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Urban Land Development for Industrial and Commercial Use: A Case Study of Beijing

Chuanzhun Sun [1,†], Chao Sun [2,†], Zhenshan Yang [3,*], Jikang Zhang [4] and Yu Deng [3]

1 College of Public Management, South China Agricultural University, No. 483, Wushan Road, Tianhe District, Guangzhou 510642, China; subject_111@126.com
2 Department of Engineering Physics, Institute of Public Safety Research, Tsinghua University, Zhongguancun North Street, Haidian District, Beijing 100084, China; slayergod@163.com
3 Key Lab of Regional Sustainable Development and Modelling, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, 11A Datun Road, Chaoyang District, Bejing 100101, China; yangzs@igsnrr.ac.cn (Z.Y.); rain00788@163.com (Y.D.)
4 Shenzhen Urban Planning & Land Resource Research Center, 8009 Hongli Road, Futian District, Shenzhen 518040, China; jikang0530@163.com
* Correspondence: yangzs@igsnrr.ac.cn; Tel.: +86-10-6488-9035
† These authors contribute equally to this paper.

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Abstract: Since the 20th century, urbanization has been the main characteristic of global land development. If we can reveal and understand the characteristics and underlying mechanisms of urban development, we can then identify a sustainable development pattern for cities. In this paper, we primarily focus on the determinants of two main types of land use in urban development, industrial and commercial, in an empirical study of Beijing. We use a spatial data analysis method to seek and model major determinants of industrial and commercial land growth in the period of 2000–2010 in Beijing. A spatial logistic regression model is used to explore the impact of spatial independent variables on these two types of land use. The study shows that: (1) newly-added industrial land during 2000–2010 received significant contributions from the number of local enterprises engaged in services in 2010, the use of land for agriculture and construction in the neighborhood in 2000 and planning orders; (2) factors contributing to land transferred for commercial use included the number of enterprises, construction land in the neighborhood and accessibility improvement.

Keywords: urban development; industrial land; commercial land; growth; Beijing

1. Introduction

Determinants of land use change are important for understanding and formulating urban development policy. These determinants also guide analysts and planners in making suitable land development strategies. Often, changes in land use result in complex interactions of various landscape functions [1], affecting social and economic activities. Therefore, it is expected that different land use changes occur because of different processes of development and are determined by different factors. However, this is not well addressed in current land use studies. In this paper, we primarily focus on the determinants of two main types of land use in urban development, industrial and commercial, in an empirical study of Beijing.

Various models and approaches have been developed to examine urban land use change. From institutional and political economy perspectives, urban land use change is viewed as an institutional process [2] that, particularly in China, is driven by reform and globalization and led by the state,

state-centered development alliances and multinational enterprises [3–5]. With the development of geographic information systems (GIS), remote sensing and spatial statistics, various models are used to analyze and simulate land use or urban growth patterns [6–8], including in the context of China [9,10], which allows for examining the extent of specific factors.

Land-centered development has aroused wide discussion as researchers attempt to understand it within the context of socioeconomic development. For instance, Deng et al. [11] found that economic growth is of overwhelming importance to the determination of urban land use. Zhang [12] applied the concept of a growth machine to understand the growth of local economies in China. The results showed that individual land-related local interest groups are emerging and economic coalitions exist to different degrees in Suzhou and Shenzhen. Jiang et al. [13] identified population urbanization and industrialization, as well as economic restructuring and growth as the demand forces underlying urban land use expansion. It is now widely believed that land use change is determined by multiple socioeconomic, physical and institutional factors. However, this analysis usually embraces a dichotomous view of urban land use, i.e., construction or non-construction, and usually does not go as far as to provide a detailed structure of the construction land use.

In practice, manufacturing and commercial uses are two main types of urban land use, which vary under different courses. Verburg et al. [14] found that expansions of industrial or commercial land were driven by a combination of transportation accessibility, spatial policies and neighborhood interactions. Though there is a significant implication for practice, the land use change under different functions is examined to a lesser extent.

In this paper, we hypothesize that industrial and commercial land uses have different determinants. These determinants are examined using a logistic regression model for urban land use change in Beijing during 2000–2010. We assess the relationship of manufacturing and commercial land use changes with locational accessibility, social and economic factors, built environment, natural factors and institutional factors; therefore, in this paper, industrial land and commercial land use are dependent variables. We use the logistic model to explore the influence of various independent variables on these two types of land use. Additionally, compared with other relative studies, transportation accessibility is the main reference factor in our study, and it includes 18 indicators, such as distance to the city center, distance to the employment center and distance to a subway station. Moreover, we take the dynamic change of these indicators into account. Existing research considers only a single transport type that impacts city land use [15–18], whereas we analyze several. Furthermore, transport accessibility was measured in terms of distance, time and transport cost, which reflect all of these aspects to be somehow less [19,20].

2. Methods and Data

Beijing is China's capital city, with a population of 19.6 million by the end of 2010 and 21.5 million in 2014 [21]. It is one of the cities witnessing the fastest urban growth in China and perhaps in the world. Urban land use is also undergoing dramatic change and in many cases out-pacing planned scenarios, in both spatial expansion and function. This rapid development is exemplified by the building up of eight commercial centers and industrial bases, including Zhongguancun High-tech Park, Olympic Park Commercial Center and Shunyi Modern Manufacturing Base. The city area is continuously extending, and the city function is likewise continuously improving. The improvement mainly features the stripping and disintegration of the city function, namely extracting the non-core function, which is not related to the core function, from the city gradually, which is mainly to alleviate the current disparities among population, resource, environment and development in Beijing, and promoting the sustainable development of the city. For example, in order to implement the strategy of coordinated development of Beijing, Tianjin and Hebei and meanwhile stripping the non-core city function, in May 2016, the central policy makers formally established a strategy of the construction of the "city sub-center of Beijing" in the suburban region of Tongzhou district. To put that strategy into practice, a large number of functional entities (such as the administrative entity, commercial entity, medical entity and education educational entity) will be gradually relocated to Tongzhou. Tongzhou New Town will become a comprehensive sub-center with administrative, cultural, economic and educational functions. In this situation, the determinants of urban land use become a critical concern of urban land development.

2.1. Choice of Independent Variables

2.1.1. Social and Economic Factors

Urban land use change is driven by social and economic development. Population density is often regarded as an important factor in determining land use, by indicating labor availability, accessibility or the presence of local markets [22,23]. Together with population, the size and distribution of enterprises to a large extent reflect agglomeration economies, which is an important driver of modern cities' land use change, especially in Beijing [24–26]. Three population factors (population in 2000, population in 2010 and the population growth rate during 2000–2010) and nine enterprise factors (number of enterprises, service enterprises and industrial enterprises in 2000 and 2010, as well as the fluctuation in that number during 2000–2010) were selected to reflect urban land use change.

2.1.2. Built Environment

The built environment, which is largely decided by existing land use, provides a main area for living, working and playing on a day-to-day basis [27]. Among others, location, particularly accessibility, significantly influences economic and human activities [28,29], and existing land use in neighborhoods is expected to guide the function of land use changes [30–32]. The built environment can be further classified as transportation accessibility and neighborhood land use.

(a) Transportation accessibility plays an important role in shaping the spatial structure of the city, which also creates and shapes economic and social opportunities [33,34]. A transportation accessibility indicator is usually considered to be the main factor driving city expansion, and it is widely used in studies of forces driving such expansion [35]. In this paper, we consider the synthesis of transport accessibility from six aspects, city center accessibility, central business district (CBD) accessibility, employment center accessibility, industrial center accessibility, subway center accessibility and high speed way accessibility, covered by 18 indicators (please see Table 1).

Table 1. Characteristics of independent variables.

Name of Variable	Type	Unit	Max [a]	Min [b]	Mean	SD [c]
Population density (2010)	Continuous	Person/sq. km	359,400	5000	89,122	57,023
Number of service enterprises (2010)	Continuous	Per sq. km	8683	82	861	766
Growth of service enterprises (2000–2010)	Continuous	Per sq. km	2.01	−0.05	0.83	0.34
Number of industrial enterprises (2010)	Continuous	Per sq. km	1461	10	304	240
Growth of industrial enterprises (2000–2010)	Continuous	Per sq. km	0.91	−0.6	0.18	0.21
Static accessibility principal factor	Continuous	Minutes	539	13	197	94
Dynamic accessibility principal factor	Continuous	Minutes	213	0	46	36
Construction land in neighborhood	Continuous	%	100	0	41.61	32.36
Forest land in neighborhood	Continuous	%	100	0	10.94	18.45
Agriculture land in neighborhood	Continuous	%	100	0	32.78	27.96
Water area in neighborhood	Continuous	%	100	0	6.23	12.68
Urban planning control	Binary	–	1	0		
DEM	Continuous	Meter	1234	−126	62	100

[a] Max: maximum; [b] Min: minimum; [c] SD: standard deviation.

(b) Land use in adjacent areas accounts for the possible effects of spatial interaction on land use decisions [30,31]. New construction is path dependent, which means that if the proportion of construction land use around some areas is larger, the probability of there being new construction land use in these regions is perhaps higher. The possibility of urbanization is most closely related to its neighborhood [9]. Construction could, however, be deterred by non-construction uses in the neighborhood, such as water and agricultural uses, particularly under circumstances similar to those in China where there is strong legislative protection of agricultural land. Thus, the role of neighborhood uses in affecting industrial and commercial land uses was discriminated into two types: promoting factors if the neighborhood is dominated by construction or restrictive factors if occupied by agricultural or forest land and water areas. When we choose the neighborhood independent variable, we take the percentage of construction land, agricultural land, forest land and bodies of water into account. It is generally acknowledged that higher construction land usage will promote land development. Meanwhile, because they are protected by land use policy, a higher percentage of agricultural and forest land will decrease the possibility of land development. However, agricultural land is always located in a plain land region, and its development cost is relatively low, which increases the possibilities for occupation, even if it is being protected.

2.1.3. Natural Factors

Natural factors, especially slope, dramatically influence population distribution, the cost of land development and the function of land use [36]. Therefore, the digital elevation model (DEM) as the topographic factor is involved in the scope of the independent variable.

2.1.4. Institutional Factors

The evolution of urban spatial structure is heavily influenced by spatial policies as they encourage or limit certain kinds of land use [9]. However, quantitative impacts of spatial policies on land use change are hard to assess [37]. A land use plan was used to indicate policies controlling and guiding new commercial and industrial land.

2.2. Data Preparation and Processing

2.2.1. Dependent Variables

Detailed land use data from 2000 and 2010, provided by Beijing Land Use Bureau (BLUB) at a spatial scale of 1:10,000, was used to measure the functional change of urban land over one of the fastest growth periods in Beijing. In 2000 and 2010, BLUB carried out a detailed land use survey of Beijing. Land use types in 2000 and 2010 included construction, agriculture, forest and bodies of water. However, owing to a change in land use classification standards, in 2010, construction land was divided into commercial and industrial land and others. Therefore, using spatial overlay analysis, we get the newly-defined commercial and industrial land uses during 2000–2010. The modified uses were mainly agriculture-related types and therefore did not affect our analysis. Industrial land (for manufacturing) and commercial land (for business and services activities, not including residential ones, which were another specific type of land use in urban planning in China) were extracted using GIS software and were dependent variables in this study. As most specified land use occurred in and around the urban center, the analysis was confined to the main urban districts in Beijing (Figure 1). In this study, we chose the region within the 6th Ring Road as the study area, which included the Core Zone of Capital Function (CZCF), the Urban Function Extended Zone (UFEZ), the New Zone of Urban Development (NZUD) and the Eco-conservation Zone (ECZ) (Figure 1).

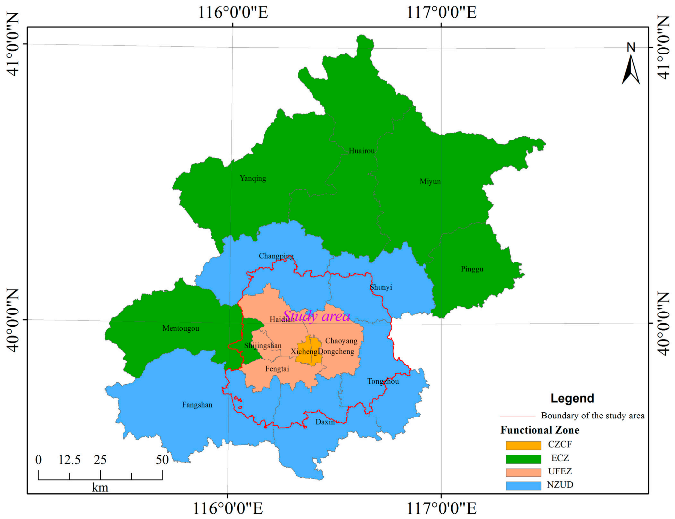


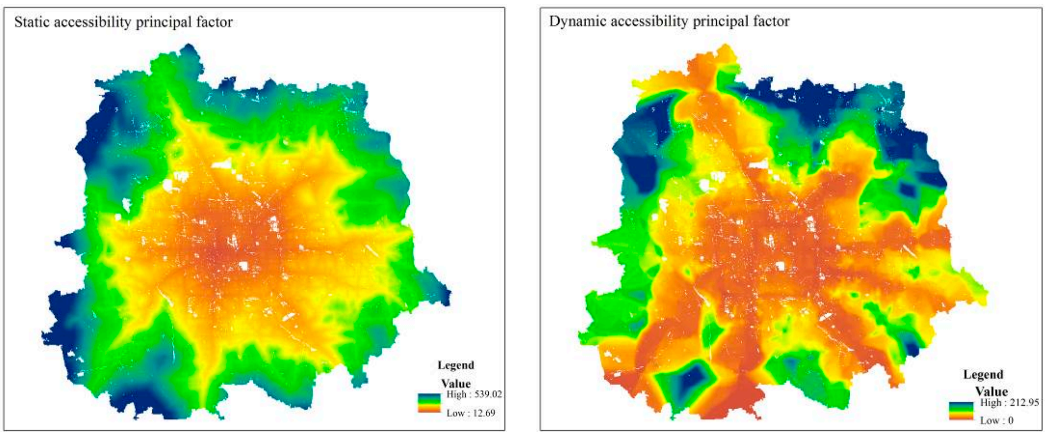
Figure 1. Study area: Core Zone of Capital Function (CZCF), the Urban Function Extended Zone (UFEZ), the New Zone of Urban Development (NZUD) and the Eco-conservation Zone (ECZ).

2.2.2. Independent Variables

(a) Transportation accessibility indicator data:

We collected transport data on different road ranges; these spatial data come from the Beijing master transport map (2004–2020), which includes the expressway, arterial traffic, secondary main roads, branch roads and urban mass transit. We gained the average speed of each level road in 2000 and 2010 by referring to existing literature [38] and reports [39]. Then, we used network analysis and weighted distance analysis [19,34] on the ArcGIS platform to generate time maps (100-m spatial resolution) encompassing the study area to the city center, CBD, industrial center and some other elements. All of these maps can be considered transportation accessibility maps, and through overlay analysis of the 2000 and 2010 maps, we acquired the dynamic change transportation accessibility map.

To eliminate the collinear relation among different indicators, we adopted a principal component analysis method to obtain the first principal factor of the static and dynamic accessibility of our study area. The first principal factors' variance explanations are 84.07% and 83.75%, respectively (Figure 2). The static accessibility principal factor revealed the pattern of monocentric transportation allocation in Beijing, while the dynamic accessibility principal factor revealed the strength of improvement of transportation in different regions in the study area.



(**a**) (**b**)

Figure 2. Transportation accessibility principal factor map. (**a**) Static accessibility; (**b**) dynamic accessibility.

(b) Population indicator data:

We used data from the fifth and sixth population censuses in Beijing to get the permanent resident population data of every town in Beijing in the years 2000 and 2010. Then, we used inverse distance weighting (IDW) interpolation to shape the population grid map (100-m resolution) in 2000 and 2010, as well as to denote the change between the two years. However, to decrease the collinearity of different population indicators, which we will input into the logistic model, we make an effort to reduce the dimensionality of the indicators to guarantee the feasibility and stability of this model. When we performed correlation analysis of all of the population indicators, we found that there was significant correlation among the different indicators (Table 2). The correlation coefficient of the population in 2010 with that in 2000 and the population change were 0.5 and 0.6, respectively; thus, the population in 2010 appeared to be the best indicator to represent all population indicators, and it was input into the logistic model. As shown in Figure 3, the average population density of the study area in 2010 was 89,122 per km^2. The higher density area was distributed around the city center.

Table 2. Parameters of the model results.

	Percentage Correct	Hosmer–Lemeshow	−2 Log Likelihood	Cox and Snell R Square	Nagelkerke R Square
Commercial land	70.30%	0.286	2260.423	0.202	0.269
Industrial land	65.60%	0.216	12,263.909	0.141	0.189

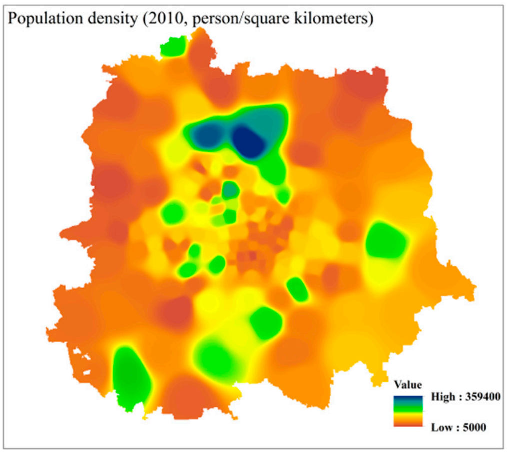


Figure 3. Population density in 2010.

(c) Economic and employment data:

Using data from the first and second economic census in Beijing, we obtained the total number of all enterprises, service enterprises and industrial enterprises of every town, which is the smallest administrative unit in China. Then, we used IDW spatial interpolation to shape the number of enterprises grid map (100 m spatial resolution) in 2000 and 2010 and the change between the two years. As with the population indicator data, we reduced the dimensionality of the indicators using correlation analysis (Table 3). Finally, we chose the number of service enterprises (2010), growth of service enterprises (2000–2010), number of industrial enterprises (2010) and growth of industrial enterprises (2000–2010) as the elements to input into the logistic model.

As shown by the spatial grid map of the above indicators, the spatial agglomeration degree of industrial density is relatively weak in the city center in 2010 (Figure 4). However, around the city center, we can identify an increasing trend in industrial density during 2000–2010. Meanwhile, the spatial agglomeration degree of service enterprises is significant in the core area and the function extension area. During 2000–2010, the activities of service enterprises trended toward extending northwards in Changping and southwards in Daxing.

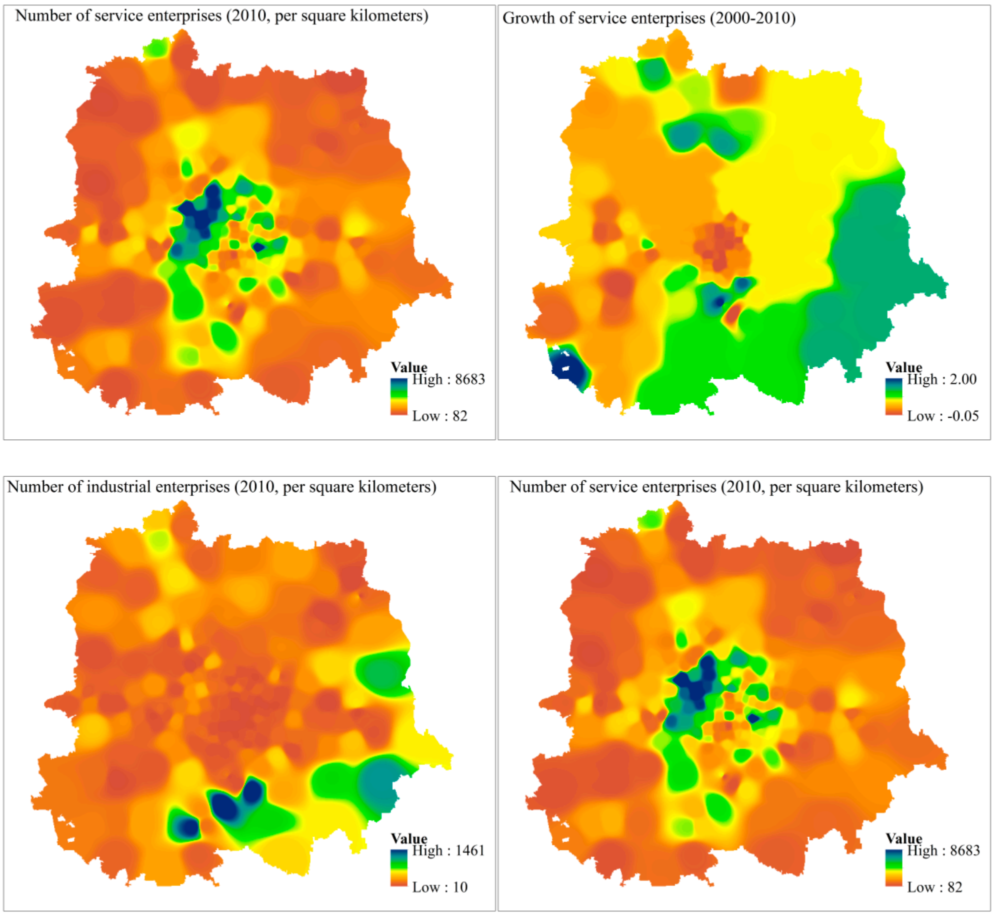


Figure 4. Economic and employment distribution in 2010 and during 2000–2010.

Table 3. Results of logistic regression of new commercial and industrial land.

Variables	Commercial Land				Industrial Land			
	β	*p*-Value	Wald χ^2	Odds Ratio exp (β)	β	*p*-Value	Wald χ^2	Odds Ratio exp (β)
Population density (2010)	0.001	0.029	4.762	1.00	−1.212	0	38.306	0.30
Number of service enterprises (2010)	7.55	0	72.169	1900.74	1.116	0	13.245	3.05
Growth of service enterprises	–	0.293	–	–	–	0.699	–	–
Number of industrial enterprises (2010)	−0.98	0.006	7.545	0.38	–	0.507	–	–
Growth of industrial enterprises (2000–2010)	−1.234	0.002	9.938	0.29		0.037	4.369	1.69
Accessibility (2010)	−1.925	0	17.322	0.15	−2.134	0	108.594	0.12
Change of accessibility (2000–2010)	0.664	0.088	2.914	1.94	–	0.341	–	–
Neighborhood construction land	0.931	0	18.318	2.54	0.767	0.001	11.372	2.15
Neighborhood agriculture land	–	0.383	–	–	0.408	0.067	3.364	1.50
Neighborhood forest land	–	0.866	–	–	−0.566	0.03	4.699	0.57
Neighborhood waters	–	0.296	–	–	−0.617	0.02	5.447	0.54
Urban planning	–	0.129	–	–	0.437	0	55.541	1.55
DEM	−11.928	0	31.799	0.00	−12.106	0	117.787	0.00
Likelihood: ratio statistic	2260				12,263			
Number in sample	1000				1000			

(d) Neighborhood data:

Based on the land use data in 2000, we take the percentages of construction, agriculture and forest land and bodies of water within 1 km^2 as the measurements to shape the neighborhood land use map (100-m spatial resolution; Figure 5). As shown by these maps, there is a high percentage of construction land in the core area and the function extension area. The distribution of the construction land expanded in the vicinity of the main road. The agricultural land is mainly distributed in the southeast part of the study area, and the forest land is mainly distributed in the west. The bodies of water are the Sha and Qing rivers in the north, the Chaobai River in the east, the Liang River in the south and the Yongding River in the west. In addition, there is a high percentage of water area in the inner city.

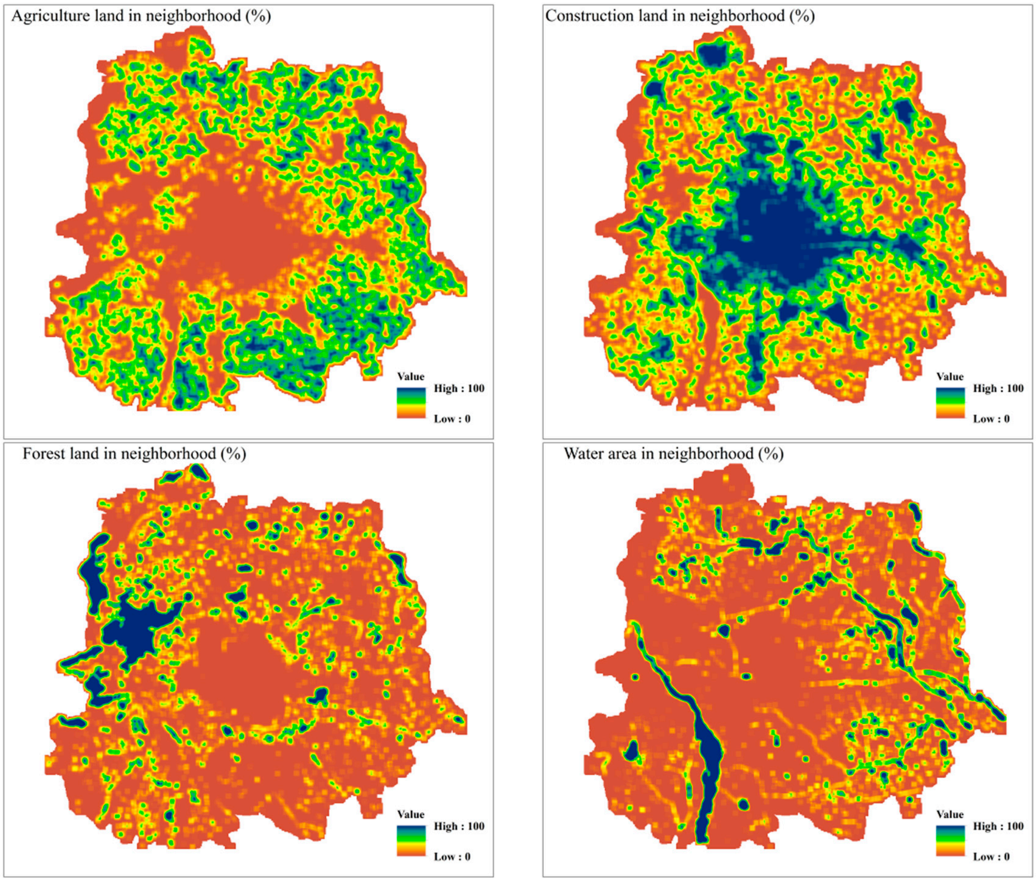


Figure 5. Neighborhood land distribution.

(e) DEM and urban planning data:

We used 90-m resolution data provided by the Resources and Environment Data Center of The Chinese Academy of Sciences. The topography in Beijing is high in the northwest and low in the southeast, comprising a mountainous region and alluvial plain, respectively. The relative difference in height between the highest and lowest points is 2295 m (Figure 6).

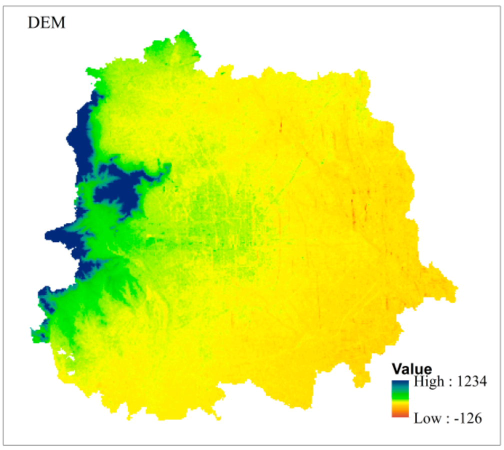


Figure 6. Topography in Beijing.

The Beijing City Master Plan (2004–2020) [40] had divided Beijing into construction and non-construction areas (Figure 7). Official urban planning maps of Beijing (2004–2020) were collected and vectorized to measure the influence of spatial policy, with the introduction of dummy variables one if the actual land use was consistent with that planned or zero otherwise.

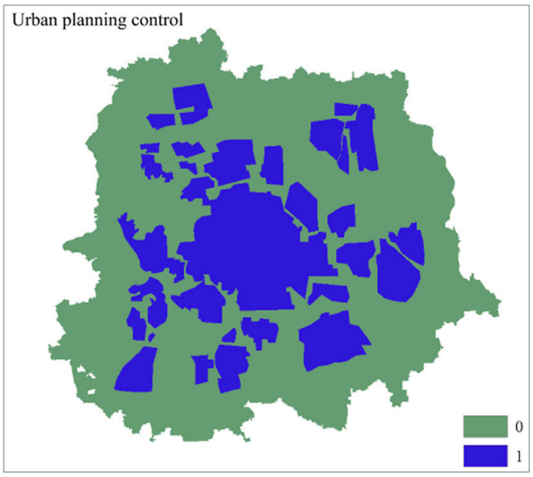


Figure 7. construction and non-construction areas in Beijing.

2.3. Spatial Sampling

It is impossible to use all data in the space to estimate the model, because of spatial autocorrelations with different spatial data [41]. Therefore, spatial sampling was necessary. In this study, input arguments of the logistic model were adopted to strictly eliminate the autocorrelation of sample points in space; otherwise, the stability and validity of parameter estimations would be affected [30]. In general, spatial sampling strategies include random sampling and systematic sampling. Random sampling is a method that ensures that each space in the overall sample has an equal chance of selection, but it lacks reliability in terms of reducing the spatial autocorrelation of samples [42]. Systematic sampling is also known as interval sampling. It is a sampling method in which the total units are arranged in a certain order [9]. It is able to overcome the issues of sample spatial autocorrelation, but it loses some information for specific spatial points; thus, spatial sampling does not reflect full representation [9]. In this study, a combination of these two strategies was adopted. Systematic or interval sampling was used, after the starting point was randomly determined and a unit was selected in a regular interval.

Specifically, using the grid layers of the 100-m resolution GIS environment, a starting point was created randomly, then the value of the layers of both independent and dependent variables were sampled in 300-m intervals. More than 5000 grids of new commercial and industrial land were included in this study area. We determined that a sample size greater than 400 was required [43]. For easy operation, we used 1000 samples in the modelling. Figure 8 shows a sample grid from this study. Note that although we omitted the land use data from the core area in 2010, this area (the white space in Figure 8) is a built up area that lacks new construction land and was therefore excluded from our analysis.

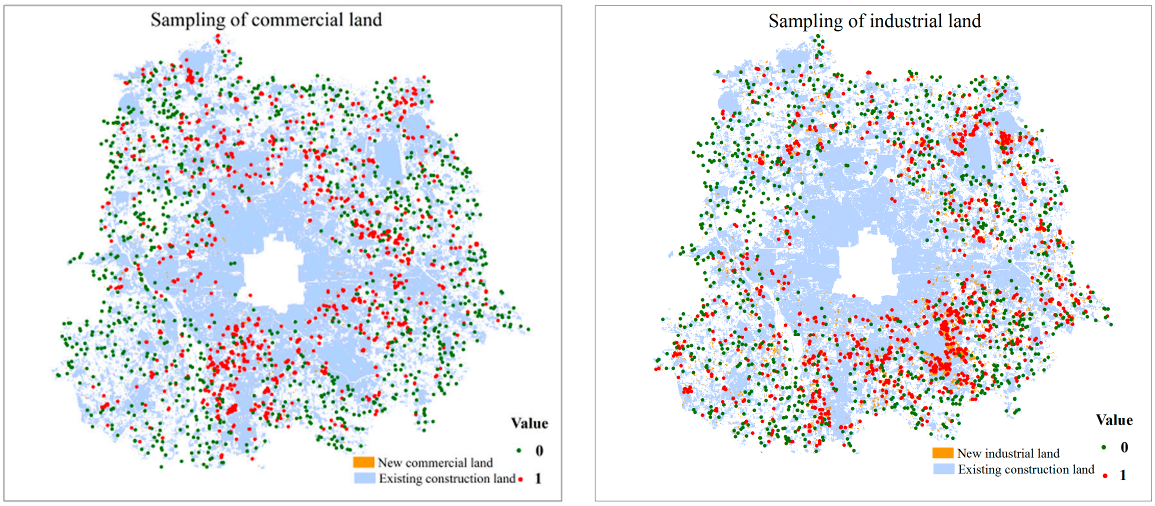


Figure 8. Spatial sampling of commercial and industrial land.

2.4. Logistic Model to Measure Land Use Change

A logistic model was used to estimate the relationship between industrial and commercial land use changes and the wide range of socioeconomic, built environment, nature and institutional factors. This model is widely used to explore the main factors that could affect urban development and its driving forces [9,34]. Specifically, assuming that X is the response variable and P is the probability of the model, the corresponding regression model should be as follows:

$$\ln\left(\frac{p_1}{1-p_1}\right) = \alpha + \sum_{k=1}^{k} \beta_k X_{ki}$$

In this formula, $p_1 = P((y_i = 1\,|X_{1i}, X_{2i}\ldots, X_{ki})$, as the values of variables $X_{1i}, X_{2i}\ldots, X_{ki}$ are determined; p_1 is the probability of an event; α is an intercept; and β is a slope. The probability of an event that occurs is a nonlinear function formed by the explanatory variable and the expression is as follows:

$$P = \frac{\exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n)}{1 + \exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n)} \tag{1}$$

Odds ratios are used to explain logistic regression coefficients of various independent variables [44]. In logistic regression, an odds ratio is commonly used to understand the effect of an independent variable on the probability of event occurrence [45], which can be expressed by the following equation:

$$\mathrm{odd}(p) = \exp(\alpha + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n) \tag{2}$$

Using binary logistic models in the SPSS tools, we calculated the regression coefficients, standard error (SE), the Wald $\chi 2$ statistic of regression coefficient estimation, the significance level (P) of regression coefficient estimation and the odds ratio (OR). Positive regression coefficients indicate that if the explanatory variables increase by an additional unit value, the odds ratio would increase accordingly. Conversely, a negative regression coefficients indicate that the odds ratio would decrease. We used the Hosmer–Lemeshow (HL) test to test goodness of fit index of the logistic model.

The significance of the HL index indicates poor model fitting, while its non-significance indicates perfect model fitting. HL is calculated as follows [46]:

$$HL = \sum_{g=1}^{G} \frac{\left(y_g - n_g\widehat{P_g}\right)}{n_g\widehat{P_g}\left(1 - \widehat{P_g}\right)} \tag{3}$$

where G represents the number of groups ($G \leq 10$). n_g represents the number of cases in group g. y_g represents the number of observed events in it. $\widehat{P_g}$ represents the probability of a predicted event in it. $n_g\widehat{P_g}$ represents the projections of the event.

3. Results

3.1. Industrial and Commercial Land Use Changes

As Figure 9 shows, from 2000 to 2010, the industrial and commercial land areas in the new scale were 14,174 and 4357 hectares, respectively. These spaces occupied up to 28.50% and 8.76% of the total new construction land in the study area. Newly commercial land was mainly distributed around the core area, and it presented a balanced distribution. The newly industrial land was mainly distributed in the north and the southeast of the study area, and it has a concentration distribution characteristic in those areas.

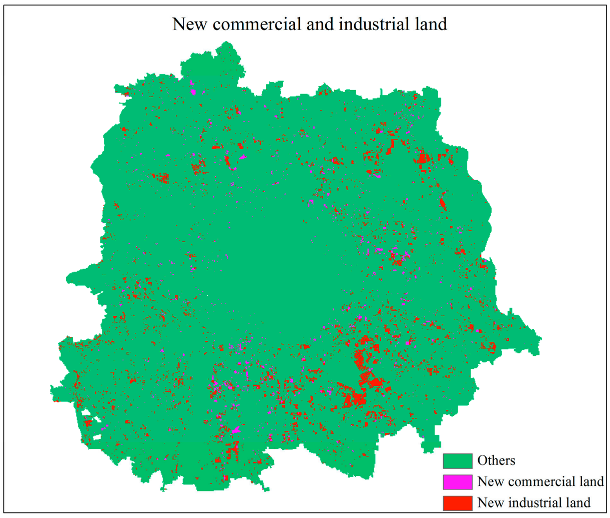


Figure 9. New commercial and industrial land (2000–2010).

3.2. Estimation of Drivers of Land Use Change

The logistic regression model of the new commercial land shows that the HL value was 0.286 and is not significant (Table 2). The accuracy of the model was 70.30%. These two indicators demonstrate that the model is a good representation of the dependent and independent variables.

The logistic regression model of the new industrial land shows that the HL value of 0.216 is not significant. The accuracy of the model was 65.60%. These results also demonstrated that the model is a good representation of the dependent and independent variables.

3.3. Determinants of Industrial Land Change

Table 2 shows the descriptive statistics of the explanatory variables. According to Table 2, factors that significantly contributed to industrial land growth in 2000–2010 were the number of enterprises engaged in services (NEES) in the area in 2010, the agriculture and construction land uses in the neighborhood in 2000 and planning orders. Among these, NEES had the largest impact on the development of industrial land with an odds ratio of 3.05, because service enterprises provide a favorable environment both for manufacturing activities in terms of producer services and for employers' daily life in terms of consumer services. For example, Deng [47] completed an industrial structure survey within 1 km of the Wanyuan subway station, located in the industrial park of the Yizhuang economic development zone. The results showed that in 2010, the manufacturing industry was 90% of all industry in the area; however, there was also a large number of existing and under construction services enterprises, which included three business centers, three finance services institution and one hotel (Figure 10). The close proximity to these services was cost effective and helped manufacturers quickly connect to the market. Apart from the NEES, construction in the area also contributed to the growth of industrial land (OR = 2.15) for a similar reason, but with wider implications regarding residential, transport and public facilities and other urban functions. The odds ratio of the independent growth of industrial enterprises (2000–2010) was 1.69. This indicates that if the number of industrial units increased by one percentage point, the possibility for future increases in industrial units increases 1.69-times. The odds ratio of the neighborhood agriculture land was 1.5, which indicates that if the percentage of agriculture land in the neighborhood increased by one unit, the possibility for new increases in industrial land will increase 1.50-times. This reflects urban expansion, especially the industrialization-driven suburbanization process, which encroached upon a huge amount of agricultural land. The odds ratio for planning orders was 1.55, which is greater than one and indicates that the amount of industrial land will increase if it is located within the construction area defined by the city plan.

(**a**) (**b**)

Figure 10. The commercial infrastructure within 1 km of Wanyuan subway station. (**a**) Libao business square (building in progress); (**b**) Agricultural Bank of China.

Factors hampering land transfer to industrial uses included DEM (OR = 0), accessibility (0.12), population density in 2010 (0.3), water in the neighborhood (0.54), forest in the neighborhood (0.57) and growth of industrial enterprises (0.76). Because of the building restrictions in Beijing, it is impossible to build industrial land on a slope >10%, which was reflected by the DEM. Urban land developed during 2000–2010 was primarily in the peri-urban area, with new construction land in this area increasing to 35,764 ha, which made up 71% of new construction land in the study area. However, Beijing is a mono-centric city with better transportation conditions in the urban center than other places. For cases where most industrial land was developed in the peri-urban area, the accessibility factor was adversely associated with the growth of industrial land. The increase of relatively large industrial land areas was also negatively related to population density. This creates an inconsistency between the distribution of large-scale residential areas and industrial areas, where there is a clear separation between the workers' residences and their workplaces. The odds ratios of forest land and bodies of water were 0.57 (1/1.76) and 0.54 (1/1.85), respectively. These values are both less than one, which indicates that the probability of industrial growth in forest or water areas was low; specifically, the probability of industrial growth decreased by 1.76- or 1.85-times as forest or water area increased by 1%.

3.4. Determinants of Commercial Land Change

Factors contributing to land transferred for service use included the NEES (OR = 1901), construction in the neighborhood (2.94) and accessibility improvement (1.94). For example, newly commercial land in Huilonguan in Changping increased by 83 ha, which was higher than the average increase by 44.46 ha in our study area. In 2000, the percentage of construction density was 70.49%, higher than the average level of 41.61% in our study area. The services enterprise density in 2000 was 1790.39 per km^2, much higher than the average level of 861 per km^2. Within 2000–2010, Subway Line 13 was built in Huilonguan, and then, the transport accessibility was substantially improved with an improvement of 15 min [47].

The odds ratio of population density was one, which indicated that the current permanent resident population had no significant influence on new commercial land. The main reason is that Beijing has a strategy guiding the population distribution for industry development, which is to first develop commercial land, then guide commercial enterprises into these areas, after which the population of the area would occur. Therefore, population increases occurred after commercial land development, and there was no significant relationship between population and new growth of commercial land.

There were also a number of factors counteracting the growth of commercial land. The odds ratios for the number of industrial enterprises and its growth were 0.38 and 0.29, respectively, implying that the probability of the area for service use would reduce by 62% and 71% if the number of industrial enterprises was larger or increased by one unit. During 2000–2010, Beijing implemented the strategy of "suppress the second industry and develop the third industry", which had a considerable effect on the city's spatial structure. It is also reflected in the movement of many industrial enterprises to outer suburban districts while the tertiary industry activities, especially the commercial activities, continuously increased in the function extension area. According to the enterprise statistics, within the third ring road, the industrial enterprise density had decreased by 1.66 per km^2, whereas within the third ring road and sixth ring road, the service enterprises increased by 526.25 per km^2.

Commercial land expanded mostly in the peri-urban area; the factors impacting the growth of commercial land and accessibility in 2010 were negatively associated. According to the economic census data of Beijing, the added value of services in Beijing increased from 942 billion Yuan in 2000 to 5577 billion Yuan in 2010, primarily in the regions of Chaoyang, Fengtai, Shijinshan and Haidian from 94.18 billion Yuan in 2000 to 557.73 in 2010.

Because of the restrictions on planning orders in Beijing, it was impossible to build on industrial land with a slope >10%, which was reflected by the DEM.

4. Discussion

4.1. Comparison of the Determinants

Comparing the determinants of manufacturing and commercial land growth is necessary, as the similarities and differences among the drivers of industrial and commercial land transfer can shed light on possible patterns and underlying mechanisms of urban development.

4.1.1. Socio and Economic Factors

The growth of industrial enterprises was positively correlated with industrial land use increase. However, both the growth of industrial enterprises and the number of industrial enterprises correlated negatively with commercial land increases, and the odds ratios were 0.29 (1/3.43) and 0.38 (1/2.66), respectively. This indicated that reducing the number of industrial enterprises by one unit would increase the commercial land use by about three times. The main reason for this was that, during 2000–2010, when the speed of city updating was faster than the last few decades, much industrial land was turned into commercial land, and much of the other land was also changed to commercial land. According to economic census data from 2000 to 2010, the production value of tertiary industry increased by 23% and 22% in core and function extension areas, respectively, and these are important areas of tertiary industry. Meanwhile, the production value of secondary industry decreased from 47.5% down to 33.8% [47].

The NEES correlated positively with both industrial and commercial land increase, with odds ratios of 3.05 and 1900.74, respectively, which indicated that service enterprises had strong attraction to all kinds of enterprises. For example, the industry park of Zhongguancun was not only a gathering place for new high-tech industrial enterprises, but also for services such as financial, commercial and catering enterprises. Moreover, an economic census showed that the service enterprise density within newly commercial land was 1186.86 per km^2 in 2010 and much higher than the average value (1015.77 per km^2) of the Zhongguancun industrial park.

The current permanent resident population had a negative correlation with increasing industrial land, whereas it had a positive correlation with increasing commercial land. However, the relationship between population and increasing commercial land was not significant because the odd ratio is 1.00. Therefore, increasing industrial land occurred in areas with low population density, creating a separation between workers' residences and workplaces in industrial areas. For example, the worker's average commuting time in the Yizhuang economic development zone as measured by Meng [48] was 37.3 min. However, increases of industrial land use are now approaching areas with high population density. According to the population statistics of the study area in 2010, the average population density within new commercial land was 105,269.90 per km^2, which is much higher than the average 89,122.04 per km^2 of the whole study area.

4.1.2. Built Environment

Changing and improved accessibility can significantly contribute to developing commercial land, but not to industrial land. This is perhaps because industrial parks dominate industrial land development in Beijing [24] and are usually located in peri-urban or remote areas that are cost-effective, but have less favorable accessibility. Conversely, services enterprises usually tend to pay relatively higher rental changes where they possess advantageous location and transport conditions. For example, Yao and Xiong [49] studied the impact of urban mass transit on land use. The results show that the proportion of commercial and financial building areas is much higher closer to subway stations, and this proportion is 40% within the 250-m range.

Land development has three kinds of effects on the areas where it occurs. Construction in the neighborhood exerts a similar effect in attracting industrial and commercial land development (OR = 2.15 and 2.54, respectively). The slightly lower odds for industrial land reflects the fact that industrial development has more flexible conditions than the location of commercial land. Agriculture in the area is positively linked to industrial land growth, but was not significant for commercial land. This reflects that industrialization processes penetrate into the peri-urban and rural areas, but this is not paralleled by services activities. Restrictive factors, including forest and water, played a role in prohibiting industrial land development, but were not significant for commercial land.

4.1.3. Nature Factor

The landform was the most significant restraining factor for these two types of land development because of development costs and building restrictions. According to the requirement of The Beijing City Master Plan, for construction in the city land must have a gradient below 10% [40]. For example, Changping district is located in the zone of transition from plains to mountains, with significant topographical differences. In this district, the area of construction land below the gradient limit is 21,118.44 ha, or 98.79% of the total construction land.

4.1.4. Urban Planning

Urban planning is one of the most important institutional factors influencing land development. Making the right decision regarding the function of each parcel of land is the primary task of urban planners. However, our model indicates that planning orders are only significantly reflected by industrial land development at an OR of 1.547, owing to the industrial park-dominated policy in Beijing [26]. This inconsistency could be due to the high speed and large volume of urban development in Beijing during 2000–2010. In 2010, the area of construction land was 183,865.70 ha, which far exceeded the planned construction land area of 107,331.50 ha in 2020.

4.2. Recommendations of Urban Sustainable Development

Land development is an important issue for the economic sustainability of the city; particularly, it requires vast infrastructure investment and construction. In addition, the uses of land are compatible with one another to some extent. Significantly affected by market forces, planned orders may not often work well, especially when planning for commercial activities. Hence, in order to justify urban infrastructure investment and effectively make use of land, planners should respect market forces and more specifically the different effects of various factors on manufacturing and commercial land use development.

Our analysis indicates that the area of manufacturing enterprises does not favor of commercial use, but land in commercial use can encourage manufacturing use for the land nearby. The analysis further indicates there are different associations for commercial and manufacturing uses of land with the improvement of transport accessibility. Therefore, the improvement of transport accessibility could contribute to the realization of Beijing transferring from an industrial city into a post-industrial and modern city, which is labeled by the prosperity of services. Compared to previous literature, our research suggests that in order to achieve economic sustainability in land development, planners should be careful about different effects of various potential factors, as examined in our research, on manufacturing and service use of land.

5. Conclusions

Using a logistic model, we conducted an empirical study of urban land development for manufacturing and services use from 2000 to 2010, primarily focused on the determinants of industrial and commercial land growth from 2000 to 2010. The following are our six main conclusions:

(1) Over the period of 2000–2010, industrial land and commercial land in the study area grew on a large scale; by 28.50% and 8.76% of the total new construction land in the study area, respectively. New commercial land was mainly distributed around the core area and was present with a balanced distribution characteristic. New industrial land was concentrated in sub-districts.
(2) The number of enterprises engaged in services (NEES) in 2010 in the locale, agriculture and construction land uses in the neighborhood in 2000 and planning orders significantly contributed to newly-added industrial land during 2000–2010. Among these factors, NEES exerted the largest effect on the occurrence of industrial land. Factors hampering land transfer to industrial uses included DEM, accessibility, population density in 2010, the presence of water or forest and the growth of industrial enterprises.
(3) Factors contributing to land transfer for services/commercial use included the NEES with very high odds ratios, construction in the neighborhood and accessibility improvement. However, the current permanent resident population has no significant influence on the increase of commercial land. The number of industrial enterprises and their growth were factors that counteracted the growth of commercial land. New commercial land expanded mostly in peri-urban areas, and accessibility in 2010 was negatively associated.
(4) Urban land use change is driven by social and economic development. During 2000–2010, the city experienced fast growth, as a large amount of industrial land turned into commercial land, in turn

creating some new commercial growth. The number of service enterprises correlated positively with both industrial and commercial land increases, which indicated that service enterprises had a strong attraction to all kinds of enterprises. Increases in industrial land occurred in areas with low population density; while commercial land showed the opposite form of development. Moreover, the phenomenon of the separation of workplace and residence was more obvious in industrial areas.

(5) Environment is a major factor in urban land use change. Improved accessibility can significantly contribute to the development of commercial land, but not to industrial land. Construction in the neighborhood exerts a similar effect of attracting industrial and commercial land development. Agriculture in the neighborhood is positively linked to the industrial land growth, but not to that of commercial land. Restrictive factors, including the presence of forest and bodies of water, play a role in prohibiting industrial land development, but are not significant for commercial land.

(6) Regarding the nature factor, landform is the most significant restraining factor for these two types of land developments because of development costs and building restrictions. With regard to institutional factors, urban planning is one of the most important factors influencing land development. However, the model indicates that planning orders are only significant for industrial land development, owing to an industrial parks-dominated policy in Beijing. Conversely, it is not significant for commercial land uses.

Supplementary Materials: The following are available online at www.mdpi.com/2071-1050/8/12/1323/s1, Table S1: All indicators selected in the article, Table S2: Result of the correlation analysis of the population indicators, Table S3: Results of the correlation analysis of economic and employment indicators.

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