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Scenario simulation of land system change in the Beijing-Tianjin-Hebei region

Yuanyuan Yang[a,b,c], Wenkai Bao[a,b,c], Yansui Liu[a,b,c,*]

[a] Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China
[b] Key Laboratory of Regional Sustainable Development Modeling, CAS, Beijing 100101, China
[c] University of Chinese Academy of Sciences, Beijing 100049, China

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ABSTRACT

Urbanization-induced land use problems have been haunting China's urban agglomerations ever since the beginning of this period of unparalleled economic progress. The Beijing-Tianjin-Hebei (BTH) region is no exception, where coordinated development planning has been implemented by the central government to further resolve attributed problems. Land use simulation models can be used to help governments and planners understand how planning and policies affect the future landscape, by developing sustainable land use strategies which may reasonably balance urbanization and eco-environmental protection. In this paper, we explored the characteristics of historical land use dynamics from 2000 to 2015 in the BTH region and simulated its future land use patterns for 2030 by combining the Dyna-CLUE model with a Markov model to deal with some short comings of existing land use models. The main conclusions are as follows: (1) The figure of merits (FoM) based on the method of three-map comparison reached 85.89 %, which indicated that the simulation model has satisfactory accuracy. (2) Land use structures and spatial patterns differed significantly under business as usual (BAU) scenario, cropland protection (CP) scenario and ecological security (ES) scenario, respectively, owing to the variation of the major objectives designed for different scenarios. (3) By scenario analysis and through tradeoffs, the land use mode under the ecological security scenario might be the optimal solution for future coordinated development in the BTH region. These results will provide theoretical basis and meaningful guidance for regional land optimal allocation.

1. Introduction

The anthropogenic processes of land use in both global and local scales have been profoundly influencing the earth ecosystem and global environmental change (Foley et al., 2005; Kalnay and Cai, 2003). In the past century, the process of land use and land cover change (LUCC) has significantly accelerated due to intensified human-mediated processes, such as deforestation, agricultural reclamation and urban expansion, etc (Meyer and Turner, 1992; Ramankutty et al., 2006). Solutions for how to efficiently manage limited land and promote sustainable development, especially in developing countries, have been major concerns for government planners and researchers alike (Liu et al., 2018b).

To maximally realize efficient land use planning and management, it is essential to reasonably predict land use demand and simulate land use pattern under possible future circumstances (Kindu et al., 2015; Nourqolipour et al., 2015). The scenario-based approach enables people to strategically experiment with their visions and provides a scientific reference for rational decision-making (Maack, 2001; Swart et al., 2004). Thus, multiple possible scenarios for the land system evolution should be simulated and discussed using LUCC models to support policy formulation and land use optimization studies (Liu et al., 2017a; Schmitz et al., 2014). Over the past two decades, a variety of LUCC models have been developed and applied to simulate land use patterns, assess the effect of land use changes on the earth system, and to study possible future land use scenarios for different scales, purposes, and in different regions (Gollnow et al., 2018; Koomen and Stillwell, 2007). Methods vary with non-spatial models and spatial models. The former based on economic theories of development and econometric applications, while spatial models are based on computational approaches such as probabilistic, cellular automata and agent-based modelling (Briassoulis, 2000; Verburg et al., 2006). The spatial model's key capability of explicitly illustrating land use changes on map distinguishes it from the non-spatial ones. Hence, the spatial models have already been more acceptable and popularized.

* Corresponding author at: Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China.
E-mail address: liuys@igsnrr.ac.cn (Y. Liu).

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Among the spatial models, CLUE (Conversion of Land Use and its Effects) is one of the most commonly used land allocation model and is easily adapted for scenario analysis (Pontius et al., 2008). The model's extensive use in many case studies from local to continental scale (Castella et al., 2007; Wassenaar et al., 2007) has proven its capability to simulate a wide range of scenarios (Rounsevell et al., 2012). The Dyna-CLUE model is the most advanced version of the CLUE model, combining the top-down allocation with bottom-up determination algorithm of land use transitions, and including an advanced autonomous development mechanism (Verburg and Overmars, 2009), which is perfectly suitable for the simulation of land use changes in a complex and large-scale study area (Verburg et al., 2010).

Since the reforms in 1978 which opened China to the world, huge amount of arable land and rural settlements have been developed and converted into urban land under the influence of large-scale rural-to-urban migration and industrial agglomeration (Liu et al., 2017b). However, due to the lack of reasonable land use planning, contradictions between limited land resources and the ever-increasing human demand for land have become increasingly prominent under this background (Liu et al., 2014b; Long et al., 2014). With this in mind, tremendous efforts have already been made by the Chinese government and experts (Bryan et al., 2018), but maintaining harmonious development between man and land should be the long-term focus in respect of realizing rational land use in China.

The Beijing-Tianjin-Hebei region is a typical developed area haunted by over-urbanization problems (Yang et al., 2018; Zhao et al., 2016). As a win-win solution to ensure economic growth and environmental protection at the same time, the strategy for BTH's coordinated development proposed in 2014 has played an important role in promoting the coordination of population, economy, resources, and environment, complementing each other with distinct advantages (Zhao et al., 2014). Through the national implementation of the related policies, regional urban-rural spatial structures and land use patterns in BTH region have been constantly changing.

Based on this, the objective of this study was to quantitatively assess and understand land use changes in BTH region during 2000–2015, and then, project land use patterns and changes up until 2030 by adopting the Dyna-CLUE model under three adaptive scenarios designed for the study area, namely, the 'business as usual' (BAU) scenario, cropland protection (CP) scenario and ecological security (ES) scenario. Ultimately, findings of this study are intended to serve as an early warning system for understanding the future effects of LUCC and as a strategic guide to land use planning process for BTH's coordinated development.

2. Materials and methods

2.1. Study area

The Beijing-Tianjin-Hebei region (113°04′-119°53′E, 36°01′-42°37′N) is located in the northeastern area of China, which includes Beijing Municipality, Tianjin Municipality and Hebei Province (Fig. 1), with the total land area of 218,000 km^2. As one of the three major urban agglomerations of China, the BTH region contributes to 9.44 % of China's GDP with 113 million people inhabiting here in 2018. The vast plain in the central and south of this region is a major grain and cash crop production base and there are many important ports and manufacturing bases distributed along the upper eastern coast. The northwest of this region has a high coverage rate of forests and grasslands, which plays an essential role in maintaining regional ecological security.

The BTH region is a highly developed zone characterized by significant internal imbalance. In 2018, BTH's urbanization rate reached 65.8 %, with 86.5 % in Beijing, 83.2 % in Tianjin and only 56.4 % across Hebei province. Beijing and Tianjin are developed metropolitan zones with relatively concentrated populations, capital and technology. However, cities located in the poverty belt around Beijing and Tianjin, such as Chengde and Zhangjiakou, have been confronted with challenges of boosting economic development and improving people's livelihood. Therefore, promoting regional sustainable development on the basis of ecological protection must be the primary focus for policy making in this region.

2.2. Data source and processing

The data used in this study included land use data, Digital Elevation Model (DEM) data, Net Primary Productivity (NPP) data, high/medium yield cropland data, national ecological function reserve data, national nature reserve data, basic geographic information data, meteorological data and relevant socio-economic data. Based on these data, simulations of land system changes in 2030 were carried out. Land use data pertaining to the years 2000, 2005 and 2015 were obtained from the Landsat TM/OLI remote sensing images through artificial visual interpretation, with accuracy of no less than 90 % (Liu et al., 2014a; Ning et al., 2018). Spatial resolution of land use data is 100 m and these data were classified into six categories: arable land, forest, grassland, water, built land and unused land (Liu et al., 2003). DEM data were downloaded from the Geospatial Data Cloud website (http://www.giscloud.cn), with spatial resolutions of 90 m, and elevation and slope data were generated from DEM data using ArcGIS. NPP data for croplands, forests and grassland were calculated based on the Vegetation Photosynthesis Model (VPM) method (Niu et al., 2016). High and medium yield cropland distribution data were generated based upon the differentiation of cropland productivity represented by mean values of time-series NPP data (Ji et al., 2015). The national ecological function reserve and national nature reserve data, gridded gross domestic production (GDP) and population data were derived from the Resource and Environment Data Cloud Platform, Chinese Academy of Sciences. The raster datasets of gridded GDP and population were generated based on the China statistical yearbook at county level in 2005 and the resolution was 1000 m. Basic geographic information data were downloaded from the National Geomatics Center of China (http://www.ngcc.cn), including provincial boundaries, administrative centers at the city and county/district levels, highways and railways, etc. Annual precipitation and average temperature data were downloaded from the China National Meteorological Information Center (http://data.cma.cn).

2.3. Methods

2.3.1. Dyna-CLUE model

The Dyna-CLUE model is composed of two distinct modules: a non-spatial demand module which is designed to predict future land use demand, and a spatial allocation module designed to conduct land use pattern simulations. Required inputting elements of the Dyna-CLUE model include four parts: spatial policies and restrictions, land use conversion, land use demand and location suitability. ① Spatial policies and restrictions indicates areas where land use changes are prohibited due to regional policy and planning, such as the allocation of nature reserve status or permanent farmland, etc. ② The land use conversion section determines conversion elasticity and provides the conversion matrix of the defining rules of conversion between land use types. ③ The land use demand section calculates annual area changes for each land use type by either simple extrapolation or through complex multi-sectoral models. ④ Location suitability is estimated through spatial associations of current land use with associated driving factors using logistic regression model.

Stepwise logistic regression was performed in SPSS (IBM SPSS, version 22) to evaluate the relation between each land use type and the associated potential driving factors. The mathematical expression is as follows (Gobin et al., 2002) :

$$\mathrm{Log}\left(\frac{P_i}{1\text{-}P_i}\right)=\beta_0+\beta_1 x_{1,i}+\beta_2 x_{2,i}+\ldots+\beta_n x_{n,i} \quad (1)$$

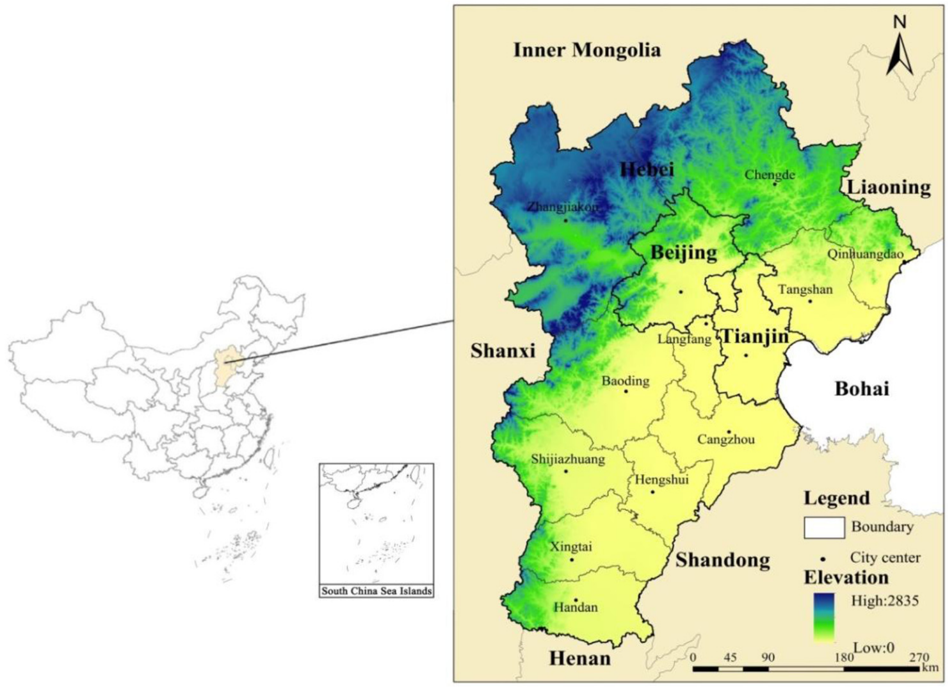

Fig. 1. Location of the study area.

Where P_i is the spatial distribution probability, X_i represents the driving factor of i, β_i is the regression coefficient of each factor. Relative operating characteristic (ROC) was adopted as a quantitative measure to evaluate the fit of the logistic regression model (Pontius and Schneider, 2001). The value of ROC ranges from 0.5 to 1.0. An ROC above 0.70 shows that the driving factors had a great explanatory power for certain land use type (Pontius et al., 2008).

The Dyna-CLUE model simulates land use distribution based on raster dataset, requiring the grid cell size, grid cell number, and spatial extent of all input data to be identical. The question of choosing an appropriate resolution for modelling has always been a challenge since the origin of the land system simulation research (Verburg et al., 2019). As the resolution improves, more land use information is involved, but the model's accuracy is likely to decrease (Pontius et al., 2008) and it may exceed Dyna-CLUE software's data processing capability. Thus, the spatial resolutions of most previous case studies were set between 100 m and 1000 m (Lima et al., 2011; Lu et al., 2015; Verburg et al., 2002; Xu et al., 2013). Considering the spatial scale of the study area, the resolution of the available data and all the limitations above, the resolution of all input data were aggregated to 500 m.

2.3.2. Markov model

The Markov model was adopted in the process of predicting land use demand. The Markov chain is a non-aftereffect process, which is in accord with the characteristic of land use change. The later state (land use type) is only related to its beginning state and transition step size, but not to any other previous states (Fischer and Sun, 2001; López et al., 2001). Prediction processes were as follows: firstly, the transition probability matrix was computed from the land use maps at the previous and current time node; secondly, the future land use demand was then produced by multiplication of transition probability matrix and the area of each land use type at the current time node (Guan et al., 2011). Transition probability matrix can be calculated through the Markov module in the IDRISI software package (Clark Labs, Worcester, Massachusetts) and its user's guide is highly useful (Myint and Wang, 2006). Hence, detailed procedures and mathematical expression will not be discussed in this paper.

2.3.3. Assessing simulation accuracy

Model validation includes a range of methods developed for assessing the accuracy of simulation results (van Vliet et al., 2016). The method of three map comparison (Pontius et al., 2008, 2011) was adopted in this study to validate the simulation model by comparing the observed change with predicted change in the land use map. The maps used for the three-map comparison includ the reference map of time 1, the reference map of time 2 and the simulated map of time 2. Observed change reflects the real dynamic changes of the land use, which were generated by overlaying the maps of reference time 1 and reference time 2. Predicted change reflects the land use changes in a simulated situation, which were generated by overlaying the map of reference time 1 and simulated time 2.

Model accuracy is determined by five types of indicators: null successes (accurate prediction due to observed persistence predicted as persistence), true hits (accurate prediction due to observed change predicted as right gaining category), partial hits (inaccurate prediction due to observed change predicted as wrong gaining category), misses (inaccurate prediction due to observed change predicted as persistence) and false alarms (inaccurate prediction due to observed persistence predicted as change). Thus, the figure of merit (FoM, Eq. 2) and total error (T, Eq. 3) are calculated using the indicators above (Hao and Pontius, 2011).

Total error reflects the model inability both in the quantity prediction and in the spatial allocation. The FoM indicates the overall accuracy of the simulation model, ranging from 0% (no overlap between observed and predicted change) to 100 % (perfect overlap between observed and predicted change), and if FoM value reaches 100 %, the simulation is completely correct. This measure enables more realistic assessments of the cell-to-cell coincidence between simulated and real maps than more commonly used metrics, such as the kappa index, which are usually calculated using the entire surface area (Santé et al., 2010).

$$\mathrm{FoM} = \frac{\mathrm{H_1}}{\mathrm{H_1} + \mathrm{H_2} + \mathrm{M} + \mathrm{F}} \times 100\% \quad (2)$$

$$\mathrm{T} = \mathrm{H_2} + \mathrm{M} + \mathrm{F} \quad (3)$$

Where H_1, H_2, M and F represent the true hits, partial hits, misses and false alarms; T refers to the total error.

2.3.4. Scenarios and parameters

Based on comprehensive consideration of regional resource endowments, comparative advantages and different development orientations, scenario simulation has been largely applied in the formulation and assessment of land use planning and land use policy (Cairns et al., 2016; Jenerette and Wu, 2001). Generally, several major aspects must be taken into account, including economic development, food production and ecological protection. Thus, combining the historical land use experience and future demand, three scenarios in 2030 were developed for the BTH region, including business as usual scenario (scenario 1), cropland protection scenario (scenario 2), and ecological security scenario (scenario 3). Then, different land use demand, spatial restriction policies and parameters were input into the simulation models for corresponding scenarios (Gong et al., 2018).

(1) Conversion rules. The conversion rules are composed of land use conversion sequences and conversion elasticity (ELAS). Land use conversion sequences were determined by the conversion matrix with a value of 0 or 1, with 0 indicating impossible conversion and 1 indicating possible conversion. By analyzing the historical land use conversions among land categories from 2000 to 2015 in the BTH region, we could conclude that all land use conversions are possible and therefore, we define each ELAS value of these six land categories as 1. Although conversion from built land to other types is generally difficult, it in deed happens in urbanization-dominant areas (Batisani and Yarnal, 2009; Gong et al., 2018).

Land use conversion elasticity (ELAS) defines the relative conversion cost for a land use type converted to another, ranging between 0 and 1. The higher the elasticity value is, the more difficult the existing land use type can be transformed. Conversion elasticity should be defined based on the knowledge of real situation, but can also be adjusted during the calibration of the model (Verburg and Overmars, 2009; Verburg et al., 2002). In this study, the ELAS for model validation in 2015 was preliminarily set based on the physical characteristics of land use type, and considering the ratio of gross loss to initial total for each land use type from 2000 to 2015 as the higher ratio indicates a lower conversion cost. For example, high ELAS were assigned to built land and forest, due to their low likelihood of being converted to other land use types. Subsequently, the ELAS for model validation was tuned during multiple tests and calibrations and finally defined to achieve satisfactory simulation accuracy.

In the BAU scenario, the ELAS was set to be the same as that for model validation in 2015. As for the CP and ES scenarios, the ELAS was adjusted according to corresponding protection measures on specific land use types. In the CP scenario, we increase the value of ELAS of arable land to prevent its conversion to other types. Accordingly, the values of ELAS of forest, grassland and unused land are reduced. In the ES scenario, the ELAS values of forest, grassland and water are raised to strengthen ecological protection while the ELAS value of arable land is moderately reduced (Table 1).

(2) Spatial distribution suitability. Spatial distribution suitability is determined by location preferences of land use types, and calculated through logistic regression models exploring the quantitative relationship between land use types and driving factors. Thus, only driving factors for which theoretical relationship with land use is known are taken into consideration, in order to avoid spurious correlations (Verburg et al., 2002). In this study, the choice for potential driving factors of land use change was based on prevalent knowledges (Lambin et al., 2003, 2001; Turner et al., 1995; Wu and Webster, 1998; Xie et al., 2017). Therefore, based on the studies above and considering the availability and usability of data, the following biophysical and socio-economic driving factors were included in the modelling process: elevation, slope, population density, GDP density, distance to the nearest railway, distance to the nearest highway, distance to the nearest city/county center, annual average precipitation, and annual average temperature (Fig. 2).

Table 1
Conversion elasticity.

Scenarios	Arable land	Forest	Grassland	Water	Built land	Unused land
BAU	0.5	0.7	0.6	0.5	0.8	0.1
CP	0.9	0.5	0.4	0.5	0.8	0
ES	0.3	1	0.7	0.9	0.8	0

(3) Spatial policies. All land use changes were restricted in the designated area where spatial policies were implemented. In this study, the maps of high/medium-yield cropland (Fig. 3a), national nature reserve and ecological function reserve (Fig. 3b), and high *NPP* value area of grassland and forest (Fig. 3c) were selected as the basic data to create restriction areas in the scenarios of cropland protection and ecological security.

Spatial policies in the three scenarios were defined as follows: (1) In the BAU scenario, no spatial policies were implemented. (2) In the CP scenario, according to the requirements underlined in the “Overall land use planning for Beijing-Tianjin-Hebei coordinated development (2015–2020)” (State Council, 2016a), the high and medium-yield cropland in the study area were classified into the restricted area to prevent the non-agricultural transformation of high-quality cropland (Fig. 4a). (3) In the ES scenario, the BTH region is designed to be a demonstration region of eco-environmental conservation. Therefore, medium and high-yield cropland, national nature reserve and ecological function reserve, high *NPP* value area of grassland and forest were all included in the restricted area (Fig. 4b) to coordinate the relationship between cropland protection and ecological construction.

(4) Land use demand. For model validation, land use demand in 2015 was simulated using Markov model based on the land use data in 2000 and 2005. The linear interpolation method was utilized to create annual land use data from 2006 to 2014.

For future land use simulation in 2030, land use demands in the three scenarios were defined in different ways. Land use demand in the BAU scenario was simulated by using Markov model based on the land use changes during 2005–2015 and the land use data from 2016 to 2029 was created by adopting the linear interpolation method. As for the CP and ES scenarios, land use demands were defined based on corresponding strategic requirements and data from regional planning. Since the regional planning for 2030 has not been available for the public by now, we have to use the latest data in 2020 planning as a reference. According to “Beijing overall land use planning (2006–2020)”, “Tianjin overall land use planning (2006–2020)” and “Hebei overall land use planning (2006–2020)”, the area of arable land in BTH region is planned to be at least 69,567 km^2 and the area of built land is planned to not exceed 26,965 km^2 in 2020. According to the “Framework agreement on promoting forestry ecology in the Beijing-Tianjin-Hebei region” (State Council, 2016b), the forest coverage is expected to reach 35 % (75,482 km^2) in 2020. Thereby, according to the planning areas of the three land categories mentioned above, adjustments were made to the transition probability matrix of the BAU scenario to create land use demands for CP and ES scenarios.

In the CP scenario, we aim to simulate the possible influences and the environmental effects of cropland protection policies and cropland reclamation activities. The area of arable land should not be less than the maximum of the area in 2015 and area of high/medium yield cropland (83059.31 km^2). Besides, the expansion of built land should be restricted and its area should not exceed the planned area in 2020. Therefore, one of the feasible methods to adjust the transition

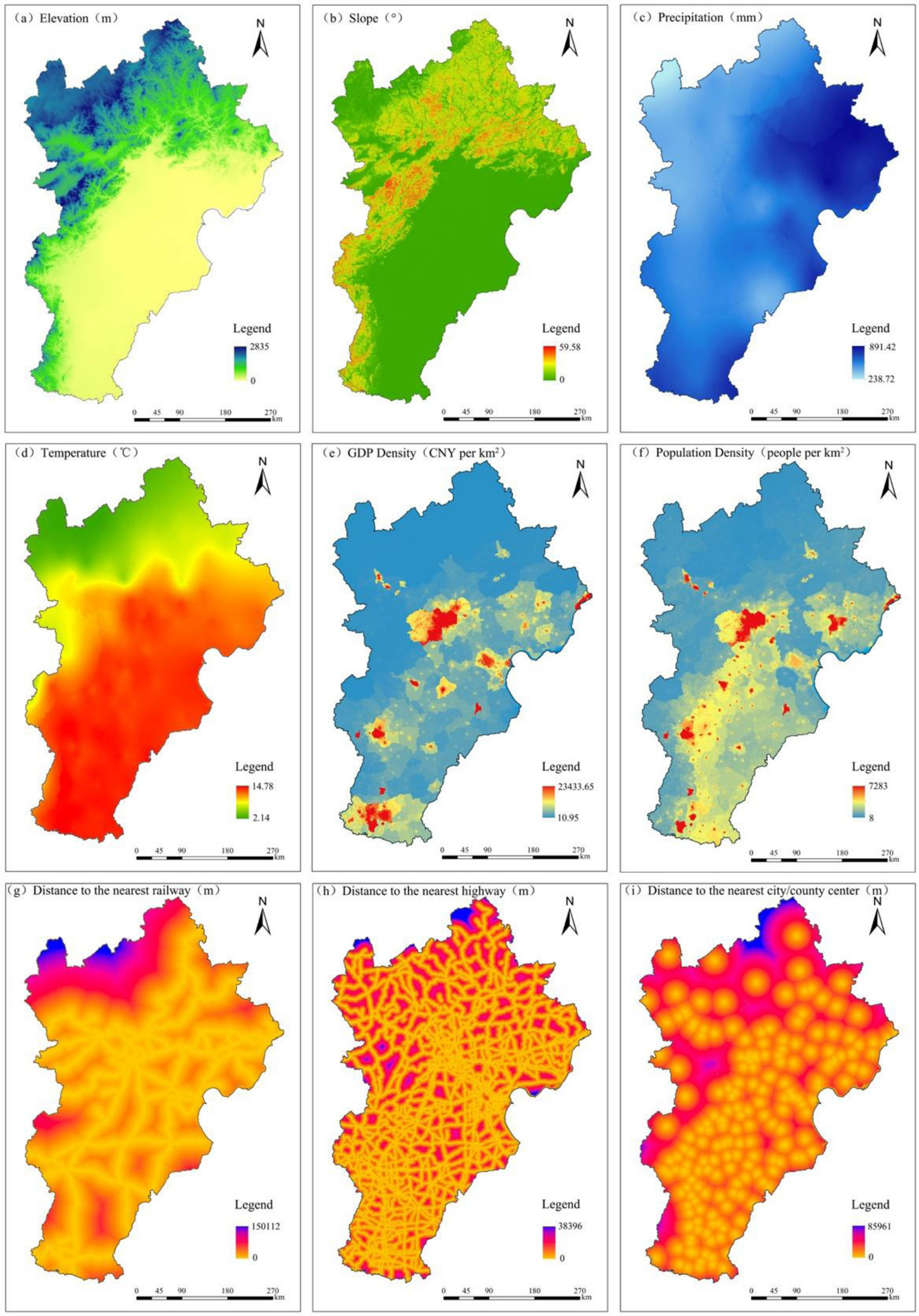

Fig. 2. Map of driving factors.

probability matrix is determined: the aggregate probability of arable land transferring to other types was reduced by 10 %, and the probabilities of forest, grassland and unused land transferring to arable land were raised by 10 %, respectively.

In the ES scenario, ecological protection policies and the effects of large-scale afforestation projects were intended to be simulated. The area of arable land should at least reach the maximum of the planned area in 2020 and area of high/medium yield cropland (83059.31 km^2), and the area of forest should be at least the planned area in 2020. The area of water should not be less than the area in 2015, and the area of built land should not exceed its planned area in 2020. So the transition probability matrix is adjusted as follows: the aggregate probability of forest transferring to other types reduced by 10 % while the probabilities of arable land, built land transferring to forest increased by 10 %, respectively, and the probability of grassland and unused land transferring to forest land increased by 50 %, respectively..

3. Results

3.1. Land use changes from 2000 to 2015

During the period from 2000 to 2015, the land use conversions in the BTH region were relatively intensive with the most predominant characteristic of significant net gain of built land (Table 2). There was an evident increase in the built land by 2,744.96 km^2, which is almost two times larger than the central urban area of Beijing (consisting of Dongcheng, Xicheng, Chaoyang, Haidian, Fengtai and Shijingshan districts). However, other land use types demonstrated decreases in

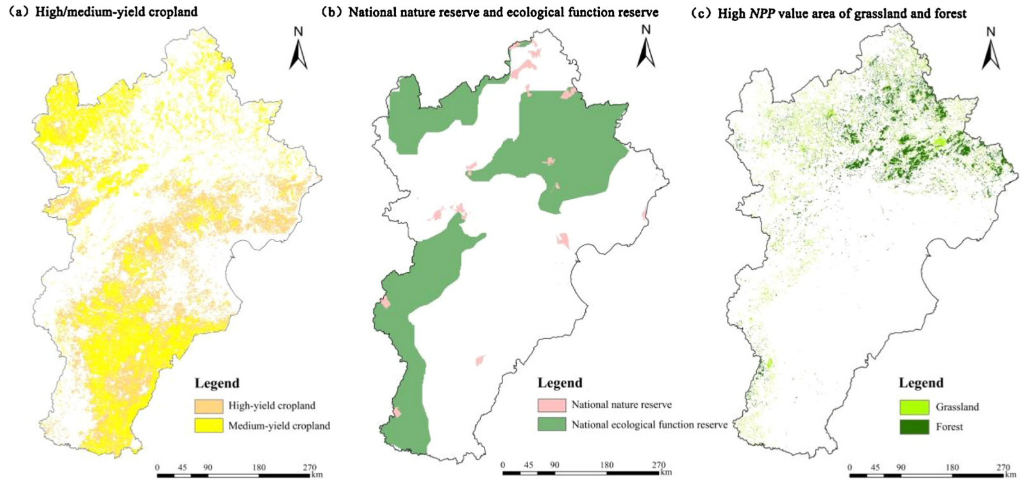

Fig. 3. Maps of high/medium-yield cropland (a), national nature reserve and ecological function reserve (b), high *NPP* value area of grassland and forest (c).

varying degrees during this time period, and the arable land experiences the largest decrease by 2,053.83 km^2.

The Sankey diagram was utilized to visualize the conversion pattern between land use types (Fig. 5). About 1.70 % of the total study area (3,669.15 km^2) experienced intensive land use conversion, and the built land and arable land were the most active types. As for the flow-out process, arable land was the largest loss category during this period, which was mostly converted to the built land. Water and grassland were the second and third largest loss categories, respectively, which were mainly targeted to the built land and arable land. As for the flow-in process, built land was the largest gain category and the smallest loss category, which indicates that the built land grows at a high speed and tends to be more stable than other types after developed.

3.2. Regression analysis of land use change

All the land use types were taken as the dependent variables for logistic regression and nine driving factors were chosen as the independent variables according to regional conditions and data availability. Then, regression coefficients for each independent variable (Table 3) were calculated using a random sample of 10 % of all the 862,648 cells, to reduce the potential influence of spatial autocorrelation (Verburg et al., 2002). Regression coefficient reflects the influence intensity that the independent variable exerts on the distribution probability of certain land use type. To be specific, if regression coefficient is positive, probability increases as the value of the independent variable increases; if regression coefficient is negative, probability decreases as the value of the independent variable increases. ROC test statistics for each land use type are all above 0.70 and the ROC values of four land use types exceed 0.8, which reveals that the selected driving factors performs well in explaining the land use pattern of the study area.

3.3. Model validation

As shown in Fig. 6, the simulated 2015 land use map, reference land use maps of 2005 and 2015 were overlaid to create the map of prediction accuracy and error. Over the entire study area, the proportion of null successes and true hits was 78.37 % and 18.58 %, respectively, which indicates that 96.95 % of the simulated map was consistent with actual land use map. Furthermore, the total error only accounted for 3.05 %, including 0.48 % partial hits, 1.15 % misses, and 1.42 % false alarms. This indicates that the quantitative prediction and spatial allocation in the modelling process is highly accurate. The FoM was 85.89 %, which is higher than those of previous case studies (García et al., 2012; Pontius et al., 2008; Yang et al., 2017). This proves that the

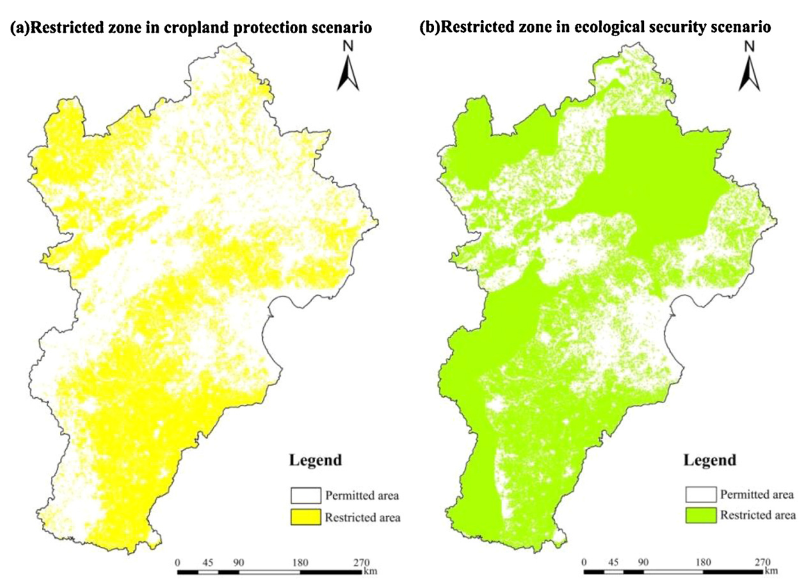

Fig. 4. Map of restricted zones.

Table 2
Land use conversion from 2000 to 2015(km^2).

2015 2000	Arable land	Forest	Grassland	Water	Built land	Unused land	**Initial total**	**Gross loss**
Arable land	106,928	63.27	9.35	169.13	2224.42	2.57	109396.74	2468.74
Forest	18.37	44477.23	5.02	11.14	122.73	0.11	44634.60	157.37
Grassland	81.33	33.34	34929.82	43.93	156.11	0.24	35244.77	314.95
Water	233.51	20.86	13.08	5975.53	262.48	13.67	6519.13	543.60
Built land	25.18	2.37	5.00	23.09	17727.98	0.76	17784.38	56.40
Unused land	56.52	2.59	2.64	30.83	35.62	1954.19	2082.39	128.20
Final total	107342.91	44599.66	34964.91	6253.65	20529.34	1971.54	215,662	3669.15
Net change	−2053.83	−34.94	−279.86	−265.48	2744.96	−110.85		

model has a satisfactory accuracy and can be used to conduct scenario simulations in the BTH region.

3.4. Multi-scenario simulation analysis

As shown in the Table 4 and Fig. 7, the land use structure and spatial pattern of the study area differ significantly among scenarios, as a result of different simulation objectives. Furthermore, spatial changes of dominant land use types from 2015 to 2030 are shown in the Fig. 8, including built land, arable land and forest. In order to deeply explore the spatial distribution differences, the selected case study area on the four maps is enlarged to a uniform scale (Fig. 9).

In the BAU scenario, the study area experiences intensive land use changes during 2015–2030, characterized by the sustained increasing trend in built land. The area of built land surges by 16031.18 km^2, with its percentage increasing from 9.52 % in 2015 to 16.95 % in 2030. Meanwhile, arable land experiences the largest decrease by 4.83 %, while forest, grassland and unused land decrease moderately by 1.58 %, 1.29 % and 0.12 %, respectively. As for the spatial pattern of land use changes (Fig. 7a), built land sprawl is characterized by spatial extension of the built-up area, and layout of major cities tends to be concentrated and well-organized in this scenario. New construction land will be mainly distributed in Beijing, Tianjin, Chengde, Zhangjiakou, Tangshan, Qinhuangdao and the eastern part of Baoding, Shijiazhuang, Xingtai and Handan (Fig. 8). Furthermore, there are two sites deserving special mention. Firstly, the Wuqing District of Tianjin, which is located in the intersection of Beijing, Tianjin and Hebei, demonstrates substantial built land expansion (areas surrounded by dotted-line circle A in Fig. 8a). This is mainly because Wuqing District is planned to be an important high-tech innovation base and place for regional industrial transfer according to the coordinated development planning (State Council, 2015). Secondly, there is a large scale of built land growth within Zhangjiakou and Chengde (circle B in Fig. 8a), which is mainly distributed among the intermontane basins and valleys in Bashang plateau and Yan mountain areas. This can be attributed to the fact that the 2022 Winter Olympics will be held in Zhangjiakou, and it is expected to promote the development of recreation, retirement and tourism industries and infrastructure construction in the nearby areas, which will create a huge demand for construction land on relatively flat terrain. The area of arable land loss is mainly distributed in the northern and southwestern part of the study area, whereas Beijing, Shijiazhuang, Chengde, and Zhangjiakou are the dominant areas of forest loss. As shown in Fig. 9, there are more built land patches characterized by concentrated distribution in the BAU scenario than the other two scenarios, while arable land and forest in situ are converted to the built land and their spatial pattern tends to be more fragmented in this scenario.

In the CP scenario, there is a remarkable increase by 3.95 % in arable land from 2015 to 2030 with the area growth of 8,514.33 km^2, while the built land still shows obvious increase by 2.54 %, and the area percentage of forest, grassland and unused land falls by 3.53 %, 2.80 % and 0.21 %, respectively. As for the spatial pattern in this scenario (Fig. 7b), existing arable land mostly remains unchanged, while newly reclaimed arable land is mainly distributed over Taihang mountain in the east, Bashang plateau and Yan mountain in the north (Fig. 8b). The layout of built land is nearly the same as 2015, and the newly

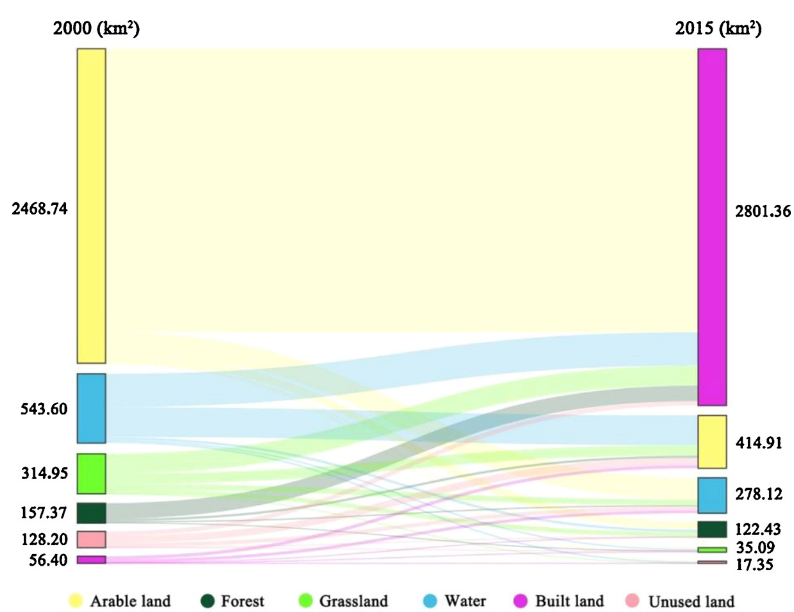

Fig. 5. Sankey diagram for land use conversion from 2000 to 2015.

Table 3
Regression coefficients and ROC values for each land use type.

	Y_1	Y_2	Y_3	Y_4	Y_5	Y_6
X_1	−9.11E-04	1.11E-03	8.57E-04	−3.02E-03	−1.70E-03	−2.26E-03
X_2	−1.69E-01	1.09E-01	2.71E-02	−1.13E-01	−1.75E-01	−2.42E-01
X_3	−3.30E-04	−3.97E-03	−1.23E-03	−1.33E-03	5.46E-04	−8.13E-04
X_4	−5.46E-05	—	−7.71E-04	1.40E-05	5.19E-05	−1.56E-04
X_5	3.84E-06	−1.44E-05	—	−7.45E-06	−6.44E-06	—
X_6	−3.84E-05	3.21E-05	−1.96E-05	−1.54E-05	—	3.71E-05
X_7	−2.24E-05	2.83E-05	7.24E-06	1.07E-05	−4.92E-06	—
X_8	−5.09E-02	7.43E-02	2.46E-02	—	—	6.58E-02
X_9	−1.92E-02	−4.95E-02	—	−3.52E-01	−1.01E-01	−6.75E-01
Constant	4.14	−5.61	−3.16	2.11	−0.48	0.99
ROC value	0.835	0.905	0.746	0.771	0.844	0.870

Note: X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8 and X_9 represent to elevation, slope, population density, GDP density, distance to the nearest railway, distance to the nearest highway, distance to the nearest city/county center, annual average precipitation, and annual average temperature, respectively. Y_1, Y_2, Y_3, Y_4, Y_5 and Y_6 represent to arable land, forest, grassland, water, built land, and unused land, respectively. All variables significant at $p < 0.05$. The mark "—" denotes the factors removed.

developed construction land scatters over Beijing, Shijiazhuang, Baoding, Tangshan, Chengde and Zhangjiakou. However, forest demonstrates intensive loss in the area where arable and built land significantly increased (Fig. 10b). Furthermore, forest and grassland show characteristics of significant fragmentation in spatial distribution due to the occupation by increasing arable land patches.

In the ES scenario, the area of forest increases by 30,949.81 km^2, with the percentage from 20.68 % to 35.03 % during 2015 − 2030. As a consequence of large scale afforestation, arable land and grass exhibit considerable decrease by 9.10 % and 4.95 %, respectively. Nevertheless, high-quality cropland, grassland and wetlands with essential ecosystem service functions are properly protected, owing to the pre-set spatial restrictions. Built land and water basically remain unchanged, while unused land will decrease remarkably from 1,971.76 km^2 to 1,079.99 km^2 during 2015-2030. As for the spatial pattern in this scenario (Fig. 7c), built land and water is basically the same as that in 2015, and new built land mainly scatters around the peripheral areas of the major cities. The majority of forest, grassland, part of the waters and wetlands are mainly distributed in the ecological function reserves, including the Beijing-Tianjin water conservation ecological function reserve, the northern foot of Yinshan Mountain-Hunshandake Desert sand-fixing ecological function reserve, Taihang Mountain water and soil conservation ecological function reserve and west Liao River water conservation ecological function reserve, and 17 national nature reserves such as Beijing Songshan Mountain National Nature Reserve and Tianjin Ancient Coast and Wetland National Nature Reserve. The forest expansion is mainly distributed over plateau and mountain areas in Zhangjiakou and Chengde, and peripheral area of Qinhuangdao and Tangshan, where arable land loss takes place simultaneously (Fig. 8). Furthermore, forest demonstrates concentrated distribution trend in this scenario as revealed in the case study area (Fig. 9).

4. Discussion

4.1. Scenario preferences under coordinated development background

The BTH region is one of the most important engines of China's economic development and scientific innovation, with an urbanization rate surging from 19.63 % in 1980 to 65.8 % in 2018. Driven by the rapid growth of urban land and population in this region, the contradiction between resources, environment and socio-economic development has significantly intensified since the implementation of the reform and opening-up policy in 1978 (Tan et al., 2005), with the most prominent characteristic of unbalanced development between regions (Huang and Lin, 2017; Yao et al., 2008). In order to further resolve problems related to the intricate man-land relationship in this region, the coordinated development of Beijing-Tianjin-Hebei has been positioned as one of the major national development strategies by the central government, aiming to take Beijing, Tianjin and Hebei as a whole to narrow the development gap between regions and solve the "megacity diseases" in Beijing. Based on this strategic background, the non-capital function transfer of Beijing should be the primary task at the current stage (Mao, 2017). Thus, more effort will be taken in the construction of Hebei Xiong'an new district and Beijing city sub-center, to promote regional industrial restructuring and optimize urban-rural configuration (Lu, 2015). Focusing on the traditional inefficient and extensive land use problems and aiming to find out the socio-economic and environmental effect of different future policies implemented to this region, land use patterns under three tailored scenarios were simulated in this study.

In the BAU scenario, the BTH region experiences remarkable built land growth. The built land expansion in Wuqing District, Zhangjiakou and Chengde is considered to be reasonable according to the analysis above. Therefore, this simulation result predicts the probable location and scale of construction activities taking place in the next 15 years.

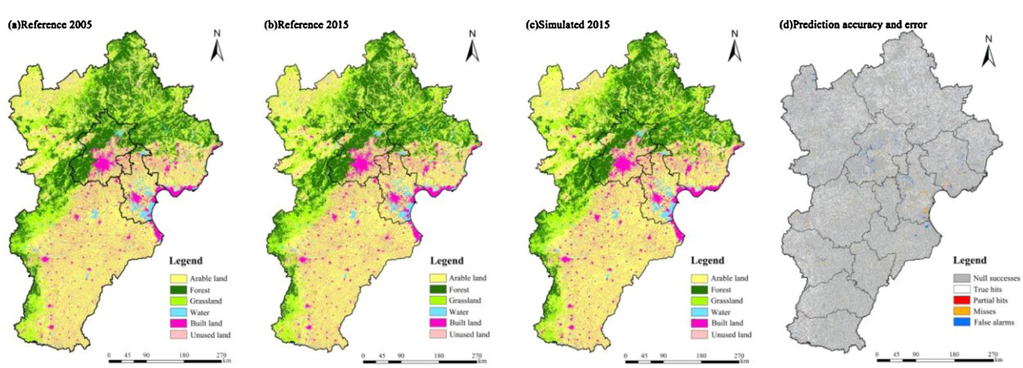

Fig. 6. Reference map for 2005 (a) and 2015 (b), simulated map for 2015 (c) and map of prediction accuracy and error (d).

Table 4
Area and proportion of land use types in 2015 and three scenarios.

	2015		Scenario 1		Scenario 2		Scenario 3	
	Area (km^2)	Proportion (%)	Area (km^2)	Proportion (%)	Area (km^2)	Proportion (%)	Area (km^2)	Proportion (%)
Arable land	107342.91	49.77	96910.19	44.94	115857.19	53.72	87712.59	40.67
Forest	44599.66	20.68	41196.15	19.10	36976.65	17.15	75550.47	35.03
Grassland	34964.91	16.21	32172.71	14.92	28917.83	13.41	24281.95	11.26
Water	6253.65	2.90	7135.06	3.31	6398.93	2.97	6385.36	2.96
Built land	20529.34	9.52	36552.88	16.95	25998.33	12.06	20651.64	9.58
Unused land	1971.54	0.91	1694.99	0.79	1513.07	0.70	1079.99	0.50

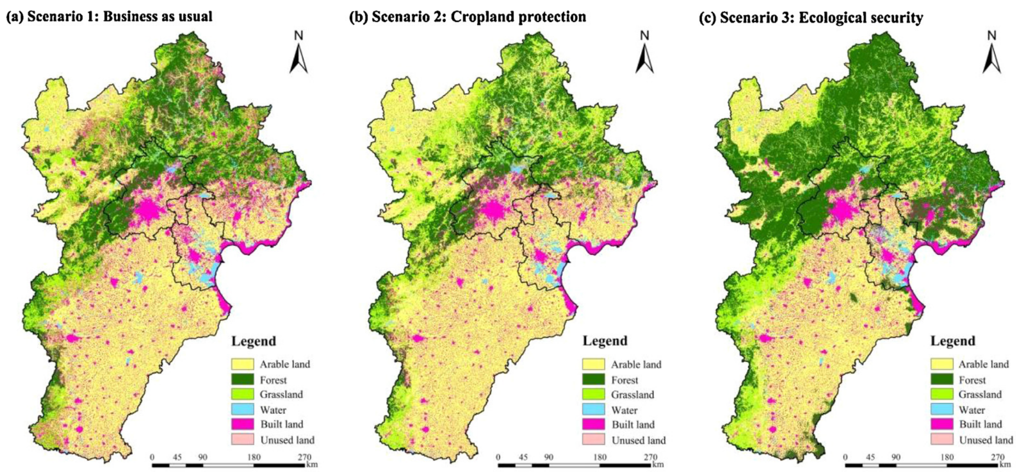

Fig. 7. Simulated land use map under three scenarios for 2030.

However, the total amount of built land under this scenario far exceeds the planned area in 2020 and it will lead to extensive destruction of cropland, forest and grassland, which violates the prerequisites of incremental construction land control and ecological land protection according to the overall land use planning for coordinated development (State Council, 2016a). In the BTH region, area that can be used for future industrialization and urbanization is only about 2000 km^2, accounting for about 1% of the total study area (Zhang and Zhao, 2016). Therefore, the amount of land suitable for future development in this area is extremely limited, posing severe restrictions on expansion of urban-rural development space and industrial configuration in the BTH region.

In the CP scenario, although arable land exhibits significant growth, the newly reclaimed arable land is mainly distributed in areas where soil, irrigation, terrain, transportation and many other conditions are relatively poor, such as Taihang Mountain, Bashang Plateau and Yan Mountain. As a consequence, more efforts need to be taken to improve tillage conditions through land consolidation and land engineering, so the input-output efficiency is worth seriously weighing and considering. In addition, under this scenario, there are still excessive built land growth and massive destruction of forest and grassland. Therefore, the land use pattern under this scenario, if it were to manifest, would be detrimental to both communities and the eco-system.

In the ES scenario, concentrated and contiguous high-quality cropland has been strictly protected, and the total amount of arable land has also been controlled within a reasonable range. In this way, regional food security can be certainly guaranteed. Meanwhile, the expansion of new construction land has been restricted, and the layout of existing built land tends to be better-organized in this scenario (Fig. 7(c)). Furthermore, forest, grassland, and water with important ecological functions are properly protected, and forest coverage reaches 35 % in the study area, which indicates that the ecological environment has been effectively improved. In addition, it can be inferred that the problem of unbalanced regional development is expected to be effectively resolved under the ES scenario according to the characteristics that differ from other two scenarios in terms of built land changes (Fig. 10). The built land growth in Beijing and Tianjin is suspended in this scenario and it enters a new stage of stock land renovation and reclamation. Meanwhile, the built land growth in Hebei demonstrates a stable and sustained trend in the future, which is essential for Hebei to further boost economic growth and narrow the gap. Furthermore, incremental construction land for pollution intensive and high resource consumption industries should be strictly restricted in this scenario, while high-tech and environmental-friendly industries such as new materials, new energy, and advanced manufacturing should be vigorously supported through more favorable land use policies (Zhou et al., 2018). In conclusion, land allocation by overall planning and other administrative measures should be the key strategy in coordinating the relationship between high-quality economic development and ecological protection.

Through tradeoff, the land use mode in ES scenario is considered to be the optimal solution under the background of coordinated development at the current stage. Under this land use mode, the BTH region will make breakthroughs in ecological construction and regional rebalance through reallocation of land resources, which is expected to lay a solid foundation for developing into a world-class urban agglomeration (Han et al., 2015; Wang et al., 2014). In terms of regional land use policy, the local government should give priority to ecological construction in the future coordinated development. Firstly, a long-term mechanism for comprehensive ecosystem management should be established, which is considered the bottom line, guaranteeing regional eco-friendly economic development. Secondly, we must utilize administrative measures such the targeted Grain-for-Green policy (Feng et al., 2005) to further expand ecological spaces and establish a more effective multi-level ecological network in this region. Furthermore, more efforts should be made by governments at all levels in optimizing the urban-

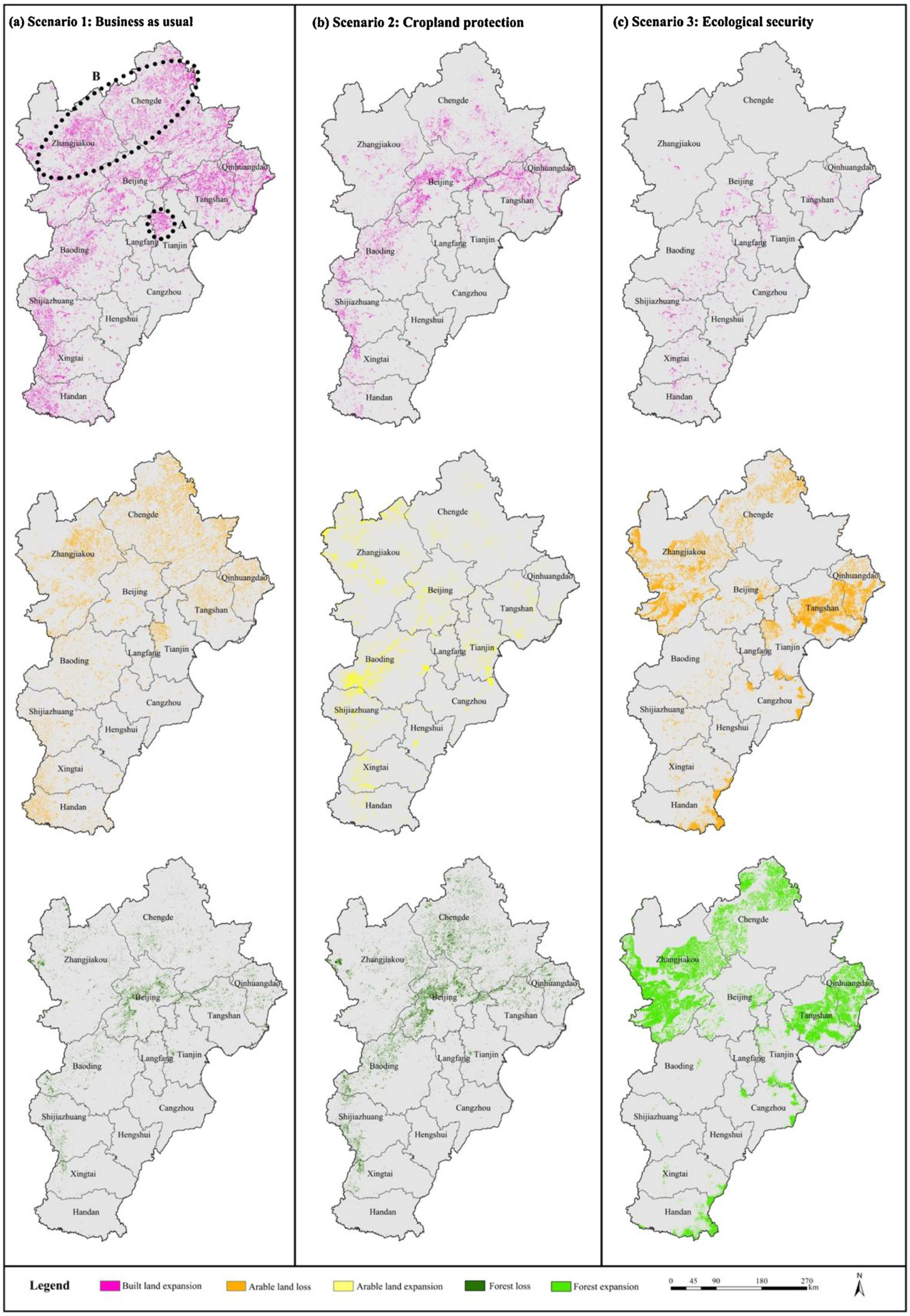

Fig. 8. Land use changes of built land, arable land, and forest from 2015 to 2030 under three scenarios.

rural production-living-ecology space structure through the two engines of new-type urbanization and rural revitalization, which has a vital role for social harmonious and sustainable development in the BTH region (Liu, 2018; Zhou et al., 2017).

4.2. Further improvement of the simulation model

The Dyna-CLUE model's cross-scale capability in simulating land use changes has already been sufficiently confirmed by studies carried out in many sites of the world (Lima et al., 2011; Lu et al., 2015; Verburg and Overmars, 2009). In this study, the modified version of CLUE-S combining the Markov model was adopted to overcome several limits of single model, and we obtained satisfactory results with relatively high accuracy, which proves Dyna-CLUE's suitability for large-scale urban agglomeration area. However, there is still room for further improvements: (1) The Dyna-CLUE model is limited due to its incapability of simulating sudden policy impact on land use, such as the construction of industrial parks or economic development zones (Liu et al., 2018a). For example, land use changes caused by the construction of Xiong'an new district, Beijing sub-center and new stadiums and facilities for 2022 Beijing-Zhangjiakou Winter Olympics are not well reflected in the simulation results. Therefore, further studies should explore how to involve policy-related factors into the simulation process, which is helpful to guide more informed and realistic decision

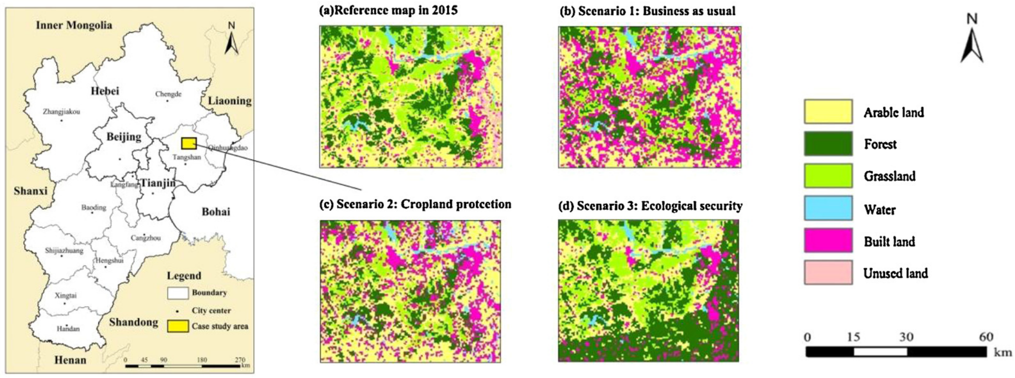

Fig. 9. Land use pattern of the case study area under three scenarios.

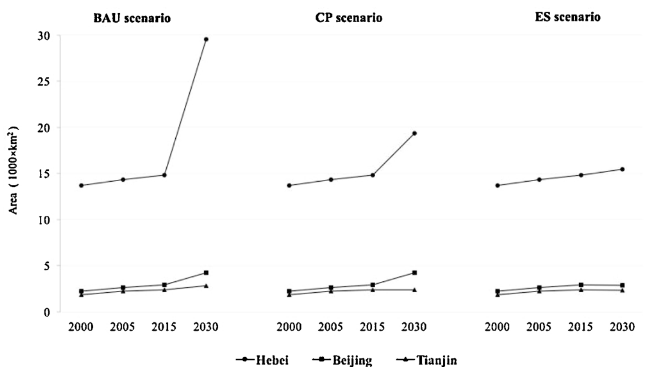

Fig. 10. Built land changes of Beijing, Tianjin and Hebei from 2000 to 2030 under three scenarios.

making. (2) This model neglects a fact that the quantitative relationship between driving factors and land use types is not fixed but changes over time, so it may cause inaccuracy especially in long-term land use simulation. Hence, practical methods that can dynamically update the regression parameters should be incorporated in the simulation process (Liu et al., 2013). (3) The model has a limit on the input raster size, which means that high-resolution simulation maps cannot be obtained for a large-scale area (Lu et al., 2015). Therefore, it is suggested that the processing capacity should be improved to support more precise planning and policy making.

5. Conclusion

Simulating regional land system change can provide scientific basis for formulating targeted and proactive land use policies, which is fundamental to promote regional development. In this paper, the Dyna-CLUE model combined with the Markov model was adopted to simulate future land use patterns in the BTH region under three tailored scenarios, namely business as usual scenario, cropland protection scenario and ecological security scenario. According to our findings, the Dyna-CLUE model is highly suitable for simulating land use change in large-scale urban agglomeration, but still has several limitations to be improved. Simulation results demonstrated that the land use mode in the ecological security scenario, which can balance urbanization, grain production and ecological protection, is considered to be the regional optimal solution. High-quality and green development should be the key for future land use management in this region. Hence, extensive built land expansion should be restricted, and the government should give priority to eco-environment improvement and regional rebalance in the next decade through differentiated land use polices, which will optimize the spatial configuration for regional economic transformation. It is meaningful to promote further research of land use optimization and policy innovation by governments at all levels in order to boost coordinated and sustainable development in the BTH region.

CRediT authorship contribution statement

Yuanyuan Yang: Conceptualization, Methodology, Writing - review & editing, Funding acquisition. **Wenkai Bao:** Formal analysis, Data curation, Writing - original draft. **Yansui Liu:** Supervision, Funding acquisition.

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