLD model, it is a top-down urban land development process. However, land development is greatly concentrated in the planned development zone and it is often facilitated by preferential policies designed to attract foreign or non-local investment to the zone.

Two phenomena characterized by the ZbLD model are special economic development zone and new suburban city construction movement. After the economic reform in late 1970s, foreign direct investments became big treasures and competition targets among local governments in China's coastal regions (Yang & Wang, 2008). In seeking for tax revenue and local economic growth, municipal governments fervently set up special economic development zones or industrial parks to attract industrial investment (Cartier, 2001; Wei & Leung, 2005; Xu, 2013). In addition to special development zones, new suburban cities are purposefully planned, developed and built to

disperse residents from over-crowded urban centers. The new satellite cities or suburban towns are associated with a variety of urban functions, including university city, themed residential town, new government headquarters, business node and district, and village for major international events (Li, 2014). These special economic development zones and new suburban cities normally locate at certain distance away from their corresponding city (Cartier, 2001). The results of ZbLD include multi-centers, leap-frog development, and urban sprawl in many large cities in China.

3.2.4 Variegated land development modes

The above discussion indicates that the land development process in China is quite diverse and complicated and it is intertwined in a local social, political, economic milieu. The changing institutional system and the involvement of state-owned organizations, private entities, various levels of government interests, and bureaucratic behaviors make the land development more than a singular, uniform process (Yeh & Wu, 1996; Wu, 2003; Lin & Ho, 2005).

Upon a systematic investigation of historical changes in the state institution and the actual pattern of land use, Lin (2009) asserts that land development in China is a juxtaposition of IsLD and CbLD processes. Coupled with ZbLD, these models provide a basic analytical framework to study land development processes in China. To date, however, there are several aspects of deficiencies in theorizing land development processes in the literature. First, it is unknown whether various types of land development are juxtaposed at a local level. If so, what are the reasons or conditions for their co-existence and how does each type of land use development shape the transformation of urban landscape? The current theorization of CbLD and IsLD is derived largely from comparing empirical studies across different regions and cities in China. Each region or city is supposed to follow one specific mode of land development process. No research has been done to investigate

the coexistence of variegated land development modes in a single city. Second, the role of government agencies in land development processes is not substantially discussed. There are extensive studies on land property rights, land resource administration systems, and land development policies in China. However, few of them systematically delineate the decision-making processes behind land development activities. Third, it is uncertain whether there are any other unidentified land development modes that need to be discerned in Chinese cities. The above literature review identifies three major land development models by theorizing the land development procedures in Chinese cities based on the existing case studies. Our field observations and interviews indicate that certain types of land development activities were not identified because the existing studies have largely focused on the dominant forms of land development activities. Therefore, there is a need to develop systematically some theoretical constructs upon which modes of land development can be uncovered.

3.3 Data and methods

Given the gaps in the current research on land development in Chinese cities, the empirical part of this paper takes Shanghai as a case to investigate systematically the variegated land development modes in China. In doing so, this study attempts to understand how government agencies, regulatory policies, and various actors are involved in the development and decision-making processes. The study also aims to assess the significance and spatial effect of each of the land development modes in Shanghai.

Shanghai is one of the four state-designated cities and it is the largest city in China with a population of about 24 million according to 2010 census. Since 1978 when economic reforms were initiated, its urban landscape, particularly the spatial distribution of urban land use has transformed

significantly. Hence, studies on the land development process in Shanghai will open a window to understand China.

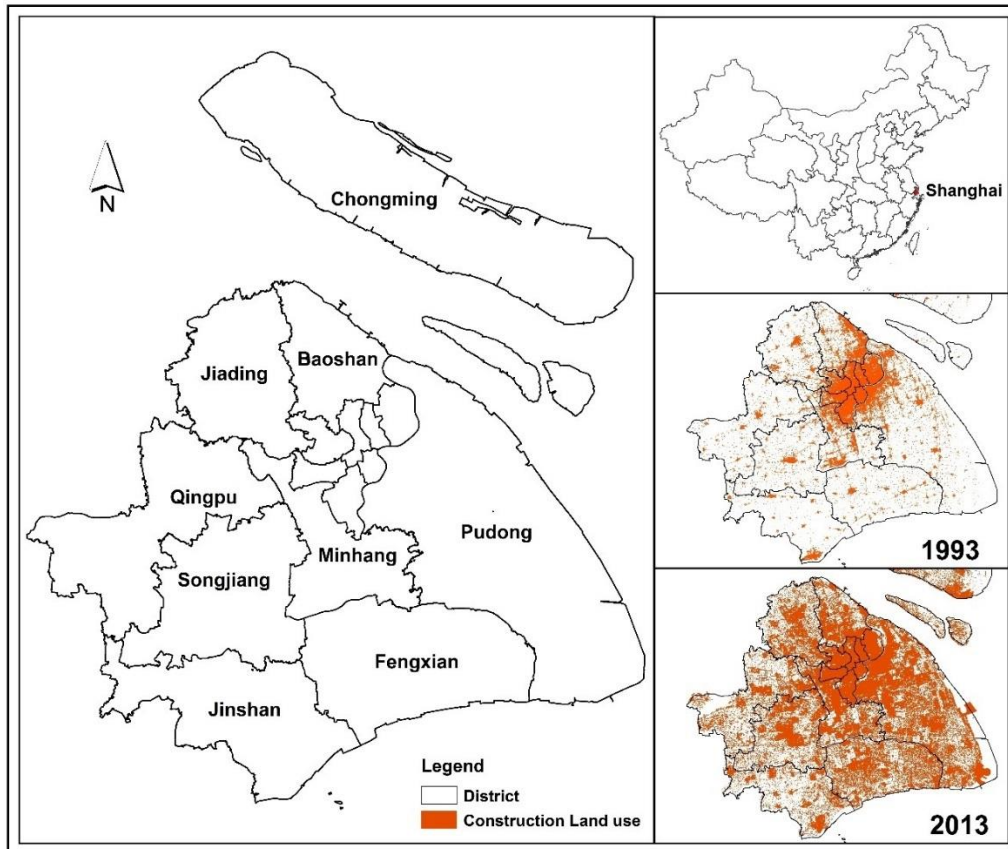


Figure 3-1: Study area and its urban land use change.

3.3.1 Interview data collection and analysis

In order to achieve the research objectives of this paper, both primary and secondary data are collected. Key informant interviews serve as the source of the primary data. A field study was carried out during the summer of 2015 to collect interview data. Both purposive sampling and convenience sampling were employed. Considering the full participation during land development process (Wu, 2015), urban planners were selected as main interview informants to investigate their perspectives and understandings on urban land development. The initial key informants were

contacted using the Shanghai Urban Planning and Verifying Center (SHUPVC) as one of the key information sources. A snow-ball sampling was followed by asking initial key informants. Six urban planners, three government officials, and two land developers were interviewed (Table 3-1).

Table 3-1. The list of interviewees.

	ID	Employer
Urban planners	SGUPD-1	Shanghai Guangjing Urban Planning & Design Co. Ltd.
	SHUPVC-1, 2, 3, 4	Shanghai Urban Planning & Verifying Center
Government officials	CPD-1	Comprehensive Planning Department
	HDUO-1	Huangpu District Urban Planning Office
	LFTCAC-1	Shanghai Lujiazui Finance & Trade Center Administration Commission
Developers	SLG-1	Shanghai Land Group Co. Ltd
	SPREG-1	Shanghai Pudong Real Estate Group Co. Ltd.

A semi-structured interview method was adopted by this study. A list of open-ended questions (Table 3-2)) was given to interviewees before each interview started and this was then followed by an in-depth interview to explore land development processes in Shanghai. Each interview lasted 40 to 90 minutes. All the interviews were recorded with the permissions from interviewees. After the field study and data collection, all information was transcribed into text documents. In addition, government documents, planning documents and other grey literature are also collected. A thematic analysis method was used to generate the categories of land development modes inductively based on interview data and published documents.

Table 3-2. The list of initial interview questions.

Q1	What are the land development modes currently adopted by the city?
Q2	Which one is dominating?
Q3	Does market or government lead the land development of the city?
Q4	What are the differences among residential, commercial, and industrial land development?
Q5	What kind of roles do city and prefecture governments play during land development?
Q6	What's the original land use type before urban planning is implemented?

-
- Q7 Who initiate the plan?
Q8 Who organize the plan?
Q9 Which departments should a developer visit before the construction permit for a land parcel is issued?
Q10 What modes of development are preferred?
-

3.3.2 Land use data collection and analysis

To assess the significance and spatial effects of different modes of land development, we obtained 1993 Landsat TM imagery data (Landsat 5, 03/06/1993) and 2013 Landsat ETM imagery data of Shanghai (Landsat 8, 14/04/2013) from the USGS website (<http://landsat.usgs.gov/>). Random Forest classification method (van der Linden et al., 2015) and GIS spatial analysis were used to generate the land use change map of Shanghai. In addition, we obtained 2002 and 2006 land survey data of Shanghai from the SHUPVC and used them to adjust the classified land-use results. A 96% classification accuracy rate is achieved for the 1993 data and 86% for 2013.

A total of 1571 urban regulatory planning data tables and maps dated from 1993 to 2013 were obtained from the SHUPVC to analyze and delineate the spatial distribution of the constructed land under each of the identified development modes. This data set contains the comprehensive information on plan's location, orgainer, approver, approved time, and development highlights. In addition to the information on regulatory plans, the study also obtains the maps that have information on agricultural land use control boundaries, concentrated construction boundaries and planned industrial land use boundaries in accordance with Shanghai master plan. Spatial overlay analysis methods in the ArcGIS software environment were used to generate the spatial distribution of land use change under each of the identified land development modes in Shanghai between 1993 and 2013.

3.4 Land use rights, regulatory control, and government agencies

Based on the analysis of interview data and government documents, it is found that the ownership of LURs, regulatory control of land use change, and intermediate agencies involved in the transformation processes of LURs function as the three key factors for the differentiation of land development modes in Shanghai.

3.4.1 Land use type and LURs

The separation of LURs from land property ownership rights and the establishment of land markets create several types of LURs. They can be collective-owned, privately-owned, shareholding-owned, state-owned, and jointly-owned (Zhang, 2002). Together with various actions by intermediary agencies, the disparate ownership of LURs is one of the determinants leading to different land development or redevelopment modes as well as trajectories of land use change.

For the purpose of land survey and resource management, the Ministry of Land and Resources (<http://www.mlr.gov.cn/>) categories land into agricultural, construction, and unused uses. In general, agricultural land is collectively owned. The construction land includes residential, commercial, industrial, transportation, facility and other utility uses. They can be owned collectively, privately, jointly or by the state. Unused land includes open water, land for ecological protection, and un-arable land. Majority of the unused land is collectively owned in Shanghai.

3.4.2 Regulatory control of urban land use

To curb the excessive expansion of urban land use and protect the limited prime agricultural land, Shanghai Urban Planning and Land Resource Administration Bureau (SHUPLRAB) establishes a

series of regulatory instruments to constrain urban land development activities (Figure 3-2). The first significant land expansion regulatory instrument is the Concentrated Construction Zone (CCZ) which is delineated as the future urban boundary in the Shanghai Land Use 2006-2020 Master Plan. In addition to the master plans, the boundaries of CCZs are also the result of consultations and negotiations between the city and its local district governments. The second regulatory instrument is the designation of Industry Zones (IZ). Based on the Shanghai Industry Development Twelfth Five-Year Plan, the establishment of Industry Zones is to control industrial land uses for the purpose of environmental protection, governmental function, and economic development. Administratively, all land development activities should be located inside the CCZ and IZ boundaries. The boundary of these two zones effectively delineates the area for controlling any future urban growth in Shanghai. The third regulatory instrument is the Regulatory Planning Full Coverage, which was requested by SHUPLRAB based on the Urban and Rural Planning Law of China. Its purpose is to govern urban construction activities. The fourth regulatory instrument is Urban Built-up Area (UBA). According to the Code for Classification of Urban Land Use and Planning Standards of Development Land (2011), UBA indicates that any construction use of land will be subject to the condition of state land expropriation. In general, UBA is contained within the boundaries of CCZ and IZ. Through delineation of these four urban land use regulatory boundaries, the city government establishes a rigorous administrative framework for governing urban land use.

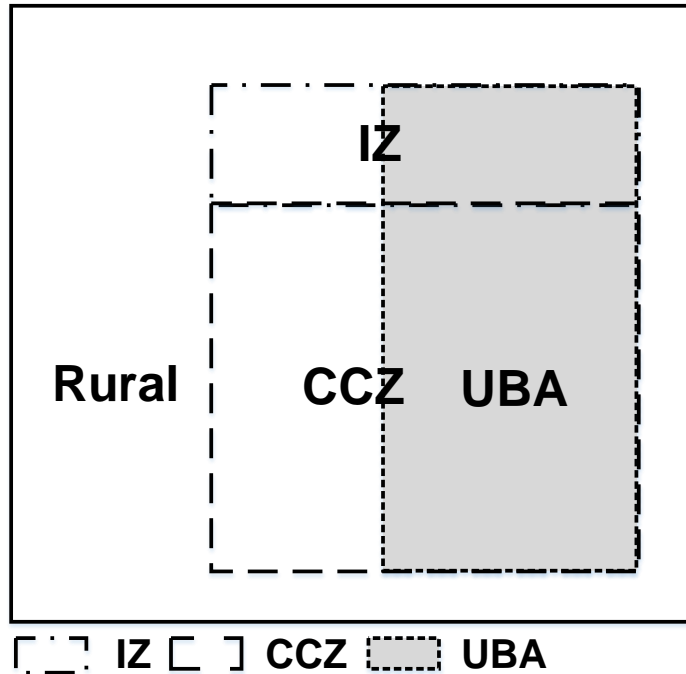


Figure 3-2. Urban land use regulatory boundaries.

3.4.3 Government agency, organization, and land supply

The interviews with planning officials and administrative professionals show that Shanghai Development and Reform Commission (SHDRC) and SHMPLRA are the two core government agencies participating in Shanghai’s land development activities (Figure 3-3).

According to government documents, SHDRC is a provincial-level macroeconomic management agency under the direction of the National Development and Reform Commission of China. Its primary duty is to formulate and implement macroeconomic policies and approve major construction tasks. The SHMPLRAB is functioned through a list of administrative units fulfilling the relevant tasks. The Master Planning Department (MPD) is responsible for compiling and implementing the master plan of the city. The Regulatory Planning Department (RPD) is responsible for compiling and implementing regulatory plans and urban design. The Land Use

Department (LUD) is principally in charge of creating land use policies, monitoring land development, and implementing land laws. The Comprehensive Planning Department (CPD) compiles the annual land supply plan of the city and balances the annual volumes of land development among administrative units. The Land Banking Center (LBC) is in charge of land banking activities including land banking fund, land acquisition, and land consolidation. The Land Transaction Center (LTC) is in charge of the land appraisal, land auction of the city. Except for LTC, each of the departments has a corresponding local district level bureau responsible for local district land development activities. Below the local district level governments are villages/townships, which are self-managed by autonomy committees.

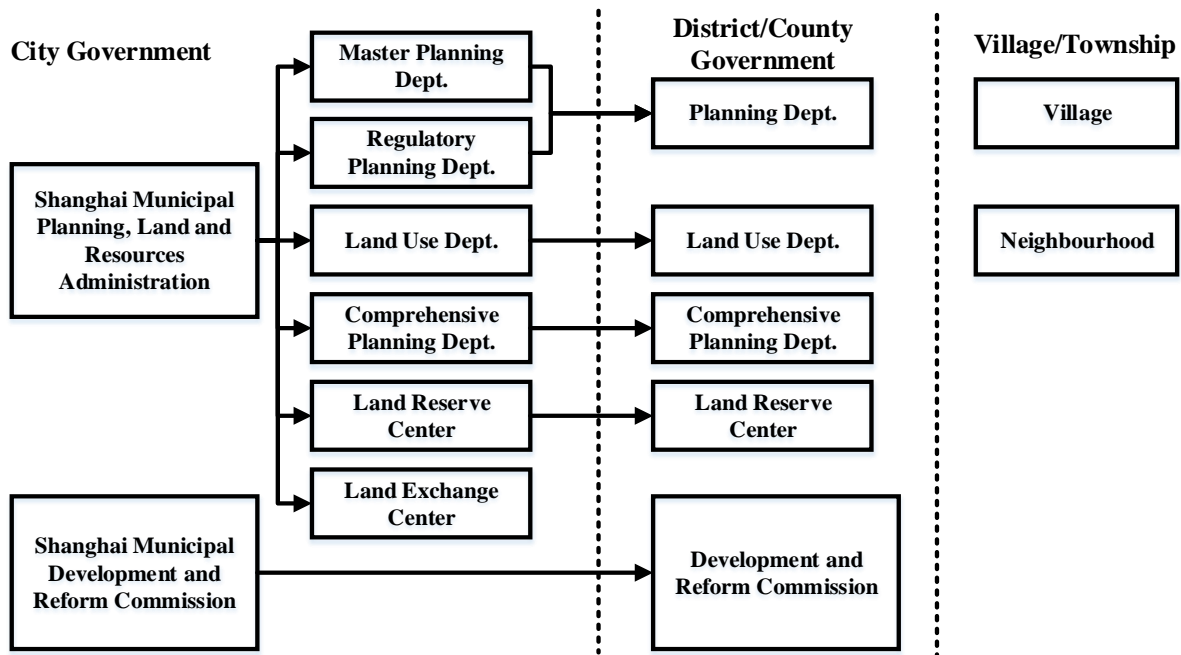


Figure 3-3. Land management administration system of Shanghai (based on interviews and government documents).

Land supply decision represents an important aspect of land development decision-making processes of a city. In a market dominated economy, the supply of land is tied closely to demand (Harvey & Jowsey, 2004). Nevertheless, the situation is more complex in a planned socialist

economy (Lin, 2009). According to the interview with CPD-1, land supply decision is made by the city CPD by compiling the annual urban land supply plan. The plan is based on multiple sources of land information, including land usage in the previous year, the midterm urban land supply plan, the economic development results of the previous year, the economic growth prediction for the following year, and the land supply plans reported by each of local district level CPDs. An important decision in the making of annual land supply plan is to balance land supply amounts across city districts (CPD-1). Since the land sales income accounts for a large share of fiscal revenue of all local district governments, all local district governments want to sell more land. The CPD has to negotiate with local district governments in order to control the total amount of land supply under the annual cap prescribed by the State Council (Lin et al., 2014).

In sum, the case of Shanghai demonstrates in detail how the government-led land development process works. The institutional arrangement on land use rights makes it possible for the transfer of land from one use to another. The regulatory instruments provide spatial and administrative framework to govern and regulate urban land use. The government agencies and organizations tightly control long- and short-term supply of land for construction uses. These government policies, regulations, and actions, coupled with land developers and other market agencies, create different modes of land development in Shanghai.

3.5 Land development modes and decision-making mechanism

The above discussion indicates that the ownership of LURs, the regulatory control of land use change, and intermediate agencies are the three major factors leading to variegated land development modes. Accordingly, the original land use type and its property ownership are logically the first criterion to differentiate land development modest. The second criterion is the

final land use types that is possibly developed under each of the land development modes. The types of intermediate agencies involved in the land development process are employed as the third differentiation criterion.

Based on the interview data, a total of five land development modes can be identified (Figure 3-4). The following part of this section interprets these five modes of land development in detail.

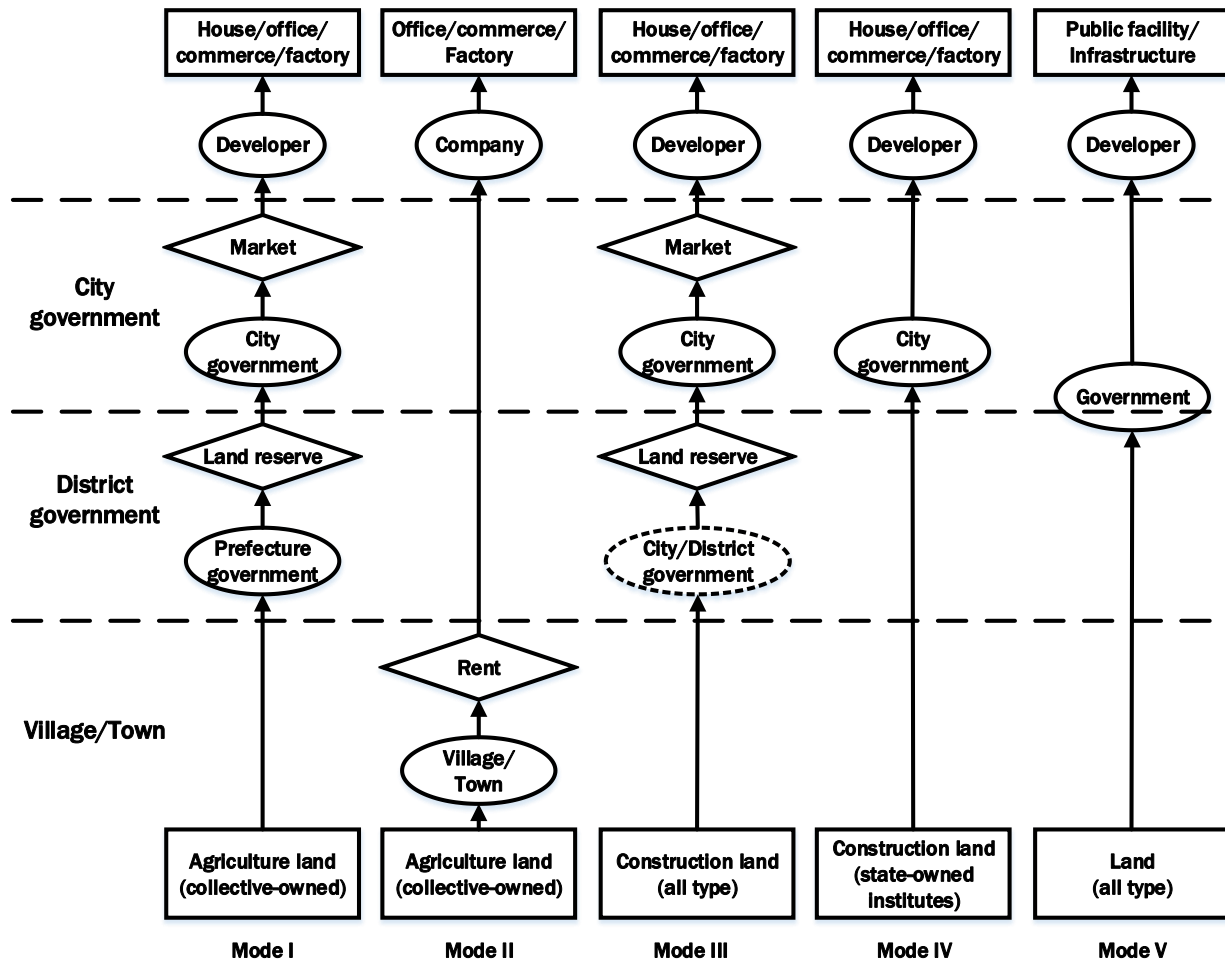


Figure 3-4. Modes of land development in Shanghai, China (based on interviews).

3.5.1 Land Development Mode I: State-led Market-based Land Development

In Land Development Mode I (Figure 3-4), the original land use type is agriculture, the LURs are held collectively by local peasants, and the current land use type is residential, commercial, or industrial uses. This part of land locates inside either CCZ or IZ boundaries and it is planned for residential, commercial, or industrial uses.

According to the interviews (UPVC-1, 2, 3, 4, CPD-1, HDUO-1, LFTCAC-1), local district governments expropriate agricultural land from rural collectives through a mechanism of land acquisition compensation. In accordance with the prescribed procedure, the LBC of the local district government will assign a primary land developer that is a state-owned property firm to develop the land. The assigned primary land developer is responsible for raising money for land expropriation compensation, site cleanup, infrastructure and utility construction. Thereafter, the assigned state-owned primary land developer will monitor the land market and seek for possible secondary developers. Once the time is ripe, the primary land developer will include the land into the annual land supply plan and prepare to sell through the LTC of the city. All the land through this developing mode will go through a public auction process. The land sale profits will be handed over to the local district government from the assigned primary developer. A revenue sharing schedule is in place to split the land sale profit between the city government and the district government. For instance, according to JinShan District Land Sales Revenue Allocation Regulation (JINFU [2004] 26 HAO), 15% of the land sales revenue goes to the city government and 85% to the local district government. Through this process, the collective land rights are transferred to the state and the LURs are transferred to property developers for a fixed amount of years, normally 70 years for residential and 50 years for commercial uses. The developed land

eventually becomes part of the UBA. Different from the perfect competitive land development process in a market economy, this land development mode in Shanghai characterizes China's socialist planning system and its transition to a market-oriented economy. It represents the unique state-led and market-guided land development procedure in Chinese cities.

Different from other provinces, according to the interviews UPVC-4 and SLG-1, all the primary developers in Shanghai are state-owned companies. No individual private agency is allowed to carry out the primary land development in the city. Many new state-owned ad-hoc property development firms are established for the property development projects. For instance, Shanghai World Expo (Group) Co. Ltd. was set up for the land development of the Expo site; Shanghai Jiading New City Co. Ltd. was set up for the development of the Jiading New City.

3.5.2 Land development Mode II: Informal Land Development

For Land Development Mode II, the original land use type is also agriculture, and the land ownership rights are held collectively by local peasants. However, the land locates outside either CCZ or IZ boundaries. According to the interviews (UPVC-1, HDUO-1, LFTCAC-1, SGUPD-1), the LURs of this type of land development cannot be transferred to private or public organizations for long term uses. Therefore, they cannot be used to build commercial houses. Nevertheless, land use legislation gives the owners of LURs the permission to lease the land for industrial uses (Lin, 2009). Local TVEs or external investors might contact with town or village officials for the purpose of developing manufacturing factories or commercial buildings. The town or village officials will report to the district DPC and LUD for the approval of land development for such projects. According to the interviewee, LFTCAC-1, in addition to locally initiated industrial projects, the other important way for industrial land development is to set up share-holding

companies or joint-ventures. Acting alike primary land developers, the village/town share-holding companies will clean up the land and build infrastructure and necessary utilities. Then the land will be rented out to factories. Different from land development Mode I, the long term LURs of the Mode II are still held by the collectives. The LURs were rented out to industrial factories only for limited number of years (normally less than 30 years). This is the so called informal land development process in the literature (Wong & Zhao, 1999; Wang et al., 2009).

3.5.3 Land Development Mode III: State-led Land Redevelopment

In this mode, the original land use type is not agriculture and the land locates inside CCZ or IZ boundaries. One source of the lands under this mode was that the land was previously allocated either to state owned manufacturing plants, public organizations, or residential homes according to the state economic development plans (Lin, 2009). The other source of land ownership is that they were collectively owned farmland and were then rented out to TVEs or other industrial factories, or homestead land for local farmers. Alongside the continuous urbanization and suburbanization, the lands need to be developed or redeveloped according to the current urban development plan.

According to the interviews (UPVC-1, 2, 3, 4, CPD-1, HDUO-1, LFTCAC-1, SPREG-1), like Mode I, the local district governments or the city government assign state-owned primary land developers to expropriate the lands from the current LURs holders. After expropriation, the land will be auctioned in Shanghai's primary land market for sale. Once the land is sold, houses, offices, commercial buildings, or factories can be built by developers or industrial firms according to urban development master plan. During this process, the collectively owned, privately owned, or state-

owned organizations holding LURs were consolidated together and then sold out to developers for long term uses. The collectively owned land rights were nationalized.

3.5.4 Land development Mode IV: State-approved Independent Land Development

The original land use type in this mode is for non-agricultural uses. The LURs are held by state owned companies or institutions. Generally, these lands were allocated to state owned organization, such as state owned companies, universities, governmental institutions. Different from Mode III, as indicated by HDUO-1 and SPREG-1, instead of expropriation and public auction, the proprietors of this kind of lands have rights and power to maintain the ownership of the LURs and will develop the land by themselves or through a collaboration with other developers. During this process, there are no transfer of land ownership rights or LURs. Land ownership rights remain in the hand of the state, but the long term LURs still belong to the corresponding state owned organizations. For example, more than 7 km² of the land was vacated by the Baosteel Group Corporation after it moved out in 2012 and the company insists to develop the land as a high density residential area which is totally deviated from Shanghai's land use and ecological plans (interview HDUO-1). The rules have to be changed here since it is a state owned, world top 500 ranking company.

3.5.5 Land development Mode V: Megaproject-based Land Development

Inherited from the socialist planning system, the state can expropriate any land within its administrative boundary directly for sizable social and economic projects, the construction of major public facilities (hospital, sport stadium, park), the state funded infrastructure development projects (highway, railway, electricity), low-income housing projects, or other significant projects

deemed to be necessary to the city. In this land development mode, according to the Land Administration Law of China, the owners of the land subject to expropriation may receive a fixed rate of land compensation. For instance, to carry out the Hongqiao Transportation Hub project, Minhang district government has expropriated more than 1,334 hectares of collectively owned agricultural land from rural collectives since 2006 (HDUO-1). The compensation fee for construction/unused land is stipulated as 39.6 yuan/m² and for agricultural land 64.8 yuan/m², according to the Shanghai Land Compensation Standard for Land Expropriation (Hufangdizifa [2008] 551 hao). In this development process, collective land rights are transferred to the state. Collective, private, or state-owned organizations that hold LURs are consolidated and allocated to state-owned companies or institutions.

The modes of land development identified above show that land development in Shanghai is a mix of government-led and market-driven processes. According to the interviews, the LURs under Mode I and Mode III are transferred through the primary land market under public scrutiny. The transfer of LURs under Mode II and Mode IV takes place either in secondary or tertiary land markets. The LURs are temporarily transferred under certain pre-negotiated terms or conditions. Mode V reflects a government-led land development process.

In the next section, we investigate the location and spatial extent of each mode of land development based on the analysis of historical land use data, urban planning data, and various urban administration boundaries.

3.6 Location and spatial extent of land development modes

As stated in the previous section, UBA is the city's current juridical urban space while CCZ and IZ are the planned future urban land use boundaries. The gaps between UBA and CCZ or IZ are where urban land development activities approved by the state are concentrated.

To identify the location of land development mode I and estimate its spatial extent, we first obtained the net change map in the construction land use by subtracting the construction land area in 1993 from that in 2013. Since Land Development Mode I is the conversion of agricultural land locating inside the CCZ or IZ boundaries, we used the CCZ and IZ boundary maps to subtract the net change map in the construction land use to generate the increased construction land inside the CCZ and IZ boundaries. As indicated in the previous section, the estimated change map includes the collective construction land before the establishment of the CCZ and IZ boundaries, which is mainly the result of Mode III. Thus, the land developed through Mode III should be masked out. Using the GIS overlay procedure, we obtained the location and spatial extent of land use change under Land Development Mode I (Figure 3-5). It shows that about 1,025 km² of agricultural land were expropriated for urban uses during the period 1993 to 2013 under this development mode. The majority of the lands are concentrated around the planned new cities in suburban Shanghai.

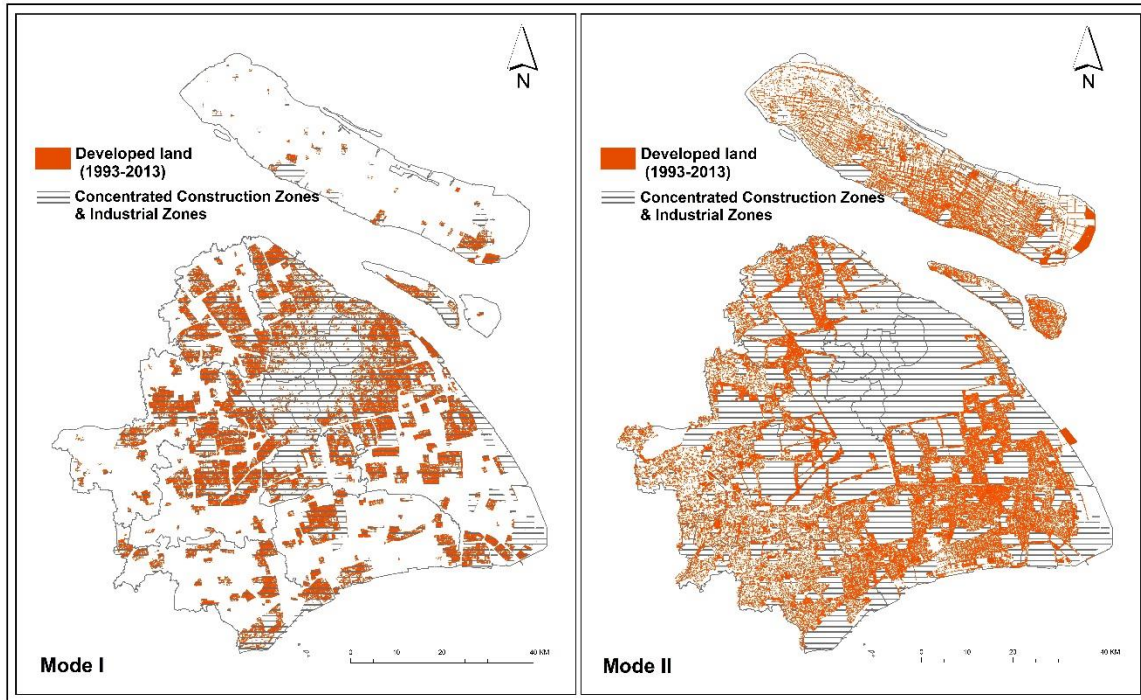


Figure 3-5. Localities of land development Mode I and II.

As identified in previous section, the conversion to construction land use outside the CCZ and IZ boundaries are mostly the result of Land Development Mode II. Therefore, by eliminating the area of the net change map in the construction land use using the CCZ and IZ boundaries, the land area developed by collective villages was obtained (Figure 3-5).

The result shows that about 1,077 km² of agricultural land was converted to non-agricultural uses by rural collectives from 1993 to 2013. There is a heavy concentration of this type of land development in between CCZ and IZ. These lands were supposed for agricultural use or ecological protection purpose.

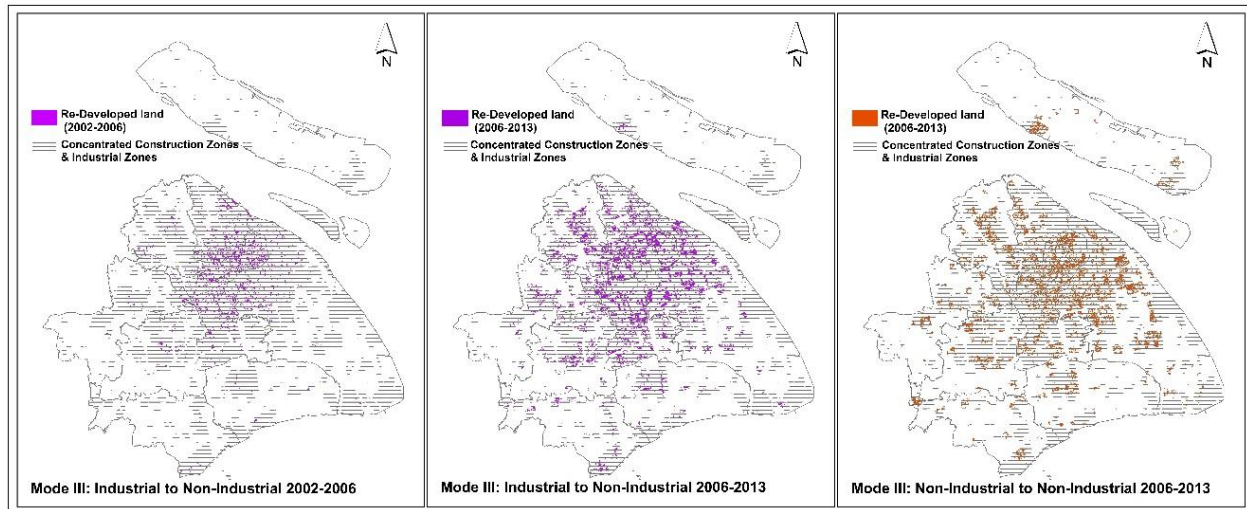


Figure 3-6. Locality of urban land development Mode III.

The development/redevelopment of construction land inside the CCZ or IZ boundaries is the result of land development Mode III. We employed 2002, 2006 land survey data, and 2013 urban regulatory planning data to locate the spatial extent of land development activities under Mode III (Figure 3-6). First, we used 2006 non-industrial (residential, commercial, facility, and utility) construction land use data to intercept the industrial land in 2002 from which we derived the converted industrial land from 2002 to 2006 (Figure 3-6). Using the same method, we generated industrial land that was converted into non-industrial construction uses after 2006. Using the 2013 urban regulatory planning data, we intercepted the planned non-industrial (residential, commercial, facility, and utility) construction land with the 2006 non-industrial construction land to generate the redeveloped non-industrial land. The outcomes indicate that about 60 km² of industrial land uses were converted into residential, commercial, facility, or urban infrastructure land uses inside the CCZ or IZ boundaries from 2002 to 2006. The amount increased to about 201 km² between 2006 and 2013. There were 211 km² of non-industrial industrial land was redeveloped from the period of 2006 to 2013. We can see clearly that industrial land uses were moved away from central areas and there were large amount urban redevelopment activities happened around the city center.

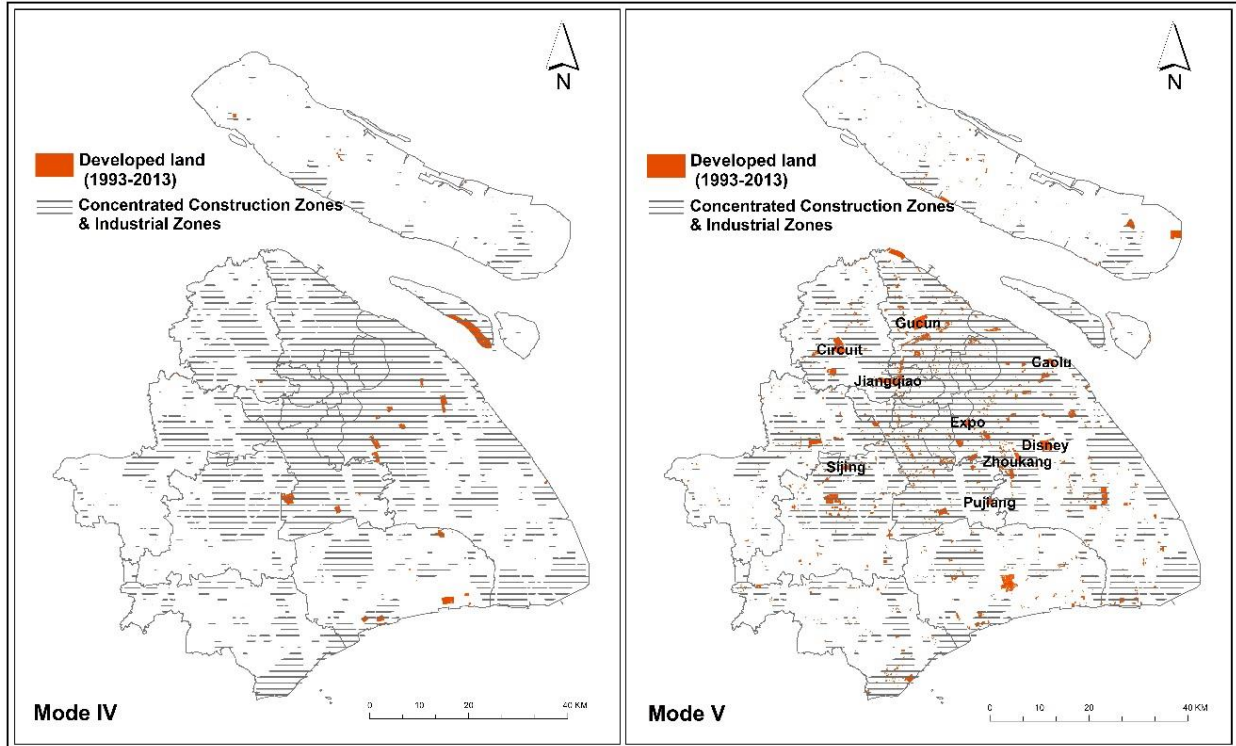


Figure 3-7. Localities of urban land development Mode IV and V.

According to the previous section, the land developed by state-owned organizations is the results of Land Development Mode IV. Therefore, we used the urban regulatory plans launched by state-owned organizations to generate the land developed by them (Figure 3-7). The results show that there were 36 km² of the land developed or redeveloped by state-owned organizations from 1993 to 2013.

The lands developed directly by local districts or the city government for specific projects are the results of Land Development Mode V. To generate the spatial extent of Land Development Mode V, we used the regulatory plans directly launched and organized by the city government. There were about 112 km² of the land that was directly developed by the city for big developmental events, public infrastructure and facilities, and low-income public housing. It needs to note that the estimated amount does not include the land that was converted for transportation uses.

3.7 Discussion and conclusions

This paper questions the existing theory that market-based land development leads to self-organized land development activities and concentric land use patterns. Different from market-based land development systems, the state interventions in the land market, exemplified by the case of Shanghai, has been prevalent to create a unique government-led land development system.

First, the separation of land ownership rights and LURs creates one of the most important barriers for a fully functional land market in China. In the identified land development modes, the collectively owned land rights can only be transferred to the state through land expropriation (as Mode I and III). Only state-held land can be transacted in the unitary land market for long term commercial and residential uses (as Mode I, III, and IV). Collectively-owned land can only be used for short term purpose through project negotiations among involved parties (Mode II). A large amount of land is excluded from the primary land market of the city. Also, only the state and state-owned primary land developers can obtain land from collectives. As it is indicated in the literature, the acquisition of rural land is clearly not a pure market land transaction (Xie et al., 2002).

Second, instead of relying on market mechanisms, municipal governments balance the land supply and demand through urban economic development planning. In a market economy, land supply is closely tied to housing, industrial and economic development demand. However, the case of Shanghai shows that the city CPD collaborates with the central state and negotiates with local district government departments to make land reserve and supply quota each year. The annual land supply plan is created based on its previous years' land use, economic situation prediction, and government financial situation. Since the land sale contributes significantly to the city and

local district revenues needed for building and upgrading municipal infrastructure (Zhang, 2002), both the city and local district governments have every incentive to dominate the process of land supply. This is surely practiced elsewhere in market economies such as Hong Kong (Peterson, 2006).

Third, the modes of land development in Chinese cities are not singular, uniform. Rather, they are divergent and contingent upon local conditions and spatiality of government policy. The case of Shanghai illustrates the coexistence of five different modes of land development in one city. Their spatial distribution and development intensity are strongly shaped by the city's spatial planning and delineation of development zones such as CCZ and IZ. Different from the crude explanation of CbLD in the literature (Lin, 2009; Tian & Ma, 2009), this paper nuances how land development processes are differentiated and localized. The case study of Shanghai illustrates the limitation of the existing CbLD theory and calls for more studies investigating different land development modes between and within Chinese cities. The finding of this study indicates why current land simulation models have limited success in the Chinese context.

Fourth, the data analysis results show that Modes 1 and II both consumed more than one thousand square kilometers of agricultural land from 1993 to 2013. Land development mode II represents the spontaneous urban growth from below as explained by the IsLD theory (Zhu, 2000; Xu, 2004; Lin, 2009). Because of lucrative economic and social benefits from leasing land to industrial factories, local villages and towns have eagerly pursued this type of land development. However, the land developed under this mode locates outside the CCZ or IZ boundaries. They are not officially recognized as the planned UBA. According to the city's land use plan and government administration policies, these construction land use should be reserved for agricultural and

ecological purposes instead of construction uses. This finding indicates that IsLD is not simply confined in rural areas away from large urban centres as documented in. The spontaneous urban growth from below is also influential in the suburb of large urban centre. Given the “illegality” of spontaneous land development outside the planned development zones, the constructed land could be subject to demolition any time in the future, which plants the seed for social conflicts and unrest between the city and the villages (Lin, 2009).

Fifth, the literature is substantial about role of the governments in China’s land development (Ma & Wu, 2004; Lin, 2009) but the research is limited on how various government agencies play the differentiated role in the process of land development. This study reveals that it is the state-owned primary land developers playing crucial role in this process. In addition, the state and state-owned organizations associated with Modes IV and V have great discretionary power and political relations in deciding how the land needs to be developed. Often, they can develop the land freely according to their needs by breaching city land use and urban control rules as exemplified by the case of Baosteel Group. This form of land development undermines the integrity of overall urban plans. The active involvement of the state agencies makes the land development processes deeply different from market-based land development processes.

Implications of the findings of this study are multifold. The multi-track land development processes in Chinese cities mean that current land development modelling and simulation cannot mimic the actual land development process properly because most of these models assume a singular mode of land development for any given cities in China. To improve the accuracy, new methodologies are needed to take into account the fact of divergent land development processes. The empirical findings of this paper also call for new theorization of land development in China.

In particular, there is a need to understand how different modes of land development interact and interfere with each other in configuring urban space in the accelerating process of urbanization in China. New case studies will be necessary to provide evidence about what is discovered in this study.

Chapter 4 Modelling and simulating urban residential land development in Shanghai

4.1 Introduction

Cities are emerging as humanity's engines of creativity, wealth creation and economic growth (Bettencourt & West, 2010). Despite the increasing importance of cities in human society, the ability to understand and manage them scientifically is still limited. Even though a variety of qualitative and quantitative methods have been adopted by urban planners and city administrators to generate plans and policies for urban resource allocation, gaps still exist because of the lack of behavioral and dynamic realism in urban modelling (Batty, 2008b; Heppenstall et al., 2016).

In order to eliminate the gaps, urban geographers, computer scientists, and interdisciplinary researchers have made great efforts to understand dynamic mechanisms behind urban growth and evolution by constructing diverse urban models. Due largely to the rapid advancement of computer technology, researchers have found that dynamic simulation models have the power to delineate the process of urban structural evolution (Batty, 1971; Couclelis, 1986; White & Engelen, 1993). Spatial simulation techniques, such as Cellular Automata (CA) and Agent-based Modelling (ABM), have been introduced into urban land use dynamics studies. The advantages of these methods are manifold, including their abilities to incorporate nonlinear, unorganized processes and cross-scale environments that can exhibit emergent properties, dynamic local interactions with spatial references, and indirect impacts and pattern-process linkages (Parker et al., 2003).

Treating cities as complex systems, a majority of researchers consider urban land use growth as self-organized (White & Engelen, 1993; Batty & Xie, 1994; Clarke et al., 1997; Clarke & Gaydos, 1998; Batty, 2008a); they often adopt a bottom-up approach such that the suitability of land or fractional spatial structure patterns determines the growth and expansion of urban land. For instance, Xu et al. (2007) built a CA model on the basis of the work of Dietzel et al. (2005) to test diffusion and coalescence theory in urban evolution; Sasaki and Box (2003) developed an agent-based model to verify von Thünen's location theory; and Filatova et al. (2009) established a bilateral agent-based land market model using the land-market and land price theory to test Alonso's mono-centric land price theory. Most of these studies are rooted in the classic land use theories and tend to neglect the social, economic, political, and cultural forces behind urban land growth and overlook institutional as well as individual decision-making processes in land development (Sui, 1998).

To address this deficiency, some researchers proposed constrained CA models to integrate administrative policy into modelling and simulating land development processes, in addition to conventional land availability and suitability factors (Wu, 1998; Li & Yeh, 2000; Wu, 2002; Yeh & Li, 2002). In these models, local, regional and global constraint scores are used to re-estimate the development probabilities that are calculated from standard CA models. This method solves the problem of neglecting spatial administrative policies and spatiality. A few studies further consider demographic factors and attempt to integrate individual housing decision making into urban land development modelling (Waddell, 2002; Waddell et al., 2003).

It is well recognized that individual variation in housing preferences can give rise to uneven spatial distribution in housing demand across a city space. Experimental studies have found a clear match between stated housing preferences and residence location choices (Levine et al., 2005). To interpret residence choice effects on land development, Waddell developed the UrbanSim model (Waddell, 2002; Waddell et al., 2003) to simulate the land-market interactions of households, firms, developers and public actors. Xie et al. (2007) constructed a dynamic household model to simulate how local household development leads to global urban landscape transformations, and White et al. (2012) used historic population and land use data to evaluate neighbourhood influences on urban land. These models all sought to investigate the relationships among individual residents' behavioral mechanisms and land development at a broad level. However, dynamic social and economic characteristics and decision mechanisms of neighbourhoods and households are rarely considered. Thus the models fail to delineate the co-evolutionary processes of demographic transformation and land use changes.

To solve these major problems in current urban modelling and improve urban land use simulations, this research develops a new theoretic model for the simulation of urban land use growth that combines CA, ABM and spatial genetic algorithm (SGA) methods. In the model, citizen agents make their location and allocation decisions based on their socioeconomic characteristics. This decision-making process leads to shifts in neighbourhoods' social, economic, and environmental statuses. Government agents make development strategies and policies to balance citizens' needs and local sustainable development goals based on regional social, economic, and environmental conditions. The development strategies are then incorporated into multi-objective planning problems that

are solved using optimization methods. SGAs are used to optimize those development strategies spatially, which determines urban land use development and redevelopment. Jiading New City, which was planned as a satellite city in metropolitan Shanghai, is selected to implement and verify the model in this study.

Following this introduction, a theoretical model of population-driven urban housing and land development is presented in section 2 and 3. The study will then introduce the study area and methods for data collection and analysis in section 4, followed by descriptions of model implementation, parameters estimation, and model verification in section 5. Model simulation results will be presented in Section 6. The paper concludes by discussing the findings and their implications.

4.2 Population-Driven Urban Land Development (PDULD) framework

Generally, a dynamic urban system is constituted by land, buildings, populations, services, and their location-relocation activities (Semboloni, 1997). From a housing development perspective, the process of land development of any area may originate from an increase of households, resulted from both natural population growth and migration. The increase in household number elevates local housing demand, and land developers and government administrators then work together to transfer land from non-residential to residential uses. After residential houses are built, household groups purchase and move into new homes based on their own financial and social status. Consequently, the socioeconomic characteristics of neighbourhoods are altered. In this land development process, two pairs of activities emerge to take important roles: land resource demand and supply and

household decisions on housing location or relocation. Figure 4-1 presents a schematic illustration of how the two different processes are related and modeled in this study.

For land resource demand and supply, a number of processes need to be considered. Firstly, the lifecycles of households initiate the formation of a general housing demand market (Mulder & Hooimeijer, 1999). The varying residential family structures and financial resources present diverse requirements in the formed market (Logan et al., 2002). Finally, the household location or relocation decision-making activities will lead to the differentiation of housing needs in space (Clark & Dieleman, 1996; Carrion-Flores & Irwin, 2004).

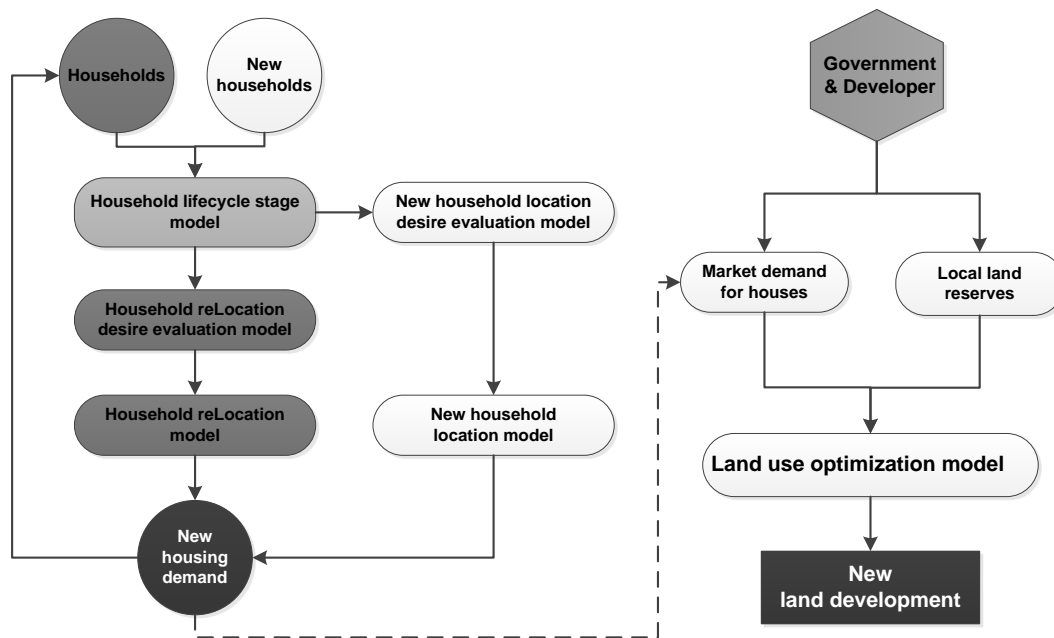


Figure 4-1. Housing demand, land supply, and development. In addition to the diverse demands generated by households, housing supplies are further shaped by land and housing developers and local governments. While land and housing developers attempt to maximize their economic returns by supplying sufficient housing

units, local governments assess local land reserves for developing residential land and build houses to meet the demands to optimize regional land use through land use planning and land development goals (Figure 4-1). Therefore, the logic of modelling new land development from the housing market perspective needs to consider all of these factors in order to build a reasonably accurate simulation model. The following sections detail each element of the model.

4.2.1 Household Life Cycle Stage Model

Numerous factors reflect the social and financial status of an individual household. Age and revenue are two important ones (Mulder & Hooimeijer, 1999; Abdullah et al., 2013). In the model, the age of a household head (A) increases with the lapse of simulation time. Assuming that an increase in household members may eventually create a need for a new or additional house unit, the probability of purchasing a house increases over time along with household head's age. The yearly household revenue (R) also increases at a defined ratio (θ) with time lapse due to the increasing seniority and, consequently, human capital in local labor markets.

Therefore, it can be defined that a household's savings at time $t + 1$ (S_{t+1}) equals the sum of the previous year's savings S_t and the difference (μ) in yearly household revenue R_{t+1} minus annual housing expenses E_{t+1} and yearly mortgage payment M . The current house residence time TR_{t+1} begins when a household moves into the current dwelling and increases each year (equation (4.1)).

$$\begin{cases} A_{t+1} = A_t + 1 \\ R_{t+1} = R_t * (1 + \theta) \\ S_{t+1} = S_t + \mu * R_{t+1} - E_{t+1} - M \\ TR_{t+1} = TR_t + 1 \end{cases} \quad (t = 0, 1, 2, \dots, n) \quad (4.1)$$

where n is the maximum simulation years.

Meanwhile, a household could also move to another city or region, for reasons including employment, life cycle, housing, neighbourhood, access to public transportation, and uncontrollable factors (Mulder & Hooimeijer, 1999). The inter-region movement of a particular household is more accidental than determined. Therefore, a random value and threshold are defined to delineate this phenomenon. If a generated random value, Rnd , is larger than a predefined move-out threshold TH_O , the household will be removed from the model (equation (4.2)). Moreover, it is also possible that a household head (and, as such, the household) can die. Accordingly, the model assumes that the probability that a household head will die is proportional to the head's age:

$$H_i \begin{cases} die\ out : if\ e^{(-\kappa A_i)} < TH_A \\ move\ out : if\ Rnd > TH_O \end{cases} \quad (4.2)$$

where A_i is the age of household H_i , κ is the corresponding coefficient, and TH_A is a predefined threshold for household die-out rate.

The average age, VA , and average revenue, VR , are employed to represent the social and financial statuses of the neighbourhoods under study:

$$\begin{cases} VA_{j,t} = \frac{\sum_j^N A_t}{N} \\ VR_{j,t} = \frac{\sum_j^N R_t}{N} \end{cases} \quad (j = 1, 2, 3 \dots N) \quad (4.3)$$

where j denotes the current neighbourhood, t denotes the current time stage, and N is the total number of households living in neighbourhood j .

4.2.2 Household Location/Relocation Desire Model

For any new migrant households who have already chosen to settle in an area, their location desire is set as full. For local households, their house relocation desires relate to their feeling about their current neighbourhood and their financial status. One of the important indicators for neighbourhood feelings is neighbourhood cohesion (Buckner, 1988; Faludi, 2010; Liu et al., 2010), which reflects a neighbourhood's residents shared norms and values and network of trusting relationships. Empirically, household groups prefer to live near similar others (Ioannides & Zabel, 2008); if there are big differences between the social and financial status of a household and its current neighbourhood, the group may consider moving. The difference, D , between a household, i , and its neighbourhood at time, t , is defined as follows:

$$D_{i,t} = \frac{|A_{i,t} - VA_t|}{\max(A_t - VA_t)} + \frac{|R_{i,t} - VR_t|}{\max(R_t - VR_t)} \quad (4.4)$$

The household, H_i , will consider relocating if D_i is greater than a predefined neighbourhood difference threshold, TH_D , and immediate household saving, S_i , is larger than new house down payment threshold, TH_S , as follows:

$$H_i \begin{cases} \text{move : if } D_i \geq TH_D \text{ and } S_i > TH_S \\ \text{stay : if } D_i < TH_D \text{ or } S_i < TH_S \end{cases} \quad (4.5)$$

4.2.3 Household Location/Relocation Model

Many factors influence where people live, such as employment, social exclusion, beliefs and values, their preferences for open space and other amenities, and commuting distance (Ng, 2008). Although these factors mostly relate to individual attributes, location decisions are generally made by households, which may comprise single individuals or groups (Fontaine et al., 2014). Generally, higher neighbourhood cohesion means greater stability (Schelling, 2006), and most household members tend to prefer more cohesive neighbourhood (Levy & Lee, 2011). In this regard, it is reasonable to assume that neighbourhood cohesion value is a function of household age and revenue. Therefore, a neighbourhood's cohesion rate can be defined as the sum of the standard deviations of all factors under consideration as follows (Buckner, 1988):

$$C_{t,j} = std.(A_{t,j}) + std.(R_{t,j}) \quad (4.6)$$

where $C_{t,j}$ denotes the cohesion of neighbourhood j at time t . The smaller the value, the higher the neighbourhood cohesion. The model reasonably assumes that a household group

will choose a more cohesive and equal neighbourhood, for example, a neighbourhood with small C and D values (equation (4.6)) and (4.4)).

In addition to neighbourhood cohesion, the physical environment is another important factor that a household will consider in selecting a potential housing location. These factors may include transportation access, available public facilities, and home quality (Levy & Lee, 2011). Public transportation is important in metropolitan areas. Many cities around the world, especially in developing countries, operate under what is called transit-oriented development (Cervero & Day, 2008). In addition, a city with a high development ratio usually has better public facilities and access to employment than do other areas (Hansen, 1959). To consider these factors, this study uses the distance to metro as a transportation access indicator and the neighbourhood development ratio (developed land divided by the total developable land in the neighbourhood) as a public facility indicator.

4.2.4 Land Supply Model

Land supply is another important issue in modelling and simulating land use changes. Most models, especially those in the field of resources management, have failed to consider the factor of land supply (Verburg et al., 2002); a city's supply of land is limited by its natural attributes. Large slopes, water bodies, and other natural barriers define the available land for urban construction use. At the same time, the location of land in various parts of a city influences its developable probability (Rose, 1989). Land parcels close to the urban center are more likely to be developed, whereas peripheral land parcels are less likely. This distance-decay phenomenon can be described as follows:

$$L = \sum_{i=1}^n s(i) * \exp(-\delta u) \quad (4.7)$$

where u represents the distance of land parcel i from the city center, $s(i)$ is the area of the land parcel i , L is the total land supply, and δ is a distance decay coefficient.

In addition, with limited land resources, a city usually constrains its yearly land use supply by planning periods. Therefore, we can define a city's yearly land supply, Y_t , as follows:

$$Y_t = L_t / T \quad (4.8)$$

where L_t is the corresponding year land supply reserve and T is the total period for which the land development is planned. The volume of Y_t changes with time.

4.2.5 Land use Optimization Model

In a city, local governments and land use management specialists need to analyze the available land resources and make optimal area development strategies and plans based on social, economic, environmental, and ecological conditions. Urban-land owners (either government agents or private developers) can be assumed to be rational economic human beings who want to achieve the highest land sale revenue (Potepan, 1996). According to the classic urban land use theory, the closer a piece of land is to the central area, the higher its appraisal price (Alonso, 1964). This is similar for main public facilities such as metro lines, schools, and hospitals. Therefore, land parcels close to urban centers and public facilities will generate higher development profits than the others, and therefore will receive higher priority.

One important factor for urban administrators and government officials is the land development compactness; low compactness is reflected in over-dispersed or leapfrog land use patterns, also known as urban sprawl. Urban sprawl usually brings low land use efficiency and high infrastructure and maintenance costs to a city (Brueckner & Fansler, 1983). To land and housing developers, correspondingly, low compactness means high offsite and operating costs. To residents, compact land use means low transportation costs and walkable, friendly environments (Levine & Frank, 2007). Therefore, urban land use compactness is one of the goals of both public and private agents.

At the same time, a given neighbourhood's social structure will also influence land development in its neighbouring areas. High neighbourhood cohesion and social and financial status will help attract more households to the area, and consequently, these areas could be more heavily promoted by private developers and local development authorities (Ding & Knaap, 2002). In addition to these social and economic concerns, residential environment is another highly pressing issue in the land development process. Maintaining certain amounts of green space usually creates better residential environments.

In sum, land development encompasses multiple social, economic, and environment goals. In this study, following a literature review of urban master planning, urban regulatory planning, and government land use policy documents in the study area, the authors of this study only consider land development revenue, land use compactness, neighbourhood attractiveness, and environmental attractiveness to simplify the model. Other factors, like local government and land developer's personal preferences and public-private partnership,

have minor impacts for the land development in a large scale. These goals are specified as follows:

$$\begin{cases} LR = f_1(RC, RS), \\ LC = f_2(CC, CP), \\ LN = f_3(NC, NS), \\ LE = f_4(EG, EA). \end{cases} \quad (4.9)$$

where LR is the land development revenue, a function of the contributions from land centrality (DI_C) and closeness to public transportation (DI_S), LC is the land use compactness, a function of land use concentration (CC) and land use type compatibility (CP), LN is the neighbourhood attractiveness, a function of neighbourhood cohesion (NC) and household social and financial status (NS), and LE is the environmental attractiveness, which connects with public green spaces (EG) and agricultural land reserves (EA). During urban land use planning and development, any given area is required not only to meet regional housing demand, but also to achieve the maximization of these social, economic, and environmental goals in order to provide better, more livable neighbourhoods.

For LR of a land parcel i , this study assumes that the closeness to the central area (DI_C) and metro line (DI_S) positively affect the revenues of local governments and land developers (Ratner & Goetz, 2013). Both distance effects decline exponentially with increased distance as follows:

$$LR_i = r_1 \exp(-\alpha_1 DI_1) + r_2 \exp(-\alpha_2 DI_2) \quad (4.10)$$

where α_1 and α_2 are distance decay coefficients and r_1 and r_2 are weights.

This study assumes that LC_i is positively related to CC_i and negatively related to CP_i as follows:

$$LC_i = s_1 * CC / N - s_2 * CP / N \quad (4.11)$$

where s_1 and s_2 are corresponding weights and M is the maximum number of land parcels.

This study considers the eight neighbouring cells (Moore Neighbourhoods) of the land under consideration.

This study also assumes that LN_i , which is closely tied to neighbourhood cohesion and neighbourhood average revenue, is conversely related to C_t and VR_t as follows:

$$LN_i = t_1 * \exp(-C_t / C_M) + t_2 * \exp(-VR_t / VR_M) \quad (4.12)$$

where C_M is the immediate maximum neighbourhood cohesion value, VR_M is the immediate maximum neighbourhood average revenue, t_1 and t_2 are corresponding weights.

The study also assumes that LE_i is positively related to EG_t and negatively related to EA_t as follows:

$$LE_i = u_1 * EG_t - u_2 * EA_t \quad (4.13)$$

where φ_1 and φ_2 are corresponding weights.

Potential land development revenue, land use compactness, neighbourhood attractiveness, and environmental attractiveness all contribute to the suitability of a developable land parcel, $SUIT_i$, with different weights as follows:

$$SUIT_i = \omega_1 LR_i + \omega_2 LC_i + \omega_3 LN_i + \omega_4 LE_i \quad (4.14)$$

One study (Qiu et. al, in progress) shows that in a planned economy, a city government makes its annual urban land supply plan based on the previous year's land usage, the midterm urban land supply plan, the economic development results of the previous year, the economic predictions for the following year, and the land supply plans reported from local district governments. Thereafter, land use administrators may evaluate developable land parcels and approve the most suitable parcels to be auctioned for development. Therefore, the total annual land supply is the optimal result of searching all potential land parcels as follows:

$$SUIT(L) = \max\left(\sum_{i=1}^n SUIT(i)\right) \quad (4.15)$$

4.3 Spatial Genetic Algorithms

As was noted in the previous section, land development is a complicated balance among efficient resource use, environmental protection, economic development, and social equity (Cao et al., 2011). As indicated in Equation (4.9), housing and land supply aim to optimize the development of available land to achieve development goals. Therefore, land development models need to identify optimal solutions with multiple objectives.

Various methods and technologies, such as multi-criteria decision-based, simulation-based, and optimization-based models, have been invented and applied to solve land allocation and optimization problems (Liu et al., 2014; Liu et al., 2015). Among them, spatial evolutionary optimization methods have the advantages of being able to incorporate many objectives and generate disparate spatial solutions (Ligmann-Zielinska & Jankowski, 2010).

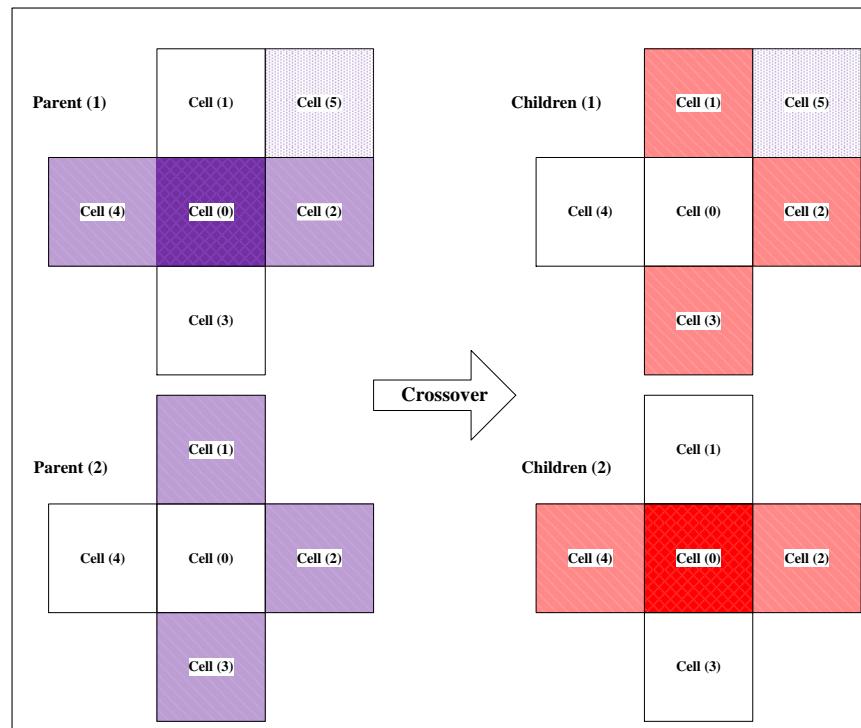


Figure 4-2. Spatial Genetic Algorithm.

In SGA as shown in Figure 4-2, a series of neighbouring land parcels (cells) are selected as the chromosomes; different land use combinations are then generated as parents for genetic reproduction. After this pairing, the “genes” (groups of parcels or cells) cross over to generate new pairs of chromosomes as children. Simultaneously, one parcel’s land use type could mutate to other types, and then better children will be selected for the next round

of reproduction according to multi-optimization goals. This process can continue until the optimal land use combination is found (Cao et al., 2011; Liu et al., 2012; Liu et al., 2015).

For instance, cells (0), (1), (2), (3), (4) in Figure 4-2 are selected as the chromosomes. Within the selected parent (1), cells (0), (2), and (4) are possible land parcels for development (the same for cells (1), (2), and (3) in parent (2)). Next, to the selected chromosome in parent (1) is a developed land parcel (5). Based on the parent (1) development choice, cell (5) only has one von Neumann neighbour (4-neighbour) (cell (2)). After pair-cell crossover with parent (2) (cells (0) and (4)), cell (5) in children (1) has two Moore neighbours (cells (1) and (2)). In the case of land use, generated child (1) is apparently more compact than parent (1) before the genetic operations. This way allows for randomly generating a group of possible land use patterns as initial parents, using multiple land development goals as objective functions, and completing the reproduction, crossover, and mutation processes to determine the optimal land development order.

In a next step, the proposed PDULD model and SGA method were implemented and tested in one of the fastest-developing areas in Shanghai, Jiading New City.

4.4 Study area and data

Located at the tip of the Yangtze River Delta, Shanghai is the largest city in China by population according to the 2010 Sixth National Population Census of the People's Republic of China; one of the city's suburban districts, Jiading, is located northeast of the central city (Figure 4-3). The area has undergone rapid urbanization in the past three decades; the urbanized area has nearly tripled since 1990.

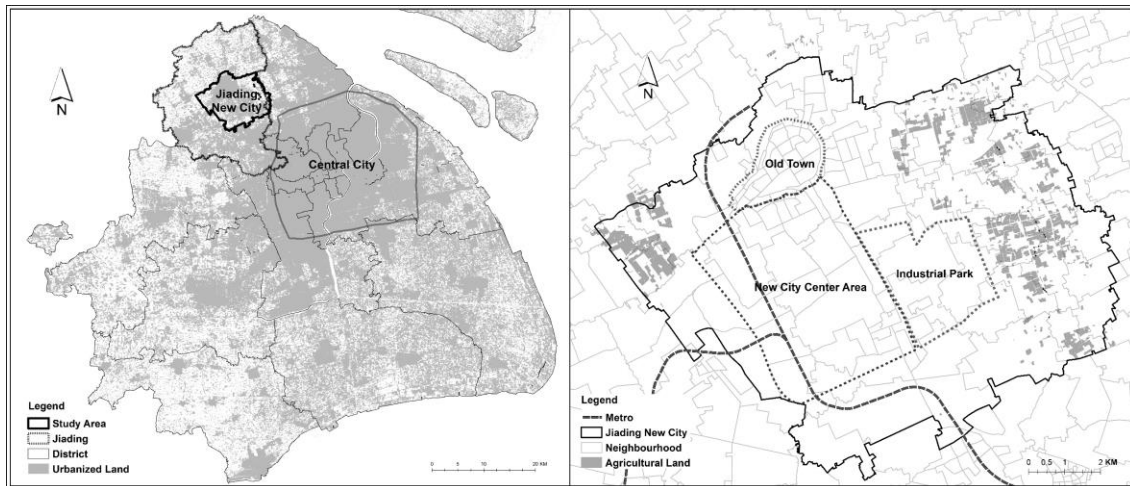


Figure 4-3. Jiading New City.

In the heart of the Jiading district is Jiading New City (Figure 4-3 left), which was planned as a satellite city as early as the 1960s. The original goal of the satellite city plan was to redistribute the over-crowded population in Shanghai's inner city proper. The initial 1959 urban master plan for the city described the area as a satellite city with 100 to 200 thousand people, along with certain industrial land uses and independent well-built public infrastructure. In the master plan that was compiled in the 1980s, the new city was re-articulated as a satellite city with 200 to 300 thousand people. The population prediction was changed again to 800 thousand to one million people in 2004 due to the rapid urbanization and suburbanization in the surrounding areas of the New City.

Inside the New City (Figure 4-3 right) at the north end is the Jiading Old Town, with a long history of development. In the lower middle part is a planned provincial industrial park. The east and west sides are agricultural land set aside for ecological protection, and the remainder, especially along the metro line, is the planned central area of the New City for residential, commercial, public facility, and government uses.

According to the Shanghai Jiading New City Master Plan 2004–2010, the region represents one of the city’s three new development hubs; it is a well-planned modern city with a rational allocation of resources and balanced strategic goals. Meanwhile, the current (2013) land use map (Figure 4-3 left) shows that the majority of the land is developed and the area now is connected to Shanghai’s central city proper. Therefore, the study of this area provides a promising case for understanding land development in Shanghai in recent decades.

The empirical data include time-series Landsat Thematic Mapper satellite images from 1987, 1993, 2000, and 2010, historical thematic land use maps, urban planning data, and social and economic statistics. The 30-m remote sensing data were obtained from the U.S. Geological Survey website (<http://www.usgs.gov/>), and a Random Forest Classifier, EnMap Box (van der Linden et al., 2015), was adopted to classify the remote sensing data into urban versus non-urban land use. 2002, 2006, and 2013 land use survey data were obtained from the Shanghai Urban Planning and Land Use Administration Bureau to verify the classification results. Around 90% classification accuracy rate were achieved for the four years’ data. Historical urban land use data were also used to calibrate, and validate the developed model. Statistical data were obtained from the Shanghai Municipal Statistics Bureau, and the urban planning data were obtained from individual urban planning departments. In addition, detailed 2000 and 2010 neighbourhood-level population census data were used to project and model household location-relocation activities. Because the 2000 and 2010 census data were the only available neighbourhood-level population data for the city, this study used 2000 as the model and simulation start year and used the 2013 land survey data to calibrate the model.

In addition to the land use and population data, an extensive field study of the area was carried out in the summer of 2015, which entailed interviewing 11 urban planners, urban land use and planning administrators, and government officials to understand the land development processes, government policies, and institutional organization and mechanisms of the city and the study area (see Qiu and Xu, in progress, for details). Furthermore, this study conducted a questionnaire survey of 400 citizens about their household location-relocation choices, and a field study was conducted to check the on-site implementation of the Jiading Master Plan, Jiading New City Detailed Plan, Jiading North Industry Park Plan, Juyuan Detailed Plan, and Nanxiang Detailed Plan in order to observe and confirm the neighbourhood population, land use types, and lifestyles. The researchers walked around the focal areas of these plans and checked whether the plans matched the actual land use, populations, and lifestyles of the residents in these areas. Video and photo images of the landscape and everyday street life were also taken randomly analysis. All of this collected information assisted in a better understanding of the test area.

4.5 Model parameters and calibration

To simulate the land development process in Jiading New City, the study area was first divided into cells of $30 \times 30 \text{ m}^2$ to match the 30m spatial resolution of Landsat data; because there were no population survey data from 2000, the urban land use boundary of the classified 2000 Landsat 6 Enhanced Thematic Mapper imagery was used to subtract the urban land in the 2002 land survey data and took that as the initial stage of simulation. Land uses include residential, industrial, green space, agriculture, water, and public

facilities; this study assumed that residential land use had a high compatibility with green space and a negative compatibility with industrial land use.

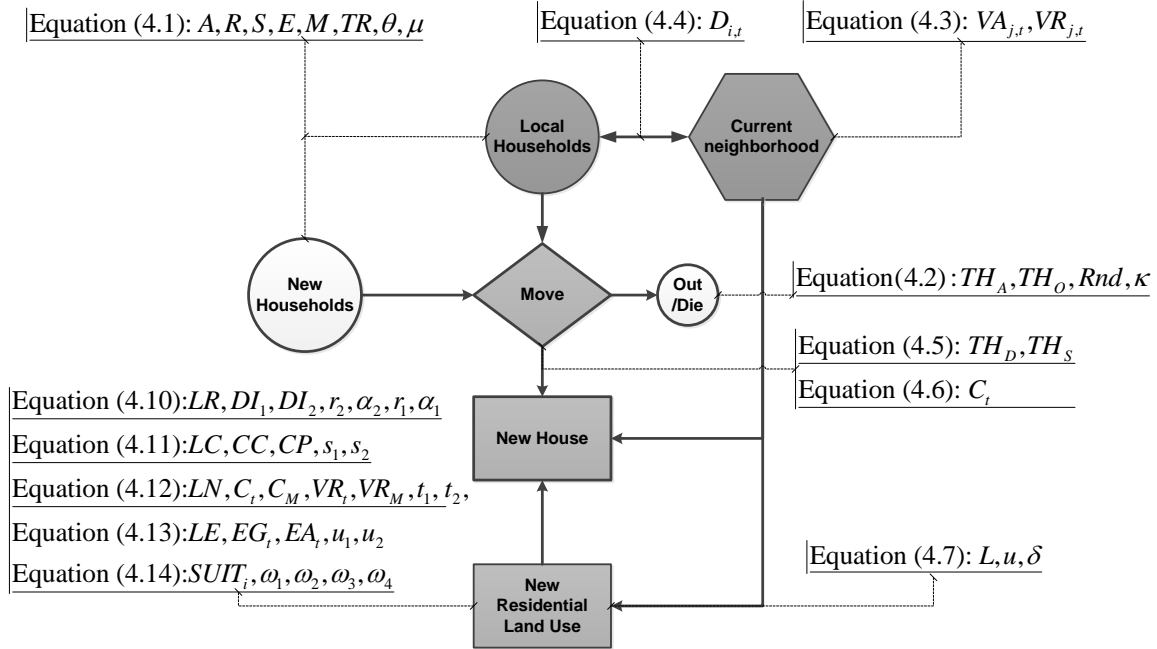


Figure 4-4. Model and parameters.

I. Household status

As is discussed in the PDULD model in the Section 2, households include both local and new migrant ones. All of the variables and parameters are summarized in Figure 4-4, equation (4.1).

Because there were no household-level population statistic data available for the area, the authors projected the household groups that lived in each residential cell using neighbourhood population statistic data. Firstly, the number of male citizens age 25 years and older in each neighbourhood; these were treated as the household heads. Each household head was then assigned an age (A) based on the male age group data from

neighbourhood-level statistics; next, the household heads were evenly distributed among the residential cells with each neighbourhood. Treating each household head as an agent generated a total of 52,422 household agents to represent the total number of households in the study area in 2000. According to the Shanghai Statistical Year Books, the area enjoyed a 12% average annual household increase during the decade since 2000.

To estimate the annual revenue R and annual savings S of each household agent, the authors obtained the annual average household revenue, annual household increase rate (μ), and household saving rate (θ) data from the 50 Years of Investment and Construction of the Shanghai Statistical Yearbook. In 2000, the average household revenue was 21,976 RMB, with an annual increase of 10% and an average household savings rate of 50%. To represent the variations among households, a random value for each household agent was generated using a random normal distribution ($\sigma = 2197.6$) based on the fact that more than 70% of household incomes were within 10% deviation from the 2000 average according to the yearbook. Moreover, the housing price that a household agent pays was set as 20 times the annual household income. The year 2000 down payment (E) on a new house was set as 50% of the housing price, and the yearly mortgage payment (M) was defined as the total mortgage amount divided by 20 years. The household agent's yearly savings rate was then set to 50% of the annual household income minus the annual mortgage payment. All these defines are based on observation. For instance, the least expensive housing in Jiading in 2015 cost approximately 12,000RMB/m², and a 100 m² apartment costs 1.2 million RMB; meanwhile, the average annual salary in Jiading in 2015 was approximately 60,000 RMB, and the mortgage down payment was roughly 30% of the

house price, five times the annual income. Both of these were defined based on multi-time-simulation-result observations. Accordingly, all household parameters required were known.

II. Neighbourhood status

In addition to household agents, 114 neighbourhood government agents were also generated to represent the studied 114 neighbourhoods in the Jiading New City. The simulation incorporated, for each neighbourhood agent, the average household age (VA), the average household income (VR), and the calculation of the neighbourhood cohesion value (C). All of the variables in (4.3) and (4.6) could be calculated automatically during the simulation.

III. Household activity

Local household agents, once they change their personal statuses, will check how they feel about the connection with their new neighbourhoods. If the difference $D_{i,t}$ is larger than a defined threshold, TH_D , and household savings, S_i , is greater than the new house down payment threshold, TH_S , the household agent will consider moving out of that neighbourhood to another one in the same region. Meanwhile, household agent's action generates a random number ($0 \leq Rnd \leq 1000$) that is compared with a predefined threshold, TH_O , to determine whether the household will leave the region or not. In addition, each household agent will generate a probability value through Equation (4.2) that can be compared with threshold, TH_A , to determine whether the agent (and thus the household) will die off.

All the variables were calculated in Equations (4.2), (4.4), and (4.5), except for κ , TH_D , TH_S , TH_O and TH_A . For age coefficient, κ , and threshold, TH_O , the model results revealed that by grouping household age from 10 to 1 and setting κ equals 1, TH_A equals 0.3, the annual death rate was close to the actual death rate of the Jiading District (9 ‰ according to population statistics). The study defined threshold, TH_S , is five times the average household income according to filed observations explained above. Neighbourhood difference threshold TH_D is set as 0.5 based on multi-time-simulation-result observations. Lastly, the move-out threshold, TH_O , was set as 998 to correspond to the average 2‰ move-out rate in the Jiading District.

IV. Land supply and development

With the increasing housing demand, new residential land needs to be developed. The annual land supply is defined through Equation (4.7). Because the study area was divided into regular grids, the area of each cell (s_i) was defined. Moreover, the Old Town center was treated as the origin point because at the time of the study, it was still the center of the region, and the Euclidian distance (μ) was calculated for each land cell to the Old Town center. After multi-time simulations, the annual land supply Y was found to be close to the actual urban land increase rate when δ was close to the reciprocal of the maximum distance.

With all the developable land cells, the model used SGA to determine the best land development order. All of the parameters in Equations (4.10), (4.11), (4.12), (4.13), and (4.14) had to be estimated. Once the most suitable land cells are chosen, houses will be

built on them. To determine the number of houses that could be built on each residential cell, this study used floor area ratio data from the Jiading New City Regulation Plan (2013) and Kriging interpolation to generate the maximum construction volume surface of the study area (Figure 4-5). Next, the study assumed a normal apartment home size of 120 m² and divided the maximum construction volume to generate the maximum number of houses that could be built on each residential cell. Once new houses are built, household groups that wish to move will choose to move to a neighbourhood with the most similar households (the smallest *D*).

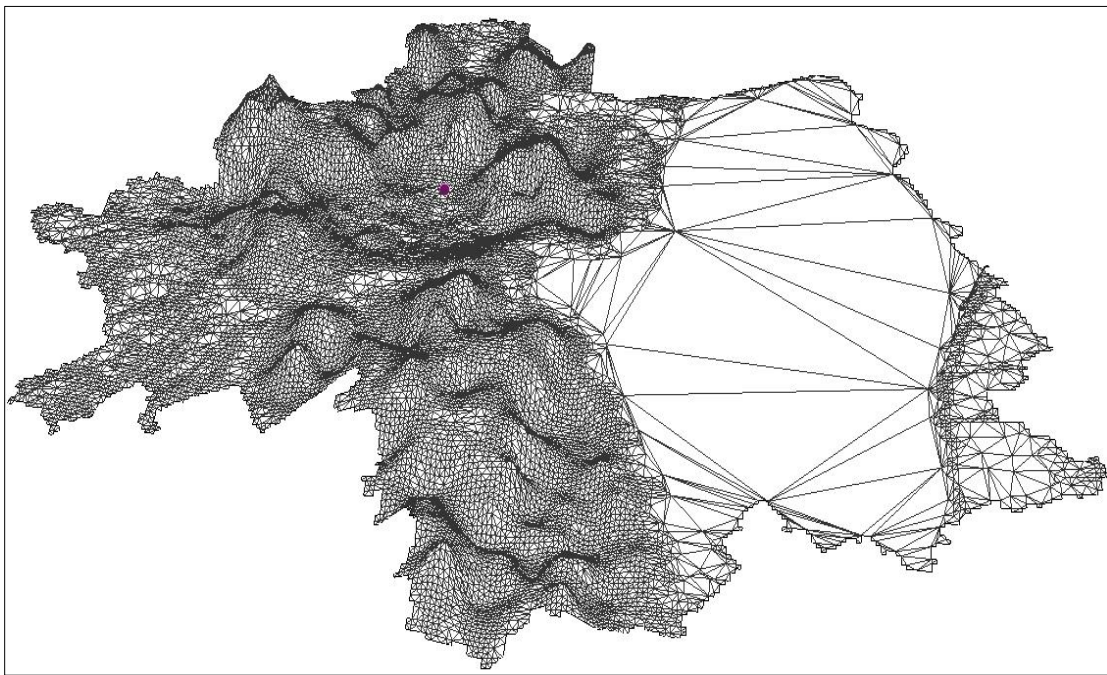


Figure 4-5. Maximum housing built surface.

All of the land use maps and boundary data were first digitized and stored in the GIS database as vector data and were then converted into raster grids. To simulate land development using the developed models, the raster data were transformed into ASCII files, and then the ArcGIS Euclidean Distance tool was used to generate the distances from each

cell to the metro lines and the city center. The generated raster distance data were also transformed into ASCII files with the same cell sizes as the others. After all the data were in place, the model was coded and run in one of the most popular simulation platforms, NetLogo (Wilensky, 1999) (see Appendix 2: Population-Driven Urban Land development Model.). The ASCII data files were imported into the model directly using the GIS extension in NetLogo.

To estimate the unknown parameters, this study employed R software and a GA to evaluate them with the help of the RNetLogo extension package (Thiele et al., 2012). As denoted in the following simplified source codes, a 14×10 data matrix (*a*) was first created to store all the possible values for the 14 unknown parameters. The NetLogo model *Residential Model.nlogo* was then called using *NLLoadModel* and *NLCommand* was used to assign the 14 global parameters to their possible solution values. After the model was run multiple times (*NLDoCommand*), an objective value was returned to the GA model. The GA model was run with real values, the initial parent population size set at 10, and maximum number of generations set at 20. The optimization objective of the GA method is to maximize the volume of cell-by-cell matched residential land cells between simulated data and actual 2013 land survey data. The result is a list of 14 estimated parameters (Table 4-1).

Simplified source codes:

```
library(RNetLogo, GA)
```

```
a1 <- seq(0, 1, by = 0.1) → a14 <- seq(0, 10, by = 1)
```

```
a <- rbind(a1,a2,a3,a4,a5,a6,a7,a8,a9,a10,a11,a12,a13,a14)
```

```
NLStart(nl.path)
```

```

NLLoadModel("... /Residential Model.nlogo")
NLCommand("Setup")
NLCommand("set mu1", a[1,x1]) → NLCommand("set Omiga4", a[14,x14])
NLCommand("Initiate")
NLDoCommand(10,"RunModel")
NLCommand("GAResult")
return(NLReport("GAIResult"))}

GA <- ga(type = "real-valued", fitness =function(x) + Rastrigin(x[1], → x[14]), min =
c(1, → 1),max = c(12, → 12), popSize = 10,maxiter = 20, monitor = TRUE)

summary(GA)

```

Table 4-1. Predefined and estimated parameters.

Parameter	r_1	r_2	α_1	α_2	s_1	s_2	t_1	t_2	u_1	u_2	ω_1	ω_2	ω_3	ω_4
Estimated value	0.1	0.2	800	700	0.2	0.3	0.7	0.1	0.4	1	0.1	0.8	0.4	0.9

4.6 Simulation results

4.6.1 Residential land use

Using the calibrated model parameters, the study simulated the residential land development and population dynamics of the area. To verify the credibility of the simulation results, this study compares simulation results with actual land use and population data. Figure 4-6. is the simulated dual year urban residential land use of the Jiading New City from 2002 to 2012. Figure 7 presents the maps of the spatial evolution of the actual and simulated residential land uses after 2000. During the period of 2000 to

2010, the total number of households in Jiading New City increased from 52,422 to 143,352, and the residential land use increased by 15.6 km².

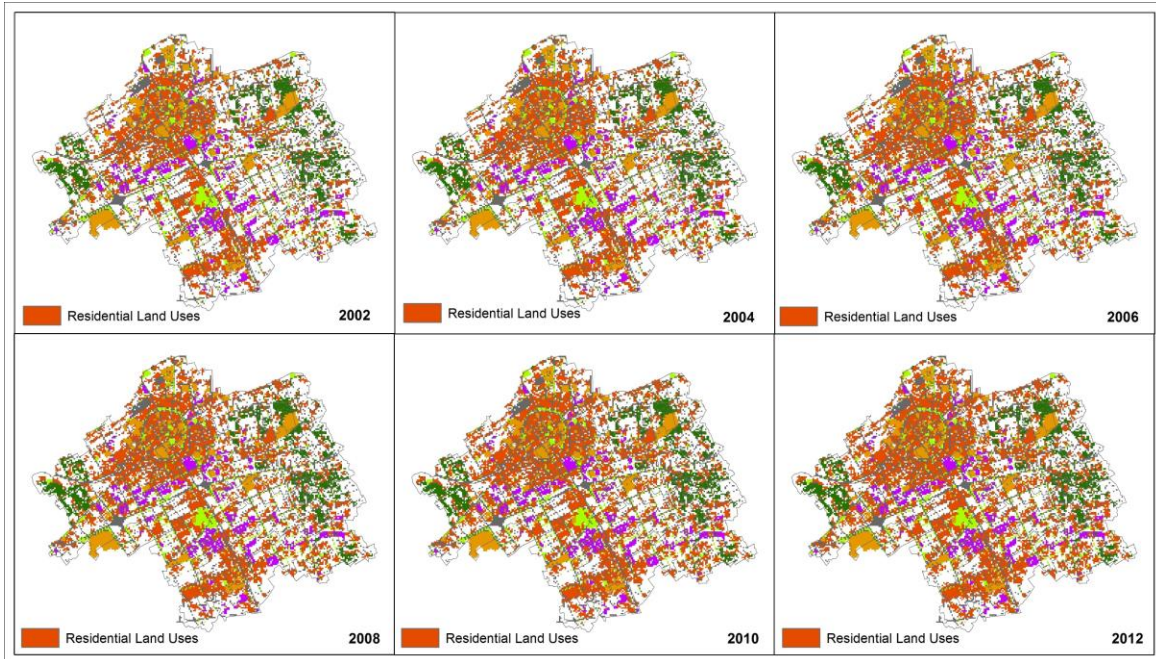


Figure 4-6. Simulated residential land use from 2000 to 2012.

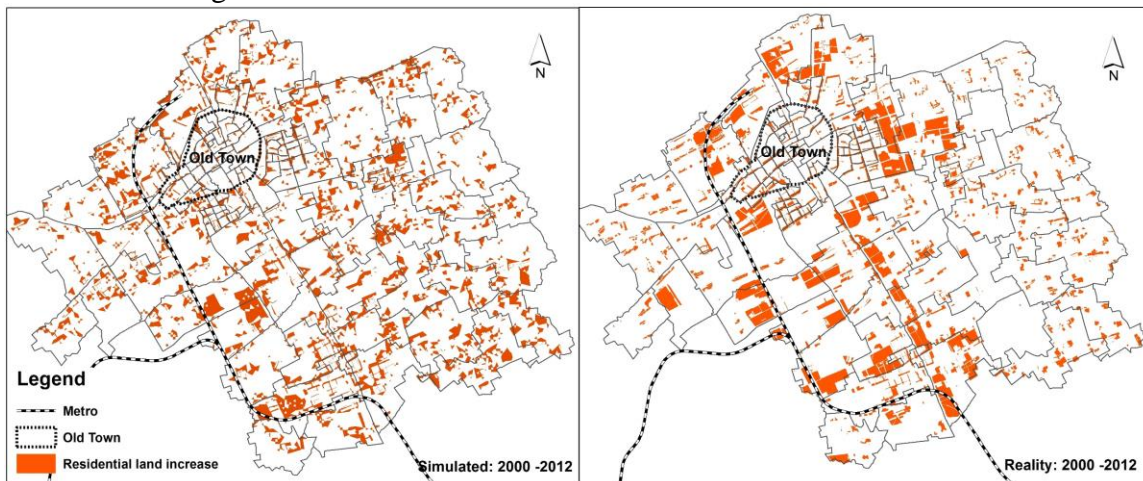


Figure 4-7. Comparison between simulated and actual land use.

The simulation results (Figure 4-7 left) show that most of the land development activities are located around the surrounding areas of the old town and scattered around the lower part of the area. However, the actual residential land development of the area from 2000 to

2010 (Figure 4-7 right) shows that the majority of housing construction is mainly concentrated in the surrounding area of the old town center and the planned new center areas. The actual increased residential land uses are more clustered than the simulated results for the past 12 years.

To further analyze the accuracy of the simulation results and investigate the land development trajectories in the study area, the authors compared the simulated results with the actual land use changes, specifically by using the simulated neighbourhood residential land increase volume minus real neighbourhood residential land increase divided by real neighbourhood residential land increase to generate the simulation result index. A positive result denoted overestimation and a negative result indicated underestimation.

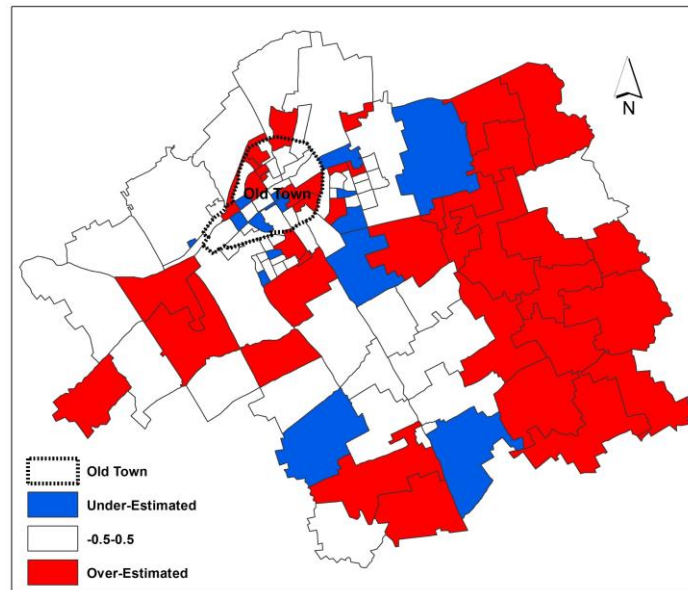


Figure 4-8. The accuracy of simulation.

The mapped results (Figure 4-8) show that for 53% of neighbourhoods, the differences in simulated and real land use were below 50%. Overestimation (greater than 50%) in the simulation results occurred in 39 of the total of 114 census enumeration areas, mainly

concentrated around the eastern and inner Old Town areas. In reality, the eastern side of the area is mainly protected agricultural land, although there are many rural residential clusters of agricultural populations. Based on the simulation, more land should be developed for urban residential uses in this area with self-organized approaches. The Old Town areas are also very suitable for residential housing based on the simulation. However, these lands were primarily occupied by either commercial or public facility uses because the financial returns per unit from these uses exceed those from residences.

4.6.2 Household and neighbourhood simulation results

There were major neighbourhood boundary changes in the study area during the period from 2000 to 2012. To compare the simulated household spatial distribution and census data, the study mapped the simulated 2012 household and the 2010 population census household densities (Figure 4-9). The mapped spatial patterns show that the simulated results matched the current household distribution quite well, with households in the study area highly concentrated around the Old Town.

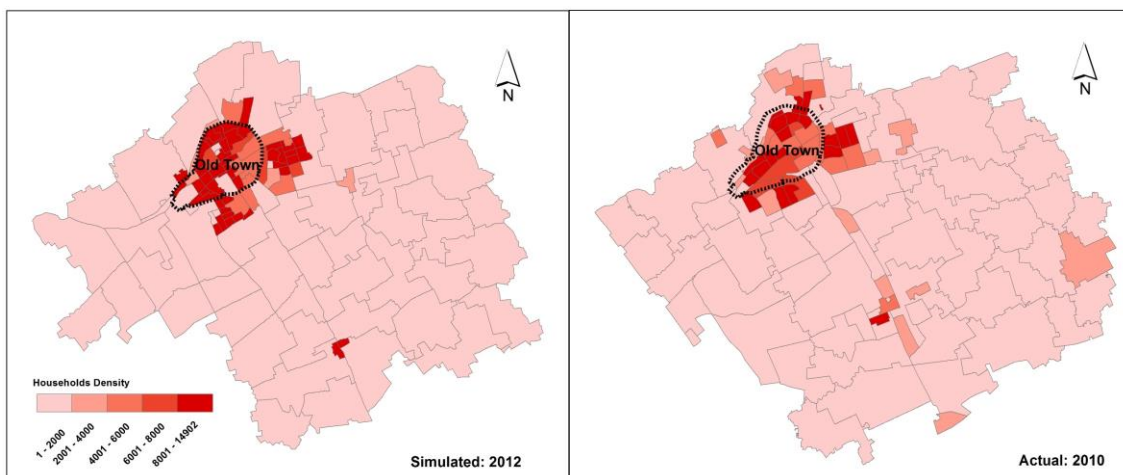


Figure 4-9. Household density comparison between simulated and real uses.

During the simulation, the model also recorded the average household age and income and cohesion values in each neighbourhood. The Figure 4-10 box plot graphs of the average neighbourhood age show that the average household age in the whole area is declining, which could be related to the continuous in-migration of young households to the area. Meanwhile, the differences in average household age among neighbourhoods converged over time, a trend that was also reflected in geographic mapping (Figure 4-11). One exception was one of the neighbourhoods located inside the Old Town (outlier in Figure 4-10 and red arrow in Figure 4-11); the average neighbourhood age increased continuously during the simulated period.

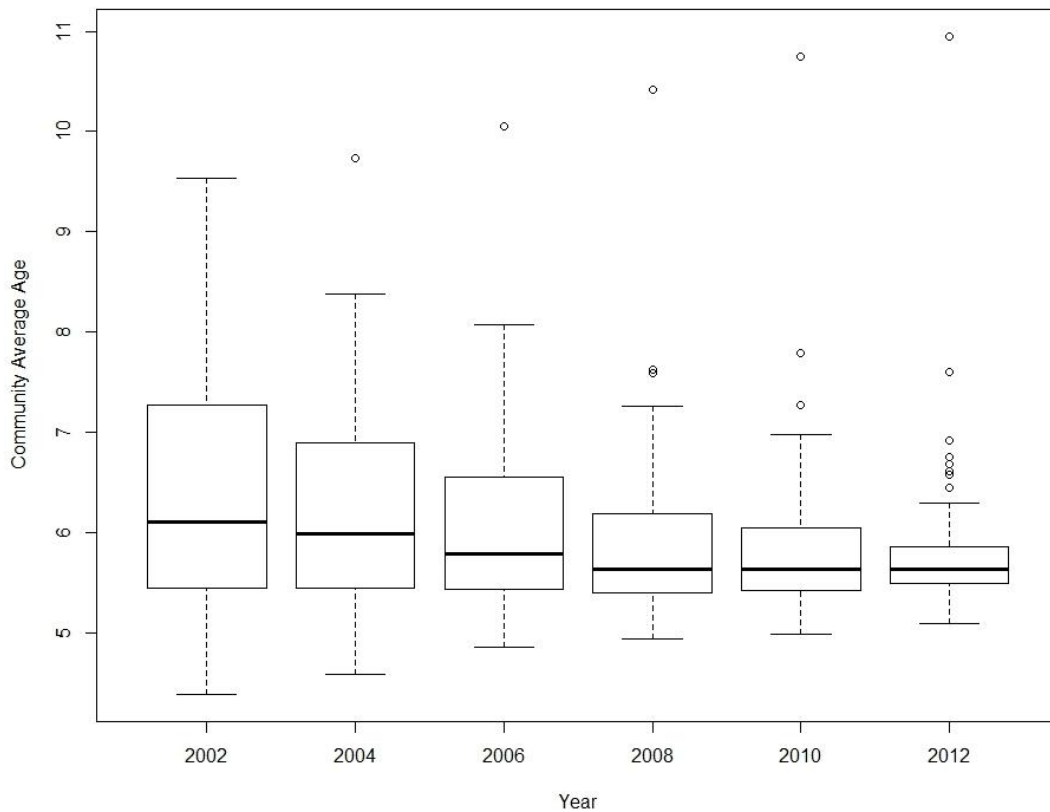


Figure 4-10. Simulated residential neighbourhood average age.

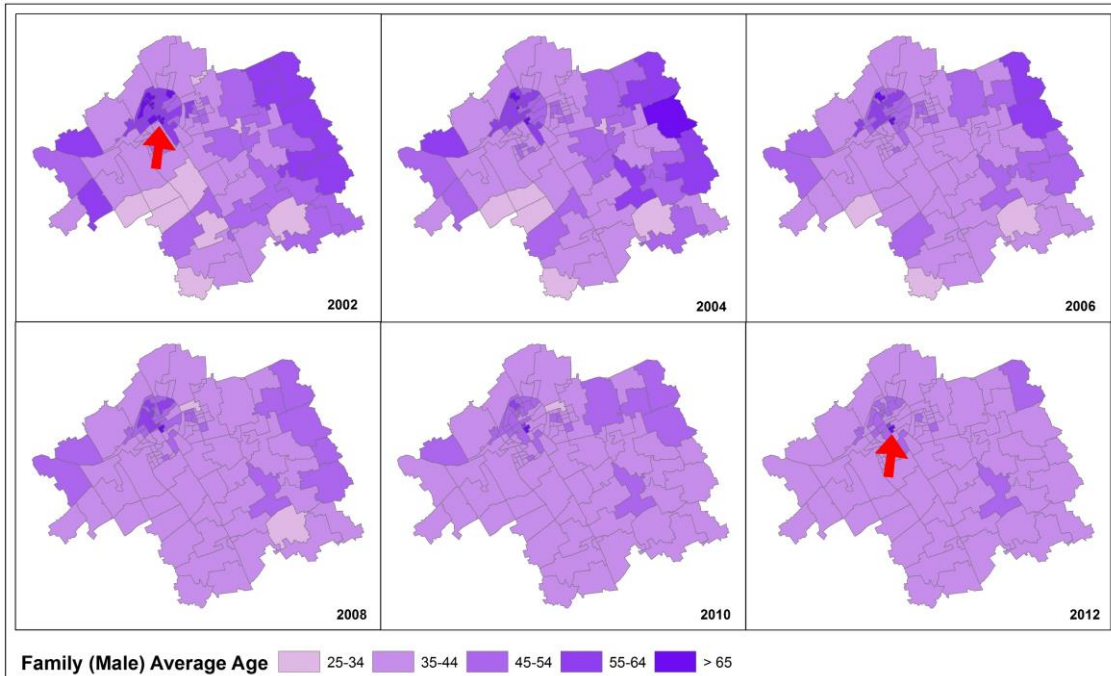


Figure 4-11. The convergence of neighbourhood average age.

The Figure 4-10 time series box plot graph and Figure 4-11 neighbourhood age maps also show that even though the general trend of average age differences across area neighbourhoods decreased in the simulation, the age gaps still exist between the Old Town communities and rest of the region: The Old Town area has a relatively high average age.

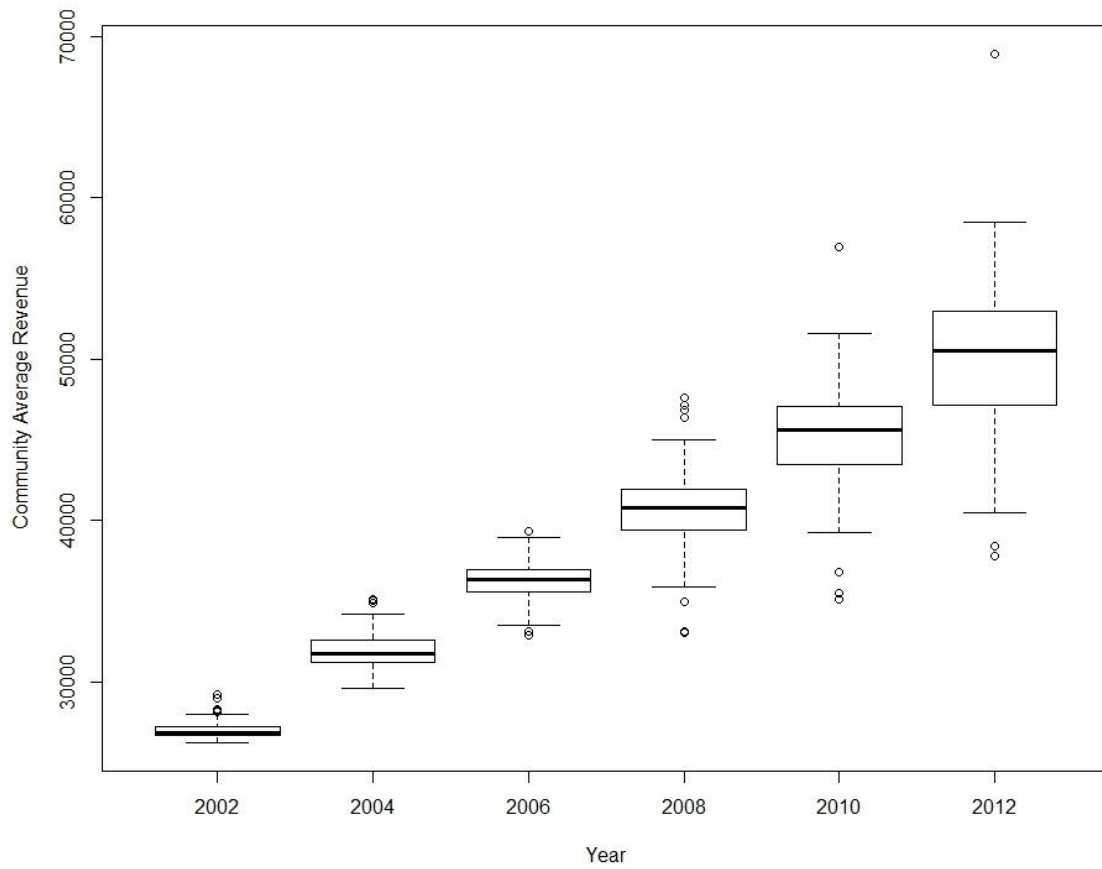


Figure 4-12. Simulated residential neighbourhood average revenue.

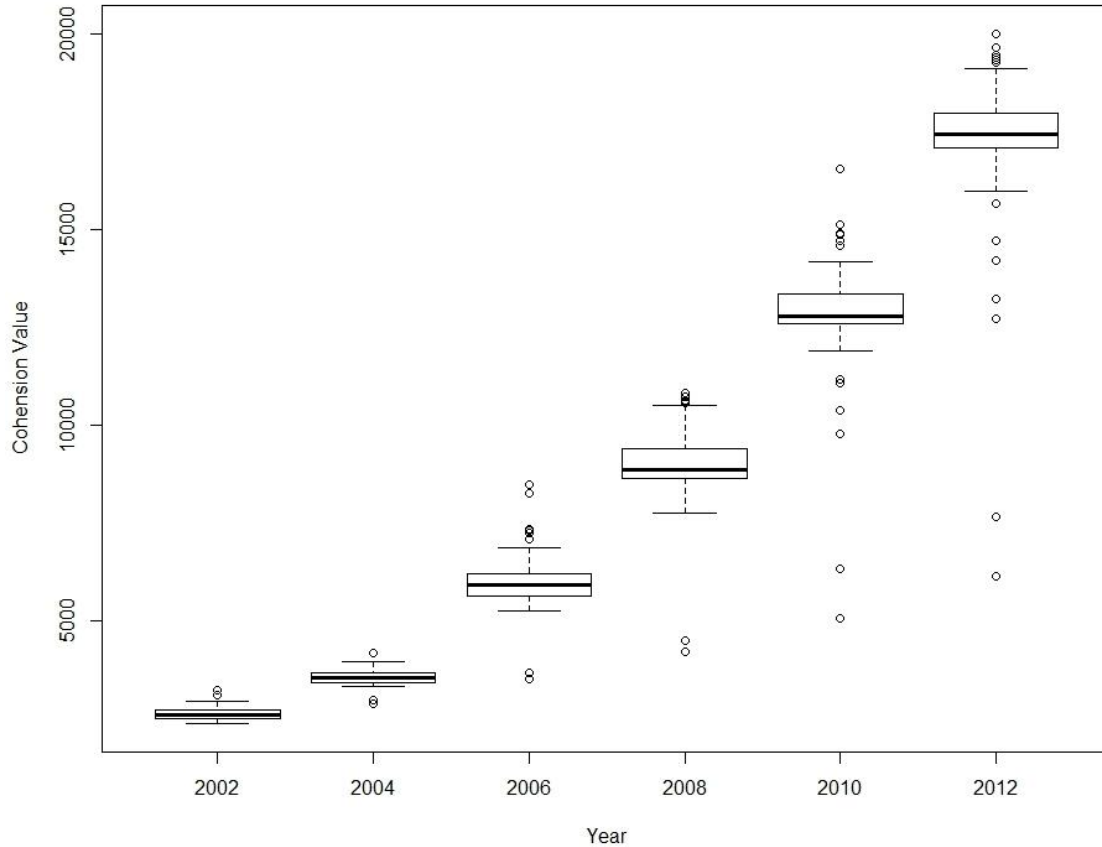


Figure 4-13. Simulated residential neighbourhood cohesion values
 Contrary to the converging of average age among neighbourhoods, the average household income in the simulation diverged from 2000 to 2012 (Figure 4-12) and the simulation results (Figure 4-13) also show that neighbourhood cohesion diverged during the study period.

4.7 Discussion and conclusion

Land development modelling and simulation provides an important computational and visualization tool for assessing the impacts of future land demand for population and economic growth. It also provides a means for understanding complex causal relations and

dynamic interactions among numerous factors ranging from economic, political, and social to environmental dimensions.

This study proposed a new simulation model of urban land use growth and evolution that combined ABM, CA and SGA methods; the model featured a proposed population-driven urban land development framework. Within the model, a household group determined its location desires and then formed the local housing demand market, and land developers and local governments then made the optimal use of the current land reserves to meet these housing demands. In this process, land development in an area is treated as a multi-goal optimization process. A spatial genetic algorithm was used to help identify the best land development choice for achieving an area's social, economic, and environmental goals.

In addition to environmental factors, this study introduced community cohesion theory into the model to illustrate the influence of populations on the spatial structure of urban land use. In the study model, household heads acted as autonomic agents who assessed the socioeconomic status of their current neighbourhoods and could choose to relocate to others, and a given neighbourhood's development status affected local land development activities. In this way, this study innovatively created a dynamic evolutionary model integrated both population and land development dynamics.

Moreover, the study proposed a new parameter estimation method by using evolutionary algorithms. Sample data regression and multi-time experiments are among the main land use and cover change model parameter estimation methods (Coullelis, 2001), except both are very time consuming and highly inaccurate. This study was the first to use evolutionary

algorithms and historic data to estimate unknown parameters through multi-generation training. It opens a new window for similar studies.

The simulation results show that the model moderately (53%) interpreted the real land use at the neighbourhood level; there were major (34%) overestimations around the eastern rural communities in the study area and the nearby outlet of the Old Town area. The data comparisons showed that the Old Town communities where there were overestimations had all been built up. One of the main explanations is that these lands were dominated by commercial uses such as office buildings and other facilities. The neighbourhood household simulation results matched the current household distribution quite well. The average household revenue and cohesion of the communities in the study area diverged from 2000 to 2012, and average residential neighbourhood age declined throughout the whole area.

The results of the modelling and simulation in this study confirm the literature (Sui, 1998) findings that urban land use development is highly affected by a city's household social, economic, and environmental characteristics. However, two key issues arose from this study: government intervention and land use profit competition.

As shown in the previous section, the land use simulation results deviated heavily from the real land use in some of the study area, even though the simulated residential spatial distributions matched the reality well; the actual residential land use increases in the study area (Figure 4-7) were clustered around the outskirts of the Old Town and the planned new center area of the New City. Compared with the sparsely distributed land use in the simulation results, the actual residential land uses were in the form of large blocks, and one

of the major reasons for this is that the area was developed according to urban planning zoning and rezoning policies. The whole area was divided into a number of large functional zones and then subdivided into large land use blocks, each of which blocks was designed for residential, commercial, industrial, or recreation use. Inside the designed residential blocks are high-density apartment buildings. The mismatch between actual land use and the population simulation results indicate that the region is regulated by artificial administration rather than natural growth based on market processes.

Historic data and field studies show that the coexistence of urban development and redevelopment in the area. With the increasing population and decreasing developable land, the area's land value is increasing continuously; for instance, residential uses exceeded industrial uses in the lower planned industrial park, and industrial factories have had to move under both government and market pressure. The commercial uses exceeded residential uses in the built-up areas around the Old Town, as old houses were demolished or converted for businesses, office buildings, and other land uses with high per-unit outputs. This process of urban redevelopment needs to be incorporated for better simulation results in the future.

Chapter 5 The transformation of urban industrial land use in shanghai: a quantitative method

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5.1 Introduction

The expansion of urban land use and transformation of industrial space are two conspicuous phenomena revolving around the development process of cities (Angel et al., 2005). On the one hand, industrial growth and agglomeration are major driving forces of urban land use change and expansion (Walker, 2001). The start-up and concentration of industrial plants lead to the convergence of residential, economic and social activities due to agglomeration effects. Spatial restructuring of industries may also reshape spatial configuration of a city (Clark & Burt, 1980; Viehe, 1981; Walker, 2001). On the other hand, residential population growth, in-migration and expansion of residential space also affect the spatial distribution of industries due to the shifting of land price and local labor market (Hudalah, Viantari, Firman, & Woltjer, 2013; Ning & Yan, 1995). The reconfiguration of urban industrial spatial distribution and urban land use expansion are therefore two complementary close-knit processes determining the spatial trajectory of urban transformation.

It can be argued that appropriate and balanced urban industrial spatial structure is imperative to steady urban growth (Anas, Arnott, & Small, 1998; Fischer & Nijkamp, 2012; Fujita & Thisse,

2013). During the process of rapid urbanization and suburbanization, any ad hoc and unplanned spatial distribution and allocation of industries may bring about undesirable consequences, including high energy consumption and waste, excessive loss of prime agricultural farmland, heavy traffic congestion, and degraded quality of life (Berrigan, Tatalovich, Pickle, Ewing, & Ballard-Barbash, 2014; Brueckner, 2000; Ewing, Meakins, Hamidi, & Nelson, 2014). In China, for example, heavily concentrated manufacturing factories around city centers have brought about severe traffic congestion and air pollution, while unordered industrial diffusion has greatly accelerated the removal of prime agricultural land during the past ten years (Chan & Yao, 2008; Tian & Zhu, 2013). Therefore, understanding the relationship between land use change and industrial spatial distribution and their co-transforming processes can help urban planners and decision makers develop a more sustainable and livable city.

Studies on industrial spatial structure can be dated back to the study of industrial structure of American cities in the late 1950s (Alexandersson, 1956) and Alfred Weber's industrial location theory (Weber & Friedrich, 1962). Economic geographers attempt to explain spatial distribution of industrial factories based on the land price theory (Alonso, 1964; Isard, 1956; Muth, 1961). For example, Weber pointed out that an industry is usually located where the transportation cost of raw materials and final products is the lowest. Alonso found that manufacturing factories choose to be located close to both market and labor in a city. These pioneering studies lay a basic foundation for the contemporary research on industrial spatial distribution. However, classic location theories say little about the transformation process of industrial structure from a dynamic perspective.

While evolutionary economic geographers have explored evolving spatial structure and distribution of industries using theoretical frameworks based on agglomeration effect, technology innovation, knowledge spillover, and industry life cycle theories (Iammarino & McCann, 2006; Krugman, 1991; Peltoniemi, 2011), most of them only focus on industrial structure alone while neglecting urban spatial processes. There is a lack of exploration into how urban land use change is linked with the spatial transformation of industrial activities. Frenken and Boschma (2007) proposed a theoretical framework to investigate industrial dynamics and urban growth, but no specific industrial space is presented or delineated although such understanding of spatial transformation is essential to urban planning and city management. In a practical sense, urban land use change is a continuous transmitting process. Industrial redistribution and residential land use transformation are critical part of urban growth. Reconfiguration of land price space can lead to a redistribution of industrial and residential land use patterns. Likewise, restructuring of industrial and residential land use can alter the spatial structure of land price. This co-transforming process can be better understood through a dynamic simulation perspective.

Drawn on biological metaphors to create computer programming systems, evolutionary algorithm is believed to be one of the promising methods to simulate dynamic transformational problems (Manson, 2005). This paper develops a dynamic simulation method for simulating the spatial transformation process of urban industries. A novel model called Location-based Firm Profit (LbFP) model is proposed. Taking Shanghai as a case, this research attempts to demonstrate how urban land use growth may lead to the spatial structural transformation of industries. After this introduction, the paper describes Genetic Algorithm as an important branch of evolutionary algorithms. It then outlines an integrated model used to investigate the spatial interaction among industrial activities in cities. Section 4 presents a theoretical model of urban industrial spatial

distribution using a modified Cobb-Douglas production function and the distance decay theory. The study area, data and other simulation parameters will be introduced in Section 5 of this paper. The parameters of core functions are evaluated and the objective function is formalized. Finally, simulation results will be presented and discussed.

5.2 Genetic Algorithms

Genetic algorithm (GA) was first introduced in the 1960s by John Holland (1992). It is originated from natural selection and natural genetics in the field of evolutionary biology. A basic GA is usually comprised of three operators: *reproduction*, *crossover*, and *mutation* (Goldberg, 1989) (Figure 5-1). In each evolutionary generation, GA selects the best parents according to their characteristics, e.g., their fitness value from a fitness function, in order to ensure that the best offspring could be reproduced in the next generation. Once the parents are selected, GA pairs them randomly and codes them into strings. After that, they will crossover with each other and produce offspring, which, in turn, become potential parents of the next generation. Through this iteration, GA updates parents from generation to generation and their best characteristics are retained and passed over from one generation to the next. GA normally uses probabilistic method to generate and mate parents. The method allows information exchange and ensures the best characteristics would survive and become dominating generation after generation. This genetic mechanism is quite similar to the natural selection process, in which the best genes and species survive. Because of its good performance among searching algorithms in practical uses, GA has been used widely and validated in many research fields (Michalewicz, Janikow, & Krawczyk, 1992; Mukhopadhyay, Balitanas, Farkhod, Jeon, & Bhattacharyya, 2009).

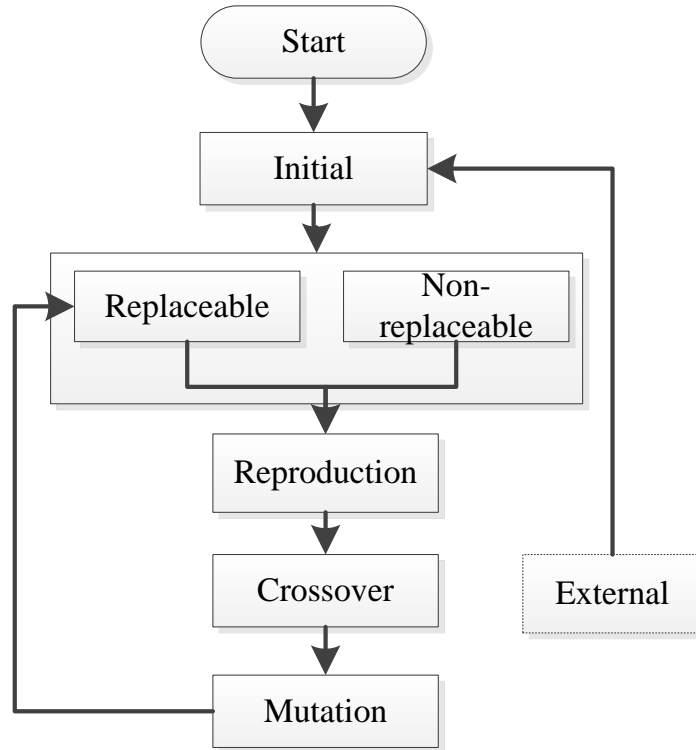


Figure 5-1. Framework of GA.

GA, acting as a closed evolution process, therefore, can be used to solve one or a group of static functions easily. External stressors will be needed to tune it up for the simulating of dynamic systems. To simulate the transformational process of industrial spatial distribution in a city, the initial condition of the searching process of GA needs to change with the elapse of time (Figure 5-1), leading to the change of searching results. As such, the optimization searching process evolves over time, which could be used to animate the dynamical process of urban space. The rest of this paper is going to use this method to simulate the transformational process of the spatial industrial distribution of Shanghai, China.

5.3 Simulating the evolution of urban industrial space

According to the classic location theory, in order to maximize profits, industrial firms tend to choose the optimum locations in a city with minimum costs (Krzyzanowski, 1927). The factors that affect the selection of optimal locations may include land price, transportation cost, urban land use policy, infrastructure, local governance or tax policy (Hayter, 1997; Weber & Friedrich, 1962). In particular, land price and operating cost are considered as the two most stable determinants that influence the site selection of factories in a perfect competitive market city (Alonso, 1964). This research attempts to develop an industrial spatial distribution model by considering the profit maximization of firms under these two factors.

5.3.1 Industrial profit

The overall profit that a firm produces consists of three parts: output value (OV), operating cost (OC) and land cost (LC), as shown by the following equation (Alonso, 1964):

$$P = OV - OC - LC \quad (5.1)$$

where P is the total profit, OV is the output value, LC is the land cost, and OC is the operating cost.

Considering industrial production is less influenced by the physical environment comparing with agriculture (Hudson, 2014), this study supposes that a city is divided into a number of regular lattices and the possible production efficiency of a firm at each lattice is the same. This uniform arrangement means the output value of each lattice is homogeneous across the city space.

Accordingly, we can estimate the profit that a factory gets at lattice i as:

$$P_i = OV_i - OC_i - LC_i \quad (5.2)$$

5.3.2 Land price

Land price in a city is tied closely to where the land is located. Generally, the overall land price in a city decreases from the city center outward (Alonso, 1964; Mills, 1967). Many researches also show that the land price correlates with the size of land parcel (Colwell & Munneke, 1997) and the volume of the construction that will be built on the land parcel. The influence of construction volume is not significant in small cities, but is very important in big cities or where available land for construction is limited. Based on the Cobb-Douglas production function (Douglas, 1976), we can define the price of land, LC_i , at location i in a city as a composite function of *area*, *construction volume* and *distance to city centre*:

$$LC_i = \theta A_i R_i / D_i \quad (5.3)$$

where θ is the coefficient value, A_i is a function of the land parcel area, R_i is a function of the *Floor Area Ratio (FAR)*, which equals the gross floor area permitted on a site divided by the net land parcel area, and D_i is a function of distance d_i to the city center.

Empirical studies show that the land price is not a linear function of distance to the city center. It is a decreasing concave function of distance (Colwell & Munneke, 1997; Kau & Sirmans, 1979).

Hence, the distance influence on the price of land can be written as:

$$p_{D_i} = \theta_1 e^{\mu d_i} \quad (5.4)$$

where p_{D_i} indicates the influence of distance on land price, θ_1 is the land price of city center, d_i is the distance to the city center, and μ is the rate at which the land price changes with the increasing/decreasing distance.

It is also found that the price of land appears as a concave function of parcel size (Brownstone & De Vany, 1991). The bigger the land size which developers ask for, the more discount they can get from land sellers. The influence of land size on the price of land can be defined as:

$$p_{A_i} = \theta_2 e^{\varepsilon(a_i-1)} \quad (5.5)$$

where p_{A_i} indicates the influence of sold land size on land price, θ_2 is the land price of city center, ε is the area elasticity of the land price, and a_i is the land size at location i in the city.

Observations show that the price of land can be a linear relationship with FAR (Gao, Asami, & Katsumata, 2006), so the influence of FAR can be defined as:

$$p_{R_i} = m + m * FAR_i \quad (5.6)$$

where p_{R_i} indicates the influence of Floor Area Ratio on land price, FAR_i is the floor area ratio at location i , m is a constant, and n is coefficient value.

The land price of location, therefore, can be wrote as:

$$LC_i = \theta * FAR_i * e^{\varepsilon(a_i-1)} * e^{\mu d_i} \quad (5.7)$$

The function above shows that θ is the initial per unit land price of the city center where $d_i = 0$, $a_i = 1$, and $FAR_i = 1$.

5.3.3 Firm production operating cost

The operating cost of a firm in a city includes several components, such as labor cost, transportation cost, and energy consumption cost. Most of these production cost factors are

isotropic and hence homogeneous across a city space where a unified and competitive local labor market operates with an exception for transportation cost. The transportation cost may include production transportation cost of a firm and daily transportations of its employee. Theoretically, the better transportation accessibility a location is, the lower the transportation cost is, and as a result the lower operating cost a firm has to bear. We propose the influence of the transportation cost on the operating cost of a firm as follows:

$$OC_i = OC / T_i \quad (5.8)$$

where OC is the universal operating cost of industry (a constant value across the city) and T_i is the transportation accessibility of a firm.

Road density is one of the important indicators for transportation accessibility. In general, the higher the road density is, the more accessible of the firm location is. We define the influence of distance on the transportation accessibility of a firm at location i in a city as follow:

$$T_i = \omega e^{\rho d_i} \quad (5.9)$$

where ρ is a coefficient, d_i is the distance to the city centre, and ω is the road density of the city center area.

5.3.4 Location-based Firm Profit (LbFP) model

Taking all above factors into consideration, this research proposes a novel Location-based Firm Profit (LbFP) model to simulate the dynamics of industrial spatial distribution in a city. The model reflects the spatial distribution of industrial firms in a city, especially metropolitan ones, where effects of urban land price are often paramount.

$$P_i = OV - \frac{OC}{\omega e^{\rho d_i}} - \theta * FAR_i * e^{\varepsilon(a_i-1)} * e^{\mu d_i} \quad (5.10)$$

In order to visualize the structure of the model clearly, the three main factors are plotted in Figure 5-2. The horizontal axis represents the distance originated from city center and the vertical axis is the average land price at the city center. The figure shows that, with the increasing distance from the city center in a city, the site cost (site cost 1 curve) decreases, but the operating cost increases quickly. Supposing the net output and per unit sale price among firms is constant across city space, the overall profit of a firm (profit 1 curve) reaches the highest point at certain distance and then declines with the increasing distance from the city center. The industrial firms in a city, ideally, will choose to cluster around the maximum profit distance from the city center.

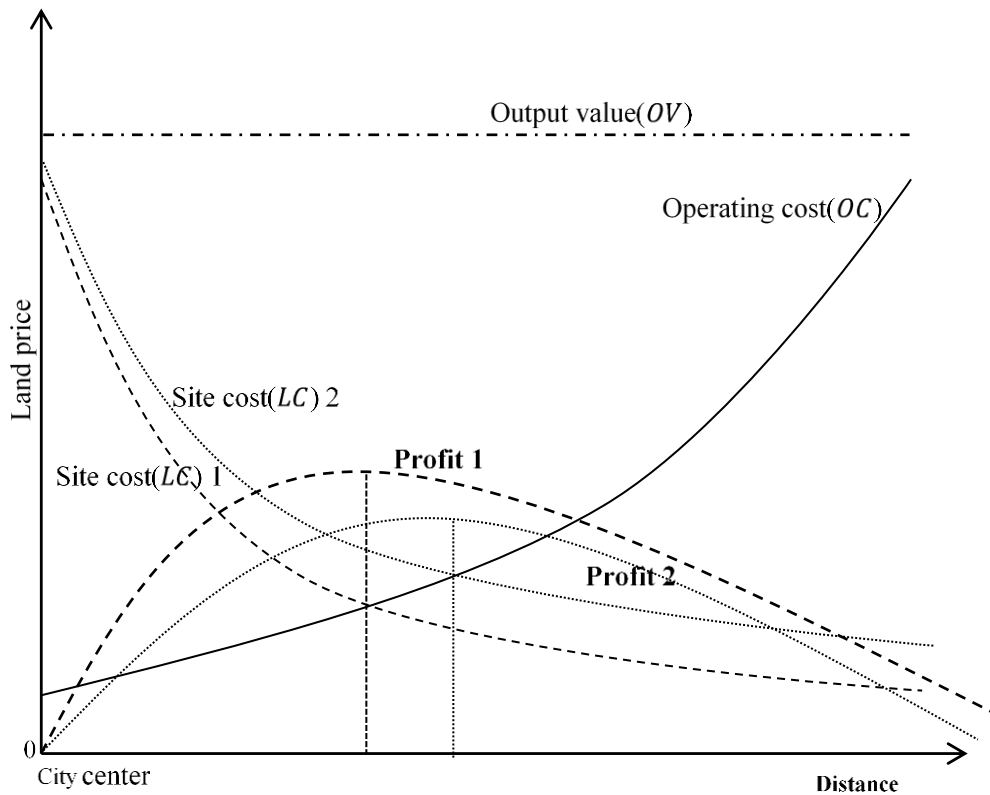


Figure 5-2. Costs, revenue and profits of the firm according to location.

However, this pattern of spatial clustering of firms in a city will change over time when the overall land price (site cost 2 curve and in Figure 5-2) increases because of growing competition for urban land of a city. This means that the firm profit curve in figure 2 (profit 2 curve) will have the same shape but the maximum profit point will move outward from the city center. Given the increasing land price, the maximum profit that a firm can generate is going to decrease if the output value unchanged. The above theoretical model will be employed to simulate the transformation process of industrial space in Shanghai, China.

5.4 Study area and data

Shanghai is located at the tip of the Yangtze River Delta. The city of Shanghai covers a land area of 6,396 km² and is the largest city in China by population according to 2010 census. Since 1978 when economic reforms were initiated, Shanghai has experienced a rapid pace of growth and development, and has been one of the fastest developing cities around the world for the last three decades. The urbanized land area of Shanghai in 2010 was almost three times as much as that in 1987. Its urban landscape, especially the spatial distribution of manufacturing firms has changed greatly. Figure 5-3 shows the city of Shanghai and its built-up areas up to 2013 based on the data from the Shanghai Urban Planning and Land Resources Administration Bureau. The research into the evolution of industrial space can shed light on the mechanisms of urban and industrial evolution in Shanghai. Such knowledge is important for urban planning and city management. One of the major goals of this study is to calibrate the theoretical land price model, LbFP, outlined in the previous section using real data of Shanghai.

Before 1978, there was no land market under the planned socialist economy in China. The commodification of land started in the later 1980s and was accelerated after 1998 when

privatization and commodification of housing were announced by the state council. In 2001, the municipal government of Shanghai launched the land auction policy in order to make the land transaction activities public and transparent and also to make the land price to reflect fully the value of the land. Since then, land developers can bid for the lands that are permitted to circulate in land market. This has made the price of urban land less influenced by non-market factors, such as governmental allocation. Hence, we can reasonably assume that the data on the land transactions reflect the real value of the land in Shanghai.

This research collected 250 traded land parcels between 2011 and 2013 from the website of the Shanghai Municipal Planning and Land Resources Administration (<http://www.shgtj.gov.cn/>). The data are formatted by the serial number of the sold land parcel, and its address, area, price, and FAR. According to the addresses provided by their transaction announcements, the research located all the 250 land parcels on the digital map of Shanghai and measured their distances from the city center using ArcGIS (this research uses the original point of Shanghai Local Coordinate System as the city center point).

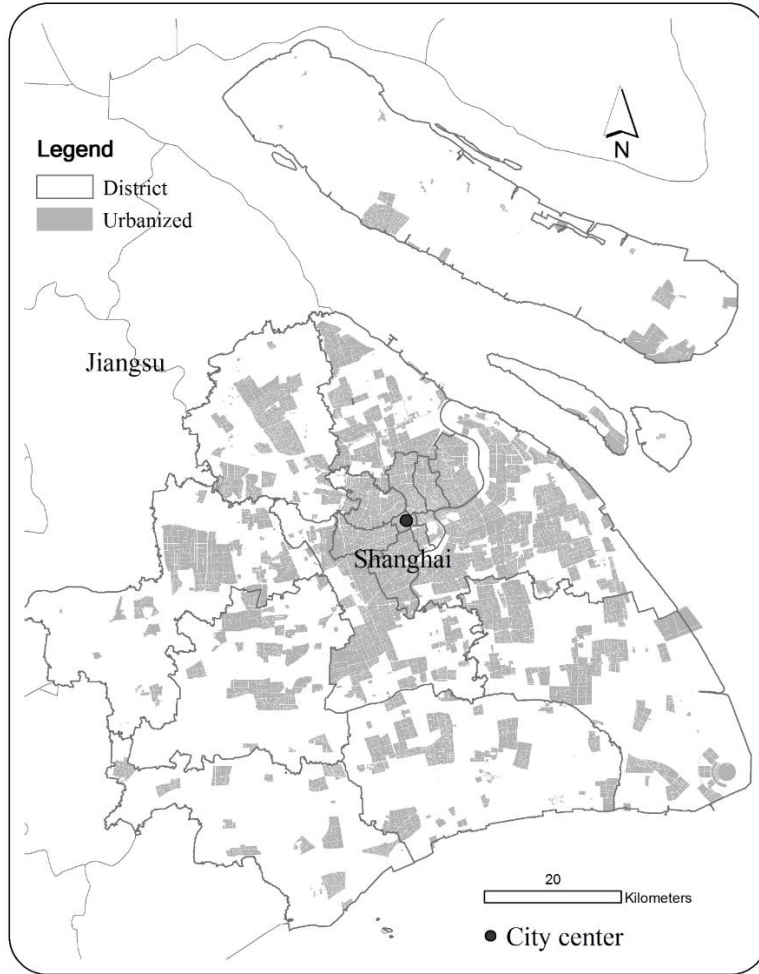


Figure 5-3. The map of Shanghai, China.

To estimate the effect of the land parcel size on the price of land, the area and price data of 100 sold land parcels were collected on the Qingpu Industry Park. The industry park was planned in the middle of 1990s. It is located around 35 km west of the city center and covers 16.1km². Since the park is far away from the city center and the majority of the land parcels were sold only for industrial use, it can be reasonably assumed that the land price of this area is less influenced by the distance to the city center and urban land use policies. The comparison of the land price and land parcel size in this area can reflect the direct influence of land size on the land price of the city.

The plots of those data and preliminary regression analysis show several important facts: 1) the land price follows a decreasing concave trend as land plot size increases; 2) the size of traded land plot has a linear relationship with the distance away from the city center; 3) the *FAR* has a linear relationship with the land price; 4) the *FAR* has a negative exponential relationship with the increasing distance away from the city center. Based on these empirical observations, several regression analyses were conducted to obtain the estimated function of land price with the parameter d_i (Table 5-1). Among them, $\lg(a_i)$ was used for the overall regression when we found the ε value of land area vs. price is too small (-2.053E6). The regression results show that almost all the models are statistically significant at a 95% confidence level. The land area vs. price model is significant at a 90% confidence level.

Table 5-1. Model estimation.

	Model	Estimated function	Model Sig.
Land Area vs. Price	$p_{A_i} = \theta_2 e^{\varepsilon(a_i-1)}$,	$p_i = 583.773e^{-(2.053E-6)(a_i-1)}$	0.074
Land Price vs. FAR	$p_{R_i} = m + n * FAR_i$	$p_i = -29914.595 + 20191.179 * FAR_i$	0.000
Land Price vs. Distance	$p_{D_i} = \theta_1 e^{\mu d_i}$	$p_i = 56098.395e^{-0.120d_i}$	0.000
Overall regression of land price and distance	$p_i = \theta * FAR_i * e^{\varepsilon * \lg(a_i)} * e^{\mu d_i}$	$p_i = 96331.086 * FAR_i * e^{-0.315 * \lg(a_i)} * e^{-0.087d_i}$	
Land Size vs. Distance	$a_i = m + n * d_i$	$a_i = 32829.411 + 552.861 * d_i$	0.034
FAR vs. Distance	$FAR_i = \theta e^{\mu d_i}$	$FAR_i = 3.104e^{-0.021d_i}$	0.000
Road density vs. Distance	$T_i = \omega e^{\rho d_i}$	$T_i = 7.524 * e^{-0.027 * d_i}$	0.000

To investigate the relationship between the road density and the distance to city center, we use the current road network of Shanghai and divide it into 12 rings with a width of 5 km each. The result shows that the road density decreases exponentially from the city center outward (Table 5-1).

Based on the regressions above, the overall industrial spatial distribution model could be defined as the basic object function with parameter d_i :

$$P_i = OV - \frac{OC}{7.524 * e^{-0.027 * d_i}} - 96331.086 * FAR_i * e^{-0.315 * \lg(a_i)} * e^{-0.087 d_i} \quad (5.11)$$

$$a_i = 32829.411 + 552.861 * d_i \quad (5.12)$$

$$FAR_i = 3.104 e^{-0.021 d_i} \quad (5.13)$$

where d_i is the distance from location i to the city center, OV is the universal output value of the factories across the city, and OC is the universal initial operating cost. Both OV and OC are constants.

The calculation results above show that the FAR around the city center of Shanghai is 3.104 ($d_i = 0$), the minimum land size is 32,829.412 m² ($d_i = 0$), and the corresponding sale price is 72,085.996 CNY/m². This means the owner of a firm needs to pay at least 23,223.581 CNY/m² if he want to build a one floor factory around the city center of Shanghai.

5.5 Simulation and discussion

From the previous section we can see that the distance parameter d acts as the only independent variable of the LbFP model after all the real data implementation. The dependent variable P will change with the variation of distance and it will come to the maximum point when d equals to the optimal value with predefined constant values of OV and OC . The research question is then to search for the optimal value d , which can be solved by using GA. Therefore, the fitness function of the simulation process of GA could be defined as:

$$F = fitness(d_i) = OV - \frac{OC}{7.524 * e^{-0.027 * d_i}} - Ini * FAR_i * e^{-0.315 * \lg(a_i)} * e^{-0.087 * d_i} \quad (5.14)$$

$$a_i = 32829.411 + 552.861 * d_i \quad (5.15)$$

$$FAR_i = 3.104 e^{-0.021 d_i} \quad (5.16)$$

The main purpose of this model is to find the optimum location of an industrial firm disregard its production capacity and efficiency. The output value and non-transportation operating cost for any firm can be given any constant numbers. Nevertheless, if the pre-set output value is too small and the operating cost is too big, the simulating result of profit will be negative which means the firm is losing money and can be bankruptcy any time. This will deviate the purpose of simulating the restructuring of urban industrial land use. Therefore, in the simulation of industrial spatial distribution of Shanghai, we suppose that the constant initial production value (OV) of a firm at any location is 10,000 CNY and the initial operating cost (OC) is 1,000 CNY according to preliminary simulation run results. Ini is the initial land price of the city center of Shanghai with corresponding FAR and α values. The regression result shows the value of the Ini is 96,331.086 CNY/m² during the period of 2011 to 2013. To simulate the transformation of industry distribution of Shanghai, this research set Ini value at time 0 as 100 CNY and this number will increase by 100 after each iteration considering the minimum incremental change on land price market of the city. The algorithm was programmed using software Matlab according to the following simulation procedure and the simulation parameters are summarized in Table 5-2.

Simulating procedure:

begin

%% external

```

initialize ini, max-external-generation
for ini=1 to max-external-generation
    update initial population
    %% micro-GA (internal)
    initialize max-population, max-inter-generation,p-mutation,p-crossover
    for 1 to max-inter-generation
        reproduction (replaceable-parents; nonreplaceable-parents)
        %%'roulette wheel' to select parents, parents have higher fitness value have more chance
to produce next generation.
        Coding
        %%code parents(value) into binary strings
        crossover
        %%exchange parts of parent strings to generate new generation strings
        mutation
        %%some part of parent strings can mutate during crossover
        'tournament elitism' to produce nonreplaceable-parents
    end
end
results report
end

```

Table 5-2. Parameters for the Micro-GA calculation.

Parameter	value
Max external generations	300
Max internal generations	2000
Crossover probability	0.8

Initial internal population	10
Initial external population	10
Selection operator	Tournament
Crossover operator	Single point
Encoding method	Binary
Mutation operator	0.0001

During the simulation, the model recorded the optimization distance of an industrial factory to be located from the city center and the corresponding land price. The vertical axis of Figure 5-4 represents the increasing land price (CNY/m²) at the city center over time and the horizontal axis is the optimum distance of a firm away from city center. The simulation results show that the distance of maximum profit location for a firm increases very quickly outward from the city center before the land price value of the city center reaches 5,000 CNY/m². But, the distance effects of land price change decrease when the land price at the city centre is higher than 5,000 CNY/m². This result means industrial companies will move outward very quickly in response to the early rise of land price when land market is initially introduced in Shanghai. Such outward push effect becomes smaller over time when the land price is above 5,000 CNY/m². This can be one of the shocking point in urban land use when land suddenly becomes highly valuable. The results also show that at the time when the land price of city center is 23,223.581CNY/m², as it is the case during the period of 2011-2013, the best profit location for industries is somewhere between 40 and 50 km away from Shanghai's city center.

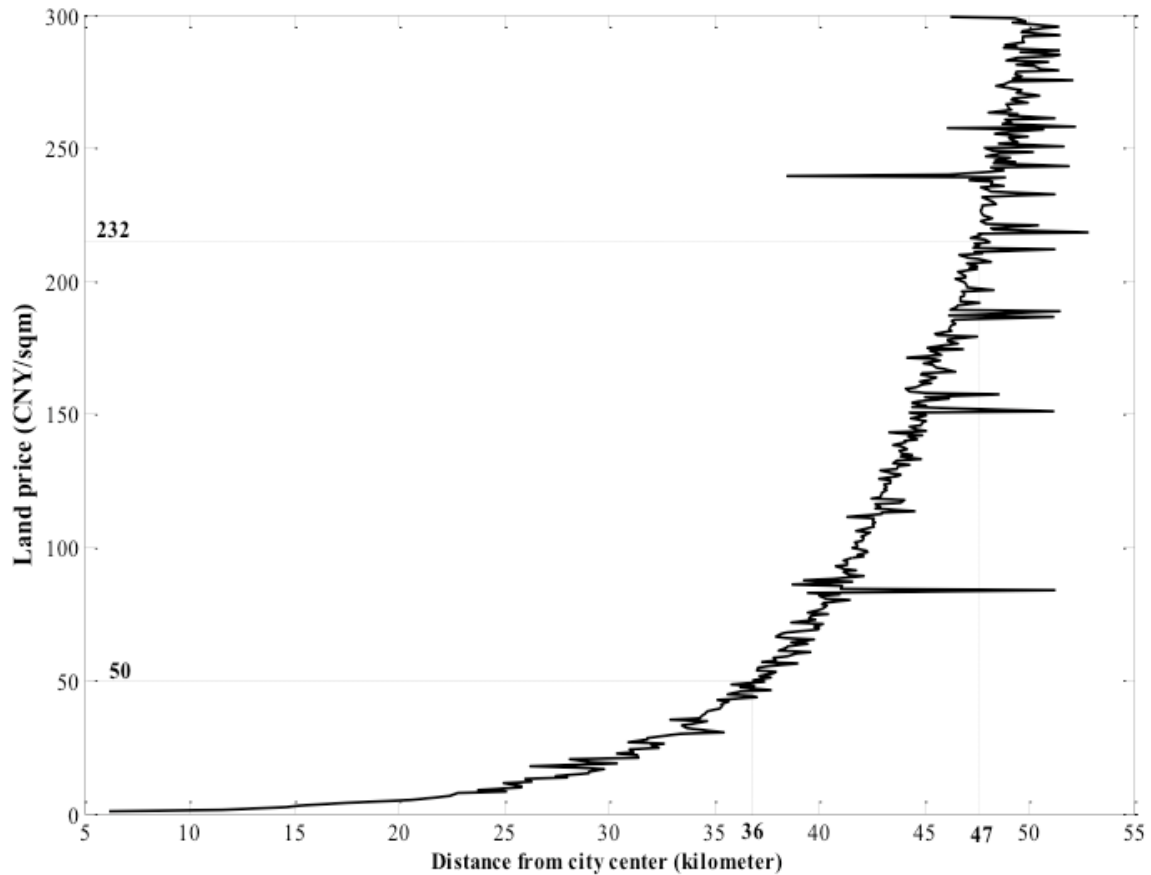


Figure 5-4. Changing optimum location of industrial firms under different price scenarios.

Figure 5-5 presents the changing maximum profits assuming different land price level at the city. The horizontal axis of the figure represents the land price increment at the city center and the vertical axis is correspondingly the maximized profit with the varying optimum distance of firm location from the city center. The figure shows that the maximum firm profit decreases steadily because of the growing operating costs resulted from increasing transportation costs, even though industrial firms move adaptively to the best location due to increasing land price of the city center. From a long-term view, if the land price at the city center climbs up to a point which makes the profit lower than what is expected by the firm owners, these firms will probably move to other provinces due to the fact of decreasing profit.

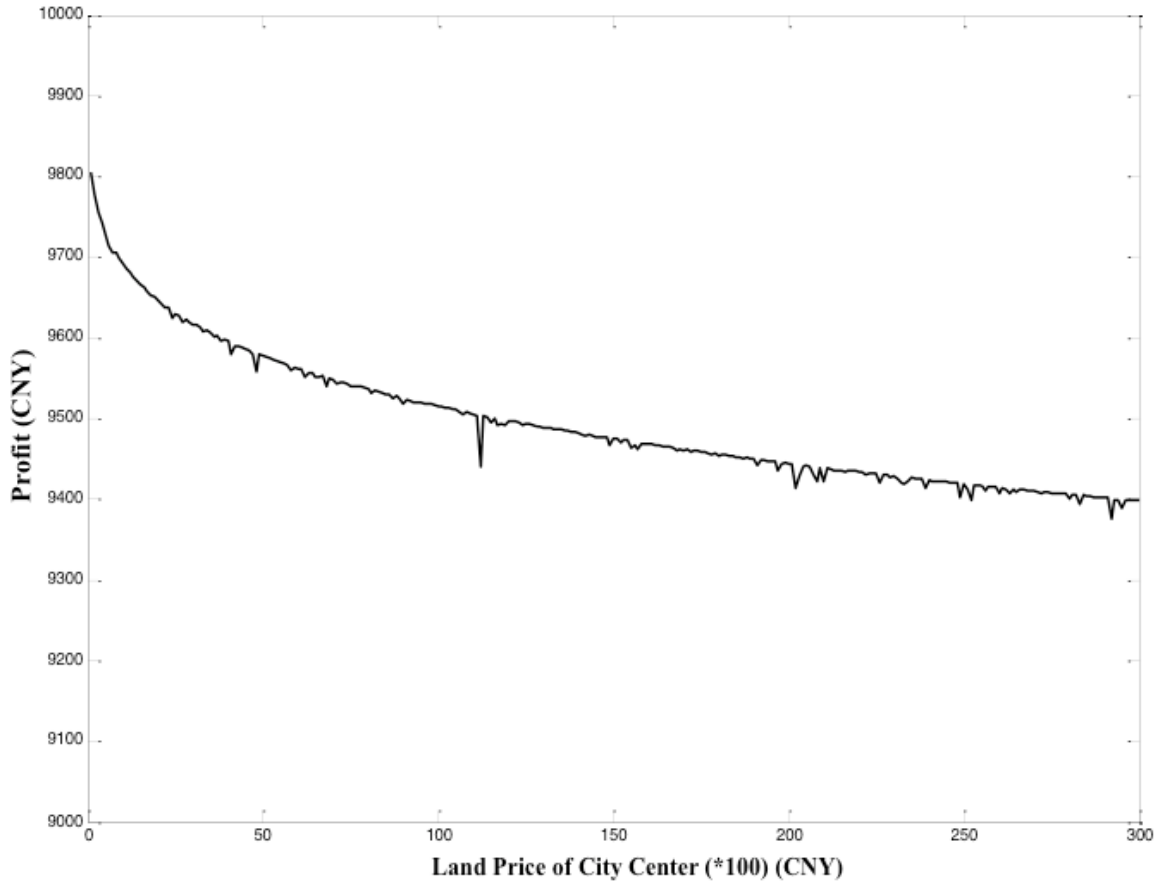


Figure 5-5. The maximum profit location vs. city center land price in Shanghai.

Considering it is hard to trace one or several firms' location-relocation activities led by the evolutionary processes of urban land use change historically, this research will validate the simulated results through the comparison of actual change of industrial land use directly. To facilitate the visualization of industrial land use distribution, we first divide Shanghai into concentric areal rings with a width of 5 km each and overlays the concentric rings with the industrial land use maps in 2002 and 2013 (Figure 5-6). Prior to 2000, industrial land use in Shanghai was not the result of land market transaction but rather the planned land allocation. Therefore, the 2002 industrial land use does not reflect the transaction price of land. The 2002 map shows that the distribution of industrial firms was mainly located inside of the 25 km circle around the city center, which

accounted for 80% of the total industrial land use in Shanghai (Figure 5-6: left). Since 2000, several reform policies and regulations have been launched in an effort to speed up the market transaction of land use. As a result, the average land price of the city center has soared quickly from 6,000 CNY/m² in 2000 to 16,000 CNY/m² in 2013. Because of rising land prices, a large number of manufacturing firms have been forced to move out the central city area outward from their previous locations to suburban regions. The 2013 land use map (Figure 5-6: right) shows that the distribution of industrial firms was mainly located more than 15 km out of the city center and most of them resided between 30 km to 40 km from the city centre, accounting for 54% industrial land use of the city.

According to the simulation results, the majority of industrial factories should reside 40 km to 50 km away from the city center when the land price of the city center reaches to 23,223.581CNY/m². Comparing Figure 5-6 with Figure 5-3, we can see that the main directions for spatial industrial expansion are in the west and the north of the city and the city boundary in these two directions are about 40 km from the city center of Shanghai. This means that the firms in these areas would have to move further to cross the city boundary if they want to have better profit margins. Such cross border industrial development is actually quite evident in the regions neighbouring Shanghai, such as Kunshan, Taicang and Suzhou. Take Kunshan as an example. It was a rural county before 1990, but has since grown up to a city of more than one million people during the last three decades. The total industrial output value of Kunshan in 2003 was only 106.7 billion CNY, but rose to 700.1 billion CNY in 2010 (according to Kunshan Statistical Bureau 2011: <http://www.kstj.gov.cn>), expanding almost seven times since 2003.

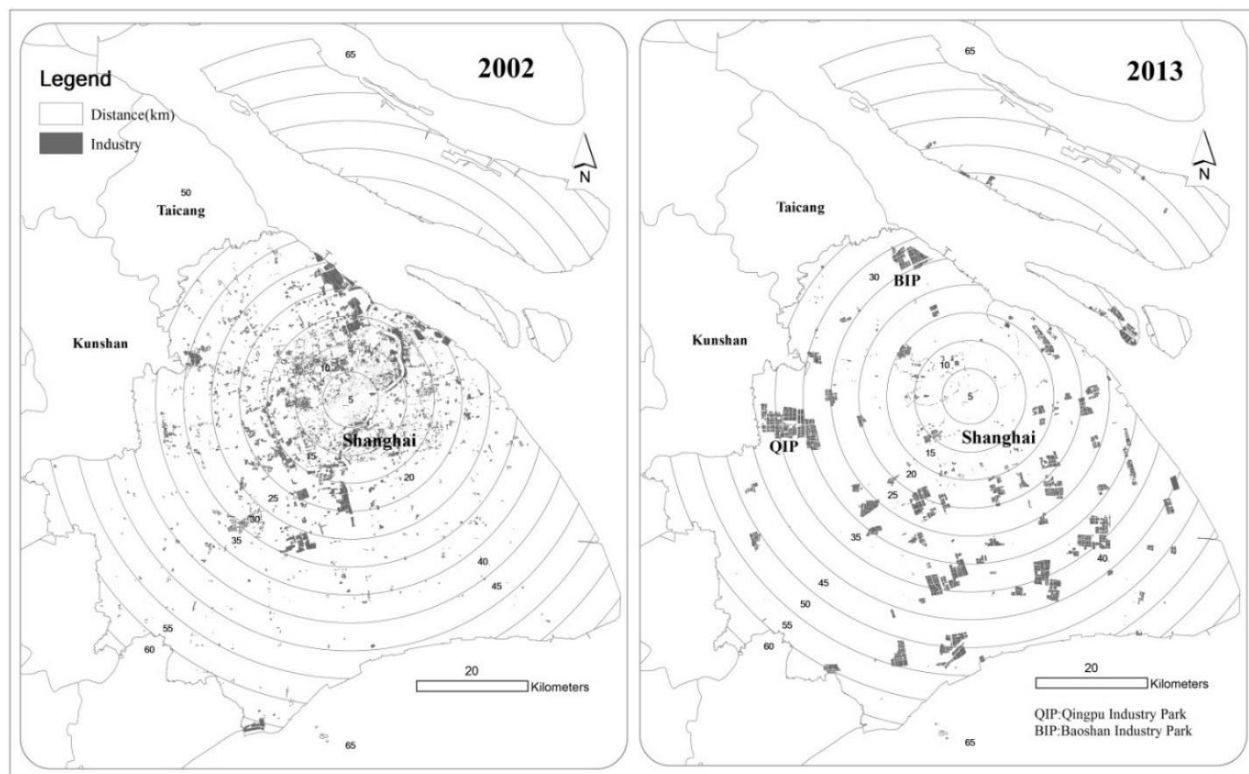


Figure 5-6. Spatial distribution of industrial firms in Shanghai (Year 2002 & 2013).

From the 2013 industrial land use map (Figure 5-6: right) we can see that the west and north directions are associated with two main industrial parks of the city: Qingpu Industrial Park (QIP) and Baoshan Industrial Park (BIP). The map shows that these two industrial parks were pushed to the locations very close to the border of neighbouring Jiangsu province, but still are located inside the city's boundary. According to the simulation results, the factories at these areas should move further away from the city center if they want to make better profits. In practice, the municipal government of Shanghai introduced a set of policy measures and incentives to mitigate the effects of escalating land prices in order to keep industrial firms inside of the city boundary by providing better infrastructures and giving tax reduction. Compare with the boundary limit of available land use in the west and north directions, we can see there are more industrial parks in the south and east directions and a lot of them locate further away from city centre than those in the west and

north directions. Some of these industrial parks are located even further than 50 km away from the city center. This means that industrial firms would move further outward from city center given the current land price level, if there were no boundary and other geographic limiting conditions.

5.6 Conclusion

Urban development and evolution are closely associated with growth and distribution of industrial firms. The spatial restructuring of industrial space shapes significantly city structure and its spatial configuration. In the meantime, the continuous expansion of city size also alters the spatial distribution of industrial location. The research into the transformation of industrial spatial distribution provides insights into the mechanisms of urban growth and industrial land use dynamics and help to derive valuable information for urban planning and city management.

This paper develops a dynamic industrial spatial distribution model based on evolutionary theory and Genetic Algorithms and applies it to simulating the industrial transformation process in Shanghai, China. The results show that given the increasing land price over time, industrial firms move gradually from the areas close to the city center to distant suburban areas. Given the continuous increase of land prices in the city center in the near future, the location of industrial firms may move further out in the area close to the municipal boundary, because of the administrative system in China. While the relocation of industrial firms is to maintain high profit, the maximum profit a firm could produce is, however, decreasing over time because of increasing land value in the city. The analysis of the current industrial land use of Shanghai demonstrates that the developed model delineates well the dynamical process of industrial spatial distribution and reveals clearly the land price is a significant mechanism in reconfiguring industrial space in Shanghai, China.

With the successful simulation of industrial spatial evolution in Shanghai, China, this research shows that it is possible to build a computer simulation model to delineate the dynamical evolutionary urban land use process through appropriate modelling methods. Different from main stream industrial spatial redistribution research, which delineate the deconcentration or suburbanization process of manufacturing industry among mega cities qualitatively (Henley, 1994; Hudalah et al., 2013; Viehe, 1981; Walker, 2001), this research simulates the dynamic industrial deconcentration quantitatively. Moreover, the use of recent land auction and historical industrial land use data helps to validate the simulation results. The findings of the spatial industrial diffusion process in the study area are in general consistent with the empirical observations in literature (Marton & Wu, 2006; Ning & Yan, 1995; Wu, 2008). The results of this study can greatly help urban managers and planners to understand the city better.

There are still several things that need further exploration and research. Firstly, this model was built up based on classic urban geography theories which presume isotropic urban surroundings. The land price of a city conforms a concentric circle declining tendency according to the LbFP model. There is no delineation about natural, human, political environmental discrepancies among different directions and sub-districts.

Secondly, the model takes the land price as one of the core factors, which determine the location and relocation of industrial firms. There are many other factors which may influence land use decision making by an industrial firm. For example, a firm will not move from its current location easily considering its path dependency, and firms will also put local government policies and other preferences into their consideration when they choose the location for their future production activities.

Thirdly, the simulation model developed in this research is a one-dimensional computer simulation model. One of the main simulation results is the optimum distance of an industrial firm location from the city center under the given land price. It is possible to build a Cellular Automata (CA) based or agent based model to simulate the dynamical processes of industrial spatial distribution in two dimensional geographic space in future.

Even though the case study of Shanghai shows that there is great potential to apply the built up LbFP model to other cities, there are several challenges needed to be considered. Firstly, as a metropolitan city, the land price of Shanghai took a key role in determining land use, especially industrial land use. This can not be compared with a medium or small city where there are no obvious land price various among difference location. Secondly, market, instead of policy and other factors, dominated the decocentration process of industrial land use in Shanghai. Hence, it is hard to apply the model to a city where government policy, planning strategy, and other factors dominate land use type and direction.

Chapter 6 Simulating industrial land use change in Shanghai, China

6.1 Introduction

Computer-based simulation provides a computational and visualization framework upon which significant spatial and temporal information on mechanisms of landscape evolution can be revealed (Berry, 1964). Not only is such an exercise essential for unraveling historical trajectories of urban growth, but it also helps reveal future growth possibility and expansion direction (Al-shalabi et al., 2012). Further, it provides an important tool to assess the impact of future land development strategy, coping with population and economic growth (Al-shalabi et al., 2012). Many studies have applied the cellular automata (CA) modelling method to simulate urban land use evolution (White & Engelen, 1993; Batty et al., 1997; Wu, 1998; Parker et al., 2003; Batty & Hudson-Smith, 2005; Moreno et al., 2008). However, in these models, residential, commercial, industrial, and other land uses are often lumped together as non-agricultural uses. There is no differentiation among them and industrial land use transformation is likely ignored in mainstream studies.

The miss-out of industrial land use can bring major risks regarding credible modelling and simulation results facilitating urban administration policy-making, especially in industrializing nations. Generally, industrial growth and agglomeration are the major driving forces of urban land use change and expansion (Walker, 2001). The establishment and concentration of industrial firms lead to the spatial clustering of residential, economic and social activities due to agglomeration effects. Meanwhile, the spatial structure of industrial distribution in cities reconfigures urban spatial morphology, linked with land use,

transportation, economic activities, housing, etc. (Anas et al., 1998). Appropriate and balanced urban industrial spatial structure is essential to steady urban growth (Anas et al., 1998; Fischer & Nijkamp, 2012; Fujita & Thisse, 2013). Understanding the relationship between land use change and industrial spatial distribution and their co-transforming processes can help urban planners and decision makers achieve the goal of developing sustainable and livable cities. Therefore, modelling and simulation work may fail to reflect the actual situation without considering industrial land use activities.

Moreover, urban land is developed in a competitive manner. Because of the declining developable land, the value of land parcels in central city proper increases continuously. More competitive land use type dominates others in an open-market competition process (Alonso, 1964; Mieszkowski & Mills, 1993; Harvey & Jowsey, 2004). Generally, industrial use outcompetes agricultural use in suburban and rural areas and the land is converted to industrial use. Commercial and residential uses in inner city outcompete and displace agricultural or industrial land concentrically from inner cities outward (Walker, 2001). In a market economy, the urban land development process in a city is largely regulated by this market competition mechanism. Any study on urban land use transformation is inconceivable without a delineation of land use competition theory.

While the classic and neoclassic urban industrial land use theories established foundational knowledge for the study of urban industrial activities (Weber & Friedrich, 1962; Pellenbarg et al., 2002), they tend to neglect the historical, path-dependency, and evolutionary perspectives of urban industrial land changes. The evolutionary economic geography explains the spatial evolution of firms, industries, networks, and cities from elementary

processes of the entry, growth, location, and relocation sequences (Ning & Yan, 1995; Walker, 2001; Boschma & Frenken, 2006). The current models and theories on urban industrial land use are largely based on neoclassic theories and often tend to be static and discrete. Few studies have incorporated dynamic theories in land development modelling and simulation. There is a lack of useful models to dynamically delineate the spatial structuring and restructuring processes of urban industrial land use.

Therefore, this paper develops a CA-based dynamic industrial land development model to simulate the spatial transformation process of urban industries. In this model, industrial and residential land development activities coexist and coevolve during the course of urban land redevelopment processes. To delineate the competition relationship between industrial use and residential use, an integrated logit model was developed: the Industrial and Residential Land use Competition Model (IRLUCM). Through integrating with classic land use and industrial activity location-relocation theories, the model delineates the competition relationships among agricultural, industrial, and residential land uses. Focusing on the industrial landscape transformation in Shanghai, this study seeks to demonstrate how urban land use growth may lead to new spatial configuration of industrial land uses over time. Taking historic land use data as a benchmark, this study invents a new method to calibrate computer simulation models by deploying genetic algorithms.

The next section introduces the industrial land use transformation in Shanghai. It then proposes an integrated model to investigate spatial interactions among industrial activities and land use in cities. This is followed by a discussion of model parameter evaluation and calibration. Simulation results and empirical findings are presented and then discussed.

6.2 The industrial land use transformation in Shanghai

Shanghai is situated at the tip of the Yangtze River Delta of mainland China and has been one of the fastest developing cities around the world during the last three decades. The urbanized land area of Shanghai in 2010 (3131 km²) was almost five times as big as in 1987 (635 km²) according to remote sensing data classification. Its urban landscape, particularly the spatial distribution of manufacturing factories, has shifted outward significantly. The ground surveying data obtained from the Shanghai Urban Planning and Land Resources Administration Bureau show that there was 313 km² of industrial land located inside the city's administration boundary in 2002, and 678 km² in 2013 (Figure 6-1). There was a net increase of 545 km² of industrial land uses during the past decade.

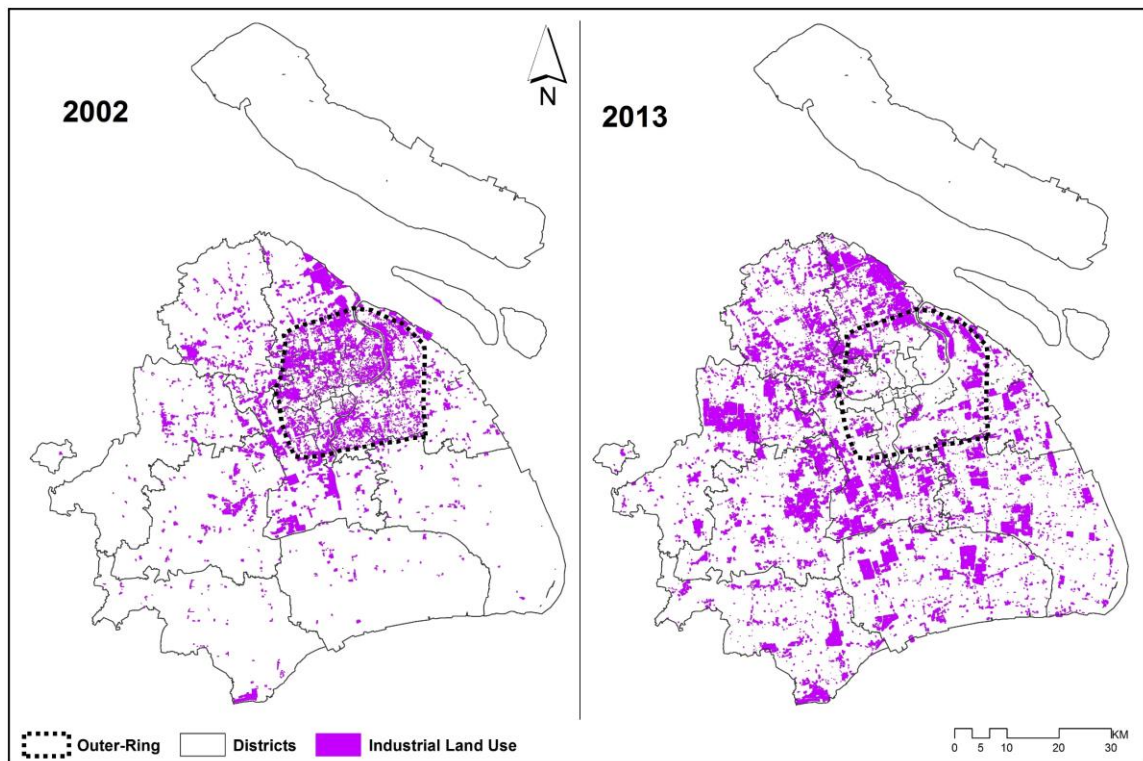


Figure 6-1. Industrial land use of Shanghai, 2002 and 2013 (data source: Shanghai Urban Planning and Land Resource Administration Bureau).

Meanwhile, a large number of factories were relocated away from the inner city to suburban areas in the years 2002 to 2013. In 2002, there was 133 km² of industrial land uses located inside the Outer-Ring Road, and 152 km² in 2006. Accordingly, there was a 19 km² net industrial land use increase from 2002 to 2006. However, data analyses show that there was 58 km² of industrial land turned into residential or commercial uses during the same period (Figure 6-2). The area of industrial land decreased to 77 km² in 2013. Nearly 92 km² of industrial land in the inner city was converted to other land uses during the past decade. The mapped results clearly demonstrate the suburbanization of industrial land uses of the city. One of the main drivers behind this land use conversion was the continuous increase in land price in the city center. Data (China Urban Land Price Dynamic Monitor <http://www.landvalue.com.cn/>) shows that the land price of the city has increased from 6,000 yuan/m² in 2000 to 16,246 yuan/m² in 2013, which forced industrial factories to move out to suburban areas or other cities.

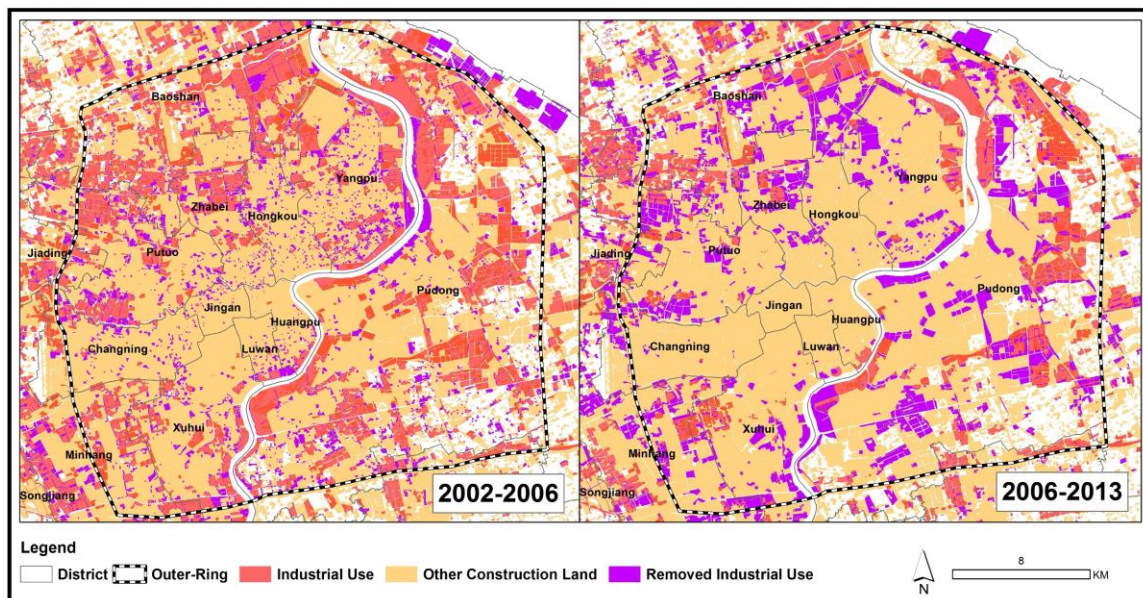


Figure 6-2. Industrial land use change 2002–2006 and 2006–2013 (data source: Shanghai Urban Planning and Land Resource Administration Bureau).

To curb the disorderly sprawling of industrial location-relocation activities, the city implemented strict land use policies through a series of industrial land use plans, including the Shanghai 12th-Year Plan and the Shanghai Industrial Land development Plan. These plans delineate the boundaries for future industrial land use and identify 104 industrial land blocks. These blocks are divided into urban industrial land, industrial park, and industrial base (Figure 6-3). Among them, industrial bases sit at the highest development order because of their specific industrial types, such as the petrochemical industry, automotive industry, and shipbuilding industry.

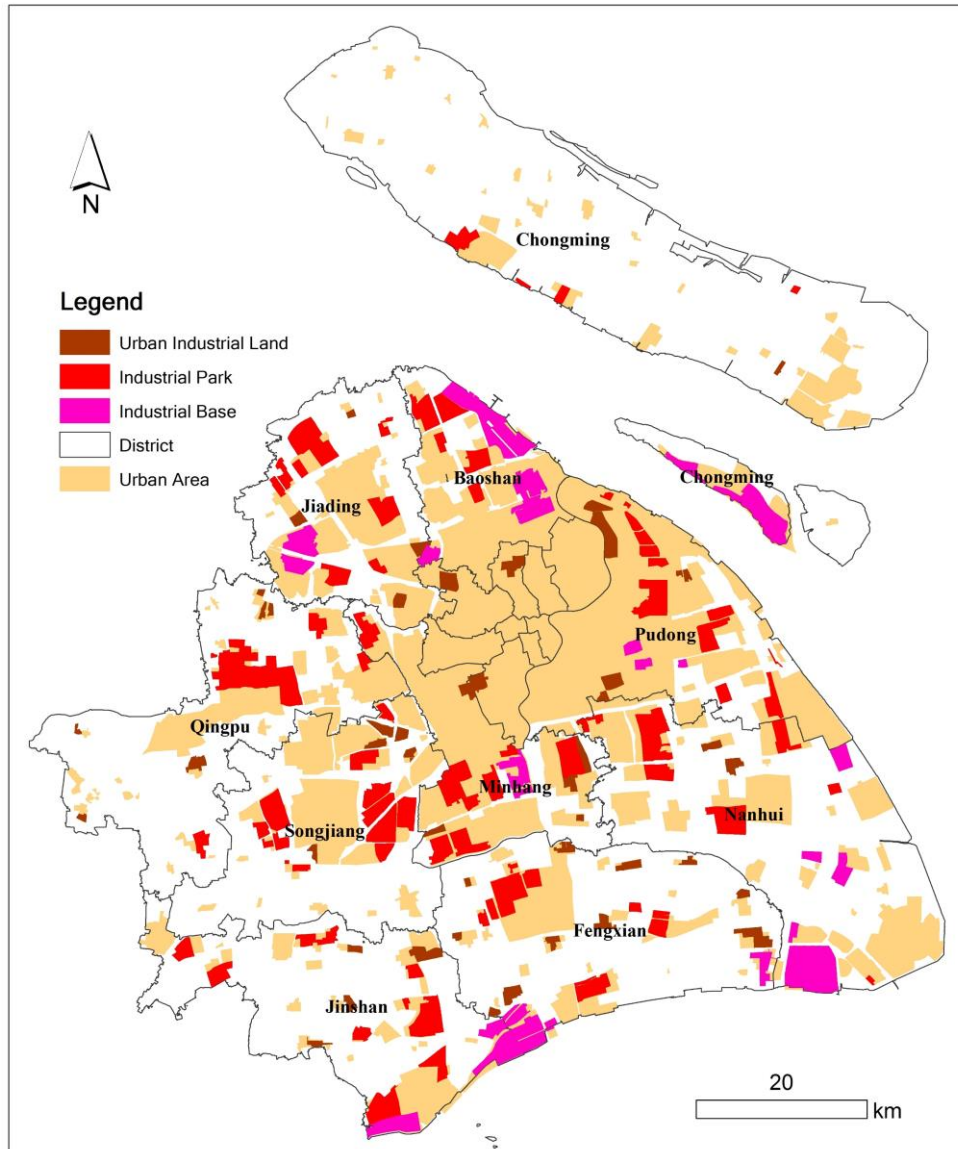


Figure 6-3. Planned industrial blocks in Shanghai (data source: Shanghai Urban Planning and Land Resource Administration Bureau).

In addition, the city enacted strict land use compatibility policies to direct land use planning and development (Table 6-1). For instance, polluting industrial land uses are not compatible with residential, government, commercial, public facility, and business office uses. Non-polluting industrial uses are compatible with work camp uses and acceptable with commercial and business uses.

Table 6-1. Shanghai industrial land use compatibility matrix*.

Other land uses	Residential						
	Low density	High density	Work camp	Commercial	Facility	Office	
Industrial uses	Non-	×	×	√	○	×	○
	Polluting	×	×	×	×	×	×
	Research	×	×	○	○	○	√

(*Data source: Shanghai Urban Planning and Land Resource Administration Bureau; √ denotes compatible, ○ denotes neutral, × denotes non-compatible)

The transformation of the industrial land use spatial structure clearly demonstrates that the industrial land use of the city was in an intense competition relationship with residential and commercial uses. The delineation of special industrial development zones and the implementation of compatible land use policies further impact the spatial distribution of other non-industrial construction uses. Hereinto, the distribution and redistribution of its spatial structure carves the spatial morphology of urban land use in Shanghai. The modelling and simulation of urban land use and land-cover changes will be extremely biased without a clearly delineation of industrial uses. In the next section, we propose an integrated model for the simulation of industrial land uses.

6.3 Industrial and Residential Land use Competition Model (IRLUCM)

6.3.1 Theoretical framework and base model

Because of resource scarcity and locational advantage, the use of land in metropolitan areas is determined by market logic of competing activities among various entities (Alonso, 1964). Generally, residential, industrial, commercial, and other land use types compete for developable land parcels through market or non-market channels, such as bidding in a market or government allocation. The more economically profitable or socially and

environmentally desirable land use types will succeed the competition, and the land will be developed or redeveloped accordingly. For instance, agricultural land will be transformed into industrial (Figure 6-4: Ari-Ind) or residential (Figure 6-4: Ari-Res) uses if their expected utilities are higher than agricultural production activities. With the continuous urban population growth and land use expansion, land price around the central area of a city increases over time given its superior accessibility. If the price for produced industrial goods are fixed, the net profit per unit of land in the city center that is generated from industrial production activity declines. However, the profits of land use produced from residential housing developments or business activities increase, due to rising demand for residential and commercial space. As a result, industrial factories have to relocate away to suburban areas and the former industrial land will be redeveloped for residential or commercial uses (Figure 6-4: Ind-Res).

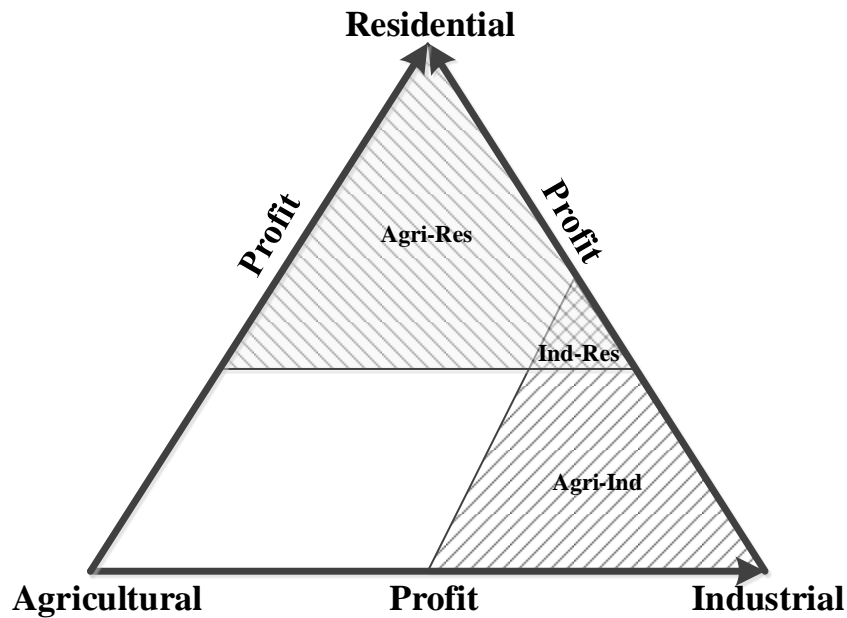


Figure 6-4. Urban land use competition framework.

Theoretically, when it comes to selecting a particular parcel of land, land development decision makers usually have several choices and make land use decisions according to a series of land use goals and constraints. This process is called land suitability decision, which can be represented by a logit decision model (Hilferink & Rietveld, 1999; Schotten et al., 2001) as follows:

$$S_{cj} = \frac{\exp(\omega^*TR_{cj})}{\sum_j \exp(\omega^*TR_{cj})}, \quad (6.1)$$

where c is a land parcel, j is a possible land use type, TR_{cj} is the profitability value of the land use type j , ω is the coefficient for suitability value, and S_{cj} is the probability that the land use type j could be developed on land parcel c .

According to the illustrated urban land use competition framework, the decision-making process of land development is driven by profit-maximizing equilibrium conditions. Classic and neoclassic urban land use theories indicate that the profitability of a particular land parcel is determined by transportation accessibility, land use compatibility, land development agglomeration effect, and governmental strategies and planning policies (Bodenmann & Axhausen, 2010). Thus, a land use profit maximization approach can be delineated through the classic Panzar-Rosse revenue test model (P-R model) (Bikker et al., 2012) as follows:

$$\log TR = \alpha + \sum_{i=1}^m \beta_i \log w_i + \sum_{k=1}^n \delta_k \log CF_k + \varepsilon, \quad (6.2)$$

where w_i is the profit of the i th input factor, such as fixed asset interest profit, and noninterest profit, CF_k denotes k th specific control factors, such as shareholders' equity, α is a constant, β , and δ are respective coefficients, and ε is residual.

Urban land use studies indicate that industrial productions are the basic non-agriculture revenue-generating activities among metropolitan areas, if we consider that farmers can simply lease out their land for short-term industrial uses (Zhu, 2000; Xu, 2004; Lin, 2009). Therefore, we can treat industrial land use profit P as the base point and replace constant α in the P-R model. Also, if we consider transportation accessibility (A), land use compatibility (C), land development agglomeration effect (G), and administration policies (Z) as influencing factors and land-supply limitation as control factor (LP), we can define industrial land use profitability (TR_I) and residential land use profitability (TR_R), respectively, as

$$\begin{cases} \log TR_{cI} = P_c(1 + \beta_{1I} \log A_c + \beta_{2I} \log C_c + \beta_{3I} \log G_c + \beta_{4I} \log Z_c + \delta_I \log LP) + \varepsilon \\ \log TR_{cR} = P_c(1 + \beta_{1R} \log A_c + \beta_{2R} \log C_c + \beta_{3R} \log G_c + \beta_{4R} \log Z_c + \delta_R \log LP) + \varepsilon \end{cases} \quad (6.3)$$

Where c is a land parcel, $\beta_1, \beta_2, \beta_3, \beta_4$, and δ are corresponding coefficients, I denotes industrial use, and R denotes residential use. We name this the Industrial and Residential Land use Competition Model (IRLUCM). In this model, we assume all the considered influencing factors (A, C, G, Z, LP) have add-on effects on industrial land use profit, P , and control each of their influence values and their coefficients under 1. Each of them will be further defined through an explanation model facilitated by classic/neoclassic location-price theories.

6.3.2 Industrial Land Use Profit Model

Understanding the land use profit generated from industrial factories should be used to investigate individual factory's production activity. The suitability of land for industrial factory uses should be evaluated in relation to its possible industrial profit given the site advantages and constraints. According to Alonso (1964), the overall profit that a factory produces is a function of three variables: output value (V), operating costs (O) and land cost (L), as demonstrated by the following equation:

$$P = V - O - L, \quad (6.4)$$

where P is the total profit, V is the output value, L is the land cost, and O is the operating cost.

It can be reasonably assumed that the labor and capital costs for any factory are constant in a city and per unit output value (V) usually stays the same across the city space, assuming a free and competitive market. The variables of land price (L) and operating cost (O) can be considered as the two most important determinants that influence the site selection of factories in a perfectly competitive urban market (Alonso, 1964; Brueckner, 2011). Meanwhile, the land price in a city is tied closely to where the land is situated (Figure 5-2). The overall land price in a city generally decreases from the city center outward (Alonso, 1964; Mills, 1967). The operating costs include labor, transportation, and energy consumption. Most of these production cost factors can be reasonably assumed isotropic and, hence, homogeneous across a city space with an exception for transportation cost. However, with the increasing distance from the city center in a city, the operating cost increases quickly due to increasing transportation cost to a factory. Therefore, the total

profit of a factory reaches the highest point at a certain distance from the city center and then declines with a further increase in distance away from the city center (Figure 6-5). The industrial factories in a city, ideally, will choose to cluster at a concentric belt around the maximum profit distance from the city center (Wheaton & Torto, 1990).

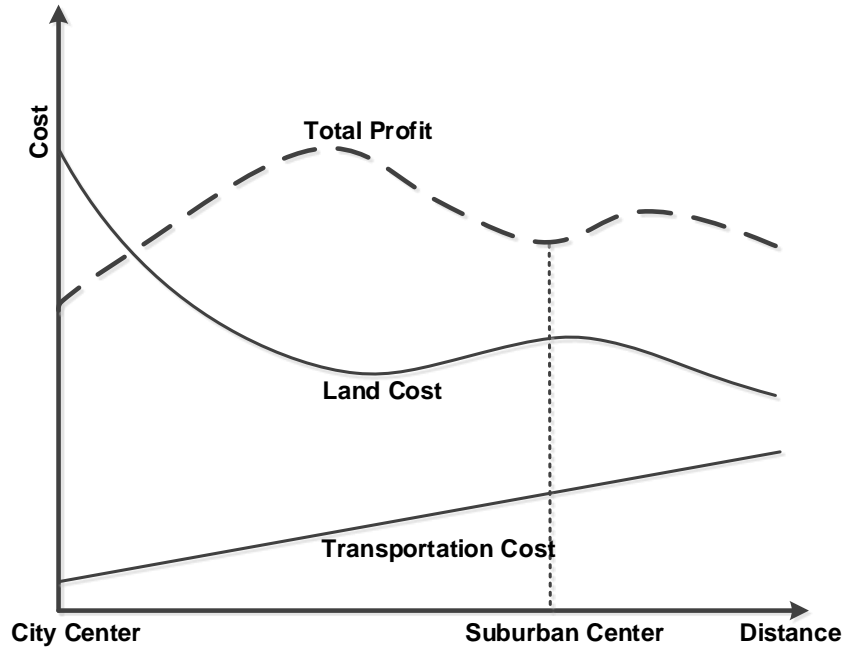


Figure 6-5. Cost, revenue, and profit of the factory according to location.

This is described in the literature as the Location-based Factory Profit (LbFP) model (Qiu et al., 2015) and can be interpreted in functions in detail as follows:

$$\begin{aligned}
 P_l &= V - \frac{O}{v e^{\rho d_l}} - \theta * FAR_l * e^{\phi(a_l-1)} * e^{\mu d_l}, \\
 a_l &= m + n * d_l, \text{ and} \\
 FAR_l &= \lambda e^{\phi d_l},
 \end{aligned}
 \tag{6.5}$$

where P_l is the profit at the location l , V is the output value, O is the operating cost, d is the distance between location l and the city center, FAR is the floor area ratio, which impacts the selling price of land at the location l , a is the land size at location l , which

will impact the land price at the location l through scale discount at sale, and ω , ρ , ϕ , μ , m , n , φ and λ are coefficients.

6.3.3 Land-Accessibility Model

Accessibility is one of the key factors that can be used as a surrogate measure of urbanization economy. A well-developed infrastructure system of a city can benefit industrial factories through better accessibility to larger labor pools, potential suppliers and customers (de Bok & van Oort, 2011). In addition to the distance to the city center, the spatial distribution of highway and metro systems have significant spatial impacts on urban industrial land uses. The mobility in industrial production activities, especially space extensive industries, depend highly on the transportation network for the transport of goods (De Bok & Sanders, 2005). For instance, the construction of a highway network promotes the de-concentration of manufacture factories both in developed and developing countries (Nadiri & Mamuneas, 1996; Hudalah et al., 2013). In addition to highways, investment in new transportational infrastructure, for instance urban rail lines and stations, will generate significant land use impacts (Cervero & Landis, 1993). Case studies show that the construction of new metro lines can significantly increase residential dwelling prices in the areas close to the stations due to the improved accessibility (Christodoulou, 2010).

Even though both highway and metro lines contribute to the hiking of land value, their impacts are not equal. In a metropolitan region where a majority of households do not own cars, public transit systems are prioritized for daily commutes. The urban rail system produces a major influence on residential land development compared to other ground

transportation networks, while the highway network is more important for space extensive industries than other public transportation networks in a city region.

The attractiveness brought by highway and metro systems onto land accessibility can be described as follows:

$$\begin{cases} A_{cI} = \varphi_{1I}T_{HI} + \varphi_{2I}T_{MI} \\ A_{cR} = \varphi_{1R}T_{HR} + \varphi_{2R}T_{MR}, \end{cases} \quad (6.6)$$

where T_H is the transportation accessibility impact of the highway, and T_M is the transportation accessibility impact of metro lines, I denotes industrial use, and R denotes residential use. Both highway and metro impacts can be defined as a negative exponential relationship with distance based on distance-decay theory (Levy et al., 2011).

$$\begin{cases} T_{HI} = e^{-\mu_1 d_{1c}} \\ T_{MI} = e^{-\mu_2 d_{2c}} \\ T_{HR} = e^{-\mu_1 d_{1c}} \\ T_{MR} = e^{-\mu_2 d_{2c}}, \end{cases} \quad (6.7)$$

where d_{1c} is the distance of land parcel C from the nearby highway line, d_{2c} is the distance of the land parcel from the neighboring metro lines, μ_1 and μ_2 are coefficients for the influence of highway and metro respectively.

6.3.4 Land use Compatibility Model

The fact that the use of land generates spillover or externalities is explicitly recognized in urban economics (Willis et al., 1998; Irwin & Bockstael, 2002, 2004; Taleai et al., 2007). Positive externality will promote more compatible land to be developed. Negative externality will discourage non-compatible land development. For instance, studies find

that the open space preservation of a community will repel residential land development (Irwin & Bockstael, 2002). Polluting industrial or external transportation land uses will discourage housing developments within a certain distance (Espey & Lopez, 2000). Thus, a regulatory land development control method is adopted among cities to minimize the negative external effects or to maximize the positive ones (Willis et al., 1998; Taleai et al., 2007).

Land use compatibility of land parcel c can be defined as follows:

$$\begin{cases} C_{cI} = \alpha_1 N_I + \alpha_2 N_R \\ C_{cR} = \alpha_1 N_R + \alpha_2 N_I \end{cases}, \quad (6.8)$$

where N is the number of neighbouring land use parcels of the same type, I denotes industrial uses, and R denotes residential uses. α can be positive or negative. α will be positive if the potential land use type of parcel c is compatible with neighbouring land use type j to n , and α will be negative if neighbouring land use type repels the potential land use type.

6.3.5 Agglomeration Effect Model

In addition to internal economies of scale, the spatial externalities of industrial factories can benefit each other in cost saving and labor pool sharing (Rosenthal & Strange, 2003; de Bok & van Oort, 2011). In addition, the spinoff dynamics drive the incubation of new factories. The agglomeration of industrial factories will cultivate a strong knowledge creation and diffusion environment in a region (Boschma & Wenting, 2007). These will encourage industrial factories to cluster together.

Meanwhile, the development of edge cities on the outskirts of a metropolitan area may gradually attract more and more residents and businesses, because of comparatively lower housing prices and better social or physical surroundings (Garreau, 2011). This will contribute to an increase in residential land use in suburban areas, and eventually, it may be merged into the city's continuous expansion. A polycentric urban morphology with a number of concentrated sub-centers may be taking form (Anas et al., 1998).

Emerging edge cities in the suburban areas defy the classic land price theory, which indicates a declining trend of land price from the city center outward as delineated through the LbFP model (Luo & Wei, 2004). The planned and controlled growth rules of edge cities make some land zones away from the city center cost more than normally expected (Henderson & Mitra, 1996). Therefore, the agglomeration effects of edge cities characterize another aspect of the spatial structure of the urban landscape.

Empirical studies show that the variation in land price of a region may be spatially dependent and the high land price of a zone can spread to its neighbouring areas (Nanda & Yeh, 2014). This phenomenon can be modeled through a diffusing process. Suppose that a central cell has value $D_{O,t}$ and can diffuse D_{Rate} of its value to the neighbouring cells at time t : for Moore neighbourhoods (8-neighbour), at time $t+1$, each of them will get $D_{MN,t+1}$; for von Neumann neighbourhood (4-neighbour), each of them will get $D_{vN,t+1}$.

The value of center cell will be as $D_{O,t+1}$. The model can be defined as follows:

$$\text{Moore Neighbour: } \begin{cases} D_{O,t+1} = D_{O,t} * (1 - D_{Rate}) \\ D_{MN,t+1} = D_{MN,t} + D_{O,t} * D_{Rate} / 8 \end{cases} \quad (6.9)$$

and

$$\text{von Neumann Neighbour: } \begin{cases} D_{O,t+1} = D_{O,t} * (1 - D_{Rate}) \\ D_{vN,t+1} = D_{vN,t} + D_{O,t} * D_{Rate} / 4 \end{cases} \quad (6.10)$$

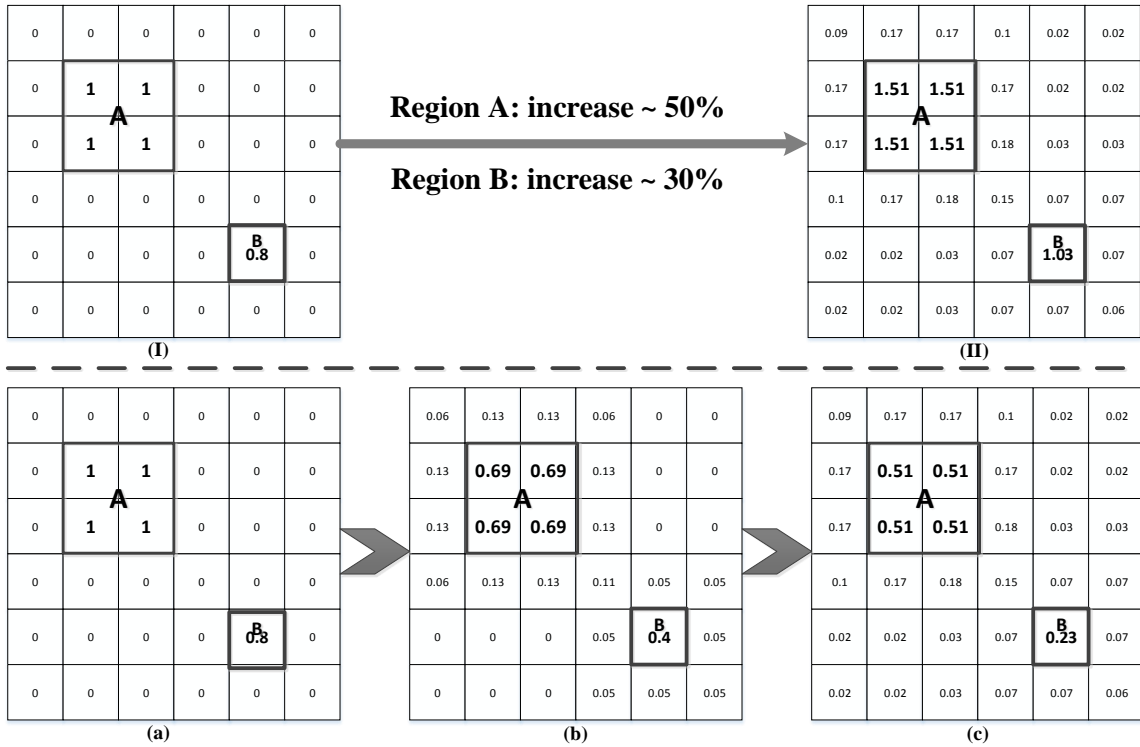


Figure 6-6. Land Price Agglomeration Model.

For example, in a city space represented by Figure 6-6(I), suppose a region A is a city center and region B is an edge city. The land price around A is higher than in region B (1 vs. 0.8). Firstly, we assume at time $t=0$ the land price at regions A and B both initially increases by 100% (Figure 6-6(a)) and the price change of the center cell can drive the land price of surrounding areas to increase by 50% in total. Then after one-time diffusion ($t=1$), the possible land price increase in the whole area will be like the situation in Figure 6-6(b), (After diffusing 50% of its value, the price increase of a cell in area A will be 0.5. Meanwhile it will receive $0.06*3$ from three neighbour cells.) If we run the diffusion model for one more time with the same diffusion rate ($t=2$), the results will be Figure 6-6(c). The land price surface will be like Figure 6-6(II). The rate of actual land price increase in

region A will be around 50% and it will be around 30% in region B. We call this land price evaluation method the Land Price Agglomeration Model (LPAM), which can be used for both industrial (indicated as I) and residential (indicated as R) land uses.

One problem when implementing the model to generate the land price surface is that time t is unknown. However, if we define the land price increase rate of the industrial land use for a city center as D_I , and define a high value D_{OI} as starting point, then we run the diffusion model with diffusion rate D_{Rate} continuously until the land price increase rate of the central land parcel equals D_I . As the case in Figure 6-6, suppose $D_{OI} = 1$ and $D_I = 0.51$. After running the diffusion model two times, the increase rate of the central land parcel comes to 0.51, which is close to reality. Therefore, through adjusting the initial diffusion value D_{OI} and diffusion rate D_{Rate} , we can generate a land price surface that is highly consistent with reality.

6.3.6 Measuring the effect of government policy

Urban land use zoning systems are widely adopted to foster and support industrial development (Lefcoe, 2005; Fan & Li, 2009). Industrial factories located inside specific functional zones will receive more support from local government than those ones outside the planned functional zones.

The implementation of preferential government policy in a region can be described as follows:

$$Z_{cj} = \kappa * \begin{cases} 1 \\ 0 \end{cases}, \quad (6.11)$$

where 1 means current land parcel c is located inside a planned functional zone, while 0 means it is located outside.

6.3.7 Land demand and supply

In a city, the supply of land is usually constrained by its site attributes. Large slopes, water bodies, and other natural barriers define the available land for urban construction use. At the same time, the varying situation of land location in a city also helps create a geography of urban land supply. In general, due to the deterrent effect of distance, land parcels near the city center have a higher likelihood of being developed, while peripheral land parcels have less chance (Rose, 1989). This phenomenon can be described as

$$LS = \sum_{n=1}^N s(n) * \exp(-\delta u), \quad (6.12)$$

where u is the distance of land parcel n to the nearest undeveloped land parcel from the city center, $s(n)$ is the area of land parcel n , LS is the total land supply, and δ is a distance decay coefficient.

Generally, the limitation of land supply will have a negative effect on the profitability of industrial factories and a positive effect on the profitability of residential housing development. The declining undeveloped land reserve will increase the land rent price for industrial uses and force industrial factories to move to make room for residential uses (Raymond, 1998). Conversely, the decline or restriction of developable/re-developable land reserves can lead to higher housing prices and real estate development profit (Peng & Wheaton, 1994). The impact of land reserve on industrial and residential profits can be described as follows:

$$\begin{cases} \frac{\partial LP_I}{\partial t} = a_I \frac{\partial LS_A}{\partial t} \\ \frac{\partial LP_R}{\partial t} = a_R \frac{\partial LS_{AI}}{\partial t}, \end{cases} \quad (6.13)$$

where LP_I is the profit control for industrial use, P_R is the profit control for residential use, LS_A is the agricultural land reserve, LS_{AI} is the combined agricultural land reserve and current industrial land, a_I is the coefficient for industrial use, and a_R is the coefficient for residential use. a_I is negative and a_R is positive. For computational convenience, we further define P_I and P_R as follows:

$$\begin{cases} LP_I = a_I LS_A / T \\ LP_R = a_R LS_{AI} / T, \end{cases} \quad (6.14)$$

where T is the land supply reserve planned for development by a city for the planning period.

6.4 Parameter estimation and model calibration

In addition to the 2002, 2006, 2013 land survey, industrial land use policy, industrial land use plan data, digital road networks, digital metro networks, and city administrative division maps were collected from the Shanghai Urban Planning and Land Resource Administration Bureau for the simulation of industrial land use growth and evolution in Shanghai. From the current industrial land use map, the city includes two detached islands. Considering the spatial connectivity effect, the study excludes the islands (Figure 6-1).

Before simulating the evolutionary process of industrial and residential land uses in Shanghai, model parameters need to be evaluated and calibrated based on actual land use

data. Figure 6-7 presents a summarized simulation procedure in which individual model input factors and unknown parameters are identified to illustrate the determinants of industrial and residential land use competition processes in the city.

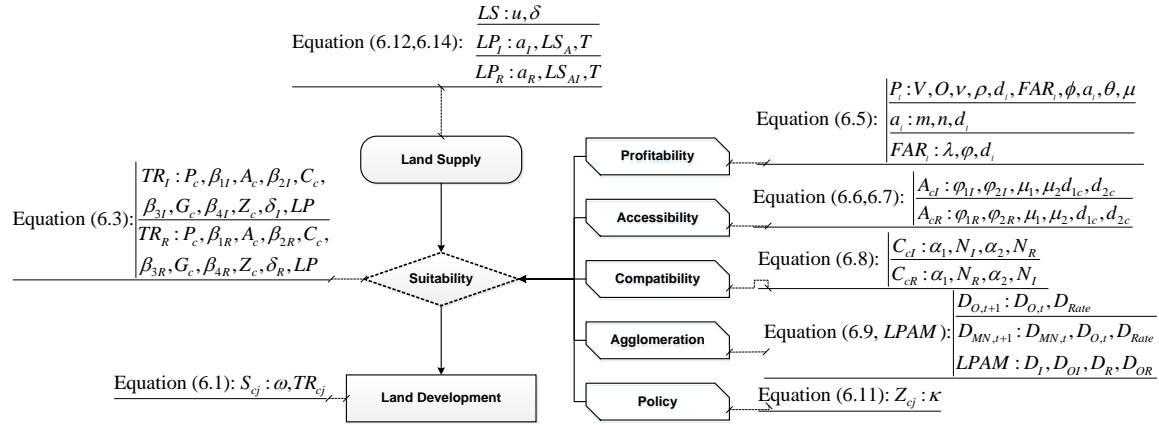


Figure 6-7. Simulation model framework and parameters.

6.4.1 Land use Profit Model parameters

As land profitability is the precondition of the dynamic model, this study first generates the theoretical land price surface of the city. We collected 250 parcels of the traded residential land and 100 parcels of the traded industrial land between 2011 and 2013 from the website of the Shanghai Municipal Planning and Land Resources Administration (<http://www.shgtj.gov.cn/>). The collected land parcel data include several attributes for each sold land parcel: the serial number, the address, the area, the price, and the floor-area-ratio. All these data are employed in regression models to evaluate all the parameters in the LbFP model (Figure 6-7: equation (6.5)). Therefore, the theoretical land price surface of the city can be delineated as a function of distance to city center (d_i) (Qiu et al., 2015):

$$P_i = 96331.086 * FAR_i * e^{(-0.315 * \lg(a_i))} * e^{(-0.087 d_i)}$$

$$a_i = 32829.411 + 552.861 * d_i$$

$$FAR_i = 3.104e^{-0.021d_i}$$

The distance of each land parcel to the city center (d_i) is estimated by using the ArcGIS spatial analysis toolsets (Euclidian Distance). The original point of the Shanghai Local Coordinate System is used as the city center to calculate the distance.

6.4.2 Agglomeration effect model parameters

The land prices generated from the LbFP model deviate from reality as they do not consider agglomeration effects. To take this into account, the theoretical land price model is adjusted by introducing the Land Price Diffusion Model (Figure 6-6) as discussed in Section 2. Three parameters need to be evaluated in the proposed method (Figure 6-6 and LPAM): the diffusion rate (D_{Rate}), the diffusion increase for residential land use D_{OR} , the diffusion increase for industrial land use D_{OI} , the diffusion limit for residential land use (D_R), and the diffusion limit for industrial land use (D_I). Diffusion increase represents the initial land price increase at the starting point of diffusion, and the diffusion limit represents the actual land price increase. According to the statistics from the Shanghai Statistical Yearbook, there was an 8% annual increase of land price across the city in both residential and industrial categories. Therefore, the diffusion limit for both residential (D_R) and industrial (D_I) land is specified as 0.08. Before simulation, diffusion increase values (D_{OI} and D_{OR}) are assigned to all residential or industrial land parcels. Then the diffusion model is the employed across the space until the maximum value equals the predefined diffusion limit (D_I, D_R). Through the multi-round diffusions, the central area land parcel will contain a yearly land price increase equal to a diffusion limit, and the rates of land price increase in

other places will be lower than in the central portion. Then we use the simulated land price surface to adjust the theoretical one by keeping the theoretical price if it is higher than the simulated one and replacing the theoretical price if it is lower than the simulated one as follows:

$$P_i = \begin{cases} P_{i,simulated} & : \text{when } P_{i,simulated} > P_{i,theoretical} \\ P_{i,theoretical} & : \text{when } P_{i,simulated} < P_{i,theoretical} \end{cases} \quad (6.15)$$

Figure 6-8a shows the theoretical land price surface generated from classic land price theories. The land prices of the city are decreasing from the city center concentrically outward. Figure 6-8b shows the adjusted land price surface of the city by using the proposed LPDM. It demonstrates obviously that the prices in the areas around edge cities are higher than other land parcels in the same stop zone. Clearly, the adjusted land price surface is more consistent with reality.

Thereafter, the unknown parameters in this model include D_{OI} and D_{OR} .

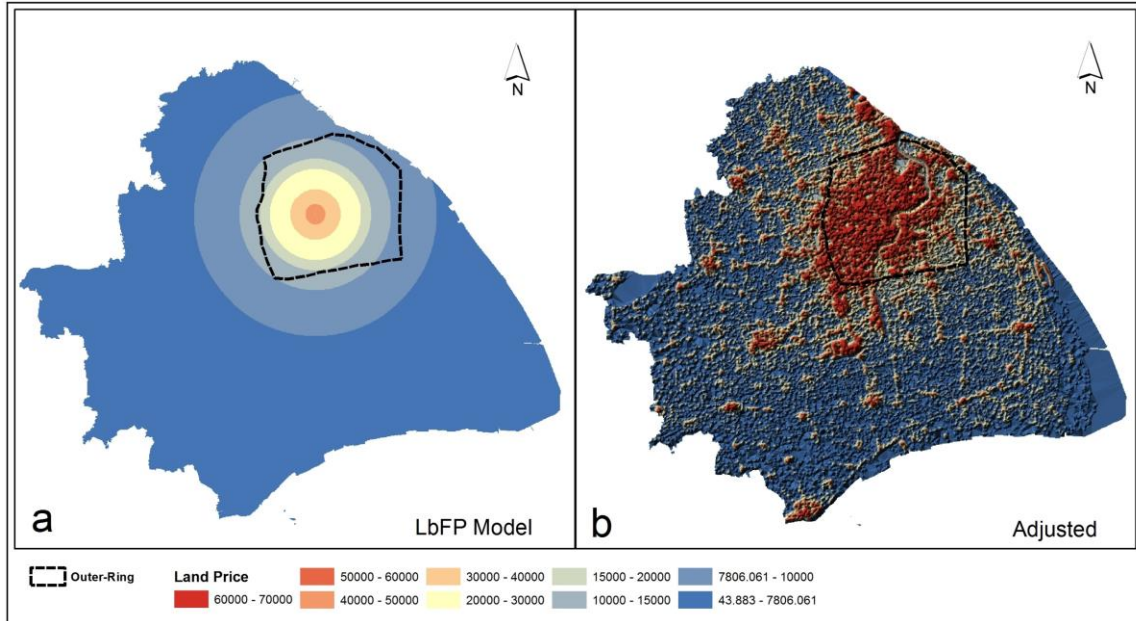


Figure 6-8. Theoretical and adjusted land price surface.

6.4.3 Industrial land use policy model parameters

To curb urban sprawl, the city introduced the Concentrated Construction Zone (CCZ) and Industrial Zone (IZ) systems. According to the regulation, all of the residential land development should be located inside of each CCZ, and all of the industrial land should be located inside each planned industrial land use zone. To model the constraining effect of this regulation, the maps of concentrated urban construction zone across the city were collected. If a newly residential land is located inside the planned CCZ, it will be assigned a value of 1, if not it will be assigned a value of 0.

Moreover, according to the Shanghai 12th Five Year Plan, urban industrial land use in Shanghai is divided into three categories: general urban industrial land, industrial park, and industrial base. Industrial park includes city-level and state-level industrial parks.

State-level industrial parks and industrial bases sit in the highest order, because they are supported by the state. City industrial parks are delineated and supported by the city and have higher orders than general urban industrial land. Therefore, this study takes general urban industrial land as the baseline and applies a weight κ to each category of industrial land. The land parcels located inside the planned general urban industrial land zone boundaries get a single weight ($\kappa = 1$), while the land parcels located inside city industrial parks get a double weight ($\kappa = 2$) and the land parcels located inside national industrial parks get a triple weight ($\kappa = 3$) for industrial purposes.

6.4.4 Model parameters for accessibility, compatibility, and land supply

The parameters generated from the metro and highway model include: distance decay coefficient (equation: (6.7) μ_1 and μ_2), their corresponding impact weights for residential use (equation: (6.6) φ_{1R} and φ_{2R}) and industrial use (equation: (6.6) φ_{1I} and φ_{2I}). All are unknown parameters and need to be estimated.

For land use compatibility (equation (6.8)), we assign $\alpha_1 = 1$ for the same land use compatibility, and assign $\alpha_2 = -1$ for non-compatibility. N_j is the compatible Moore Neighbour ratio (out of 8) and N_k is the non-compatible Moore Neighbour ratio.

β_{1I} , β_{2I} , β_{3I} , β_{4I} , β_{1R} , β_{2R} , β_{3R} and β_{4R} (equation (6.3)) are the coefficients for the contribution of theoretical profit, transportation accessibility, land development compatibility, and urban planning policy respectively. They all are unknown and need to be estimated.

For land supply (equation (6.12)), we treat $S(u)$ as number of regular land parcels instead of area. Then after many rounds of simulations, we found the annual land supply rate close to reality when $\delta = 1$. As one of the goals of this study is to delineate the competition relationship between industrial and residential land uses, we treat industrial and residential land supply equally and designate both a_I and a_R (equation (6.14)) as the reciprocal of total remaining developable land. This means there is no land supply bias, such as reducing industrial land deliberately in the city.

Moreover, as the model only considers industrial and residential land use types, the value of ω in the suitability logit model (equation (6.1)) makes no difference between the two probability results. Therefore, we assign ω as 1. Also, to model the randomness of land development activities, we assign ε in equation (6.3) as 0.1. It means that the suitability of the current land parcel is high, but still has a 10% chance of not being developed. The assigned value comes from multi-time simulations.

6.4.5 Model implementation and calibration

All the land use maps and boundary data were first digitized and stored in the GIS database as vector data and were then converted into raster formats using a raster grid of 120 * 120 square meters. To simulate land development using the developed models, the raster data were transformed into ASCII files. Then we used “Euclidean Distance” tool in ArcGIS to generate the distance of each cell to highway and metro lines, respectively. The generated raster distance data were also transformed into ASCII files with the same cell size as the others. With all the data, we coded the model in one of the most popular simulation

platforms, NetLogo (Wilensky, 1999). The ASCII data files were imported into the model directly by using the GIS extension in NetLogo.

With all these unknown parameters, this study employs R and Genetic Algorithm (GA) for evaluations, with the help of the RNetLogo extension package (Thiele et al., 2012). As denoted in the following simplified source codes, we first created a 19*10 data matrix (*a*) to store all the possible values for the 19 unknown parameters. We then call the Logo-language programmed model (*Industry Model.nlogo*) by using *NLLoadModel()*, and use the *NLCommand* to assign the 19 global parameters possible solution values. After the model is run several times (*NLDoCommand()*), an objective value is returned to the GA model. The GA model runs with real value, population size is set as 10, and the maximize generation is set as 20. The objective function of the Genetic Algorithm method is to maximize the volume of matched simulated pairing 2006 industrial land cells.

Simplified source codes:

```
library(RNetLogo, GA)
```

```
a1 <- seq(0, 1, by = 0.1) → a19 <- seq(0, 10, by = 1)
```

```
a <- rbind(a1...a19)
```

```
NLStart(nl.path)
```

```
NLLoadModel("... /Industry Model.nlogo")
```

```
NLCommand("Setup")
```

```
NLCommand("set mu1", a[1,x1]) → NLCommand("set Iparkweight", a[19,x19])
```

```
NLCommand("Initiate")
```

```
NLDoCommand(10,"RunModel")
```

```
NLCommand("GAResult")
```

```

return(NLReport("GAIResult"))}

GA <- ga(type = "real-valued", fitness =function(x) + Rastrigin(x[1], → x[19]), min
= c(1, → 1),max = c(12, → 12), popSize = 10,maxiter = 20, monitor = TRUE)

summary(GA)

```

The evaluated parameters are shown in Table 6-2.

Table 6-2. Calibrated parameters.

Parameter	μ_1	μ_2	φ_{1R}	φ_{2R}	φ_{1I}	φ_{2I}	D_I	D_R	D_{Rate}	
Estimated value	0.5	0.6	0.8	0.2	0.3	0.7	0.075	0.074	0.3	
Parameter	β_{1I}	β_{2I}	β_{3I}	β_{4I}	β_{1R}	β_{2R}	β_{3R}	β_{4R}	δ_I	δ_R
Estimated value	0.6	0.7	0.5	0.8	0.5	0.8	0.7	0.5	0.4	0.5

In the following section, this study is going to validate the model based on industrial land survey data (2006) of Shanghai and simulate its future industrial land use.

6.5 Simulation results and discussions

Using the parameters and coefficients calibrated above, the study simulated the industrial land development and its co-evolutionary processes with residential land uses. The simulation results not only prove the validity and effectiveness of the newly proposed model, but also predict the future industrial land use pattern of the city.

6.5.1 Historical land use verification

To validate the proposed model, we simulated the industrial land use pattern of the city in 2006 to compare with the available land survey data. Figure 6-9a shows the simulated 2006 industrial land use distribution in Shanghai and Figure 6-9b is the actual industrial land use

of the city in 2006. Visually, it can be seen that the simulated 2006 industrial land use is highly correlated with the actual industrial land use in both quantity and distribution. Comparing to the industrial land use of the city in 2002 (Figure 6-1), the simulated results (Figure 6-9) illustrate clearly that the spatial repositioning of industrial land uses from central areas to suburban-rural areas. The actual industrial land use map (Figure 6-9b) also confirms that the majority of industrial land use of the city was re-distributed to outside the Outer-Ring Road, which is around 15 kilometers from the city center. The simulated industrial land use spatial pattern is highly consistent with the historical land use data.

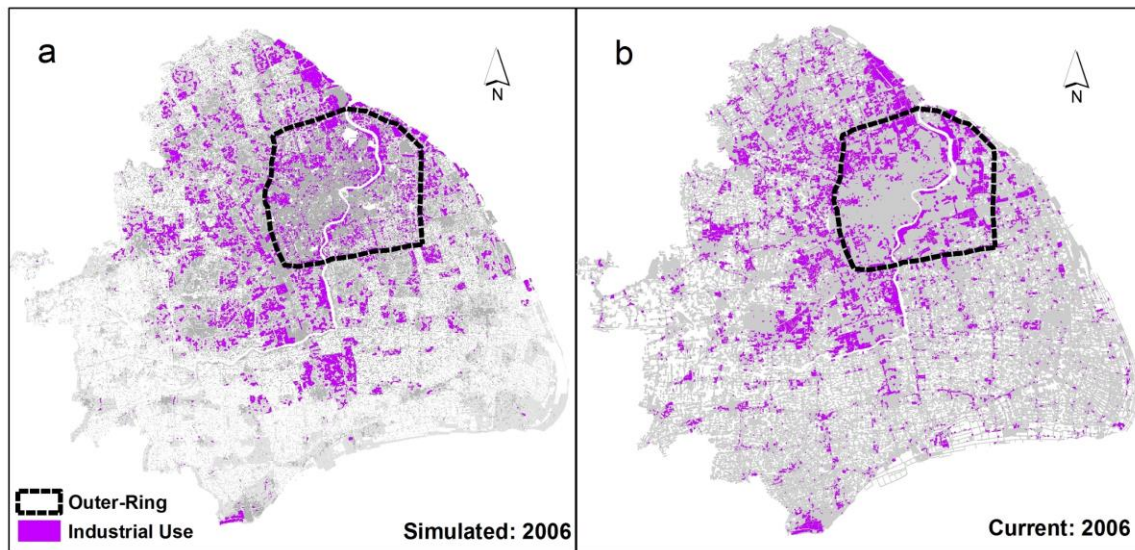


Figure 6-9. Comparison between simulated and actual industrial land use (2006).

To further validate the accuracy of the simulation results, we divided the city space into 5 km quadrat rings to compare the simulated and actual land use in each of quadrat rings (Figure 6-10). The mapped results show that the built-up model simulated the actual industrial land use with a high accuracy inside the 30-km ring from the city center. The simulated industrial land uses are consistent with reality in more than 51% quadrats inside the 40-km ring at less than 30% deviation level. However, there are high-spatial

correlations among deviated quadrats. For instance, the model over-estimated the industrial land use between the 20 and 35 km rings in the southwest direction. Meanwhile, the model under-estimated the industrial land use at the area close to the city administrative boundaries.

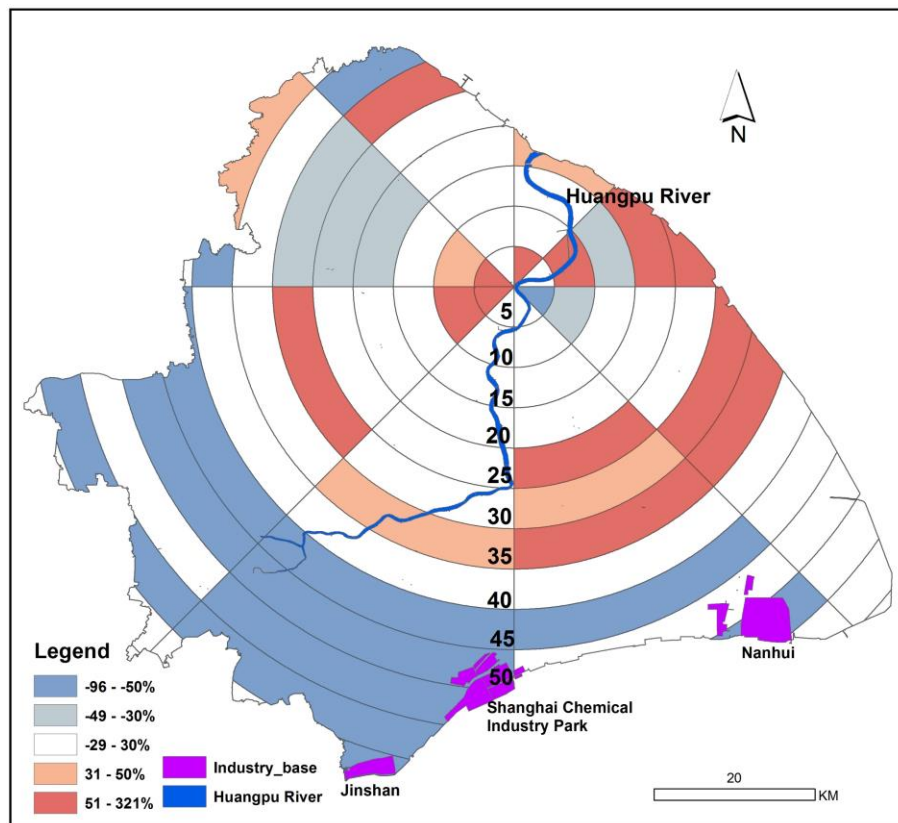


Figure 6-10. Quadrat rings simulated and real land use data comparison.

For the over-simulated area in the southwest direction, the comparison between simulated result and real land use shows clearly that the Huangpu River prevents the continuous industrial land use expansion to the south side of the city (Figure 6-10). For the outskirts areas, the balanced regional development strategy and polluting industrial factory isolation policy are possible factors promoting the development of fringe areas. For example, the

Shanghai Chemical Industrial Park (Figure 6-10) is located at the very south end of the city and next to the East China sea.

6.5.2 Impact on urban land use and land cover change (LUCC) simulation

To further verify the effectiveness of the proposed model, we simulated the construction land change of the city without a differentiation of various land use types (Figure 6-11a). We then compared it with the simulated results from the proposed model in this study (Figure 6-11b) and the actual land-cove of the city (Figure 6-11c).

By using exactly the same theoretical logit model and land use profit model, only without the industrial-residential competition theory, there are major differences between the two results. The result without consideration of different land use types (Figure 6-11a) clearly demonstrates a deconcentrating pattern (as indicated by dash line), while the proposed model result (Figure 6-11b) more closely resembles the actual land use pattern of the city, forming a natural development spatial structure. This provides a convincing example that it is necessary to differentiate various land use types for a credible land use modelling and simulation result.

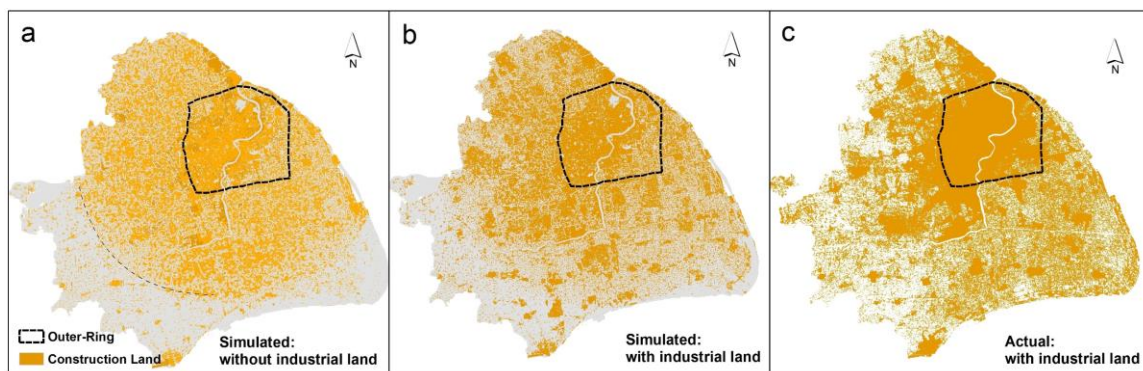


Figure 6-11. Comparison results between models with/without differentiation of industrial uses.

6.5.3 Land price prediction

The proposed IRLUCM simulates industrial uses, competing against residential and agricultural uses. According to the classic urban land price theory, the land price decreases from the central area outward concentrically (Alonso, 1964; Brueckner, 2011). This means that the optimal distance of industrial profit increases from the city center if the increasing land price continues. Previous study found that the most profitable distance for Shanghai in 2013 is 40–50 km away from the city center (Qiu et al., 2015). Therefore, industrial factories should be located around the 40–50 km ring belt. The de-concentrating trend is confirmed in the simulation results illustrated above. However, the current and predicted spatial pattern of industrial land uses also demonstrates discrete trends (Figure 6-12).

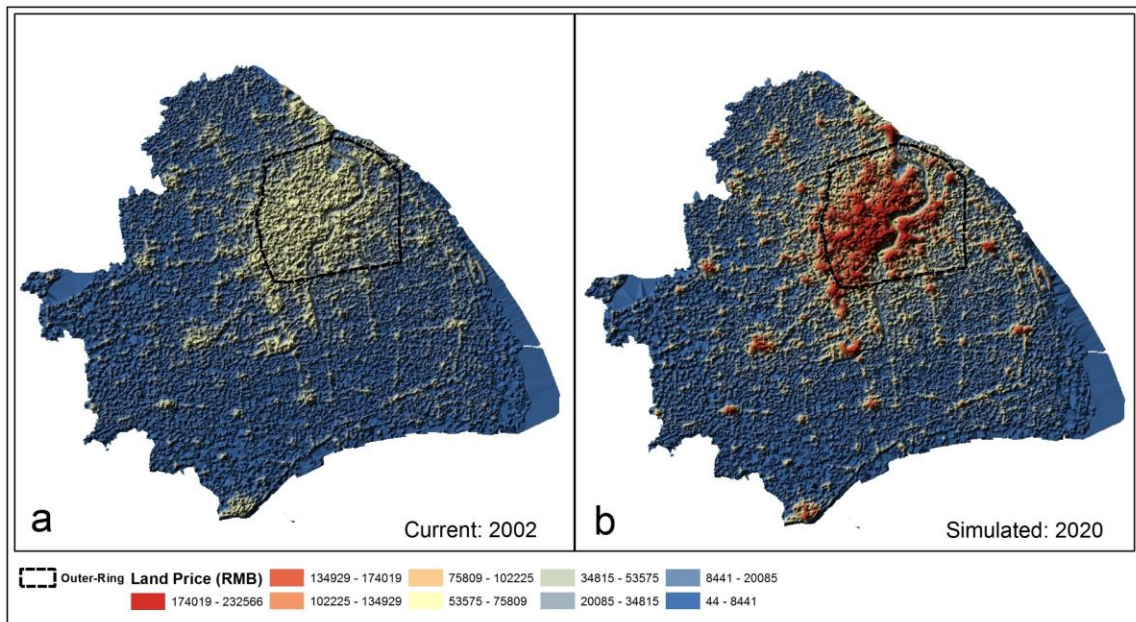


Figure 6-12. Land price surfaces.

To better understand the driving forces behind the location-allocation of industrial land use of the city, this study generated the land price surfaces of the city in 2002 and 2020,

respectively. Figure 6-12a is the adjusted land price surface of the city in 2002 based on the Land Price Agglomeration Model simulation results and land price sample data. The simulated land price surface (Figure 6-12b) demonstrates that the land price of the central city might increase quickly if urban land development continues to expand. Different from traditional concentric circles of diminishing land value away from the city center, the simulated land price has a multicentre pattern that resembles more closely the urban space reality and indicates that the existing land use pattern impacts the land prices of the surrounding areas. In this case, the growth of edge cities and new centers in suburban areas alters the land value surface significantly. As a result, the industrial land use pattern of the city is heavily influenced by the varying land price distribution around the suburban nodes.

6.5.4 Industrial land use prediction

The simulated 2020 industrial land use spatial distribution shows that the industrial land use of the city will further suburbanize and cluster in and around planned industrial parks, especially those located in the suburban and rural areas outside of the Outer-Ring Road (Figure 6-13a). A current industrial land use map (2013) clearly confirms that industrial land use around the city center will be pushed further out to the suburban area (Figure 6-13b). The suburbanization phenomenon of the industrial land use of Shanghai is consistent with case studies in metropolitan areas around the world (Clark & Burt, 1980; Viehe, 1981; Walker, 2001).

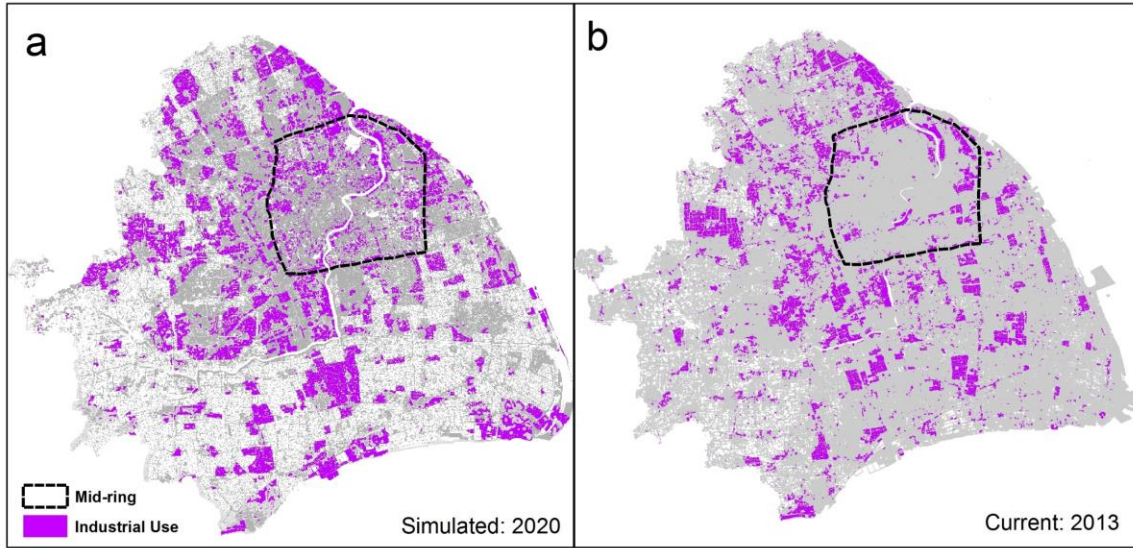


Figure 6-13. Simulated industrial land use in 2020.

Meanwhile, both the current and predicted industrial land uses of the city show that the industrial land use of the city is clustered around planned IZs. Spatial statistics of the current and predicted industrial land use data show that 59.0% of industrial land of the city in 2006 was located inside or within a 1-km buffer zone of the planned IZs. This number was estimated to be 71.2% in 2013 and will decrease to 60.1% in the predicted 2020 land use map. This result is inconsistent with the industrial development strategy of the city. According to the Document on Optimizing Industrial Land use Spatial Distribution issued by Shanghai Municipal Government (HUFUFA [2013] 33), the city is going to congregate industrial factories inside the planned IZs and reclaim the dispersed industrial land. However, the simulated results show that the policy may be violated, because of the path-dependency of land development.

6.6 Conclusion

This paper develops the IRLUCM model to simulate the evolutionary process of industrial land uses. Instead, of treating land development as a unitary process of single land use, the IRLUCM internalizes the competition mechanism that regulates the relation between industrial and residential land use in a city. Embedded in the spatial modelling framework of cellular automata, the IRLUCM implements classic urban land use theories to simulate dynamically the development and redevelopment processes of urban industrial land in Shanghai, China. Findings of this study contribute to the field of land development simulation and modelling in several aspects.

Firstly, land development simulation fails to differentiate different land use types and their competition relationships in the literature. As such, the results from conventional land development simulation tend to have limited success in estimating land development quantity and delineating its spatial pattern and process. To overcome this limitation, this study develops the urban land use competition framework that differentiates agricultural, industrial, and residential uses and incorporates their competition relationships into the IRLUCM model to improve the simulation results. The comparison experiments between models with and without differentiation of land use types clearly demonstrate that there are major differences in modelling results (see Figure 6-11). The simulated results generated from the proposed model closely resembles the actual land use transformation patterns. The study illustrates that any urban land use policies generated from conventional modelling and simulation will be misleading in guiding land development activities if

researchers continuously ignore the impacts of different land use types and their competitive relationships.

Secondly, in developing the IRLUCM model, this study implements the P-R test method well-known in competitive conduct study. In the model, transportation accessibility, land use compatibility, land use agglomeration, and government policy are integrated as land profit contributing factors, while the developable land reserve is treated as a control factor. Each of the factor is defined using classic urban study methods. From the land use competition perspective, the IRLUCM model not only can simulate land development process, but it also can delineate the redevelopment process of urban land development. The urban redevelopment process is often omitted in land use and land-cover change models (Yeh & Wu, 1996; Batty, 1998; Wu & Martin, 2002; Moreno et al., 2008; White et al., 2012). However, most of the cities around the world are undergoing redevelopment processes for various reasons. The omission of the delineation of the land redevelopment process will fail to simulate LUCC in metropolitan areas.

Thirdly, in addition to the classic urban land price theory, this study introduces the LPAM to simulate the price surface of a city. Land price diffusion and local agglomeration effects are considered in addition to classic distance-decay theory (Alonso, 1964; Brueckner, 2011). Instead of a concentric-declining pattern, the simulated land price surface is more consistent with reality in reflecting the multicenter phenomenon in a large metropolitan area.

Fourthly, the study proposes a new parameter estimation method by using evolutionary algorithms in the IRLUCM model. Sample data regression and multi-time experiment,

which also indicated as analyzed and designed methods, are two of the main LUCC model parameter estimation methods (Couclelis, 2001). Both are very time consuming and highly inaccurate. This study first uses evolutionary algorithm and historic data to estimate unknown parameters though multi-generation training. It opens a new window for similar studies.

With the successful simulation of industrial spatial evolution in Shanghai, China, this study indicates that it is possible to build a two-dimensional model to delineate the evolutionary process of industrial land use temporally and spatially. Different from mainstream industrial spatial redistribution research, which delineates the de-concentration or suburbanization process of the manufacturing industry among mega cities qualitatively (Viehe, 1981; Henley, 1994; Walker, 2001; Hudalah et al., 2013), this study simulates the dynamic industrial de-concentration quantitatively. The findings of the spatial industrial diffusion process in the study area are, generally, consistent with the empirical observations in the literature (Ning & Yan, 1995; Marton & Wu, 2006; Wu, 2008). The outcomes of this study can greatly help urban managers and planners to understand the city better.

There are still several issues that need further exploration. Our model holds land development profit as one of the core factors that determines the location and relocation of industrial factories. There are many other elements which may influence land use decision-making process of an industrial factory. For instance, a factory will not move from its current location easily considering its path-dependency, and it will also take local government policies and other preferences into its consideration when it chooses a location for its future production activities.

Even though the case study of Shanghai shows that there is a great potential to apply the proposed model to other cities, there are several challenges that need to be considered. Firstly, as a metropolitan city, the land profit of Shanghai plays a major role in determining land use, especially industrial land use. This cannot be compared with a medium-size or small-size city where there are no obvious land price changes among different locations. Secondly, the market, instead of policy and other factors, dominated the de-concentration process of industrial land use in Shanghai. Hence, it might be difficult to apply the model to a city where government policy, planning strategy, and other factors dominate land use type and direction.

Chapter 7 Conclusion

Through these four papers, this study finds that:

First, the modes of land development in Chinese cities are not singular and uniform. Rather, they are divergent and contingent upon local conditions and spatiality of government policy. The case of Shanghai illustrates the coexistence of five different modes of land development in one city. Their spatial distribution and development intensity are strongly shaped by the city's spatial planning and delineation of development zones such as Concentrated Construction Zone and Industrial Zone. Different from the crude explanation of City-based Land Development in the literature, this paper nuances how land development processes are differentiated and localized and shows why current land simulation models have limited success in the Chinese context. The case study of Shanghai illustrates the shortcomings of City-based Land development theory and demonstrate the need for more studies investigating different land development modes between and within Chinese cities. The multi-track land development processes in Chinese cities mean that current land development modelling and simulation can not capture the actual land development process properly because most models assume a singular mode of land development for any given Chinese city. New methodologies are needed to take into account the fact of divergent land development processes.

Second, in addition to government policy and environmental factors, this study introduces community cohesion theory into the model to illustrate the influence of population on the spatial structure of urban land use. In it, households act as autonomic agents who “feel”

the social, economic status of the current neighbourhood and can choose to relocate to other ones. Afterward, the popular and development status of a neighbourhood impact land development activities. Through this way, this study innovatively creates a dynamic evolutionary model integrating both population and land development dynamics. Moreover, this study first uses evolutionary algorithm and historic data to estimate unknown parameters through multi-generation training. It opens a new window for similar studies. The success of the modelling and simulation in this study confirms the literature that urban land use development of a city is highly affected by its household social, economic, environmental characteristics.

Third, with the successfully modelling and simulating the industrial spatial evolution in Shanghai, China, this study shows that it is possible to build a computer simulation model to delineate the dynamical evolutionary urban land use process through appropriate modelling methods. Different from main stream industrial spatial redistribution researches, which delineate the deconcentration or suburbanization process of manufacturing industry among mega cities qualitatively, this study simulates the dynamic industrial deconcentration quantitatively. The findings of spatial industrial diffusion process in the study area are in consistent with the empirical observations in literature. The results of this study can greatly help urban managers and planners to understand the city better.

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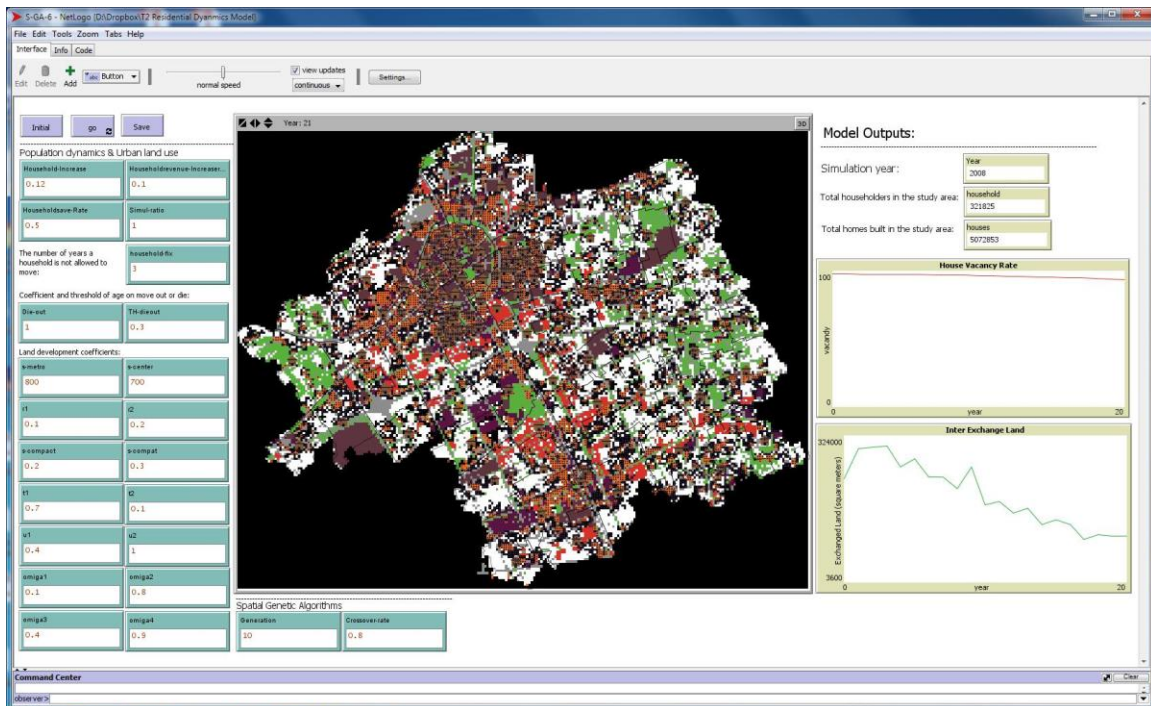
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Appendix 1: Land development model summary.

	Market economy		Socialist market economy (China)		
Land development model	MbLD	GILD	CbLD	IsLD	ZbLD
Land attribute	Commodity		Social, political, food security		
Land rights ownership	Privately owned		Urban state-own, rural collective-own		
Intermediary agencies	Independent legal entities	Independent legal entities, City government, government-funded institutes	Independent legal entities, state, state-owned enterprises	Local governments, collectives, TVEs	state, state-owned enterprises
Institutional system	Juridical individualism, Well-defined legal system		State policy, legal system		
Market efficiency	Competitive market, efficient market		Limited competition market		
Mechanism	Bid for price, profit seeking	place-making, profit-seeking, favourable policy, government subsidy	Housing policy relaxation, industrialization, infrastructure upgradation	production process transformation, foreign investment attraction	special development zone fever, new city movement
Results	concentric land use expansion	spatial inequality, multi-centers, social equality	urban land use expansion, suburbanization	rural construction land boom, agriculture land loss	leap-frog development, multi-centers, urban sprawl

Appendix 2: Population-Driven Urban Land development Model.



Appendix 3: Industrial and Residential Land use Competition Model

