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Article

Scenario Simulation and the Prediction of Land Use and Land Cover Change in Beijing, China

Huiran Han, Chengfeng Yang and Jinping Song *

School of Geography, Beijing Normal University, No. 19, Xinjiekouwai Street, Haidian district, Beijing 100875, China; E-Mails: hanhuiran@mail.bnu.edu.cn (H.H.); phoenixycf@mail.bnu.edu.cn (C.Y.)

* Author to whom correspondence should be addressed; E-Mail: songjp@bnu.edu.cn; Tel.: +86-10-5880-7454 (ext. 1623); Fax: +86-10-5880-6955.

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Abstract: Land use and land cover (LULC) models are essential for analyzing LULC change and predicting land use requirements and are valuable for guiding reasonable land use planning and management. However, each LULC model has its own advantages and constraints. In this paper, we explore the characteristics of LULC change and simulate future land use demand by combining a CLUE-S model with a Markov model to deal with some shortcomings of existing LULC models. Using Beijing as a case study, we describe the related driving factors from land-adaptive variables, regional spatial variables and socio-economic variables and then simulate future land use scenarios from 2010 to 2020, which include a development scenario (natural development and rapid development) and protection scenarios (ecological and cultivated land protection). The results indicate good consistency between predicted results and actual land use situations according to a Kappa statistic. The conversion of cultivated land to urban built-up land will form the primary features of LULC change in the future. The prediction for land use demand shows the differences under different scenarios. At higher elevations, the geographical environment limits the expansion of urban built-up land, but the conversion of cultivated land to built-up land in mountainous areas will be more prevalent by 2020; Beijing, however, still faces the most pressure in terms of ecological and cultivated land protection.

Keywords: LULC change; spatial pattern; CLUE-S model; Markov model; scenario simulation and prediction; Beijing

1. Introduction

Since the land use and land cover (LULC) change project was launched by the International Geosphere and Biosphere Program (IGBP) and the International Human Dimensions Program (IHDP) on Global Change, land use research programs on a global scale have become central to international climate and environmental change research [1–3]. In recent years, the land use change process on a regional and local scale has also drawn the interest of scholars, who argue that the more local scales may be capable of testing and verifying the spatial patterns of LULC change on a global scale and that they also reveal the connection between land use change and human activity [4]. Some scholars focused on the impact of urbanization on LULC change [5–8], who considered that population growth and economic development drove urban land expansion and resulted in a great quantity of water bodies and agricultural lands being converted to built-up areas, which significantly affected the local, regional and global environment, including habitat quality [5], green spaces [7], environmental degradation [6,8], water quality [9,10], and so on. For instance, taking the Greater Dhaka of Bangladesh as the study area, Dewan *et al.* found the increasing contribution of GDP to the national economy and industrial growth was the major factor driving rapid LULC change, which led to environmental degradation and landscape fragmentation [6,11,12]. We know the LULC change process is dynamic and resulted from the interaction between natural and socio-economic elements at different scales. Because of the scale effect and the scale sensitivity of land system patterns [13], the related factors affecting LULC change differ, so it is important to understand their interaction and reasonably predict the future demand of land, which is key in land use planning and management.

Land use models are powerful tools that can be used to analyze the causes of LULC change and to evaluate land use policy [14]. Based on model analysis and the simulation of land use spatial patterns, the driving factors of LULC change can be revealed, clarifying the rate of land use and making possible multiple LULC scenarios in order to predict future land use demand. At present, models of LULC change have been developed to explore where, when and why it occurs based on the goals of a particular study. Existing studies on the LULC offer both global scale [15], national and regional scale [12,16–18], as well as some other research on different basins, such as Erhai Basin [19], the Mississippi River Basin [20], and different climate zones [18,21]. In these studies, the models involved mainly refer to the agricultural land dynamics (ALADYN) model [18], ant colony optimization [19], artificial neural networks and cellular automata [20], and so on. According to different research objectives, the relevant LULC models can be divided into three categories. Firstly are empirical-statistical models, such as regression models, *etc*. These models are developed based on mathematical equations to carry out statistical analysis on the factors affecting LULC change; however, they lack the consideration of social factors [22]. Secondly are spatially explicit models or rule-based models, such as the cellular automata model [23,24]. These spatial models are primarily used to determine the pattern and process of LULC change and to project the locations of future changes; however, it is still difficult to simulate the effect of human activities on LULC change [25]. Thirdly, agent-based models have been developed to simulate LULC change by individual agents [26]. However, due to the large number of interacting agents that need to be taken into account, most current multi-agent LULC models are only able to simulate simplified landscapes [26].

Previous models have attempted to incorporate biophysical and socio-economic data into land use simulations, but it still remains a major research challenge, because of the discrepancy among these different datasets [27,28]. As noted by Verburg *et al.*, no single model is capable of considering all of the processes of LULC change at different scales [29]. Some current LULC models have improved the analysis of the influence of a single factor on LULC change, but are unable to consider the effects of multiple factors and different processes that reflect spatial dimensions [30]. In view of the stability and resilience of LULC systems [31], LULC models should not only analyze land use at a single scale, but should also address the multiscale characteristics of land use systems and pay more attention to the interaction of the driving factors. The method for the selection of an appropriate integrated LULC model has therefore become important in LULC simulation studies.

The Conversion of Land Use and its Effects at Small regional extent (CLUE-S) model is a scale dynamic model with multiscale characteristics based on system theory. The scale is better suited than others to understand the relationship between LULC change and its driving factors and to explore possible process changes in various LULC scenarios at different spatial scales [11]. Compared with the above-mentioned models, the CLUE-S model incorporates the natural factors and social-economic factors, spatial and non-spatial distribution by combining a top-down with a bottom-up method, so the model is more comprehensive, open and extensive [32]. The CLUE-S model is preferred for addressing the spatial allocation of LULC change [14,31], but has some limitations in that it requires another mathematical model to calculate future land use demand.

The Markov model can most importantly depict the direction of LULC shifts, providing a framework for analyzing future land use demand. The model has been widely used to predict LULC change [33]. However, the traditional Markov model's ability to provide spatial analysis is weak, and it therefore has some difficulties in allocating predicted land requirements to geographical space. Moreover, existing research on LULC prediction, for the most part, takes the transition probabilities for land use types as a constant value, with little adjustment for socio-economic development and is thus also limited [34]. Based on the above discussion, we propose an approach by combining the Markov model and the CLUE-S model to deal with some shortcomings of the existing LULC models, taking the LULC prediction module and spatial analysis module as a whole to achieve the spatio-temporal simulation and prediction of LULC change. In this model, the Markov model assigns a transition probability to each single pixel at the time steps [35], and the CLUE-S model undertakes the simulation of the spatio-temporal dynamics of each single pixel. The CLUE-S and Markov model integrate human decision-making to achieve a more realistic simulation of LULC changes, which can provide a scientific method for LULC planning and management.

China has experienced a transition from its planned economy to a market economy, the rapid development of the economy and society, the acceleration of the urbanization process and the implementation of a regional development and ecological protection strategy, all of which significantly influence the spatial pattern of its LULC change [3]. Since the establishment of the market economic system, the real estate market has continued to develop, inspired by housing demand, leading to a rational readjusting of urban industrial structure, which, in turn, results in a large amount of agricultural land that has been transformed into urban land. As a result, the landscape of Chinese cities has changed dramatically. As the capital of China, the characteristics of LULC change in Beijing are typical and representative as a result of the faster economic and population growth. The objectives of the study are to: (1) propose an approach by developing a CLUE-S model that will transfer and allocate land demand from the Markov model to improve LULC change projection; (2) describe the temporal and spatial characteristics and identify the primary driving factors of LULC change patterns; and (3) predict and simulate the evolution tendency of land use spatial patterns under different scenarios.

2. Materials and Methods

2.1. Study Area

Beijing, the capital of China and one of the largest cities in the world, covers 16 districts and two counties with a land area of 16,410 km^2. The administrative region of Beijing is traditionally divided into three parts: the central city, the suburbs and the outer suburbs. The central city includes two districts, Xicheng and Dongcheng. The suburbs are made up of four districts, Haidian, Chaoyang, Fengtai and Shijingshan, and the outer suburbs are made up of eight districts and two counties, Tongzhou, Shunyi, Fangshan, Daxing, Changping, Mentougou, Huairou and Pinggu districts and Miyun and Yanqing counties (Figure 1). Beijing has undergone rapid urbanization and economic growth since the economic reforms of 1978, and in 2013, the population was approximately 21.15 million. Within the administrative region, the urban population is 18.25 million, which accounts for 86.31% of permanent residents. The new population will need new space and so creates a higher demand for residential land, thus encouraging rapid expansion of the region's urbanized area. Beijing's built-up areas grew from 397 km^2 to 1268 km^2 from 1980 to 2013, and the expansion of urban built-up land areas led to the decrease of cultivated land from 4258 km^2 in 1980 to 2317 km^2 in 2008. According to the overall land utilization plan in Beijing (2006–2020), the amount of reserved cultivated land cannot be less than 2147 km^2 by 2020, which means that the amount of cultivated land converted to built-up land is very limited. However, rapid population growth and expansion of built-up areas represent a daunting challenge to cultivated land protection, all of which lead to some traffic congestion, pollution and other issues.

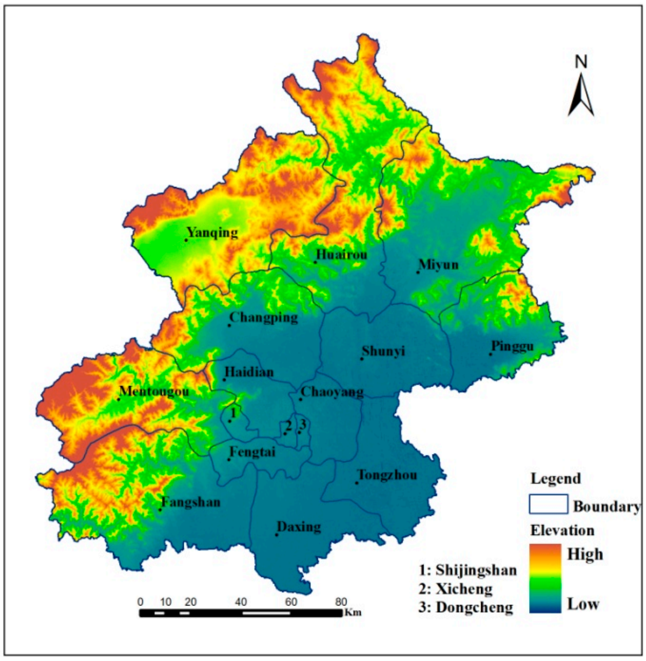


Figure 1. A map of the study area.

2.2. Data

Multi-annual socio-economic statistical data and spatial data were collected for evaluating the LULC change process. Among these data, the socio-economic statistical data came from the Beijing statistical yearbook, the Beijing area statistical yearbook and population census data and included permanent resident population, population density, GDP, per-capita living area, urbanization level and investment in fixed assets. Spatial data included remotely-sensed data that were obtained from Landsat TM images in 1985, 2000 and 2010. The TM image has a spatial resolution of 30 m. In addition to the remotely-sensed data, topographic maps were collected for establishing the digital elevation model (DEM) to obtain other biophysical data and also had a spatial resolution of 30 m. Moreover, landform and soil vector data were extracted from a digital geomorphology database and soil database in China at a 1:1,000,000 scale. All of the spatial data had unified projection and spatial registration, and the remote sensing image data were pretreated using Erdas image-processing software. We cut the remote sensing image according to the administrative boundary of the study area and then extracted the remote sensing information using the supervised classification method and a man-machine interactive interpretation.

Based on the characteristics of LULC change in the study area, we followed the classification system of the national resources and environmental background dynamic remote sensing survey database. Six LULC types were identified, including cultivated land, woodland, grassland, construction land (mainly referring to built-up land, that is land for the construction of buildings, fixtures and their auxiliary facilities, including commercial and industrial land, residential land, warehousing land, traffic-dominated land and other infrastructure, such as roads), water and unused land. After that, field investigation and Google Earth were used to check and correct the accuracy of the interpreted images, which allowed obtaining the land use maps for 1985, 2000 and 2010.

The classification accuracy of LULC types by Kappa coefficients for 1985, 2000 and 2010 had values that were greater than 0.80, which confirmed that the interpretation results met the analysis requirements. We estimated the slope direction of Beijing based on the DEM, and then, we calculated the spatial accessibility of LULC types to the administrative center, to roads and to main water bodies, as well as the corresponding distance layers. In addition, the spatial distribution of population and socio-economic data could be obtained by spatial interpolation using the method of kriging and natural neighbor. According to the requirements of the CLUE-S model combined with the actual situation of Beijing, the LULC maps and spatial layers were transformed to a grid format with a resolution of 300 m × 300 m in the same projection coordinates. Finally, the grid maps, including three periods of land use and some driving factors, were prepared for the model. Considering the periodic variation of LULC change and the rate of socio-economic development, the time span of the prediction could not be too short, so we selected 1985, 2000 and 2010 as the time nodes to simulate Beijing's LULC pattern in 2020.

2.3. Methods

2.3.1. Land Use Dynamic Degree

The land use dynamic degree refers to the rate of change in land use types for a specific time horizon, including quantitative changes in land resources and spatial changes in land use patterns [36]. It is an index that describes the regional difference of the rate of LULC change and reflects the comprehensive influence of social and economic activities on LULC change. The land use dynamic degree (S) in the period *t* is calculated as follows:

$$S = \left\{ \sum_{ij}^{n} (\Delta S_{i\text{-}j}/S_i) \right\} \times (1/t) \times 100\% \quad (1)$$

where S_i is the area of land type *i* in the beginning of the period, $\Delta S_{i\text{-}j}$ is the total area of land type *i* converted into other types and *t* is the study period.

2.3.2. Markov Model

LULC change is not unidirectional in nature; a given land type might theoretically change from one category of land use to any other. The Markov model can represent all of the possible directions of LULC change among all of the land use categories [23]. The Markov model is closely related to dynamic distributed lag models and consists of two primary land components: the transition matrix and the transition probability matrix, which represent the number and the probability of land shifting from one land use group to other groups in some observed period [34]. The transition probability matrix can be expressed as follows:

$$P_{ij} = \begin{vmatrix} P_{11} & \cdots & P_{1n} \\ \vdots & \vdots & \vdots \\ P_{m1} & \cdots & P_{mn} \end{vmatrix} \left(0 \leq P_{ij} \leq 1, \textstyle\sum_{j=1}^{n} P_{ij} = 1\right) \quad (2)$$

where P_{ij} denotes the probability of land use *i* shifting to land use *j*; *m* and *n* are the number of land use types.

The Markov model is a random process of a state with no aftereffect characteristics, that is to say, a state of the system at some point $t + 1$ is only relevant to the state that is currently known at time *t*, but is unrelated to the moment before *t*. Land use demand is closely related to regional socio-economic development, which is mainly driven by human factors. The Markov model effectively combines human factors and land use. The land use distributions at the beginning (S_t) and at the end (S_{t+1}) of a time period, as well as a transition probability matrix (P_{ij}) representing the LULC change that occurred during that period are used to construct the Markov model [23], which is expressed as follows:

$$S_{t+1} = P_{ij} \times S_t \quad (3)$$

where S_{t+1} and S_t represent the states of land use at given point $t + 1$ and *t*, respectively.

Based on local socio-economic information, land use planning and related policies in Beijing from 1985 to 2010, three future socio-economic scenarios have been defined to predict land use demand for 2020 using the Markov model. The first scenario is characterized by natural development in which we assume that the factors that currently influence land use keep pace with the trend of LULC change from 1985 to 2010 and will not have changed greatly from 2010 to 2020. The second scenario is characterized by rapid development, in which we assume that areas of LULC change quickly by considering the growth rate of GDP and population, urbanization level, per capita living space and the floating population to obtain the demand for land use in 2020. The third scenario is characterized by ecological and cultivated land protection. In this scenario, woodlands and water bodies are designated as nature reserves that play an important role in ecological security and cannot change to any other land use categories, and the basic farmland is then taken as a restricted area in which the cultivated land cannot be converted into other land use types.

2.3.3. CLUE-S Model

The CLUE-S model was developed by Dutch scholars for the spatial simulation of LULC change on a small and medium-sized scale [31]. It was primarily used to explore the relationship between LULC change and related natural and socio-economic factors using a quantitative method, which was then used to simulate the LULC change process and to analyze the basic rule of the spatial-temporal evolution of land use [37].

The CLUE-S model has two parts: a spatial analysis module and a non-spatial analysis module. The spatial analysis module allocates land demands from the Markov model to spatially explicit land use patterns according to different transition probabilities and transition rules in land use categories and then will conduct a spatial simulation of land requirements in different scenarios [31]. The non-spatial analysis module focuses on factors that influence the spatial pattern of LULC change, such as socio-economic variables, regional spatial variables and land-adaptive variables. Socio-economic variables include population, economic factors, marketing conditions and related policies that are used to discuss the relationship between LULC change and economic development. Regional spatial variables mainly refer to the accessibility of land use types to the administrative center, roads and main water bodies, which are used to restrain the land use demand. The location suitability is a weighted average of suitability based on empirical analysis and capturing the historic and current location preferences in response to location characteristics [29]. Land-adaptive variables in this study include slope, soil, temperature and altitude, which are regarded as the potential LULC change factors. The contribution of different variables to the driving effect for one specific land use type presents the difference, so in this study, a logistic regression model is selected to estimate the influence of related factors on different land use types. The equation is expressed as follows [31,37]:

$$Log\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} \cdots\cdots + \beta_n X_{n,i} \tag{4}$$

where P_i is the probability of a grid cell for the occurrence of land use type i. X is the related driving factors; β represents the regression coefficients between land use types and driving factors.

3. Results and Analysis

3.1. LULC Change Characteristics

We obtain the LULC maps for 1985, 2000 and 2010 with the help of Erdas image processing software and the ArcGIS platform (see Figure 2). The rate of LULC change during the different periods is illustrated by the index of the land use dynamic degree. From 1985 to 2000, the value of the land use dynamic degree is 0.99, which indicates that the rate of LULC change is relatively slow. From 2000 to 2010, the value of the land use dynamic degree is 1.64, which demonstrates that the rate of LULC change has accelerated compared to the previous period and that the effects of socio-economic activities on the land use pattern have become more intense.

On a spatial scale, the expansion of construction land is strikingly clear from the center to the edges, which confirms a spatial pattern of urban growth. The direction of construction land expansion is primarily along the Ring road from Chaoyang and Haidian in the suburbs to Tongzhou and Changping in the outer suburbs. In addition, the area with reductions in cultivated land is primarily in the eastern and southern regions of Beijing, which coincides with the extension direction of radioactivity along the highways and national roads.

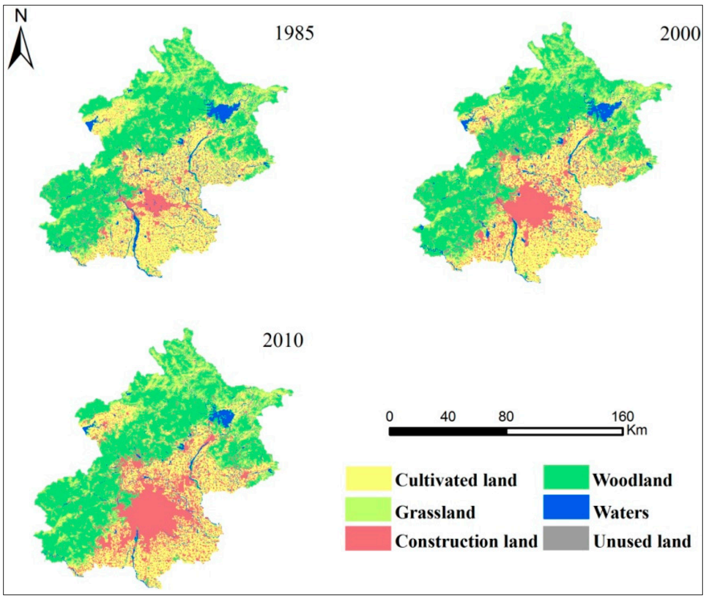


Figure 2. Land use pattern by year in Beijing (1985–2010).

3.2. Regression Analysis of the LULC Change Process

A logistic regression model was constructed to explore the relationship between LULC change and the related driving factors that play an important role in revealing the internal mechanism of LULC change. A logistic regression model is run for each of the land use types in 1985, 2000 and 2010, respectively. We test the statistics of the driving factors using the ROC curve proposed by Pontius [38], which evaluates the predicted probabilities by comparing them with the observed value [31]. Pontius Jr found that any ROC above 50% was better than random [38]. The obtained value was greater than 50%, indicating a probability distribution consistent with the actual distribution of land use types. Generally, an ROC above 70% shows that the driving factors had a greater explanatory power for a certain land use type.

Due to the statistical caliber inconsistencies for 1985 and a lack of restrictions on basic farmland, the regression results are poor. The ROC test of three land types is less than 0.6, so we list only the results for 2000 and 2010 (Table 1). Some driving factors, including altitude, slope, GDP, urbanization, population density, distance to the urban center, distance to the local road, distance to the railway, distance to the highway and distance to the river, are selected to evaluate their influence on land use types. As shown in Table 1, the ROC test statistics for various land use types is above 0.7, which shows clearly that the spatial distribution for all land use categories can be explained by the related driving factors, but different driving factors result in some differences in various land use types.

Traffic and socio-economic factors may play an important role in the conversion of land use types, especially their accessibility to the administrative center and roads, as well as their urbanization level. In terms of topographic factors, the effect of the slope on land use types is clearer, with a higher slope conducive to forest land and a lower slope good for other land types.

Table 1. Logistic regression results of the spatial distribution of land use types in Beijing from 2000 to 2010.

Driving factors	Years	Cultivated land		Woodland		Grassland		Waters		Construction land		Unused land	
		β	Exp(β)	β	Exp(β)	β	Exp(β)	β	Exp(β)	β	Exp(β)	β	Exp(β)
Elevation	2000	−0.0011	0.9989	0.0004	1.0004					0.0011	1.0011		
	2010	−0.0008	0.9992	−0.0003	0.9997					0.0015	1.0015		
Slope	2000	−0.2270	0.7734	0.0331	1.0337			−0.0264	0.9739	−0.0220	0.9783	−0.0581	0.9435
	2010	−0.1121	0.8980	0.0171	1.0173					−0.0217	0.9785		
Distance to the river	2000	−0.0614	0.9404	0.0917	1.0960	−0.0476	0.9535	−0.1784	0.8366	0.0620	1.0640		
	2010	−0.0606	0.9412	0.0954	1.1001	−0.0430	0.9579	−0.2470	0.7812	0.0260	1.0263		
Distance to the urban center	2000	0.0234	1.0669	0.0185	1.0187	0.0519	1.0533			−0.0838	0.9196	0.0609	1.0628
	2010	0.0088	1.0212	0.0155	1.0156	0.0633	1.0654			−0.0877	0.9160	−0.0859	0.9177
Distance to the local road	2000			0.0351	1.0358					−0.1481	0.8623		
	2010			0.0505	1.0518	0.0296	1.0301	0.0464	1.0475	−0.1658	0.8472		
Distance to the railway	2000	0.0504	1.0517	−0.0630	0.9389	−0.0410	0.9598	0.0367	1.0640			−0.0423	0.9585
	2010	0.0331	1.0336	−0.0491	0.9521	−0.0215	0.9787	0.0513	1.0603				
Distance to the highway	2000	0.0432	1.0577	0.0606	1.0625	0.0204	1.0206			−0.0546	0.9468		
	2010	0.0357	1.0349	0.0628	1.0648					−0.0657	0.9364		
GDP	2000	−0.0225	0.9777	−0.0185	0.9815	0.0322	1.0327						
	2010					0.0015	1.0015	0.0015	1.0015	0.0013	1.0013		
Urbanization	2000	−0.0274	0.9726	−0.0985	0.9062	−0.0807	0.9225	−0.0173	0.9828	0.0362	1.0369		
	2010	−0.0055	0.9943	−0.0146	0.9855	−0.0347	0.9659						
Population density	2000			0.0006	1.0006	0.0002	1.0002			−0.0002	0.9998		
	2010	−0.0404	0.9584	−0.0011	0.9989	−0.0005	0.9995	−0.0014	0.9986	0.0013	1.0013		
Constant	2000	−0.3677	0.6923	0.9723	2.6440	−1.7567	0.1726	−3.3856	0.0339	−1.3041	0.2714	−6.5598	0.0014
	2010	−0.0352	0.9654	−0.8484	0.4281	−3.1322	0.0436	−4.3192	0.0133	0.2457	1.2785	−4.8677	0.0077
ROC value	2000	0.7730		0.8460		0.8100		0.7470		0.8250		0.7990	
	2010	0.7080		0.8300		0.7970		0.7980		0.8390		0.7320	

Note: β represents the regression coefficients between land use types and driving factors, Exp(β) represents the probability of land use type change. All driving forces are significant at $p < 0.05$. When Exp(β) > 1, this indicates the probability increases of land use types upon an increase in the value of the driving factors, and when Exp(β) < 1, this indicates the probability of land use type reductions.

3.3. Analysis of Transition Probability Matrix

The transition probability matrix shows the transfer direction of land use types (see Tables 2 and 3). From 1985 to 2000, construction land, woodland and grassland are the most stable classes, with 0.99, 0.99 and 0.94 probabilities, respectively. The most dynamic classes are unused land, water and cultivated land, with transition probabilities of 0.62, 0.63 and 0.83; in these classes, cultivated land was primarily transformed into construction land, and cultivated land that is occupied for urban expansion is evident. From 2000 to 2010, the transition of various land use types is consistent with the previous period; the most stable classes are still construction land, woodland and grassland, with 0.94, 0.97 and 0.92 probabilities, respectively. The most dynamic class is unused land, which was primarily transformed into woodland with transition probabilities of 0.61, indicating that the afforestation policy played a role in Beijing. Moreover, the transition of construction land to other types of land is also clear.

Table 2. Transition probability matrix of land use types in Beijing from 1985 to 2000.

	Cultivated land	**Woodland**	**Grassland**	**Waters**	**Construction land**	**Unused land**
Cultivated land	0.83	0.02	0.00	0.02	0.13	0.00
Woodland	0.00	0.99	0.00	0.01	0.00	0.00
Grassland	0.01	0.03	0.94	0.02	0.00	0.00
Waters	0.21	0.06	0.01	0.63	0.09	0.00
Construction land	0.00	0.00	0.00	0.01	0.99	0.00
Unused land	0.25	0.02	0.01	0.02	0.08	0.62

Table 3. Transition probability matrix of land use types in Beijing from 2000 to 2010.

	Cultivated land	**Woodland**	**Grassland**	**Waters**	**Construction land**	**Unused land**
Cultivated land	0.78	0.03	0.00	0.01	0.17	0.01
Woodland	0.01	0.97	0.00	0.01	0.01	0.00
Grassland	0.02	0.04	0.92	0.00	0.02	0.00
Waters	0.17	0.05	0.04	0.58	0.15	0.01
Construction land	0.04	0.01	0.00	0.00	0.94	0.01
Unused land	0.04	0.61	0.14	0.00	0.05	0.16

3.4. Predicting LULC Change Based on the Markov Model

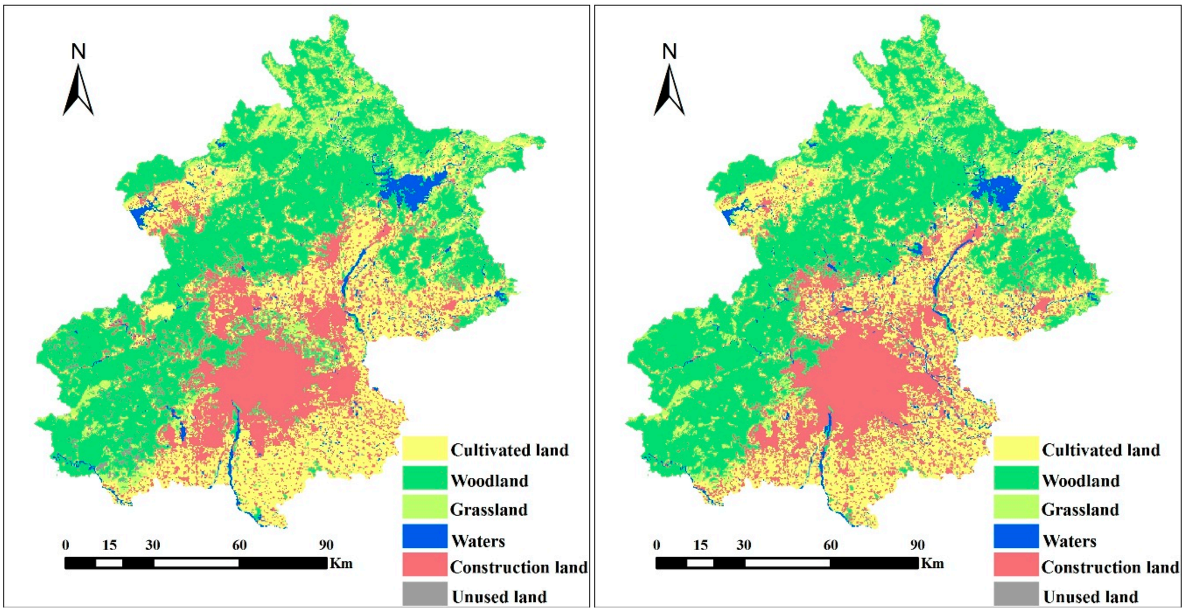
Based on LULC change from 1985 to 2010, the Markov model is used to predict the land requirements for the different land use types in 2020 according to the three future socio-economic scenarios discussed above. The prediction results are presented in Table 4. The table shows that the areas of cultivated land, grassland and water have a decreasing trend, as do woodland and construction land. A large difference is found in the land requirements for various land use types under different scenarios.

Table 4. The prediction results of land use under different scenarios, 2010–2020 (units: ha).

Years	Scenario design	Cultivated land	Woodland	Grassland	Waters	Construction land	Unused land
2010	Actual land use	406,692	741,789	119,772	44,082	311,013	10,305
2020	Natural development	333,279	756,891	115,083	21,330	400,014	7056
	Rapid development	328,535	757,223	114,975	17,333	408,672	6916
	Ecological-cultivated land protection	360,912	751,635	116,718	34,890	364,575	4923

3.5. Model Validation

Combining the results of the logistic regression model, the transition matrix of the land use types and land-type conversion elasticity, the CLUE-S model is used to simulate the distribution of land use patterns in order to derive the simulated map of land use pattern for Beijing in 2010, then the simulated land use map is compared with the actual satellite-derived land use map for 2010 based on the Kappa statistic (see Figure 3).



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

Figure 3. Comparison of simulated (**a**) and observed (**b**) land use situations in Beijing, 2010.

The Kappa statistic, which can reflect the simulation accuracy of the model, was used as the validation method to evaluate the ability of the model to simulate the spatial pattern of land use [39]. Its expression is as follows:

$$Kappa = (P_o - P_c)/(P_p - P_c) \quad (5)$$

where P_o is the percent correct for the output, P_c is the expected percent correct due to chance and P_p is the percent correct when the classification is perfect.

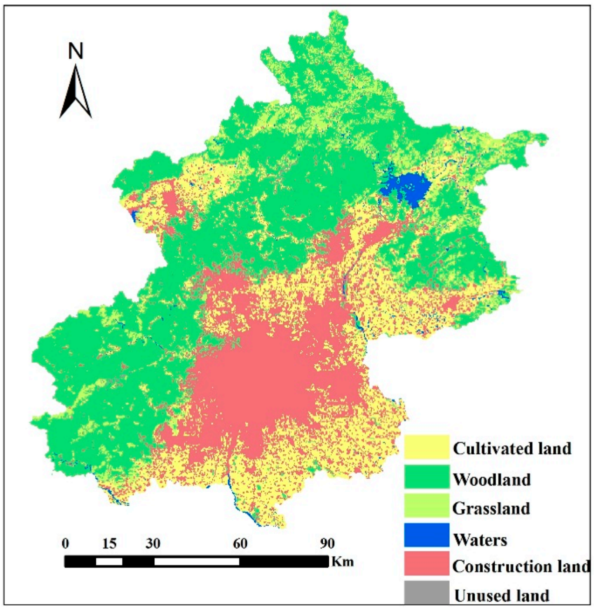
The value of the Kappa statistic is 0.87, which indicates that the consistency is good between the predicted results and the actual land use situation, and it shows that the model is reliable for Beijing and can be used to predict LULC change under different scenarios. Figure 3 shows that although more similarity is found between the simulated map and the empirical map of land use in 2010, it still exhibits a certain bias. Cultivated land, woodland, grassland, waters and unused land in the simulated land use map are relatively similar to the corresponding classes in the actual land use map for 2010, while the construction land class is poorly simulated. Analysis of the simulated land use maps reveals that the model generally underpredicted the location of the construction land class. There are three explanations for this difference. On the one hand, the CLUE-S and Markov model employs the contiguity rule, which is used to simulate the growth of a land use type near the existing similar land use class [40]. This suggests that the model's simulation accuracy increases with the proportion of a given land class relative to others [41]. Therefore, when a few of the nearby pixels belong to a land use type, such as construction land, then the transition potential is down-weighted, which may possibly result in the poor simulation of construction land [41]. On the other hand, the constraint layer of the simulation of land use is primarily based on the appropriate adjustments to basic farmland in 2002, which cause a small discrepancy on the bound level. Besides, the socio-economic data obtained in this simulation are mainly at the county level and do not cover the *jiedao*-level data, which influences the accuracy of the simulation to some extent.

3.6. Analysis of Simulation Results

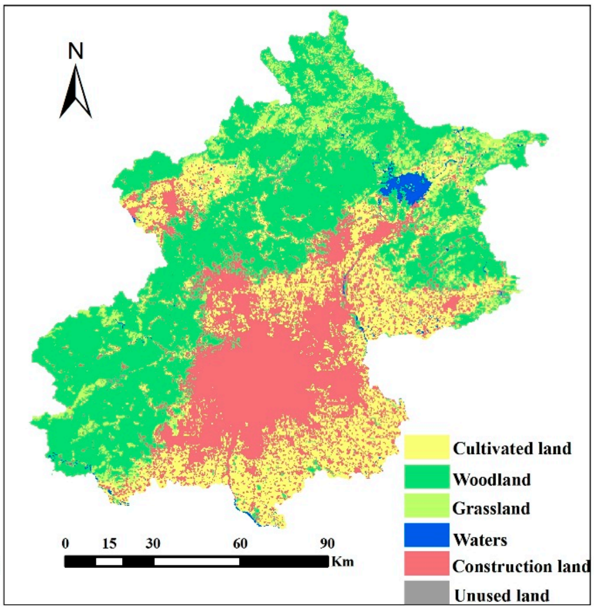
Combined with the land demand under different scenarios, land transfer rules, related driving factors and constraints, we conduct the simulation and prediction of the spatial distribution of Beijing's land use in 2020 (see Figure 4).

Under the natural development scenario (Figure 4a) and rapid development scenario (Figure 4b), the trend of construction land expansion is clearly along the direction of main traffic arteries, such as the airport express rail. Comparing the simulated scenarios for 2020 with the actual map for 2010, this conversion to urban land occurs primarily in the northeast, northwest, southwest and east of Beijing, in districts, such as Tongzhou, Shunyi, Changping, Fangshan and Huairou, and in Yanqing County. Affected by the development policy of the new town, the functions in the inner city gradually transfer to the new town, which attracts population concentrated in Changping and Shunyi, and leads to the expansion of residential land, with the area of cultivated land and waters greatly reduced. The results of the simulation in the rapid development scenario are similar to those in the natural development scenario, but the changes in land use types are more fundamental. The dramatic change in land use types, including water area reductions of 60.7% by 2020, will lead to water-resource shortages, most seriously in Beijing. In addition, construction land increases 31.4% and primarily comes from cultivated land, waters and unused land; the change trend of woodland and grassland is more subtle.

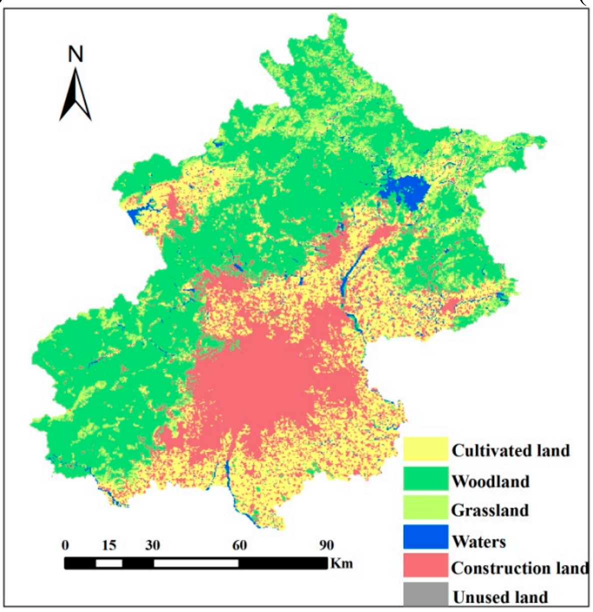
Under the ecological and cultivated land-protection scenarios (Figure 4c), the study assumes a land use that is under a strict cultivated-land protection policy from 2010 to 2020. Similar to the above scenarios, the expansion trend for construction land is relatively moderate and occurs mainly in the east, northwest and southwest, in districts, such as Tongzhou, Shunyi, Changping and Fangshan. Woodland area increases slightly, and the increase rate of construction land is 17.2%, which decreases by 11.4% compared with the natural development scenario. Waters and cultivated land areas decrease 20.9% and 11.3%, respectively, which indicates that the regulation has a significant effect on restricting the expansion of construction land. However, the conversion trend of cultivated land and woodland to construction land is also more clearly in the mountainous area of Mentougou and Shijingshan districts and in Yanqing County, which indicates that Beijing still faces the pressure of ecological and cultivated land protection.



(**a**)



(**b**)



(**c**)

Figure 4. Simulation of land use demand under different scenarios in Beijing, 2020. (**a**) Natural development scenario (**b**) Rapid development scenario (**c**) Ecological and cultivated land protection scenario.

4. Discussion

To better simulate land use patterns, a group of LULC models were specifically developed for a particular case study [14,42], which provided some opportunities to select an approach that would best address the research questions and characteristics related to the study area. It was important to acknowledge that no single model or approach can sufficiently describe the different processes at all spatial and temporal scales [42]. Because of residents' travel being determined by the land use spatial pattern, some researchers linked land use with traffic demand and put forward the land use and transportation interaction model (LUTI model) to describe the relationship between urban land use and transportation, which improved the simulation accuracy of the model. However, these models just focused on the external results and had not explained the internal reason for individual behavior choices, so it was difficult to simulate the interaction between different behaviors [43]. Since then, other scholars proposed an urban spatial equilibrium model by combining spatial economics and the LUTI model, such as the TRANUS model (an integrated land use/transportation model was developed by Barra *et al*,) [44], which was mainly used to assess the social-economic impact of planning policy in a large spatial scale [45]. Due to the lower spatial precision of the macroscopic model, it was not conducive to capturing the individual behavior activities, so someone proposed spatial non-equilibrium models with macroscopic and microscopic characteristics, such as the IRPUD model (The model was initially designed and implemented at the Institute of Spatial Planning of the University of Dortmund) [46], the DELTA model (The model has been developed by Simmonds, which was used to extend relatively conventional transport models into land-use/transport interaction) [47], the UrbanSim model [48] and TIGRIS XL model (an land-use and transport interaction model for the Netherlands is developed for and owned by the Ministry of Infrastructure and Environment and the Netherlands Environmental Assessment Agency) [49]. The research objects of these models were still urban land and traffic system, but they adopted a bottom-up method. Taking UrbanSim as the example, this system is composed of four modules, such as employment location choice model, residential location choice model, land development choice model and real estate price model [48]. Compared with the previous models, spatial non-equilibrium models had difficulty in accurately simulating the complex economic behavior and agglomeration effect driven by market price [43,45]. According to the above discussion, we know that the interaction model is an applied urban model more fit for application, which is not limited to simulating LULC change, but can also be used for location selection and policy evaluation.

Recent validation studies have indicated that most spatial models still contain a high level of uncertainty [50]. In this study, we develop an approach by combining the Markov model and CLUE-S model to deal with some shortcomings in existing LULC models and characterize the land change processes and predict LULC change under different scenarios. The Markov model can depict the direction of LULC shifts and predict the future land requirements for land use categories by taking into account the influence of related factors on land use requirements. The CLUE-S model can allocate the predicted land requirements to geographical space using the Markov model. The results of the combined Markov and CLUE-S models indicate that the model is capable of representing LULC change in Beijing, which suggests that the approach is a useful tool for the analysis of related driving factors and the estimation of their influence on LULC change. The methodology can be effective and realistic for predicting possible LULC change under different scenarios and for providing a scientific basis for land use decision making and planning.

The complexity of the LULC system requires that the selection of driving factors for the CLUE-S model be based on the theoretical relationships between driving factors and land use [31]. We select the related driving factors that affect LULC change from land-adaptive variables, regional spatial variables and socio-economic variables, but there are still some other factors that are difficult to quantify. The selection of variables and indicators, to a certain extent, may cause some differences in the simulation results or model parameters, which will produce certain effects on the driving factors and the prediction of LULC change. For example, changes in household sizes may have an impact on housing demand and the land use spatial pattern. In the planned economy era, most of the families in China were three generations, even four generations under one roof. Now, the family structures have changed gradually to a nuclear family, and every newlywed couple generally requires a separate entrance from the newborn small family or nuclear family; DINK (a DINK household in which there are two incomes and no children) families and empty nesting are growing along with the development of society. The miniaturization of household sizes must put forward more requirements on housing. Increased housing demand is largely caused by shrinking household sizes, population growth, property taxes and other factors [51]. Housing demand stimuli will certainly change the land use pattern. When urban centers still have space, increased households may cause its development to be more compact. On the contrary, increased housing demands may lead to sprawl if not accommodated by high-density or not afforded by high housing price, particularly in the city center [52]. In this situation, the rapid spatial expansion of the city will lead to more rural and arable land converting to built-up areas and simultaneously putting immense pressure on the land use pattern in future. Therefore, the identification of the methods for the selection of the more scientific variables that reflect the influence of human activities on LULC change is critical.

The method of combining the Markov model and the CLUE-S model is found to have the potential to reflect the complexity of LULC change, but if we select different forecasting models for land demand, it may produce different results. In many cases, it may even be most appropriate to use different model approaches to study the same region and to then compare the outcomes of such forecast models, which may lead to a better and more complete understanding of the LULC change process [53]. The method has therefore become an important direction for current research and could involve using a different model in combination with the CLUE-S model, such as the grey interconnect degree, the system dynamics model or multi-agent system models [26], which offer a reasonable alternative to predict and simulate land use patterns. In addition, as a megalopolis in the process of rapid urbanization, urban development and planning and major infrastructure construction, the related policies of functional dispersal from the central city could have significant impacts on the formation and evolution of land use patterns in Beijing. Now, many LULC models, for instance generic urban models [54], the TIGRIS XL model [49] and the SILENT (the Sustainable Infrastructure, Land-Use, Environment and Transport) model [55], have transformed some policies, such as infrastructure or land use zoning, into spatial parameters in simulating and predicting land use demand, so this can help decision makers to anticipate the impacts of the proposed policy. However, in this study, we do not consider the effects of various policy factors in the simulation process. A further study could employ regional spatial factors, land-adaptive factors, socio-economic and policy-related factors together in the simulation of further LULC change in Beijing, which could guide more informed decision making.

5. Conclusions

This paper explored the characteristics of LULC change and simulated future land use demand by combining a CLUE-S model with a Markov model, which overcame their respective disadvantages in demand prediction and spatial allocation and gave some insight into a better understanding of possible changes in land use. The study chose Beijing as its case study, recognizing the related driving factors from land-adaptive variables, regional spatial variables and socio-economic variables, then performed the simulation on land use demand and revealed LULC change trends in 2020.

The results suggest that following a rapid urbanization process, cultivated land converts to urban built-up land, which will become the main feature of LULC change in the future. The pattern will be more serious in the mountainous areas, such as the Mentougou, Shijingshan and Huairou districts and Yanqing County. From three scenarios, we find that the expansion trend of urban land occurs mainly northeast, northwest, southwest and east of Beijing, in districts, such as Tongzhou, Shunyi, Changping and Fangshan. The simulation of land use also shows, however, that the major difference between development scenarios (natural development and rapid development) and protection scenarios (ecological and cultivated land protection) occurs because the mountainous areas of Beijing are important ecological barriers and water conservation areas and the geographical environment with a higher elevation limits the expansion of urban land. The relationship between construction land and the ecological environment should therefore be comprehensively studied and estimated [37]. By protecting ecological and cultivated land and strictly controlling the expansion of built-up land, important adjustments can be made to the regional land use structure, the regional ecology can be accelerated and the sustainable economic development of Beijing can be prioritized.

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Author Contributions

Huiran Han played an important role in the conception of the study, performing the data analyses and drafting and revising the manuscript. Chengfeng Yang contributed to the data gathering and played an important role in interpreting the results. Jinping Song contributed to the conceptual framework of this paper. All authors read and approved the final manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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