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Simulation of Land-use Scenarios for Beijing Using CLUE-S and Markov Composite Models

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Abstract: This study investigated and simulated land use patterns in Beijing for the year 2000 and the year 2005 from the actual land use data for the year 1995 and the year 2000, respectively, by combining spatial land allocation simulation using the CLUE-S model, and numerical land demand prediction using the Markov model. The simulations for 2000 and 2005 were confirmed to be generally accurate using Kappa indices. Then the land-use scenarios for Beijing in 2015 were simulated assuming two modes of development: 1) urban development following existing trends; and 2) under a strict farmland control. The simulations suggested that under either mode, urbanized areas would expand at the expense of land for other uses. This expansion was predicted to dominate the land-use conversions between 2005 and 2015, and was expected to be accompanied by an extensive loss of farmland. The key susceptible to land-use changes were found to be located at the central urban Beijing and the surrounding regions including Yanqing County, Changping District and Fangshan District. Also, the simulations predicted a considerable expansion of urban/suburban areas in the mountainous regions of Beijing, suggesting a need for priority monitoring and protection.
Keywords: CLUE-S model; land use; Markov model; scenario simulation; Beijing

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1 Introduction

Land use is a direct indicator of human interaction with the landscape. The causes, processes, and effects of land-use/cover change (LUCC) have been a critical and challenging area of research (Wu *et al*., 2011). Mathematical models, especially dynamic models based on actual spatial data, are important tools for investigating the mechanisms, dynamics, and trends driving land-use changes (Deng *et al*., 2008). Accurate LUCC models facilitate systematic analyses of the quantitative relationships between land-use changes and the underlying driving factors. Moreover, these models are essential for defining and predicting land-use scenarios and changes, and are valuable for guiding reasonable land planning and management. The simulation of global and regional land-use changes is a new method for LUCC studies (Wu *et al*., 2010). Several models have been widely used in earlier studies, such as the System Dynamics Model, Cellular Automata Model, Agent-based Model, and the 'conversion of land use and its effects at small region extent' (CLUE-S) model (Wu *et al*., 2012).

The CLUE-S model is a typical empirical statistical model (Sheng *et al*., 2008). Unlike other quantitative models, the CLUE-S model treats the competition between different types of land-uses based on systems

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theory, simulates different land-uses simultaneously, and produces a spatially explicit display of the simulation results. This model has been recognized as an excellent tool for simulating land-use changes (Overmars *et al.*, 2007; Sohl *et al.*, 2007; Sun *et al.*, 2011; Pan *et al.*, 2011; Zhang *et al.*, 2011). In the CLUE-S model, the demand for land-use needs to be predicted using other models, and Markov model has been found to be suitable for doing this (Pan *et al.*, 2010). Therefore, the combined use of CLUE-S and Markov models can effectively improve the accuracy of land-use simulation and prediction.

Beijing is the capital of China and also the economic center of the Beijing-Tianjin-Hebei region. In the past two decades, the economic development and urbanization of Beijing have been accompanied by a rapid expansion of the urban space and loss of farmland (Xia, 2010). This has created an imbalance between sustainable development of urban regions and the preservation of rural regions in and around Beijing.

The present study used the CLUE-S and Markov models based on high-resolution imaging data to simulate future land use changes in Beijing. Objectives included understanding the dynamics of land-use and the processes of change in Beijing and the vicinity, identifying key areas susceptible to land-use changes and identifying the trends of such changes. The major driving mechanisms underlying these land-use changes were clarified. Reference information for sound planning and management of the land resources in Beijing were provided.

2 Materials and Methods

2.1 Study area

Beijing (39°28′–41°05′N, 115°24′–117°30′E) is located at the north end of the North China Plain, and the terrain of this city slopes from the northwest to the southeast (Fig. 1). The city is surrounded by mountains on the north, northwest, and northeast sides. Beijing covers an area of 6410.54 km^2, of which 1/3 is flat and 2/3 is mountainous, and consists of 14 districts and two counties. As of 2010, Beijing is home to 1.962×10^7 permanent residents with a density of 1195 residents/km^2 and has a gross domestic product of 1.41×10^{12} yuan (RMB). Rapid economical development in the past two decades has created newly urbanized areas in Beijing that have been expanding dramatically at the expense of farmland. According to an incomplete survey, the farmland area of Beijing was reduced by 42.09% between 1992 and 2004, and the urbanized areas increased by 35.58%. Since 2005, the expansion of urbanized areas slowed and the loss of farmland was arrested. As of December 2008, urbanized areas accounted for 20.58% of the total area (and 46.47% of the total flat area) of Beijing (Han *et al.*, 2010). This data indicates the urbanization of Beijing

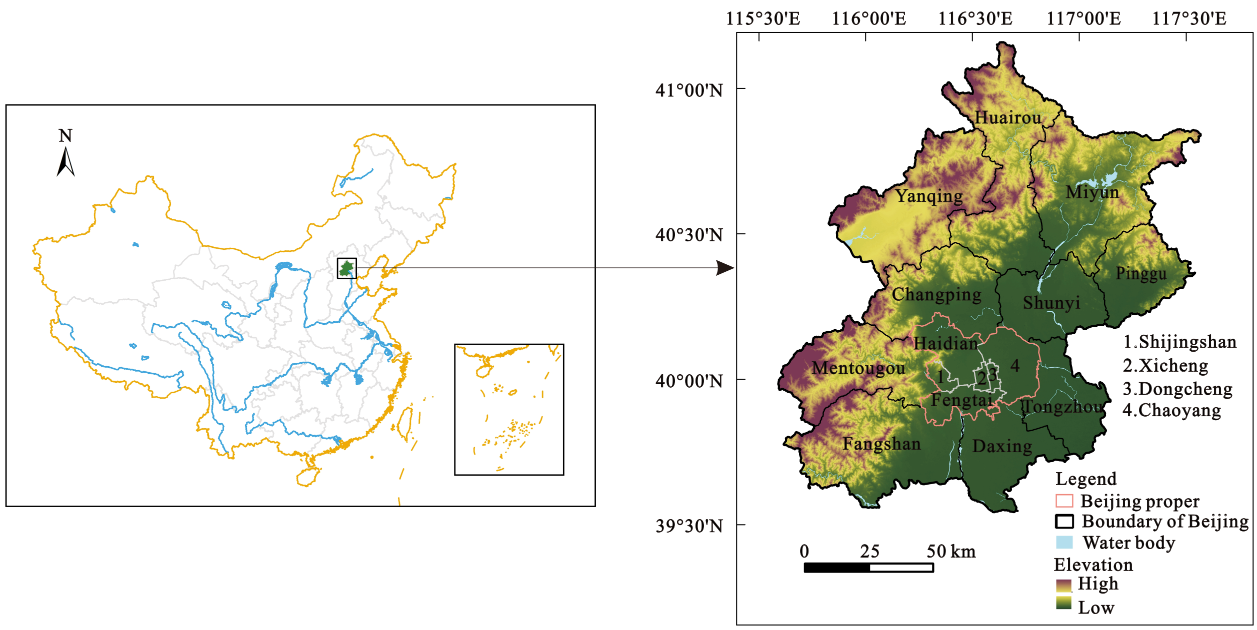

Fig. 1 Location of study area

has been accompanied by a rapid expansion of urban space and a dramatic loss of farmland. Therefore, to balance the urban and rural development in Beijing, it will be necessary to identify key areas susceptible to future land-use changes and facilitate the rational creation of land-use policies.

2.2 Data and processing

Data were obtained from four sources and processed as follows: 1) Landsat thematic mapper image data (acquired in 1995, 2000, and 2005; resolution: 30 m) for Beijing was obtained and processed by geometric correction, radiometric correction, and false color (RGB) composition. Land-use information was extracted from the data by human-computer interactive operations using ArcGis 9.3 (Esri, Redlands, CA, USA) with rasterized images as the background. The imaged areas were classified into six types of land use: farmland, water body, urban/suburban land, rural residential land, other construction land, and other uses. Image areas that were difficult to accurately interpret were confirmed by sampling and on-site surveys. These procedures were confirmed to produce a classification accuracy of 98.72%. 2) Digital elevation model data for Beijing acquired by the Shuttle Radar Topography Mission (National Aeronautics and Space Administration, USA) were obtained and used for analyses. 3) Data collected from the Statistical Yearbooks of Beijing (Beijing Municipal Bureau of Statistics, 1996; 2001; 2006) were also incorporated in the analyses. 4) Data drawn from vector maps describing transport accessibility were used for analyses, such as the analysis of road locations.

Raster images describing natural conditions for slope, aspect, and elevation were created from the digital elevation model images using ArcGIS 9.3. Data describing socioeconomic conditions such as urban/suburban density or rural residential sites were derived from actual land-use maps. All data were transformed into consistent spatial coordinates and resolutions, and converted into text files for subsequent analyses.

2.3 Methods

2.3.1 Markov model

Markov model represents a mathematical technique for predicting future changes of a system. The technique is suitable for predicting the conversion of land-use in a given region because such conversion is ′memory-less′, the fundamental requirement of Markov model, and also because the land-use status in a region is structurally stable over a short period (Quan *et al*., 2011; He *et al*., 2011; Wang *et al*., 2012). In this technique, the changes in the land-use status of a region or system are modeled as follows:

$$X(n)=X(n-1)P_{ij} \tag{1}$$

where $X(n)$ and $X(n-1)$ are the system statuses at the time-points n and $n-1$; P_{ij} is a transition probability matrix satisfying the following conditions, where i, j are the land use types at the time-points n and $n-1$.

$\sum_{j=1}^{n} P_{ij}=1$ (i, j = 0, 1, 2, …, n) (the sum of the elements in each row equals one);

$0 \le P_{ij} \le 1$ (i, j = 0, 1, 2, …, n) (all matrix members are non-negative and range between 0 and 1).

2.3.2 CLUE-S model

The CLUE-S model is based on high-resolution, usually better than 1 km^2, spatial image data and is suitable for simulating land-use changes over medium or small spatial scales (Verburg *et al*., 2002). This model is divided into a spatial module and a non-spatial module. The non-spatial module calculates the demands for land-uses based on analyses of natural, social, and economical factors. The spatial module translates these demands into land-use changes according to the probabilities and rules of different land-use types using a raster-based system (Verburg *et al*., 2002). In our simulations with this model, the land-use conversion included six aspects as follows.

(1) Logistic regression analysis

In the CLUE-S model the probability of land-use conversion is calculated for each raster cell by binary stepwise logistic regression (Zhou *et al*., 2011). In the present study, 14 regression factors were selected based on their availability, stability, relevance, and the suitability of the data. These included elevation, slope, aspect, distance to the nearest main road, distance to the nearest local road, distance to the nearest railway, distance to the nearest park, distance to the nearest river, distance to the nearest lake, distance to the nearest urban center, distance to the nearest suburban center, distance to the nearest rural residential site, urban/suburban density (defined as the proportion of urban/suburban land in an area of 10 km × 10 km), and rural residential density (the proportion of land occupied by rural resident sites in an area of 10 km × 10 km) (Liang *et al.*, 2011). These driving factors and land-use types for each raster cell were determined using ArcGis 9.3 and transformed into an ASCII text format. The ASCII data were further transformed using the *Convert* module in CLUE-S into a column format compatible with SPSS 19.0 (SPSS, Chicago, IL, USA). Then, the data were analyzed by binary logistic regression (SPSS) to determine the relationship between each land-use type and the factors influencing it.

(2) Temporospatial scale selection

In this study, spatial scale refers to the spatial resolution, such as raster cell size, used during a simulation. According to information theory, a higher spatial resolution provides more information but also increases the entropy of the image, thereby potentially impairing the certainty and accuracy of predictions (Huang *et al.*, 2009). Therefore, a higher spatial resolution should be used as long as the prediction accuracy is not impaired. In this study, the resolution was initialized at 1000 m (default configuration in CLUE-S) and then increased stepwise (100 m/step) for comparisons. Trials found a resolution of 220 m produced optimal simulation results. This 'optimal' resolution was used in subsequent experiments.

The temporal step-size for simulation was selected as 5 years. The actual land-use maps for 1995 and 2000 were analyzed separately with the CLUE-S model to predict the land-use scenarios in 2000 and 2005, respectively, and the predictions were verified for accuracy. Then, the actual land-use maps for 2005 were similarly analyzed to predict the scenarios in 2015.

(3) Configuration of elasticity for land use conversion

Elasticity (ELAS) for land use conversion characterizes the ease or difficulty of land-use conversion (Liang *et al.*, 2011). For a given type of land-use, the ELAS ranges between 0 and 1, and the value is positively related to the difficulty for this type of land-use to be converted to other types. Table 1 shows the ELAS rating for each land-use type in this study, determined from the actual area converted from this type of land use to other types.

(4) Rules for land-use conversion

The CLUE-S model requires the establishment of rules for conversion between different types of land-uses. In this study the conversion between any two types was accepted based on the actual status of land conversion in Beijing.

(5) Land-use policies and restrictions

The CLUE-S model provides the definition of land-use policies and areas restricted from land-use conversions. In our simulation, based on the actual policies in Beijing, several regions such as Xiangshan Park and Tiantan Park were restricted from converting to other land use types.

(6) Prediction of land-use demand

The demand for future land-use was predicted from the actual land-use maps for 1995, 2000, and 2005 using the aforementioned Markov model.

2.3.3 Simulation of urban development scenarios

Two land-use maps for Beijing in 2015 were simulated assuming two potential modes of development: development following the existing trends, and development under a strict policy of farmland protection. To simulate the two scenarios, the conversion probabilities in the Markov process and the CLUE-S input parameters were adjusted based on the results predicted by the Markov model.

(1) Simulation of development following existing trends

The percentages of various land-uses in 2015 were simulated using the Markov model at a simulation step of 5 years based on the actual percentages of different land-uses in 2005 and the land-use conversion matrix (calculated from the actual conversions between 2000 and 2005).

(2) Simulation of development under a strict farmland protection

The *General Plan for Land-use in Beijing* clearly points out that farmland and other agricultural-use land in Beijing is strictly protected from being converted to other applications such as industrial and civil construction lands. Assuming an effective enforcement of this policy between 2005 and 2015, the probabilities of farmland converted to other uses were adjusted follow-

Table 1 Elasticity (ELAS) for various land-use types

Type	Farmland	Water body	Urban/suburban land	Rural residential land	Other construction land	Other uses
ELAS	0.8	0.7	0.8	0.7	0.3	0.9

ing the methods used in a previous study (Lu *et al.*, 2009). This guidance reduced the probabilities of farmland converted to urbanized areas, water bodies, and other land-uses by 80%, 25% and 50%, respectively.

3 Results

3.1 Simulation accuracy

The regression results were evaluated using the Relative Operating Characteristic (ROC) method (Pontius, 2002). An ROC of greater than 0.7 suggested a good explanatory power by the selected driving factors. The ROCs (Table 2) were greater than 0.8 for all land-use types, suggesting successful correlations and strong powers to explain the land-use patterns by the selected driving factors. The resulting regression coefficients for the driving factors were used in subsequent experiments.

The accuracy of a simulation can be evaluated by several methods, such as a multi-scale test and the use of Kappa indices (Wang *et al.*, 2010). The present study used Kappa indices to evaluate the overall simulation accuracy, and then investigated the accuracy of predicted change for each type of land-use. The simulated land-use maps for 2000 and 2005 (Fig. 2 and Fig. 3) were compared with the actual maps for the two years using IDRISI, an integrated geographic information system and remote sensing software package (Clark Labs, Clark University, Worcester, MA, USA). The Kappa indices were found to be 0.7554 for 2000 and 0.8827 for 2005. Then, the simulation accuracy for each type of land-use was calculated (Table 3).

The CLUE-S simulation gave excellent Kappa indices and accuracies for all land-use types (Table 3). Compared with the simulations for 2000, those for 2005 were more accurate, suggesting the model captured the trends in land-use changes. Specifically, the simulations for other construction land and rural residential land in 2000 (Table 3) were less accurate when compared with those for farmland, water body, urban/suburban land, and other uses, which were generally accurate. In comparison, the simulations for all types of land uses, except other construction land, in 2005 were accurate.

The differences between the simulated land-use scenarios and the actual maps can be attributable to two major causes. First, Beijing has planned 14 satellite towns, such as Tongzhou, Fangshan, Changping, Yanqing, Huairou, Miyun, Pinggu, and Shunyi, around the central urban area. Active renovation and construction

Table 2 Results of logistic regression for different land-use types in Beijing

	Farmland	Water body	Urban/suburban land	Rural residential land	Other construction land	Other uses
ROC	0.864	0.875	0.898	0.894	0.820	0.946

Note: ROC (Relative Operating Characteristic)

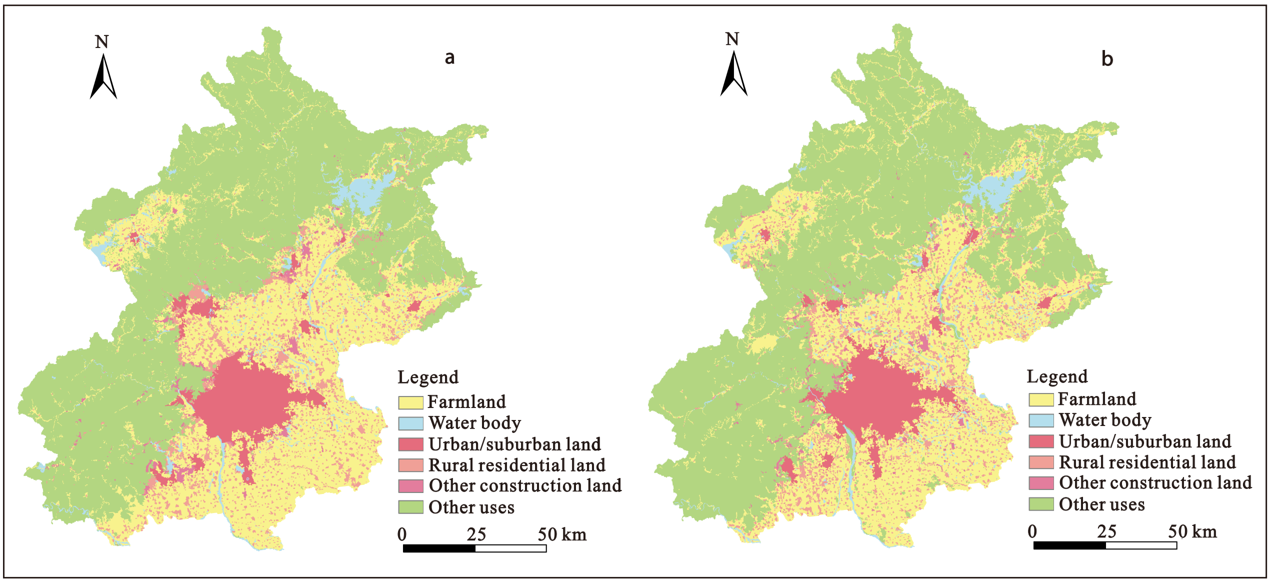

Fig. 2 Comparison of simulated (a) and actual (b) land-use maps for Beijing in 2000

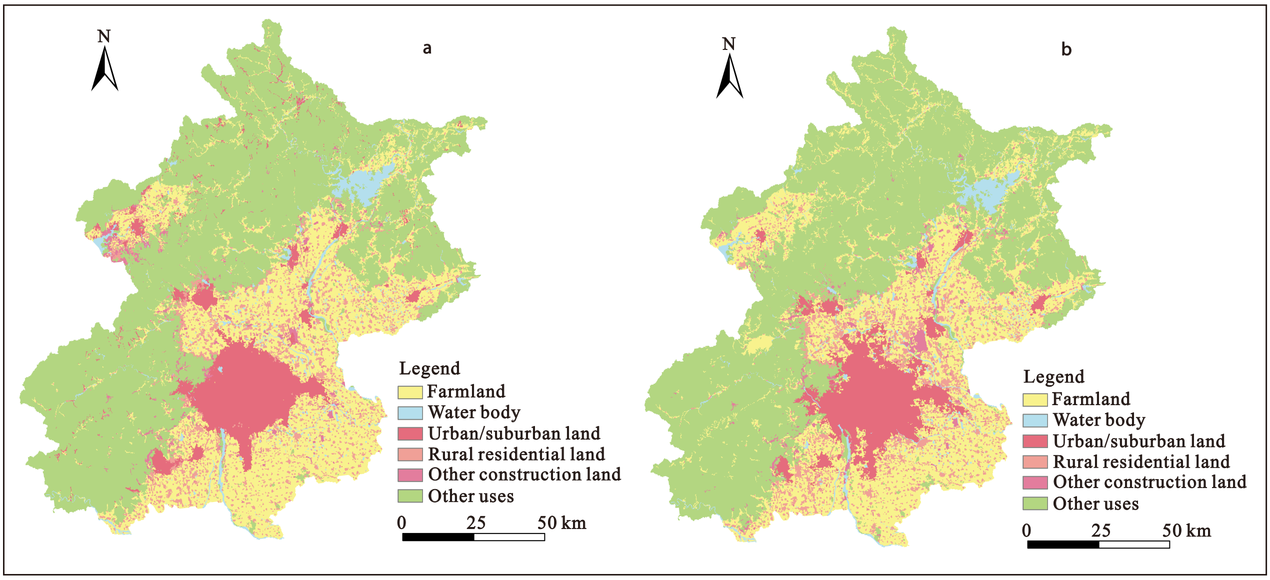

Fig. 3 Comparison of simulated (a) and actual (b) land-use maps for Beijing in 2005

Table 3 Simulation accuracies for different types of land-uses (%)

Land-use type	2000	2005
Farmland	80.24	90.33
Water body	73.10	92.70
Urban/suburban land	86.98	78.55
Rural residential land	60.99	81.35
Other construction land	29.65	62.01
Other uses	92.18	98.42

of new residences in these satellite towns may have impaired the simulation accuracies for rural residential sites. Second, the 'other construction land' in this study included industrial plants, mines, oil fields, salterns, quarries, airports, the Daxing Industrial Park, and land used for special applications. Reasons underlying changes in these land-uses were usually complicated and unclear; therefore, such changes could not be accurately simulated simply by adjusting driving factors or other parameters.

3.2 Prediction of land-use in 2015

The land-use maps in 2015 (Fig. 4) were simulated from the actual data for 2005 assuming two separate development modes.

3.2.1 Simulations assuming urban development following existing trends

Assuming urban development follows the existing trends, from 2005 to 2015 the farmland in Beijing would be primarily converted into urban/suburban lands, followed by conversions into other construction land, and then into rural residential land. Comparing the simulated scenarios for 2015 with the actual map for 2005, this farmland-urban/suburban conversion would occur mainly in the northeast, southwest, and northwest flanks of the Beijing proper, as well as in the peripheral regions of Yanqing County, and in the Fangshan, Changping, and Huairou districts. Specifically, the predicted farmland-urban conversion areas in the northwest flank included the following communities: Jindingjie, Pingguoyuan, Sijiqing, Wanliu, and Jilongqiao. In the northeast flank, the predicted conversion areas included the following villages and towns: Dougezhuang, Dongba, Jiangtai, Cuigezhuang, Miguangying, and Dongxiaokou. In the southwest flank, the conversion areas included: Xincun, Huangcun, Beizangcun, Changxindian, Wanping, and the southwest stretch of Wanping. The conversion areas in Yanqing County included the following villages and towns: Yanqing, Zhangshanying, Dayushu, Shenjiaying, Jiuxian, Jinzhuang, and Yongning. The conversion areas in Fangshan District included parts of the east side of Chengguan and west side of Yancun. The conversion villages (towns) in Changping District included Changping Town, the peripheral areas of Changping, and the areas surrounding the border between Liucun and Yanchi. The conversion areas in Huairou District included Beifang and the junction between Yanqi and the north downtown area.

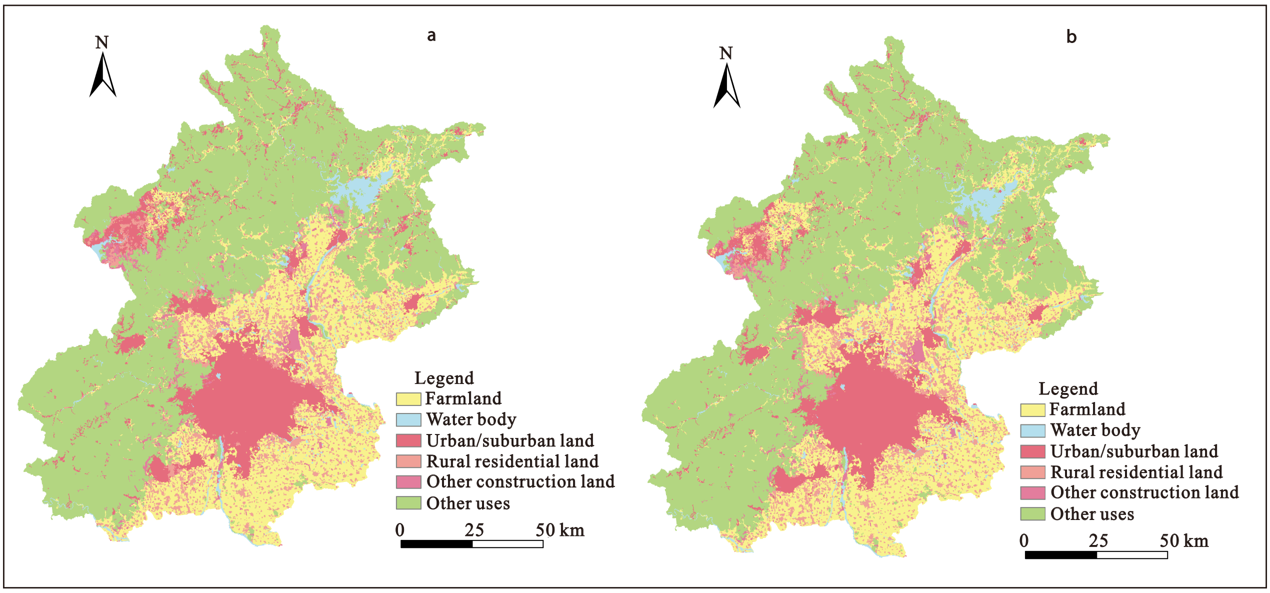

Fig. 4 Simulated land-use maps of Beijing in 2015 assuming two urban development modes: assuming development following existing trends (a); assuming development under policy of strict farmland protection (b)

3.2.2 Simulations assuming urban development under strict farmland protection

Assuming an urban development under a strict farmland protection policy, from 2005 to 2015, the farmland would be also primarily converted to urban/suburban areas, followed by conversion to other urbanized areas. Similar to the above results (section 3.2.1), the farmland-urban/suburban conversion would occur mainly in the northwest, southwest, and northwest flanks of the Beijing proper, as well as the peripheral regions of Yanqing County, Fangshan District, Changping District, and Huairou District. The predicted conversion areas in the flanks of the Beijing proper were similar to the former results (section 3.2.1). The conversion areas in Yanqing County included Yanqing Town and its surrounding regions. The conversion areas in Fangshan District included the region between Chengguan Town and Liangxiang Town. The areas in the Changping District included Changping Town and its surrounding regions, and the region around the junction between Liucun Town and Yanchi Town. The areas in Huairou District included Huairou Town, Beifang Town, and Miaocheng Town.

3.2.3 Comparison of land-use changes under different urban development modes

The simulations revealed similar land-use changes regardless of the selection of development modes. The results suggested that urbanized use would dominate the land-use changes and urbanized areas would expand at the expense of other types of land. In the flat area of Beijing, farmland-urban/suburban conversion was expected to occur in the northwest, northeast, and southwest flanks of the Beijing proper via expansion of the existing urban/suburban areas. In the mountainous area, such conversions would occur in Huairou District, Yanqing County, Changping District, and Fangshan District via expansion of the existing urban/suburban areas, as well as in the junction between Changping District and Mentougou District. Under the second mode (section 3.2.2), the urban/suburban space expansion was moderately suppressed, resulting in an attenuation in farmland loss. Also, regardless of the selected development mode, the farmland-urban/suburban conversion was more severe in the mountainous areas than in the flat areas. These results suggest that the aforementioned areas (sections 3.2.1 and 3.2.2) could be susceptible to farmland loss. Farmland in the mountainous area of Beijing should be especially protected from conversions to construction land.

4 Discussion and Conclusions

In the present study, the CLUE-S and Markov models were combined to overcome their respective disadvantages in demand prediction and spatial allocation, and thus enhanced the accuracy of simulation. Based on previous review regarding the driving forces of land use change in Beijing (Jiang *et al.*, 2006), socioeconomic properties were used as driving factors to simulate the land-use map of Beijing in 2015, including the distance to the nearest urban center, the distance to the nearest town center, as well as urban and suburban densities. Natural conditions, such as elevation and slope, and even policy factors, such as governmental zoning or other restriction policies, were also used. The simulations suggested and identified key areas which will be susceptible to land-use changes, and revealed the trends and major driving factors for such changes. These findings may facilitate reasonable planning and management of land resources in Beijing.

As the results suggested, urban expansion of cultivated land occupancy will continue to be the main characteristics of land use change in the future, which will be more severe in the mountainous areas than in the flat areas. Research also suggests that the Beijing mountainous areas entered a more active development stage, which has become the focus zone of industry development and population transfer. This research also supports a rapid growth in the next 10 years for the real estate construction land (Jiang *et al.*, 2006). The simulation results showed that the outward expansion and inhomogeneity of punctate expansion of construction land is obvious for most mountainous districts, and farmlands will be still the main source of construction land expansion, which is especially obvious in Huairou District, Yanqing County, Changping District, Fangshan District, as well as in the junction between Changping District and Mentougou District. Because the Beijing mountainous areas are important ecological barriers and water conservation areas, the land used for construction purposes should be moderately developed. The special position the Beijing mountainous areas occupies demands that land development activities should be scientifically supported and particular attention given to the scale, site, and layout of all construction locations. The relationship between construction lands and transportation networks, and between construction lands and ecological environment should be comprehensively studied and estimated. Internal mining of inefficient land use in rural residents and cities should be monitored, while construction land arrangements optimized to reduce construction invasion of farmland.

The fundamental idea of the CLUE-S model uses logistic regression to determine the relationship between various types of land uses. Logistic regression allows a flexible selection of driving factors and spatial driving factors such as distance to the nearest urban center. However, dependence on logistic regression and the requirement of spatialized driving factors are also disadvantages of this model. Also, logistic regression alone is insufficient, because the regression results represent only the statistic relationship between land-use types and the driving factors, but not the causal relationship between them. Therefore, to enhance the reliability of simulation, future studies should focus on driving factors for various types of land uses.

Land-use change scenarios are not definite schemes. Instead, they only represent the possibilities of these changes. The main purposes of land-use change predictions are to visualize the trend in land-use changes under different policies, providing reference information for the creation and modification of land polices. A limitation of the present study is that it did not consider the effects of administrative polices during different periods on land-use changes, primarily because of the lack of mature methods to transform these policies into quantitative spatial parameters. However, we acknowledge these policies have significant impacts on the formation and evolution of land-use patterns. Therefore, the determination of appropriate spatial constraint schemes based on regional land policies is a critical requirement for land-use simulation using CLUE-S or other models.

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