Driving forces of urban land-use change in Taiyuan, China

A MASTER THESIS

Fei Ma

(2619627)

Faculty of Economics and Business Administration Department

Spatial, Transport and Environmental Economics

Vrije Universiteit Amsterdam

Abstract

In order to understand the urban land-use changes and the factors affecting the transition in Taiyuan, China, this study examines the changes in major land-use categories in Taiyuan from 1995 to 2015, and develops systematic models in analyzing the spatiotemporal characteristics, dynamics and transitions among these categories. By establishing logistic regression model, this study investigates the driving forces of urban land-use changes and explains the heterogeneity of the effects of these factors in different regions of Taiyuan. This study provides insights for the study of urban land transition in small- and medium-sized cities.

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Contents

1. Introduction

The land is the material basis of human activities on the earth. Land use and land-cover changes directly influence the biodiversity and climate processes, and such changes also play a key role in shaping the economic and socio-political conditions (Bettencourt & West, 2010). In the 1990s, the International Geosphere Biosphere Programme (IGBP) introduced Land Use and Cover Change (LUCC) project to develop the understanding of dynamics of land-use changes and improve the capacities land-use prediction. A growing number of researches concerning LUCC lead to the establishment of 'Land Change Science', which combines sociology, economics, geography and nature sciences (Moran et al, 2004). Since 2005, land use scientists have been organized through the Global Land Project (GLP) (Ojima, 2005). In this project, a concept of land system has been introduced, which is aimed at analyzing the interactions between human activities and natural surroundings within an integrated socio-ecological system (Verburg et al, 2015).

Urbanization is a gradual process of long-term accumulation and development, which is accompanied by the changes of economy, social structures, technologies and land use distribution (Brenner, 1998). In China, this process is extremely intensified in the last three decades. The urbanization rate has increased from 26.4% in 1990 to 59.58% in 2018 (National Bureau of Statistics of China, NBSC). According to recent literatures, it is predicted to maintain a strong upward trend in the next couple of decades and will reach 70% by 2050 (United Nations, 2018). The fast pace of urbanization in China leads to the concentration of population and the accumulations of capital and industry agglomeration in urban area within a short period of time, which inevitably brings about a series of impacts on socio-economic and ecological environment, for instance, air quality deterioration, traffic jam, agricultural frustration, etc (Chen & Frauenfeld, 2016).

Furthermore, most of the influences are, directly or indirectly, related to the unreasonable use of land, which is mainly embodied in the disorderly expansion of construction land, continuous de-agriculturalization, and reduction of vegetation (Xie et al, 2005). Therefore, the efficient and rational use of land is one of the key factors to facilitate the socio-economic and ecological sustainable development in the future. According to the government policy, The "National Land Planning Outline (2016-2030)" issued by the State Council in 2017 emphasizes the necessity to accelerate the transformation of land use and utilization methods, and to improve the quality and efficiency of the land development process. The study of investigating the spatio-temporal characteristics of land-use and its driving forces not only contributes to examining the mechanism of urban land-use changes, but also provides insights in the sustainable way of land utilization in the future process of urbanization.

Among the study of land use changes in China, most of the researches are focused on mega cities in the core and coastal areas, such as Beijing (Han, 2015), Shanghai (Shi et al, 2018), and Guangzhou (Ye et al, 2018), or on the emerging cities that has been invested with colossal resources like Shenzhen (Qian et al, 2016) and Chongqing (Guan 2019. On the other hand, it is argued that urbanization in the future will majorly occur in medium- and small-sized cites instead of mega cities (Cohen, 2004). Meanwhile, in China's top 100 cities based on the ranking of GDP, there are 43 cities that are medium-sized cities where the urban population is lower than 6 million (NBSC), but there is little discussion on the landscape changes in these medium-sized, especially inland cities, the study of which is supposed to provide significant insights in understanding the general characteristics of urbanization in China (Xiao, 2006).

Taiyuan is the capital city of Shanxi Province, which has been an important energy and chemical industry base of the north China. In the last two decades, Taiyuan experienced high-speed economic, social, cultural development. Until 2018, the population has been over 4.4 million, among which the urban population constitute 84.7% (NBSC 2018). And the GDP has reached 388 billion Yuan, taking up one fifth of the provincial GDP (NBSC 2018). In China's five-tier city system, Taiyuan locates at the lower second tier, which has the medium development scale in China (Ni, 2016). The study of Taiyuan's land use changes, therefore, can be used as a proper reference of the medium-sized cities, especially in the central and western regions.

On the other side, Taiyuan has its own uniqueness comparing with other cities in the aspects of geographical and economic structure. Taiyuan is positioned at the northern end of the Taiyuan Basin. Unlike most Chinese provincial capitals, Taiyuan is surrounded by mountains on three sides, and the whole terrain is high in the north and low in the south. Meanwhile, Taiyuan is a typical industrial city that heavily depends on traditional energy industry, and the monotonous industrial structure is always one of its labels. To some extent, these factors, without excluding the others, distinguish its spatial-change particularity from other cities. In this sense, this study is an attempt to introduce new perspectives for urban space research about China.

In order to understand the general and particular features of urban land-use change in Taiyuan, this study proposes to answer the main research question: what are the major factors contributing to the urban land expansion in Taiyuan from 1995 to 2015? The research also attempts to address the following more specific questions:

1. What is the spatiotemporal characteristic of urban land change in Taiyuan from 1995 to 2015?
2. How do factors of economy, population, and policy influence urban expansion?
3. How and to what extent does the socio-economical and geographical difference within Taiyuan influence the impact of the driving factors? What are the reasons behind?

4. What will the urban land distribution in Taiyuan become in the future 10 years?

The study is divided into three main parts to evaluate the urban land-use change in Taiyuan. In the first part, based on the land use remote-sensing data of Taiyuan's land use in 1995, 2005, and 2015, I employed econometric geographical models to analyze and describe the spatiotemporal characteristics of land use change, especially of urban land in the study area. In the second part, referring to relevant studies and combining the characteristics of the study area, I built logistic regression models and base on the result of regressions to explore the impact of different drivers and the spatiotemporal heterogeneity within the city. At last, I proposed the conversion rule of different land-use types, and performed a simulation in GIS to predict the land use situation in Taiyuan in 2025.

2. Literature Review

2.1 Spatiotemporal characteristics of land-use change

The study of the dynamic characteristics of land use changes describes and analyzes the trend of land conversion through the comparison between different land distributions in different historical periods. The literatures on the dynamic characteristics can be divided into two major types. One is quantitative characteristics study, in which the Markov transition matrix is mainly used by researchers. By using the conversion matrix scholars can not only quantify the amount of land use conversion, but also reveal the transition probability of different land types in spatial and temporal evolution of land use change (Teferi et al, 2013).

For instance, Qiong (2016) normalized various indexes through the Markov transition matrix to explore the space-time changes of land use and cover in the Qiantang River Basin. He introduced the dynamic degree that refers to the amount of changes per year in a certain area to standardize the changing rate, which provided a comparable indicator among different land use types in different time periods (Sun et al. 2016). Shannon's diversity index based on Markov matrix was also used widely in landscape analysis, which is based on the concept of entropy to reflect the heterogeneity of the landscape. It is especially sensitive to the non-equilibrium distribution of each type of patch in the landscape, and it can well reflect the influence of human activities on the boundary change of two adjacent patches. Carranza et. al (2007) employed this method to investigate the evolution of city boundary in Isernia (Carranza et al, 2007).

Another is spatial characteristics study. Scholars applied GIS spatial overlay function and combined it with models in ecological landscape science to analyze the patterns of land use types such as mutual conversion relationship and land use dispersion. Gravity center was used by Peng et al (2017) to describe the direction and speed of urban land expansion in Shenzhen, China, and to relate the direction and distance to regional factors to reflect the tendency of land use change. Jiao (2015) introduced a new urban land density function that fits well in many big cities. in which he used concentric rings to divide the cities by the distance from city center and calculated the density in each ring to get a 'Inverse S-shape Rule' that depicts the distribution of build-up land density along with the distance to city center.

2.2 The driving forces of land use change

The study of driving forces aims to explore the causes and process of land use change and predict the trends and direction of future situation. Meanwhile, it is one of the important research contents of LUCC program to provide scientific basis for relevant decisions such as efficient and rational use of land resources and sustainable development (Chang 2018). For the present study, the identification of driving forces is a necessary step to establish the regression model. It can be seen from existing literature that the population structure change, the economic growth, and the development of technology have direct effect on land use change; at the same time, the stages of urbanization, the government intervention, and the land resources protection attitude also indirectly contribute to the changes to a certain extent (Plieninger et al, 2016; Qian et al, 2016; Kleemann, 2017).

In recent years, the issue of urban land expansion and its drivers has received wide attention in large cities. Hernández-Flores and his colleagues (2015) used the Landsat image of the north margin of Mexico from 2000 to 2014 to analyze the motors of urban expansion. Their results showed that the warfare, population structure and distance to roads have significant effects on urban land conversion. Additionally, the geographic conditions and local cultural also strongly determined this process (Bürgi et al., 2004; Hirt, 2007). Steto and his colleagues (2011) argued that the population and the increase rate of economy have remarkable promoting effect to the city expansion. The population increases the demand for residential land and suitable activity space for residents, and from a global perspective, urban land expansion rate is higher than or equal to urban population growth rate. But there is a different view in Hu and Lo's (2007) study in Atlanta, America. They argue that the area with low population density may have higher probability of converting to urban land. Han (2015) in his study on the urban expansion in Beijing points out that the demand of housing is the major factor shaping the extension of urban boundary. The demand of housing, according to Han, is consequent to the increase of population, decrease of household size, and changing tax policies. In the study of urbanization in Shanghai from 1990 to 2010, Shi (2018) analyzes the relationship between average housing area and urban expansion and finds that the standard of living now becomes the major driving factor of changes of land distribution. Meanwhile, national large projects and activities also play a key role in shaping the landscape of urban area. Ye (2018) studies land change in Guangzhou, a region advanced by implementing the Reform and Open Policy since 1978, and points out that rapid industrialization is the major factor of changes in urban land expansion.

There are also, on the other hand, several studies focusing on small- and medium-sized cities emerging in recent years. Guan and his colleagues (2011), in their study of urban land use change in Saga, Japan, argues that, except for the effects of slope, population density, GDP and land value, the expansion of urban planning areas, the arrival of motorization society, and the transformation of urban industrial structure will lead the business land use move from city center to outskirt and decrease the population density in city center, which can facilitate urban expansion as well. Geographic conditions like slope and altitude are also prominent influencing factors in small- and medium-sized cities (Lu et al, 2018). In the study of Xu et al. (2016), it is argued that urban expansion of small and medium cities is mainly driven by rural-urban transition, while edge-expansion is the dominant form of urban expansion in large cities. The industrial structure also has a great impact on urban expansion in medium-sized cities. For example, in cities that are dominated by manufacturing industries, economic growth will be accompanied by a large demand for land (Sun, 2015).

There are also some interesting factors analyzed by scholars, such us household size (López, et.al, 2001), UTM coordinator (Hu & Lo, 2007) and economic development zone, etc. The impact of economic development zone is an important factor that should not be ignored in analyzing the urban land growth in China. Basically, all the land in China is officially owned by state, thus the influence of government intervention is stronger than market power. Generally, the economic development zone may receive political and financial support from the government, so the zones are always the most competitive and vigorous area in the region, which have strong effect on urban growth (Seto, et, al, 2011).

At the same time, the change of cultivated land also concerns many scholars. Tan (2005) argued that, from 1990 to 2000, there were 74% of the new urban land converting from arable land in Beijing-Tianjing-Hebei region. And the percentage was correlated to the city size: the smaller the city is, the higher the percentage is. Meanwhile, the rapid population growth and the development of the real estate market have aggravated the loss of agricultural land in urban fringe and rural areas.

The present study will incorporate proper factors based on the analysis of particular conditions of the object city, which will be further discussed in Chapter 3.

2.3 The land use change model

In the recent decades, scholars have been developing a variety of land use change models, which are widely applied in the assessment and prediction of land use and land cover situation. This not only implies the growing need of land management, but also serves to stabilize both human society and ecological system (Costanza and Ruth, 1998; Veldkamp & Lambin, 2001). The practically suitable model of land use change should be built on the comprehensive understanding of the driving forces.

The Markov chain model and logistic model are widely used in researches. Markov chain model is mainly based on the existing historical data of multiple periods of land use to calculate the conversion probability between land types and to predict the state of land use in future. This theory assumes that the probability of land use type conversion is related to the previous land use type. López (2001) applied Markov chain model to analyze the changes of land use from 1965 to 2000 and used linear regression to investigate the relationship between urban land change rate and population increase rate. Muller and Middleton (1994) also used Markov chain model to analyze the transformation between urban land, farmland and forest land in Niagara, Canada. According to the past experience and evaluations from scholars, the Markov chain model is good at describing the land use changing process. But it also shows a lack of consideration of other drivers, which is only applicable to the prediction of short-term land use change.

On the other hand, logistic model assumes that the land use conversion is a process of the landowners' decision making that the land tends to be transformed into the type compatible with the activity yielding the highest value. The combination of driving forces (land location and characteristics) reflects the expected future value of land in alternative uses. The final result is the transfer probability score of each sub-district, which can be used for further analysis and prediction (Chomitz, & Gray, 1999; Dendonckeret al, 2007).

Logistic regression analysis is a rising research method in recent years. At present, great progress has been made in LUCC driving force research field, and many scholars have applied it in driving force analysis, land change prediction simulation and other aspects (Jiao & Qing, 2003; Xu et al, 2013; Gobin et al, 2002). Compared with markov chain model, this method has obvious advantages: (1) The relationship between the dependent and independents is a nonlinear relationship, which can well fit the nature of the land use change process; (2) LUCC drivers in most situation have a high degree of spatial heterogeneity (Lin, et al, 2011), and logistic regression can take spatial variables into account; (3) in the research on spatial changes of land use types, the dependent variable is the categorical variable, and the logistic regression is a good statistical method to model the probability of a binary dependent variable.

With the maturity of remote sensing and GIS technologies, the spatial data of land use are becoming more and more abundant. The results obtained from logistic model are also useful in predicting the trend of land transition in future (Shahbazian et al, 2019; Wang, 2016; Qin et al, 2015).

There are also some new methods to improve the performance of logistic model. Lin (2011) compared logistic regression, auto-logistic regression and artificial neural network model (ANN) on quantifying the relationships between land use change and its driving forces. The ROC and kappa statistic were employed to evaluate the ability of the three models in influence assessment and subsequent trend prediction. The result shows that the three model has similar performance in urban land distribution, but for other types of land use (arable land, wood land) the logistic model has weaker performance than others, the reason was explained as that there exists a complex relationship between the changes and drivers, which other two models have a better explanation for this situation. For this study, I mainly focus on urban land change and its drivers, so logistic is enough to use.

In previous researches on the driving forces of urban land use change, most of the scholars just take all the urban land as the research object, which ignores two important things. One is that the urban land can be divided into two parts: old urban land and new growth. The driving forces of the two parts may be different, or may be same but with different impact power. Second, the agglomeration effect of old urban land can, to a certain extent, cause urban growth in the surrounding area. Therefore, in order to comprehensively understand the mechanism of urban land growth, researching on the emerging new urban land alone is necessary, which can provide a more scientific and specific reference for the process of urbanization.

3. Study Area and Data Description

3.1 The geographical situation

The study area, Taiyuan, is the capital city of Shanxi province, which locates in the North China between the range of 111°30′E~113°09′E and 37°27′N~38°25′N with elevation of 760 to 2670 meters above the sea level. The total land area is about 6,988 km^2, the dominant land forms of which are mountain land and hill area, and the plains make up about one fifth of the territory. The temperate continental monsoon climate dominates Taiyuan year-round, with mean annual rainfall of 470 mm and annual average temperature of 9.6 °C. The city includes a main urban district (Jiancaoping, Wanbolin, Xinghualing, Jingyuan, Yingze, Xiaodian) that lie on the two banks of the Fenhe plain valley, and 4 rural towns (Yangqu Xian, Gujiao Shi, Qingxu Xian, Loufan Xian) scattered around (Figure 1).

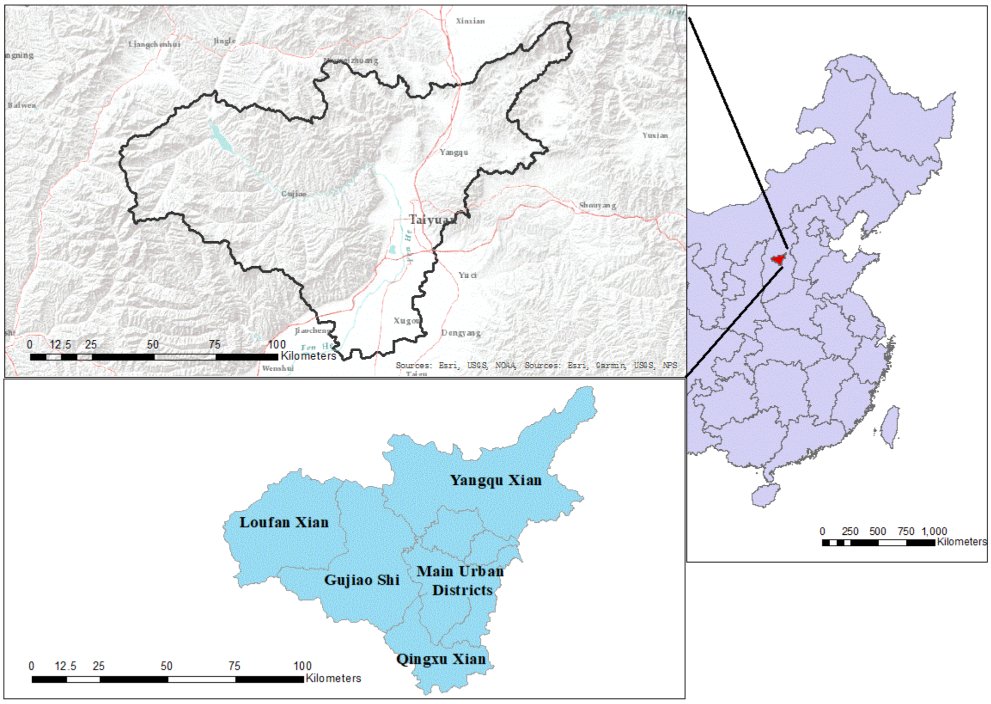


Fig. 1. Location, spatial organization and geography of Taiyuan, China

3.2 Study area

As a capital city, Taiyuan is the economic, political and cultural center of Shanxi province. Additionally, it is an important energy and heavy chemical industry base of China. In the 1990s, China follwed the unified distribution of productive powers under the traditional planned economy system. The central government decided the distribution according to the resources endowment and the structure of labor force. In this context, Taiyuan was positioned as a heavy industry city and strategic energy base. In addition, national and local investment was mostly concentrated in resource industry, which made Taiyuan's economic structure over-reliant on heavy industry. This led to a series of issues, such as infrastructure construction lags, environmental pollution, slow economic development, single industrial structure and so on, that threatened the sustainable development of Taiyuan. Since 2005, the Taiyuan governemnt lunched sets of policies in economic structure and urban spacial plan to improve urban functions and to optimize the industrial structure. Until 2018, Taiyuan has experienced dramatical growth in various aspects.

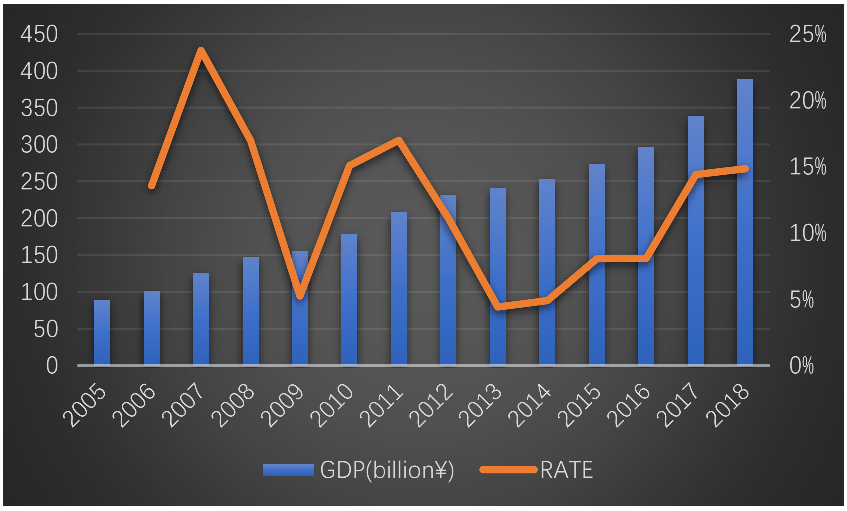
i. Population

In 2017, the residential population of Taiyuan was 4,379,700 with 1,184,452 units of households. It increased about 28.3% compared to that of 2005 (3,413,800), and the average annual rate of growth is about 1.5%. Among the totale population, the urban population is 3,709,680 that accounts for 84.7% of the total. Compared with the previous year, it experenced a small growth of 0.5%.

ii. Economic Situation

The Gross Domestic Product (GDP) in 2005 only amounted to 98.38 billion Yuan (1USD≈6.88CNY). Until the end of 2018, the GDP reached to 388.4 billion Yuan. Among all the industries, the GDP of primary, secondary and tertiary industry are respectively 4.105, 143.9, and 240.43 billion Yuan. Compared to the previous year, fixed asset investment increased by 26.2%, and the added value of industries and total retail sales of consumer goods also experienced a growth of 10.8% and 8.1% respectively. In addition, 33.64 billion Yuan was invested in urban infrastructure construction, taking up 27.6% of the local investment.

Figure 2. GDP and increase rate from 2005 to 2018



iii. City planning

Since 2005, Taiyuan has experienced two major urban planning formulations featured by the transformation from a "heavy industry city" to a "regional central city" that was supposed to bring about the concentration and radiation effects to facilitate the economic development of Shanxi province.

The first major urban planning was implemented in 2007, which emphasized the development of main urban districts (Jiancaoping, Wanbolin, Xinghualing, Jingyuan, Yingze, Xiaodian). It outlined the "twin cities, two districts, four corridors, six axes, multi-center (*shuang cheng, shuang qu, si lang, liu zhou, duo zhongxin*)" spatial structure.[1] Through expanding the new city zone, the whole territory kept sprawling

[1] "Twin cities" refers to the main city and the new city. "Two districts" refers to Jinyang cultural ecological area and the northern ecological barrier area. "Four corridors" refers to Fenhe River ecological corridor, South Taigang ecological corridor, South Longcheng avenue ecological corridor and South new city ecological corridor. "Six axes" refers to six major urban-road that expand urban development. "Multi-center" refers to the three-level urban

towards South. With the improvement of express ways alongside the east and west bank of Fenhe River, the development of both sides became more balanced by 2015. The urban traffic also experienced a great improvement that structural main routes were established between 10 districts and linked to the surrounding cities. Especially, in the main urban districts, internal truck and high-speed loop made the area become a continues and integral system. The ecological system was also an important part of the planning: building industrial park in the outskirts, establishing urban greening system based on Fenhe River, and remediating ecological system in the East and West Mountains led to a significant improvement of the environmental quality in Taiyuan.

In 2017, the Taiyuan government published the “Overall Urban Space Plan of Taiyuan (2016-2035)” that purposed to build a national central city suitable for living, working and traveling in the next 20 years. The new urban plan predicted that the population in 2035 will reach 6.8 million and the building up area will meet 920 km^2. There are four new programs that may influence future urban land distribution worth highlighting:

1) the metro system will join urban public transportation system, and eight lines will cover all areas of the major city zone;
2) the new beltway will be completed in next 5 years, which can conveniently access to national high way system and replace current high-speed loop’s function, and the current loop will be incorporated as the internal highway (Fig. 3);
3) the airport will be moved to Qingxu Xian, which can release the space in north of Taiyuan for urban expansion (Fig. 3);
4) seven Development Areas are under planning to fuel the local economy (Fig. 4).

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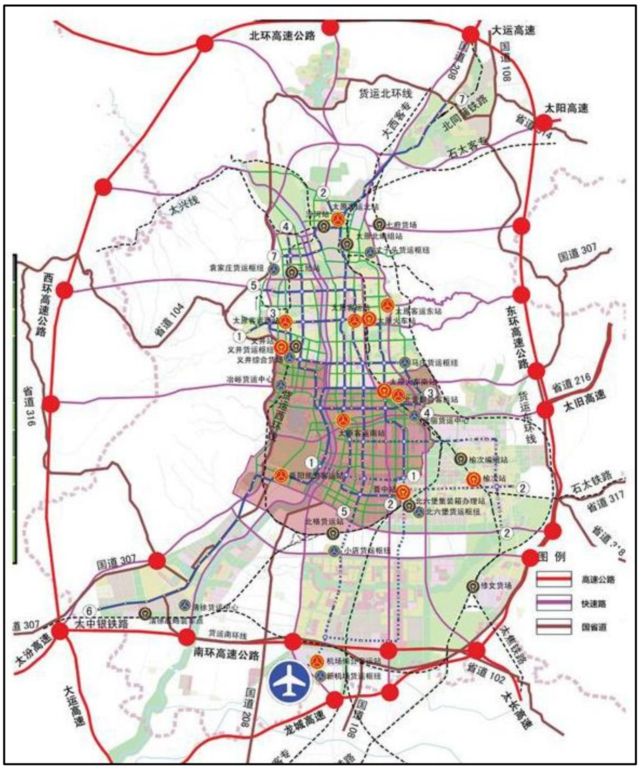
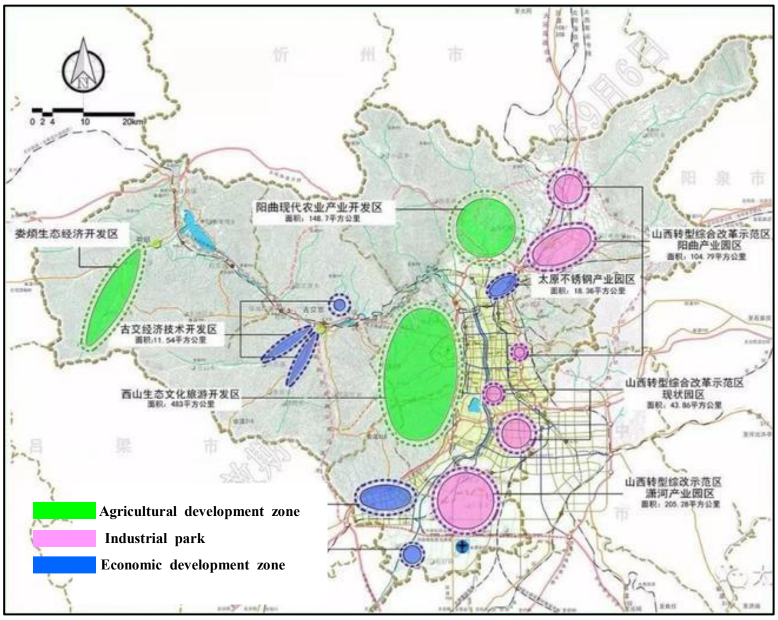
public service system planned to form five municipal centers, seven regional centers and several community centers.

Figure 3. The Map of New Beltway and location of new airport



Resources from Overall Urban Space Plan of Taiyuan (2016-2035)

Figure 4. The map of development area



Resources from Overall Urban Space Plan of Taiyuan (2016-2035)

3.3 Data

This study applied land use data in Taiyuan in three periods (1995, 2005, 2015) to generate the land use change maps. The maps of land use distribution, population density and 1 km Grid GDP were collected from China Resource and Environment Data Cloud Platform (http://www.gscloud.cn/), the accuracy of which was over 90% that met the requirements for analysis. The classification of land use applied "GB/T21010-2017" (Table. 1).The related data about economic factors (GDP per capita, total population, urbanization rate, etc.) were gathered from the website of the Shanxi Bureau of Statistics (http://tjj.shanxi.gov.cn/) and National Bureau of Statistics (http://www.stats.gov.cn/).

Table 1. Land Use Classification System

Land use type	Description
1. Arable Land	Includes cropland, orchards, irrigable land, non-irrigated farmland, etc.
2. Wood Land	Mainly refers to natural forest and man-made forest that canopy density is higher than 10%.
3. Grass Land	Refers to all kinds of grassland dominated by growing herbaceous plants with coverage of more than 5%, including shrub grassland dominated by grazing and sparse forest and grass land with canopy density of less than 10%
4. Water Body	Rivers, lakes, reservoirs, etc.
5. Urban land	Refers to urban and rural residential areas and other land used for industrial, mining and transportation purposes.
6. Others	

Note: there are some geography dislocation issues across the land use maps, matched by georeferencing tool in ArcGIS.

Other data resources are showed in table 2.

Table 2. Data Resources

Data	Resource	Date	Descript
Administrative Map;	http://www.gov.cn/	2008	The district division
Urban Plan	Overall Urban Planning of Taiyuan City (2007-2020)	2008	Government intervention on land use change
	Overall Urban Planning of Taiyuan City (2016-2035);	2017	
Location of POI	www.openstreetmap.org	2019	The location of roads, railway station and airport.
DEM Map	https://gdex.cr.usgs.gov/gdex/	2018	Used to derive the slope map

4. Spatio-temporal characteristics of land use change

Land use change presents complex and dynamic transformation rules in terms of time, space, quantity and structure. In order to better reveal the process and patterns of land use temporal and spatial conversion in the study area, this study applies qualitative and quantitative methods, from the quantity change, type change and spatial change, to analyze the characteristics of land use change in Taiyuan city from 1995 to 2015.

4.1 Land use dynamic

This chapter statistically summarizes the data of land use statues in the three years (1995, 2005, 2015), and describes the area size, proportions and changes of different land use type (Table. 3).

Table. 3 Taiyuan city 1995, 2005, 2015 land use classes and areas in sqkm

Land Use Type	1995		2005			2015		
	Size (sqkm)	Proportion (%)	Size (sqkm)	Proportion (%)	K[2] (%)	Size (sqkm)	Proportion (%)	K (%)
Arable Land	2191.68	32.14	2125.41	31.17	-0.30	1896.62	27.81	-1.08
Wood Land	2292.77	33.62	2277.55	33.40	-0.07	2401.97	35.22	0.55
Grass Land	1922.34	28.19	1903.79	27.92	-0.10	1767.35	25.91	-0.72
Water Body	78.19	1.15	86.4	1.27	1.05	72.28	1.06	-1.63
Urban land	333.06	4.88	425.71	6.24	2.78	680.17	9.97	5.98
Others	1.8	0.03	0.98	0.01	-4.56	1.45	0.02	4.80

[2] K refers to *single dynamic degree of land use and cover*, which is used to represent the change rate of a land use type and reflect the intensity of the change within a certain period of time in the research area. The formula is expressed as follows:

$$K = \frac{U_b - U_a}{U_a} \times \frac{1}{T} \times 100\%$$

Where U_a and U_b stands for the size of land use at the beginning and in the end.

T stands for the length of the study period.

The result shows that the agriculture, forest and grass land account for around 90% of the total area, and the water area only takes up around 1% of the total area. It is related to the inland geological structure of Taiyuan city that mountain land and hill area have accounted for four-fifths of the territory. From 1995 to 2015 the urban land presents a dramatic increasing trend. Especially, in the period from 2005 to 2015, the value of K increases from 2.78 to 5.98. The size of urban land expands about 1.5 times from 2005 to 2015, which reflects the rising land demand from economic and population increase. The agriculture land decreases progressively, the proportion of which falls by 4.33% from 1995 to 2015. It is assumed to be explained by the agriculture technology improvement, rural-urban migration and industrial structure promotion (*chanye jiegou shengji*) and gradient transformation (the proportion of primary industry decreased every period). The forest area has a small decline from 1995 to 2005, but in next period it experiences an obvious increase.

a) Land use transitions

The transition matrixes for the study area during periods of 1995-2005 (period 1), 2005-2015 (period 2), 1995-2015 are as below (see Table 4-6). The tables show that, during 1995-2015, arable land is reduced by 27.74% of its original size, and 46% (28186 hm^2) of the changes in arable land transfers to urban land. At the same time, the conversion becomes more violent in the later period (4.50% of period 1 and 9.56% of period 2). This pattern shows that the expansion of Taiyuan still depends on the territory extension. Besides, the contradiction between urbanization development and farm land protection is obvious in the current phase.

Due to the location change, the mutual transformation generally exists between two different land use types, which confuses the conversion process. For example, during 1995 to 2005, the land transferring from arable to grass is 18325 hm^2, but at the same time, 17304 hm^2 of grass land converts to arable land. The two change processes have little overall influence on size of each land type. For further study of the changes in

Table 4. Transition matrix of land use change from 1995 to 2005

1995		2005					
		Arable Land	Wood Land	Grass Land	Water Body	Urban land	Others
Arable Land	hm^2	186137	5088	17370	2084	9938	3
	%	84.37%	2.31%	7.87%	0.94%	4.50%	0.001%
Wood Land	hm^2	7287	206231	18325	121	405	3
	%	3.14%	88.75%	7.89%	0.05%	0.17%	0.001%
Grass Land	hm^2	17304	19027	155774	362	968	7
	%	8.95%	9.84%	80.53%	0.19%	0.50%	0.004%
Water Body	hm^2	1380	161	227	5884	214	0
	%	17.54%	2.05%	2.89%	74.80%	2.72%	0.000%
Urban land	hm^2	1682	155	283	217	31061	0
	%	5.04%	0.46%	0.85%	0.65%	93.00%	0.000%
Others	hm^2	2	6	16	0	70	87
	%	1.10%	3.31%	8.84%	0.00%	38.67%	48.07%

Table 5. Transition matrix of land use change from 2005 to 2015

2005		2015					
		Arable Land	Wood Land	Grass Land	Water Body	Urban land	Others
Arable Land	hm^2	161076	10752	20239	1288	20431	6
	%	75.34%	5.03%	9.47%	0.60%	9.56%	0.00%
Wood Land	hm^2	5733	213093	9331	176	2322	13
	%	2.49%	92.38%	4.05%	0.08%	1.01%	0.01%
Grass Land	hm^2	19380	18789	147555	216	5990	65
	%	10.09%	9.79%	76.85%	0.11%	3.12%	0.03%
Water Body	hm^2	1096	164	365	5372	1671	0
	%	12.64%	1.89%	4.21%	61.98%	19.28%	0.00%
Urban land	hm^2	3679	430	451	195	37900	1
	%	8.62%	1.01%	1.06%	0.46%	88.85%	0.00%
Others	hm^2	4	5	6	0	24	61
	%	4.00%	5.00%	6.00%	0.00%	24.00%	61.00%

Table 6. Transition matrix of land use change from 1995 to 2015

1995		2015					
		Arable Land	Wood Land	Grass Land	Water Body	Urban land	Others
Arable Land	hm^2	159417	10840	20980	1188	28186	9
	%	72.26%	4.91%	9.51%	0.54%	12.78%	0.004%
Wood Land	hm^2	7594	203151	18661	145	2808	13
	%	3.27%	87.42%	8.03%	0.06%	1.21%	0.006%
Grass Land	hm^2	20235	28709	137770	202	6459	67
	%	10.46%	14.84%	71.22%	0.10%	3.34%	0.035%
Water Body	hm^2	1197	151	225	5584	709	0
	%	15.22%	1.92%	2.86%	70.99%	9.01%	0.00%
Urban land	hm^2	2512	375	289	128	30094	0
	%	7.52%	1.12%	0.87%	0.38%	90.11%	0.00%
Others	hm^2	13	7	22	0	82	57
	%	7.18%	3.87%	12.15%	0.00%	45.30%	31.49%

Table 7. Net conversion for major land use types in different periods

Type change		1995 to 2005	2005 to 2015	1995 to 2015
Arable to Urban	hm^2	8265	16752	25674
Grass to Urban	hm^2	685	5539	6170
Wood to Urban	hm^2	250	1892	2433
Others to Urban	hm^2	70	23	82
Arable to Wood	hm^2	-2199	5019	3246
Arable to Grass	hm^2	66	859	745

major land types in Taiyuan city, I calculated the net transfer between two types in different periods, and extracted the changes that are my major focus in Table 7. The table shows that all the conversions from other land use types (arable, grass, wood, others) to urban land use were always positive, and the arable land provide the largest spaces for urban expansion. Meanwhile, the arable land tends to shift to wood and grass because of the green project and cultivated land degradation, which exacerbates the decrease of arable land.

4.3 Spatial distribution of urban land expansion

This paragraph mainly analyzes the spatial changes of urban land in the study area during the two periods. Through combining the urban land map of 1995, 2005 and 2015, I got the map of urban land changes from 1995 to 2015 in two periods (Figure. 5).

Figure 5. Spatial distribution of urban land expansion from 1995 to 2015

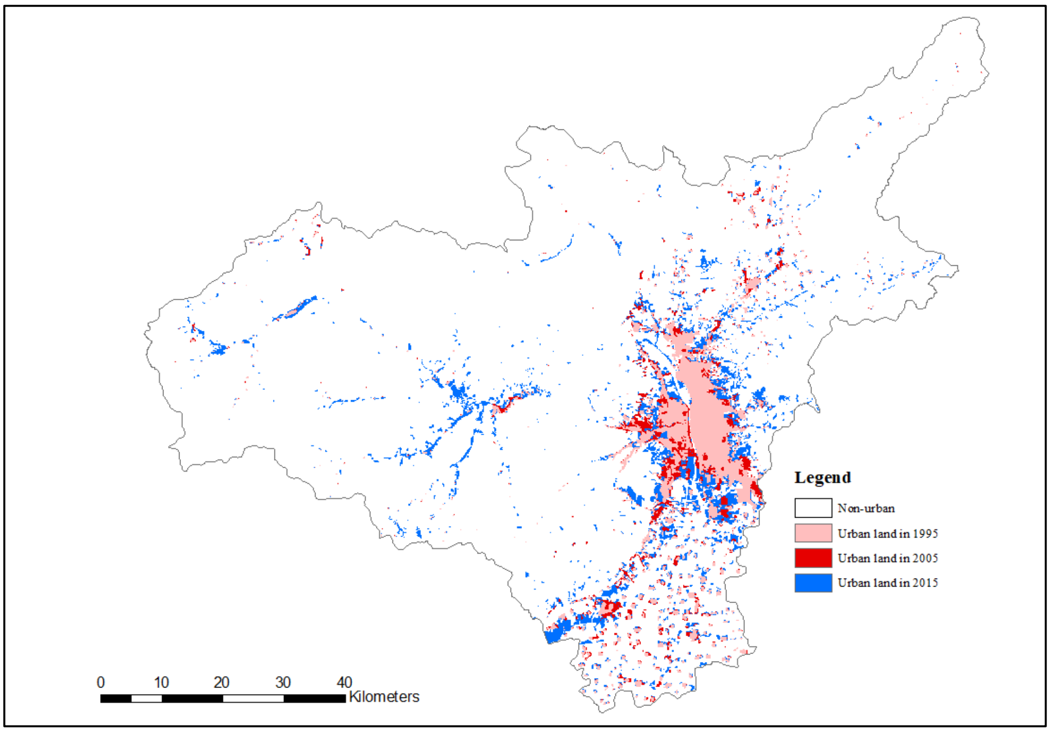


Figure 5 illustrates that the new urban land mainly occurs around the border of previous urban area. From 1995 to 2005, the new building-up land mainly transfers from the arable land and grass land inside the urban area. At this stage, through the development of urban public transportation and other infrastructure, the urban area becomes increasingly continuous, which increases the value of non-building-up land inside the urban area. In addition, the government promotes industrial transformation, which can be seen from that the primary sector output contributes to 15.7% of GDP in Shanxi in 1995, but the ratio of it decreases to 6.3% in 2005. Furthermore, the changes almost exclusively take place in the main urban districts. During 2005 to 2015, the urban land expands outward. In the main urban districts, the city expands to the northern part where the terrain is wider and flatter. Dense urban building areas emerge in the places around the economic development zones with approval from local government, and the dotted urban land scattered in the arable land gradually tends to be connected with each other and together as a belt. Meanwhile, in this period, building up area of rural towns also experienced a significant expansion alongside the highway road.

4.4 Analysis of main urban districts

This paragraph chooses the main urban districts as the object of study to analyze the characteristics of urban land expansion from 1995 to 2015. The main urban districts-Jiancaoping, Wanbolin, Xinghualing, Jingyuan, Yingze, Xiaodian, lie on the two banks of the Fenhe plain valley. These districts only take up about 20% of the total territory of Taiyuan, but more than 67% of urban land is in these areas and around 90% of GDP is produced there. The development of these districts has a great impact on the overall development of Taiyuan.

Based on the concept of center-of-gravity (COG) in physics, the direction of urban land change can be tracked by observing the trajectory of the geographic COG of urban land in the main urban districts (Table. 8). The geographic COG can be calculated with the formula:

$$X_t = \sum_{i=1}^{n}(a_{ti} * x_i) \,/ \sum_{i=1}^{n} a_{ti}$$

$$Y_t = \sum_{i=1}^{n}(a_{ti} * y_i) \,/ \sum_{i=1}^{n} a_{ti}$$

Where X_t, Y_t are respectively the longitude and latitude coordinates of the COG at time t; a_{ti} refers to the size of urban patches at time t, in this context, a_{ti} equals to 100 constantly. (x_i, y_i) refers to the combination of the patch's COG.

Table 8. the moving trajectory of the COG for 1995, 2005 and 2015

		1995		2005		2015	
		x	y	x	y	x	y
Coordinates	m	650650.16	4081481.75	650272.48	4080996.30	650263.27	4080517.03
Distance	m			615.06		479.36	
Orientation	°			N 38° W		N 1° W	

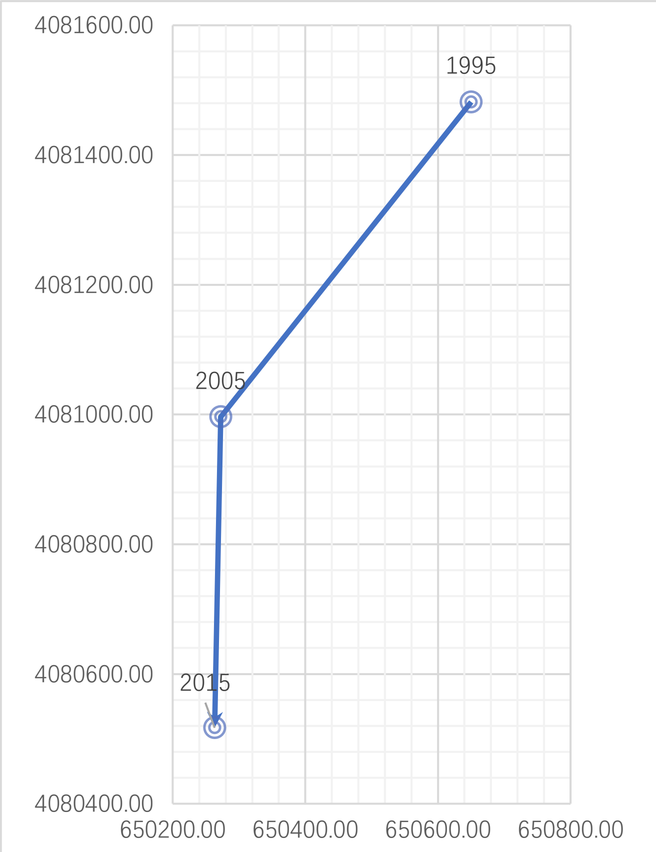


Figure 6. Schematic diagram of COG transfer in man urban districts

Table 8 and Figure 6 show that the COG of main urban districts moved 615.06 meters toward the southwest that located at Fenhe River from 1995 to 2005. Combined with Figure 5, in this period, we can see that the main areas of urban expansion in these districts are in the south and the west part of Taiyuan. There are some scattered areas suitable for urban land in the west bank of Fenhe River, which has also become the main area of urban expansion. These new urban lands eliminate the original separation and balances the development of the east and west parts. Meanwhile, in the west and northeast part emerged some large blocks of the new city area. From 2005 to 2015, the expansion to the south areas has been noteworthy. With the industrial upgrading and tertiary industry development of Taiyuan, especially the construction of Taiyuan high-tech industrial zone and the development of the airport industrial zone, there has been explosive urban expansion in north area. In addition, in the east northern area that between center of Taiyuan and Yuci (a municipal city around Taiyuan), new urban belt takes shape as a result of the increasingly deep connection between the two cities. The improvement of the traffic conditions, urban radiation and the influence of government decision-making have accelerated the north expansion during this period.

5. The driving forces of urban land expansion

Understanding the relationship between urban land expansion and its driving factors is the basis of constructing urban land prediction model. According to the selection principle of driving factors and the multivariate collinear diagnosis method, this chapter chooses 10 major factors that have important contribution to the land transformation. Logistic regression model is applied here to optimize the factors in analyzing the impacts of the chosen drivers. At last, the results of regression are tested for goodness of fit.

5.1 Logistic regression model

Binary Logistic is a further extension of the ordinary multiple linear regression model. It mainly predicts the probability of events under the comprehensive influence of multiple factors. It is a nonlinear model that can be employed effectively no matter the dependent variable is categorical or continuous. The target variable of this study is the new urban land in 2015 which is a binary variable. The dependent variable represents the presence or absence of urban land growth. In addition, the model presuppose that the probability of the change follows the logistic curve. Then the study divides the study area into grid units, and extracts the dependents' and independents' values of each cell. The probability of urban land growth in each grid can be estimated with the logistic regression model. The specific formula is shown below:

$$\text{Log}\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \qquad (1)$$

where P is the probability of other land converting to urban land. $X_1, X_2 \cdots X_n$ refer to the driven forces. β_0 is a constant. $\beta_1, \beta_2 \cdots \beta_{n1}$ refer the regression coefficient of the factors. The larger the value of β is, the higher the correlation between the independents is.

According to formula (1), the following formula (2) is derived to calculate the spatial distribution probability of urban land expansion.

$$P = \frac{\exp(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)}{1+\exp(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n)} \tag{2}$$

5.2 Variable selection and preprocessing

This chapter use logistic regression model to analysis the driving forces of urban land growth during 2005 and 2015. The dependent variable uses the binary data from the new urban area map: if the cell transforms from non-urban to urban function, the value set as 1, and 0 means no change during the period.

The occurrence of land use change is the result of different influencing factors. Obviously, land use change is restricted by natural factors, such as elevation, slope and slope direction. Especially for urban land growth, higher slope will increase the cost of construction and maintenance. The spatial impact of accessibility factors on land use will change with the distance, which is mainly reflected in the capacity of connecting with the outside and the flow of people, logistics, capital and other elements between local and other regions. In addition, population distribution, economic situation and the guidance of policy are external driving forces for urban land expansion that cannot be ignored. In order to quantify the relationship between urban growth and its drivers, a series of predictable variables are firstly selected (Table. 9). The selection of variables is very important for model construction and accuracy prediction. Variables should not only provide relevant information for studying the process of urban growth, but also can easily update in the future in order to predict.

As the purpose of this study is to analyze the drivers of new urban land expansion, and the dependent variable is the binary variable of new urban land in 2015, the cells that was urban land in 2005 should be excluded from the sample. Furthermore, the size of

Table 9. List of independents

Category	Factors	Description
Socio-economic factor	GDP per capita	The GDP per capita (1000 Yuan/p) in per 1km*1km cell is a continuous variable, which reflects the indirect impact of economic development on urban land change.
	FO_POP	The population gap refers to the difference between the maximum and minimum of population density within a radius of five kilometers. Reflects the influence of the potential of population increase on urban land growth.
	DZ[3]	According the government documents, create an economic development zone plan map to reflect the influence of policy. Generate a categorical variable that set the value as 1-4 base on the distance to the zone: Value is 1, if the cell is further than 10km Value is 2, if the cell is between 3km to 10km Value is 3, if the cell is within 3km Value is 4, if the cell is inside the zone
	REGION	According the administration partition, create a set of categorical variables to reflect the influence of districts on urban land change
Physical factor	SLOPE	Calculated by slope function of GIS, the slope has a restrictive effect on the cost of develop an urban land.
	LANDUSE_05	The land use type in 2005.
Accessibility factor	D_STATION D_AIRPORT D_HIGHWAY	Distance to airport, major road and railway station Driven from the Euclidean Distance tool of GIS, reflect the four factors effects on spatial pattern of urban land.
	D_URBAN	Euclidean distance to nearest old urban area.

water body is mainly influenced by the precipitation of the upstream of Fenhe River, Yellow River and some reservoir or artificial lake construction projects, which leads to unpredictability of the tendency of the water body change. Therefore, this study assumes that the water body is constant during the period, and excludes the cells that was water body in 2005. In addition, due to the infrequent occurrence of other land use type (account 0.01% of total land use in 2005), we exclude the observations in others land use.

[3] For the impact of DZ on urban land growth, this study made two different attempts. One is mentioned above. Another is using focal statistic to create a continues variables that present the coverage rate of development zone to weaken the "boundary issue" , that the relationship between the regressor and the regressant are flat within interval but dramatical different across the cutpoint, in of categorical variable (Bennette & Vickers, 2012). The formula is:

$$\mathrm{FO}_{\mathrm{PLAN}_{3\mathrm{km}}} = \frac{the\ size\ of\ DZ\ within\ 3km\ range}{\pi 3^2} * 100\%$$

$$\mathrm{FO}_{\mathrm{PLAN}_{10\mathrm{km}}} = \frac{the\ size\ of\ DZ\ within\ 10km\ range}{\pi 10^2} * 100\%$$

Compared the result of using two variables, the R2 is similar. Therefore, the models used the categorical variable, as it can straightforwardly interpret the impact.

Since the cost of building construction will dramatically increase when the slope of surface higher than 10°, this paper generates a dummy variable SLOPE_i that charges 1 for the cell with less than 10° of slope, and charges 0 for the rest.

According to that the concept of airport economic zone which due to the impact of the airport on the surrounding areas, capital, technology and labor force gather from other regions, thus create a busy area. The zone takes the airport as the geographical center and exits in a certain geographical range. Scholars generally argue that the range is 20 km, beyond which the area will not be affected by the airport (Wang, 2016). Therefore, this study recoded the variable of D_AIRPORT to a dummy variable AIRPORT_i that refers to a cell within or outside of the impact area, and designate 1 for the area in the zone.

Table 10. description for key data (630,167 obs)

Variable	Unit	Mean/Frequency for dummy variables	Std. Dev.	Min	Max
NEWURBAN_i	-	0.0453039	-	0	1
GDP per capita	1000¥/p	21.625	15.306	1.593	42.789
FO_POP	1000	0.312	0.447	0.001	1.800
D_STATION	Km	12.315	7.015	0	36.126
D_HIGHWAY	Km	5.201	5.117	0	30.832
D_URBAN	Km	2.470	2.221	0.1	15.761
DZ_1	-	0.591	-	0	1
DZ_2	-	0.293	-	0	1
DZ_3	-	0.079	-	0	1
DZ_4	-	0.037	-	0	1
SLOPE_i	-	0.369	-	0	1
AIRPORT_i	-	0.082	-	0	1
Arable Land	-	0.337	-	0	1
Wood Land	-	0.361	-	0	1
Grass Land	-	0.302	-	0	1

The total number of observations is 630,167. The Table 10 shows the key descriptive statistics fort all the variables that would be included in the analytical model.

Since the logistic regression model is highly sensitive to the collinearity among independent variables, the multicollinearity among variables can easily affect the interpretation accuracy of regression results. Therefore, the independent variable with severe collinearity need to be eliminated before regression modeling. This study uses Variance Inflation Factor (VIF) to assess the collinearity issues (Franke, 2011). If the VIF is higher than 5, it means that the collinearity issue between variables is significant. The result shows that, All the independent variables passed collinearity test and could be added to the logistic regression model for further analysis.

Table 11. multicollinearity assessment

Variable	VIF	R2
D_URBAN	1.62	0.3832
D_STATION	2.05	0.5113
D_HIGHWAY	2.07	0.5159
D_RIVER	1.57	0.3634
GDP per capita	1.56	0.3577
FO_POP	1.73	0.4224
SLOPE_i	1.27	0.212
DZ_2	1.53	0.3453
DZ_3	1.46	0.3145
DZ_4	1.39	0.2803
AIRPORT_i	1.53	0.3467
Wood Land	1.9	0.4746
Grass Land	1.55	0.3533

5.3 Result

Based on the eleven factors mentioned above, this study established the following models to analyze the urban land development of Taiyuan city from 2005 to 2015. After the regression, this paper employed pseudo-R^2 and relative operating characteristic (ROC) to evaluate the goodness of fitting for the regression. In spatial studies, the value of pseudo-R^2 is sufficient as goodness-of-fit if it is higher than 0.2 (Hemmert et al. 2018). If the ROC statistics is higher than 0.7, the model can well project the distribution of urban land growth in 2015.

5.3.1 Model 1

The establishment of model 1 aims to answer the research question 2- the influences of economy, population, and policies on urban land distribution. Model 1 excludes the influence of regions, and tests all the other 10 dependent variables' effects on urban land growth. The variable of land use type in 2005 was regarded as a set of dummy variables. The result is showed in Table 12.

Before analyzing the result, in order to evaluate the effect that spatial correlation has on the model, a 1/10 random sampling from total observations was conducted. Same regression was proceeded with these sample and the result is also displayed in Table 12. Through the comparison between model 1 and 1/10 sampling, there is not prominent different in the coefficient of each variable. Since the size of sample could be too small to make the coefficient of some dummy variables (D_RIVER and Grass Land) significant, this study attempts to conduct regression analysis with the total population.

Table 12. the result of Model 1

	NEWURBAN_2005		
	MODEL_1		1/10SAMPLE
VARIABLES	Coef.	OR.	Coef
D_URBAN_(KM)	-0.652***	0.521***	-0.677***
D_STATION9 KM)	-0.0301***	0.970***	-0.034***
D_HIGHWAY (KM)	-0.155***	0.856***	-0.152***
D_RIVER (KM)	-0.003***	0.997***	-0.0026
GDP per capita (1000¥/p)	0.018***	1.018***	-0.0185***
FO_POP (1000)	0.685***	1.985***	0.695***
SLOP_1	0.425***	1.530***	0.446***
Wood Land	-0.623***	0.536***	-0.529***
Grass Land	-0.188***	0.828***	-0.112
DZ_2	0.223***	1.250***	0.257***
DZ_3	0.625***	1.868***	0.654***
DZ_4	1.175***	3.239***	1.219***
AIRPORT_1	0.518***	1.679***	0.491***
Constant	-1.937***	0.144***	-1.959***
R2	0.2859		0.2862
ROC	0.8814		0.8843
Observations	630,167	630,167	63,017

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The table shows that the ROC statistic is 0.8814, which denotes that the model can fit data well and is reliable. The significance level of regression coefficient (p<0.01) shows that all the ten drivers evidently influences the urban land expansion during the period.

Same as the result of previous chapter, the arable land has higher probability of converting to urban land than forest and grass. Among the accessibility factors, the effect of distance to old urban area is strongest and negative. The odds ratio (OR) is 0.521, which means that for every 1km increase in the distance to the old urban area, the probability of converting from non-urban land to urban land decreased by 47.9% (1-0.521). This can be explained by the agglomeration effect that the closer to the old urban area, the stronger the radiation drive from downtown, which increases the demand for urban construction. In addition, the regression coefficients of the distance from the highway and railway station are both less than zero, indicating that the scale construction of urban land is likely to appear along the traffic arteries such as highway and railway. Highway is the main traffic link within the city, which is the reason that the effect of highway is higher than the effect of railway station, and the mature traffic network can magnify the agglomeration effect of capital elements and population. Therefore, the growth and change of urban land is closely related to the traffic system building. Meanwhile, the effect of population gap in an area on the urban land growth is significant, when the population gap increases 1000 persons, the probability of converting to urban land almost double.

According to the table, the effects of either the aerotropolis economic zone or the government-oriented development zone on urban land growth are significantly positive. But these two types have some differences.

The policy of economic and technological development zones has been widely used in facilitating urbanization in China. First, through urban planning and affirmative policy, the zones can attract more investment, which accelerates new urban emerge (that is a reason that the OR of "*DZ_4* is highest among the series of dummy variables). Then it can drive the development of infrastructure and traffic system, thereby, promote the process of urbanization. Therefore, the government-oriented development zone is often seen as the growth point of the city’s economy and the trigger of urban land growth. The table indicates that, compared with the place not affected by development zones (further than 10 km), the probability of converting to urban land is obviously higher. In addition, the place within 3 km has higher probability than that in 10km because the former has higher accessibility.

On the other hand, aerotropolis economic zone is caused by convenient transport, which can drive the development of the whole radiation area at the same time. The table also shows that, *ceteris paribus*, the probability of urban land growth will increase 1.679 times when the location within the airport radiation range.

Overall, the general trend of the nine drivers can be summarized as that with the slope becomes flatter, the human accessibility and mobility increase (the distance, population density differences) and the government stimulation increase, the probability of conversion to urban land increase.

5.3.2 Model 2

The districts within Taiyuan have their own centers of development. These districts can be divided into five different regions according to their development and urbanization features. The establishment of model 2 aims to answer the research question 3, that is, to analyze the heterogeneity of the drivers’ impacts in different regions. The choices of variable are same as model 1, and the result is shown in Table 13.

For the performance of the impact of airport economic zone, almost all the land of Qingxu is in this area, while Yangqu, Gujiao, and Loufan are basically outside of the zone, so the number of observations of Yangqu, Gujiao, and Loufan is too small for a certain category of categorical variable would make the coefficient insignificant.

Comparing the R-squared of each region, the performance of the model is various for different regions. To be more specific, this model can good explain the drivers of urban land growth in Gujiao, Loufan and the main urban districts.

According to the results, the influence of distance to old urban area are all obvious, and it is highest in main urban districts. It shows that the effect of urban agglomeration on urban development is uneven in different region, but generally, it is vitally important.

On the other hand, the performance of other drivers is distinctly diverse in different

Table 13. the result of Model 2 (Coef.)

	NEWURBAN_1				
VARIABLES	YangQu	GuJiao	QingXu	LouFan	Main urban districts
D_URBAN_(KM)	-0.504***	-0.366***	-0.900***	-1.391***	-1.632***
D_STATION_KM)	-0.0243***	-0.119***	-0.0312***	0.0417***	0.0018
D_HIGHWAY (KM)	-0.0681***	-0.283***	-0.176***	-0.176***	-0.326***
D_RIVER (KM)	-0.2149***	-0.1977***	0.103***	0.063***	-0.005
GDP per capita (1000¥/p)	0.0286***	0.0632***	0.0317***	-0.118	0.0007
FO_POP (1000)	-0.346***	-2.245***	-2.079***	-1.836	1.432***
SLOPE_i	0.418***	0.824***	0.402***	1.214***	0.277***
Wood Land	-0.842***	-1.063***	-1.07***	0.136	-0.576***
Grass Land	-0.042	-0.882***	0.297***	-0.493***	-0.284***
DZ_2	0.543***	0.376***	0.283***	0.441***	-0.152**
DZ_3	0.439***	0.914***	0.434***	0.557***	0.330***
DZ_4	0.465***	1.340***	1.06***	1.549***	1.05***
_IAIRPORT_i_1			0.467***		0.586***
Constant	-3.858***	-1.389***	-2.107***	-1.506***	-2.596***
R2	0.1520	0.2892	0.1058	0.3001	0.2377
Observations	201,632	148,877	52,285	123,487	103,871

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

regions. For example, the coefficients of distance to railway station and highway in Yangqu Xian are relatively small compared to other regions. There are two possible reasons: First, the output of primary and secondary industries accounted for 70% of GDP in Yangqu Xian by 2015, which means that the majority of people in the region was engaged with farming or mining industry. Therefore, people prefer to live close to the location of farm and colliery, instead of caring about the highway and railway station. Second, as the highway system failed to totally cover the region, the non-highway road plays a more important role. Furthermore, the coefficient of GDP (-0.118) in Loufan Xian is negative and insignificant, but it is positive and significant in other districts. This situation is associated with its extremely single industrial structure that the local economy strongly depends on the coal mining. The mining area is the location with high GDP per capita, but the development of urbanization facilitated by the expansion of colliery is limited, as a colliery's capacity is determined before it is established, and the community that is based on colliery has not enough potential increase on population and radiation range.

Another thing that is worth highlighting is that the effect of population gap in the main urban districts is positive, while it is negative in other districts. One reason is that the population density in main urban districts is higher and reaches the point of saturation, and old urban area needs to expand to accommodate more populations. However, in rural districts, the old urban area has lower population density, which mean that urban area can attract the population around without land expansion. At the same time, with immigration the urban land around the core urban area in rural districts may degrade to arable or natural land.

According to table 13, we can see that, generally, the arable land has higher probability to transform to urban land than forest and grass, which inevitably causes the loss of arable land in the process of urbanization. Due to the geographical conditions of Taiyuan city, especially Loufan Xian and Gujiao Xian, the area of agricultural land is insufficient. The rapid expansion of city in these years has reduced the area of the original arable land, and the supplementing land cannot fill up the loss, which poses a threat to food supply.

The positive coefficients of the development zone variable set indicate that the development zone can lead to urban land conversion. One reason is that with the strong investment, local economy will increase dramatically that can support the transformative process. Another reason is that the location chosen as a development zone must have its unique advantages (such as university town, tourist area, administrative region, etc.) for urban land growth. Even though these advantages may not be included in this model, they will inevitably influence the result.

6. Urban land prediction

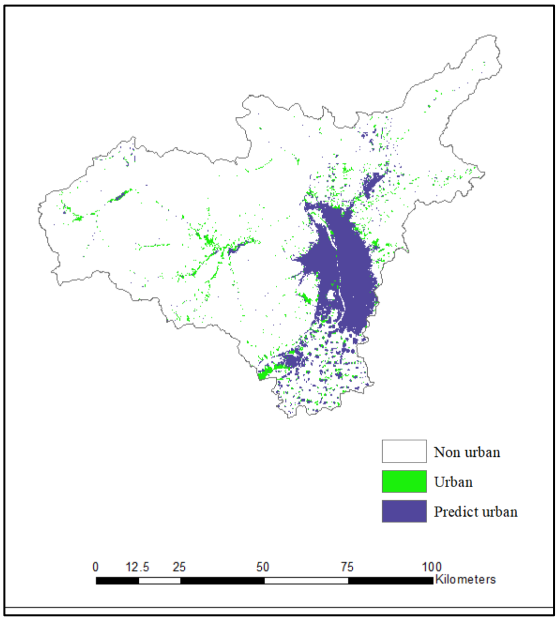
It is one of the effective tools to use the simulation model of urban land use to predict the future urban land use patterns and spatial distribution (Almeida, 2005). The analysis of the results of prediction under different scenarios can help the decision-maker to select the optimal plan (Vermeiren, 2012). Under the assumption of stationarity, this chapter uses the logistic regression model established in this paper to predict urban land growth during the period of 2015 to 2025, in order to explore the changes in the spatial pattern of land use under different scenarios. Firstly, based on the land use in 2005, the logistic model is employed to simulate the urban land distribution in 2015. Then the results are compared with the actual data through Kappa coefficient test, so as to verify the validity of the prediction models. Then this study simulates and predicts the spatial distribution of urban land use in Taiyuan city in 2025 under two different scenarios.

6.1 The simulation for 2015

In the last chapter, model 1 has been proved that the logistic regression can well reflect the impact of these factors on urban land growth. This chapter uses “raster calculator” tool in GIS to compute the distribution of urban land growth probability in 2015. Then, based on the amount of new urban land in 2015, the same number of units that has higher transfer probability were picked as the prediction of new urban land in the simulation model. At last, combining the old urban land in 2005 and the prediction, we can get the forecast distribution map of urban land in 2015 (Figure. 6)

An important step in the model is accuracy evaluation. Kappa statistics is a commonly used accuracy test model, and it ranges between 0 and 1. The higher the value is, the better the prediction matches the reality. Generally, Kappa≤0.4 indicates poor predictive accuracy, and Kappa>0.4 indicates a good predictive accuracy of the model. This paper

Fig. 6 status of urban land distribution in 2015 and forecast



used kappa test to compare the land use prediction result in 2015 and the fact status (Fig. 6). As is shown in the result, the value of Kappa is 0.6924, which reflects that there are some differences between simulation results and the real situation, but within an acceptable range. The reason behind is that the model focuses on the preferences and geographical characteristics in landowners' land use type choice, and the explanatory power of the model in the factor of policies and regulations is insufficient. On the other hand, it shows that the impact of human economic and social activities on land use change is complex. The formula is expressed as follows:

$$\text{Kappa} = \frac{P_a - P_c}{1 - P_c}$$

Where P_a refers to the proportion of agreement in prediction model, and P_c is the hypothetical probability of chance agreement.

a) The simulation for 2025

On the basis of meeting the accuracy requirement of prediction, this section updated the distribution of each drivers, employed the simulation model to get the urban land growth in 2025.

Except the changes of GDP and population distribution, there are three important changes of driver forces. First one is the expansion of highways system. A new ring road will be completed by 2020 and will cover a part of Gujiao Xian, Qingxu Xian and Yangqu Xian (see Fig. 3), which will change the map of the distance to highway. Next one is the airport will be moved south (Fig. 3), which influence the location`s distance to airport. Last one is that the government plan to build some new economic development zones around the city, the impact of development zone also will change (see Fig. 4).

Under the conditions mentioned above, this study proposes three scenarios of the anticipated size of the new urban area in 2025:

Scenario 1: assume the speed of urban expansion is constant and same as the speed of urban expansion from 2005 to 2015 (See Table 3), the increase of urban land will be 400 square kilometers from 2015 to 2025.

Scenario 2: assume the speed of growth of population is constant and same as the speed of growth of population from 2005 to 2015, according to the Overall Urban Planning of Taiyuan City (2016-2035) stating that the number of urban area per capita is expected to be 100, the increase of population from 2015 to 2025 will be 1.13 million. Therefore, the increase of urban land will be 113 square kilometers from 2015 to 2025.

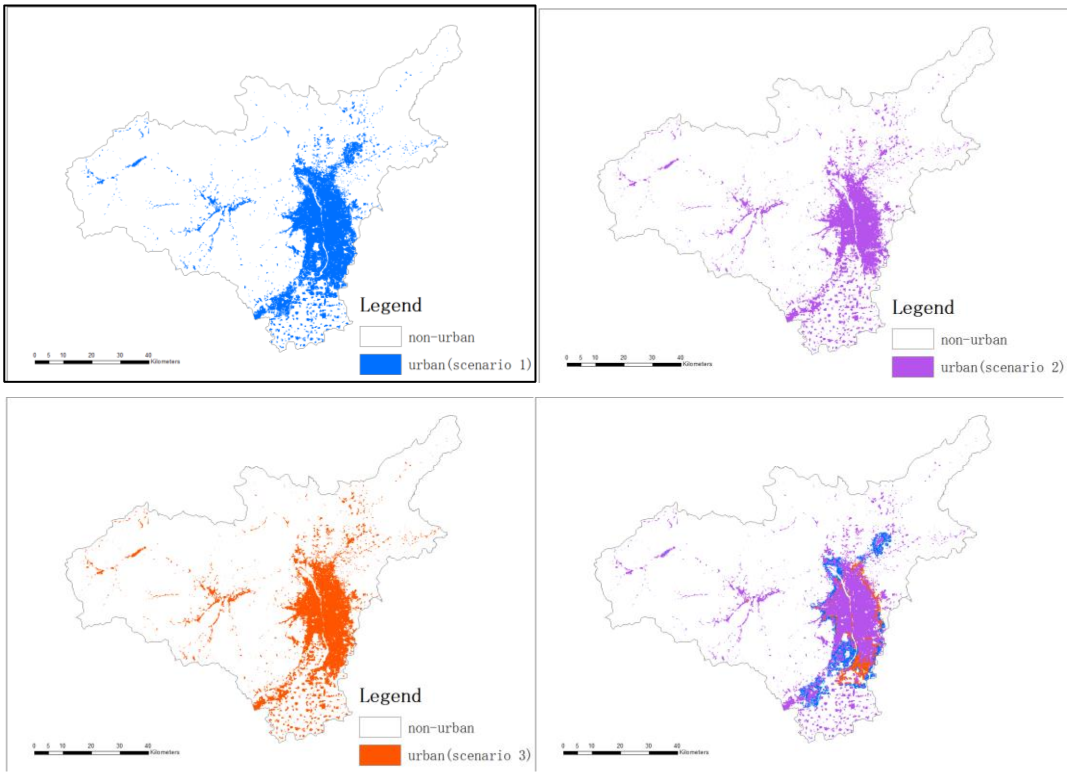
Scenario 3: according to the Overall Urban Planning of Taiyuan City (2016-2035), the increase of urban land will be 180 square kilometers from 2015 to 2025.

The simulation results of the prediction in three scenarios is presented in Figure 7. Through comparing with land use distribution in 2015, the main sources of new urban land are computed and summarized in table 14.

Table 14. The main source of urban land

	Scenario 1		Scenario 2		Scenario 3	
Change type	Unit (hm^2)	Percentage of new urban	Unit (hm^2)	Percentage of new urban	Unit (hm^2)	Percentage of new urban
From arable land	30069	73.92%	5626	49.79%	9947	55.22%
From wood land	5479	13.47%	3854	34.11%	5563	30.88%
From grass land	5130	12.61%	1819	16.10%	2505	13.91%

Figure 7. the prediction of urban land in 2025



From figure 7 it can be seen that in scenario 2, the increase of new urban area is the smallest. The major urban area tends to expand towards the northeast, and the urban patches in the south part of Taiyuan does not experience a salient change. In scenario 3, compared to scenario 2, there is a visible merge of scatters into integral urban areas in the south, especially in the places close to economic development zones. It is shown in scenario 3 that urban expansion is featured by the emergence of continuous urban area within the rural area and development zone projected by the government in the south, and the expansion centered on the existing urban area. In scenario 1, apart from the situation in scenario 3, a large number of urban patches in the south merge into a continuous urban area and link up into a single stretch with the main urban area.

The results in Table 14 show that the more the increase of urban area is, the more probable the arable land is occupied and transformed. For instance, in scenario 1, with the increase of 400 square kilometers, arable land contributes to the 73.92% of the total increase, which is the biggest among all the scenarios. It implies that if urban expansion keeps going without constraints, there will be a large amount of loss of arable land. However, limited urban expansion in scenario 2 cannot promote the development of rural area and economic development zone. In scenario 3, with the increase of 180 square kilometers, a balanced development can be realized. Therefore, the urban planning scheme is reasonable.

7. Conclusion

This paper analyzes the characteristics of urban land use change in Taiyuan city from 1995 to 2015, with particular focus on land quantity structure change, land transitions and the spatial distribution of change. Based on this, this study employed logistic regression model to analyze the driving forces of urban land change. Finally, the model was used to realize the simulation and prediction of urban land growth in 2025. From this study, the main conclusions are:

1. From the perspective of the quantity change of different land use type, arable land, grass land and water body indicate a decreasing trend from 1995 to 2015, and the decrease of agricultural land area is the largest. The expansion of urban land is the most prominent phenomenon compared to other types. From the perspective of land transition, the conversion from arable land to urban land was the most active, and it is obvious that the probability of that different land use types converted to urban land is heterogeneous.

2. The new urban land that merged in the two periods has different spatial distribution features. In the period of 1995 to 2005, most new urban area occurred on the west side of Fenhe river, while after 2005, the urban expansion shows a south-towards tendency. The movement of center of gravity can clearly show the trend.

3. The analysis of driving factors of urban land expansion indicates the importance of slope as the key natural factor, which is in accordance with the trend that most of the new urban land emerges in the Fenhe plain valley. To a large extent, agricultural land is featured with higher conversion probability when comparing to the wood land and grass land. Therefore, the loss of arable land is easily anticipated. The

availability of transportation also plays a key role. In other words, urban land tends to emerge where the cost of human intervention is relatively low.

4. In addition, the agglomeration effect of old urban area is salient in the process of urbanization. Economic development zone also shows positive influence on the emergence of new urban area in both main urban districts and remote suburbs. Airport economic zone, as well, plays an important role in land transition. The appearance and expansion of urban area relies on the existing center or developmental areas. Nevertheless, the influence of GDP and population is not that prominent.

5. Based on the city area projected by the government, the predictive model simulates the spatial distribution of Taiyuan in 2025. The result shows a further south-towards development tendency of the urban land. A large shrink of agricultural land is expected to happen, which may lead to the accelerated conflicts between the need of residents and the structural situation of land distribution. The government should implement policies on agricultural land protection in order to realize harmonious and sustainable development in future.

This study provides an empirical analysis of urban land use expansion in small-medium city. Compared to large cities, the driving factors are different. First, the influence of population exceeds the influence of economy in Taiyuan, which is different with the experience in large cities. The reason behind is that in large cities a strict institutional constraint- *Hukou* (*household registration*), and high housing price plays a significant role in limiting migration in large city, but, in Taiyuan, the barriers of population flow is relatively small, and the development potential from population growth can be easily realized. In addition, in large cities with rapid economic developmental speed, economic factors play a key role in promoting the expansion of urban land. In Taiyuan, however, the moderate economic development limits the effect of economic factors.

This distinction is also associated with different urban planning schemes. While in large cities, the scarcity of land requires a comprehensive and effective designing of land distribution, in small-medium cities inefficient urban land distribution is not a rare phenomenon that is incompatible with economic distribution (Skinner，2001).

This study also offers some insights in the analysis of inland cities. It can be seen from the result that geographic condition, especially the slope, has a prominent constraining effect in urban expansion. Since Taiyuan is surrounded by mountains in its west, north, and east sides, the only practical development planning is to construct a new urban center towards south where the relatively even land condition makes the project economically efficient.

Other factors like transportation and economic development zone show a similar effect in large and small-medium cities. The negative consequence of conflicts between urban land and agricultural land during urbanization is common as well.

There are also limitations in this study. First, the classification accuracy of land use does limit the capacity of the model to be more effective in description and prediction. Second, the unavailability of specific data also has a negative effect. For instance, factors including land value, and the growth rate of population and GDP are regarded as effective explanatory variables in the literatures, nevertheless they cannot be incorporated into the model. Finally, the influence of urban planning on urbanization cannot be simplified as economic zone only, since it is also associated with the investment and other policies. Therefore, in future studies, there are many related factors that need to be explored.

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