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Application of Land-use Change Model in Guiding Regional Planning: A Case Study in Hun-Taizi River Watershed, Northeast China

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Abstract: This paper firstly investigated the land-use and land-cover change (LUCC) in the Hun-Taizi River watershed, Northeast China from 1988 to 2004 based on remotely sensed images and geographic information systems (GIS) technology. Then, using the famous land-use change model of Conversion of Land Use and its Effects at Small regional extent (CLUE-S), this paper simulated the land use changes under historical trend (HT), urban planning (UP) and ecological protection (EP) scenarios considering urban planning and ecological protection over the next 20 years. The simulated results under UP scenario in 2020 were compared with the planning map to assess the feasibility of using land-use change model to guide regional planning. Results show that forest land, dry farmland, paddy, and shrub land were the main land-use categories. Paddy and dry farmland being converted to urban area and rural settlement characterized the land-use change from 1988 to 2004. The main land-use categories changed over time. Landscape-pattern fragmentation will be worse under HT and UP scenarios, but better in EP scenario. The comparing results of simulated map with planning map in 2020 show that land-use change model is powerful tool to guide regional planning. Land-use scenarios can support regional planning and policy-making through analyzing future consequences scientifically.

Keywords: land-use change model; CLUE-S; regional planning; Hun-Taizi River watershed

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1 Introduction

Landscape patterns affect the ecological, physical, and socioeconomic processes of a region in various ways (Forman, 1995; Brookes, 2001; Turner *et al.*, 2001). Thus, a thorough understanding of land-use dynamics is necessary to simulate future changes accurately and facilitate the development of sustainable management practices designed to preserve the essential landscape functions (Hietel *et al.*, 2004; Lin *et al.*, 2007). Modeling land-use changes can help inform policymakers of possible future conditions under different scenarios (Koomen and Stillwell, 2007).

The patterns, causes, and consequences of spatial heterogeneity with respect to ecosystem function are recognized as a current frontier for research in both landscape and ecosystem ecology (Lovett *et al.*, 2005). However, many ecosystem processes are difficult to observe directly, and landscape patterns can be derived from mapping as well as from remotely sensed data. Satellite imagery, in conjunction with GIS, has been widely applied and is recognized as a powerful and effective tool in detecting LUCC (Ehlers *et al.*, 1990; Treitz *et al.*, 1992; Harris and Ventura, 1995; Yeh and Li, 1999).

Landscape ecological studies provide many useful conceptual and analytical tools to bridge the gap between planning and ecology (Leitäo *et al.*, 2006). Land-use change models are tools that can support an analysis of the causes and consequences of land-use

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dynamics. Scenario analysis with land-use change models may benefit land-use planning and policy (Verburg *et al.*, 2004). Models are useful for disentangling the complex suite of socioeconomic and biophysical forces that influence the rate and spatial pattern of land-use change and for estimating the impacts of land use changes. Furthermore, models can support an examination of future land-use changes under different scenarios. In summary, land-use change models are helpful tools that provide reproducible data to supplement our capabilities to analyze land-use change and make better-informed decisions (Costanza and Ruth, 1998). However, as the complexity of application, land-use change model has been rarely used in regional planning in China. Most regional planning maps, especially urban planning maps, were schematic drawing without scientific supporting.

Spatial optimization and empirical-statistical models help identify the driving forces that influence LUCC and can be used to predict future land-use patterns based upon the changes in the driving forces as indicated under different scenarios (Castella and Verburg, 2007). Multiple linear regression or logit models are frequently used for this purpose. A well-known example of the empirical-statistical model is the Conversion of Land Use and Its Effects (CLUE) model, which was constructed by department of agronomy, wageningen agricultural university (Veldkamp and Fresco, 1996a). The CLUE model is designed to simulate land use conversion and change in space and time as a result of interacting biophysical and human drivers for regional applications (Veldkamp and Fresco, 1996b). CLUE-S model was specifically developed for the analysis of land use in small regions based on CLUE model. The model is suitable for scenario analysis and the simulation of trajectories of land-use change at wide range of study areas and land-use change situations. The main limitation of applying the model is its incapability to simulate land-use dynamics in areas without a land-use change history (Verburg *et al.*, 2002).

CLUE-S model has been successfully applied in simulating land-use changes based on different spatial and non-spatial policies (Verburg *et al.*, 2006; Lesschen *et al.*, 2007; Overmars *et al.*, 2007). Recently, several CLUE-S application studies have been successfully carried out in China, which proved the model's suitability in China (Zhang *et al.*, 2003; Xu *et al.*, 2008). The case studies mainly focus on simulating future land-use change and analyzing the suitability in China (Liu *et al.*, 2009; Lu *et al.*, 2009). In current urban planning, the future urban area is decided according to demographic and economic indicators. However, the spatial distribution of urban area in planning map often lacks scientific supporting due to the complexity of spatial approaches and models.

This study was designed to examine the historic LUCC and landscape pattern changes in the Hun-Taizi River watershed and investigate the short-term future changes under three scenarios based on CLUE-S model. The driving forces of land-use change were indentified from topographic, natural, neighborhood and socioeconomic factors. The investigation compared the urban area result under UP scenario in 2020 with planning map to explore application of land-use change model in regional planning. Such a case study should be helpful for planning-maker in making scientific planning scheme and for policymaker in understanding of possible land-use consequences of the relevant policy implementation.

2 Materials and Methods

2.1 Study area

The Hun-Taizi River watershed is a sub-basin of the Liao River basin and is made up of the Hun River (415 km in length) and the Taizi River (413 km in length). The eastern part of the watershed consists of low hills, while the middle and western parts are located on an alluvial plain. The study area (40°27′–42°19′N, 121°57′–125°20′E) is located in Liaoning Province, Northeast China, with an area of 2.73×10^4 km^2, constituting 18.45% of the total area of Liaoning Province (Fig. 1). It is the economic center of both Liaoning Province and Northeast China. It covers most of Central Liaoning Urban Agglomeration, which is one of ten Chinese urban agglomerations, and includes the cities of Shenyang, Anshan, Fushun, Benxi, Liaoyang, and Yingkou. For the study area, the population was 1.86×10^7, and the total gross domestic product (GDP) amounted to 59.52% of the total of Liaoning Province in 2008. The study area has well-developed equipment manufacturing industries, which rely on the abundant local coal, iron, oil, and other mineral resources. Extensive industrial development of the watershed has led to serious water,

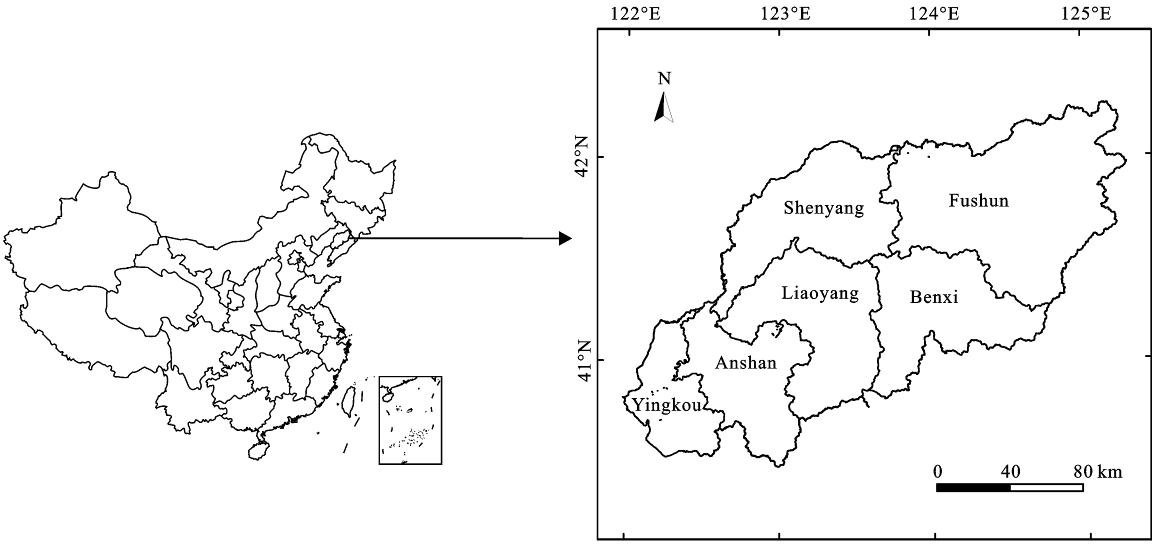

Fig. 1 Location of study area

soil, and air pollution.

2.2 Data collection

Satellite images in 1988 (Landsat TM), 1997, and 2004 (Landsat ETM) were used to derive thematic land-use maps. The 1∶100 000 topographic maps in study area were collected. A total of 2680 evenly distributed field-survey points for land use information were sampled in field surveys with the help of a global positioning system (GPS) with ±5 m error for ground-truthing including 1300 points in 1997, and 1380 points in 2004. The 4 km × 4 km grid file of study area was generated with ARCGIS9.0. Every grid central point was set as field-survey point, but parts of the unreachable points were not collected. The 1∶50 000 digital elevation model (DEM) of study area was collected. Slope and aspect maps were derived from DEM with ARCGIS 9.0.

Other data used for the study included the followings: 1) Statistical yearbooks in 1988, 1997 and 2004 of Liaoning Province (Liaoning Statistical Bureau, 1988; 1997; 2004); 2) 1∶250 000 soil maps derived from Liaoning soil maps; 3) Precipitation data derived from 18 meteorological stations in the study area; 4) The maps and texts of Central Liaoning Urban Agglomeration planning were obtained from Liaoning Survey and Planning Bureau of Land and Resources.

2.3 Methods

2.3.1 Historical land-use change

The images were geometrically corrected and geocoded to the Universal Transverse Mercator coordinate system, using 1∶100 000 topographic maps. Land-use maps were derived from satellite images based on eight categories: forest land, shrub land, grassland, dry farmland, paddy, urban area, rural settlement, and water area. Land-use types were determined by a combination of supervised classification and visual interpretation of satellite images, supplemented with secondary information on climate, geomorphology, and vegetation maps as well as information from 1300 field-survey points. The remaining 1380 field-survey points were used to determine the accuracy of the image classification. The Kappa index (Congalton, 1991) was 86.02% in 1988, 88.52% in 1997, and 90.32% in 2004. We used both ERDAS Imagine 9.0 and ArcGIS 9.0 to integrate the data using standard GIS features. The historical land use categories area changes were summarized with ARCGIS 9.0 from 1988 to 2004.

2.3.2 Land-use change prediction

We chose the land-use change model CLUE-S to simulate the future land-use change in the study area. The model is sub-divided into two distinct modules, namely a non-spatial demand module and a spatially explicit allocation procedure. The non-spatial module calculates the area change for all land-use types at the aggregate level. Within the second part of the model these demands are translated into land-use changes at different locations within the study region using a raster-based system. The CLUE-S model is able to effectively contain different types of driving factors and discriminate their contribution to land-use changes by means of a logistic regression method, which are expressed as following:

$$\log(\frac{P_i}{1-P_i}) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \cdots + \beta_n X_{n,i} \quad (1)$$

where P_i is the probability of grid cell for the occurrence of the considered land-use type i; X_1, X_2, …, X_n are the driving factors; β_0, β_1, …, β_n are the beta values of logistic regression for driving factors. A more detailed description of the model was given by Verburg *et al.* (2002). The configuration of CLUE-S model in this study is expressed as follows:

(1) Scenarios setting

In this study, three scenarios were set: historical trend (HT) scenario, ecological protection (EP) scenario, and urban-planning (UP) scenario. The HT scenario was formulated based on historical land-use changes from 1988 to 2004. In the HT scenario, land-use area demand was predicted via the autoregressive integrated moving average (ARIMA) approach, which employs a time-series analysis based on the historical land-use area changes. Except for 1988, 1997, and 2004, the land-use data for the years from 1988 to 2004 were obtained from statistical yearbooks of Liaoning Province in the study area (Liaoning Statistical Bureau, 1988; 1997; 2004). All the results attained a 0.05 significance level with Pearson's test. The EP scenario was set based on related ecological and environmental protection polices, such as a policy prohibiting deforestation that has been in operation since 2001, whereby hillsides were closed off so as to promote afforestation, and the Grain for Green program, according to which farmland in steep areas (slope > 25°) have to be returned to forest. The areas of the different land-use types in the EP scenario were adjusted based on the results from the HT scenario, incorporating the ecology-protection plans of the government's forestry and environment department. The UP scenario was set based on Central Liaoning Urban Agglomeration Planning 2020, which was completed by the Liaoning Land Resources and Planning Bureau in 2007.

(2) Spatial and temporal resolution

We set 20 test scenarios using 100-m to 1000-m resolution with 50-m steps. The results showed that the greatest spatial resolution in the CLUE-S model was 250 m in the study area. Therefore, the simulation spatial resolution was set as 250 m × 250 m in this study, including 802 rows and 1102 columns.

We simulated the land use in 2004 based on that in 1988 with the CLUE-S model to validate its applicability in the study area. The predicted land-use map in 2004 was compared with the actual land use in 2004 by utilizing the relative operating characteristic (ROC) method (Pontius, 2000). The ROC technique has been applied to any model that predicts a homogenous category in each grid cell. The ROC result was 0.85, which indicates that the two maps show a relatively high consistency. CLUE-S was then used to predict land use/cover change for the 20-year period beginning in 2004 with 1-year steps in the study area.

(3) Driving factors

Location characteristics determine the relative suitability of a location for different land-use types. The relative probability of finding a land-use type at a particular location is based on biophysical and socioeconomic conditions (Geist and Lambin, 2002; Lambin *et al.*, 2001). The land-use spatial distribution coefficients in model were estimated through logistic regression with the actual land-use pattern.

Driving factors of land-use change include bio-physical and socio-economic factors. Based on literatures (Verburg *et al.*, 2004; Castella and Verburg, 2007) and fieldwork in the study area, as fully as possible to choose the driving factors, including 16 factors belonging to four categories: 1) topographic factors: digital elevation model (DEM), slope, and aspect; 2) neighborhood factors: distance to river, distance to rural settlement, distance to city, and distance to road; 3) natural factors: precipitation, soil organic matter, and soil total nitrogen; 4) socioeconomic factors: population, rural population, GDP, gross agricultural production, gross industrial production, and residential consumption. The socioeconomic driving factors were expressed within the boundaries of the six cities.

The logistic regression results are shown in Table 1. The spatial distribution of all land-use types could be well explained by the selected driving variables, as indicated by the high ROC test statistics (scale 0.5–1.0). The derived regression models were used to calculate suitability maps for different types of land uses (Equation 1).

Spatial policies and restrictions indicate those areas where land-use changes are restricted by policy or tenure status. There were no zones or regions within the study area where special restrictions on land conversion were applicable.

Conversion settings for specific types of land use determine the temporal dynamics of the simulations. Conversion elasticity under three scenarios was set based on related studies (Veldkamp *et al.*, 2001, Verburg and Veldkamp, 2004). The number of the ELAS parameter indicates the stable percentage of one land-use type that would not change. For example, the 0.9 for grassland in the HT scenario means that 10% of the grassland area can change to other land use.

The conversion matrix was configured based on our understanding of the land-use system in the study area. Any land-use type can be converted to any other, with the exception of urban areas converting to other types.

2.3.3 Landscape pattern

Landscape pattern of simulated results based on CLUE-S model was analyzed with landscape index approach. Four landscape metrics were chosen to reflect future landscape-pattern change based on ecological meanings (Table 2), including number of patches (NP), landscape shape index (LSI), Shannon's diversity index (SHDI), and contagion index (CONTAG), which was calculated in Fragstats 3.3 at the landscape level (Mcgarigal and Marks, 1995).

3 Results and Analyses

3.1 Historic land-use area change

Through supervised classification and visual interpretation of satellite images, the area of different land-use types was obtained with ARCGIS 9.0 (Fig. 2). Forest land, dry farmland, paddy, and shrub land were the main land-use categories in the study area, amounting for 84.75% in 2004. Forest land was the largest land-cover

Table 1 Results of logistic regression

	Exp (β)							
	Paddy	Water area	Dry farmland	Forest land	Rural settlement	Urban area	Grassland	Shrub land
s_0	0.998	0.984	0.997	1.004	1.000	1.001	0.999	0.999
s_1	0.603	0.718	0.885	1.082	0.978	1.039	1.095	1.091
s_2	1.000	1.003	1.002	1.000	0.999	1.001	0.999	0.999
s_3	1.700	1.000	1.000	1.000	1.090	1.200	1.000	1.000
s_4	1.000	1.000	1.000	0.700	1.800	2.800	1.000	1.000
s_5	0.700	1.000	0.800	1.000	1.000	0.899	1.000	0.850
s_6	2.100	1.001	1.860	1.000	0.848	1.000	1.000	1.000
s_7	1.002	1.008	1.508	0.993	1.003	0.994	0.990	1.009
s_8	1.706	1.008	1.998	0.984	1.007	1.011	0.976	0.978
s_9	1.911	0.692	2.382	1.008	0.964	0.840	0.993	0.994
s_{10}	1.005	1.006	1.000	1.002	0.997	0.890	1.023	1.007
s_{11}	1.013	0.645	0.942	0.949	1.016	7.064	0.610	0.844
s_{12}	1.036	0.605	0.920	0.940	1.021	0.635	0.400	0.822
s_{13}	1.000	0.984	0.998	0.998	1.001	1.166	0.980	0.988
s_{14}	0.998	1.049	1.007	1.006	0.998	5.045	1.069	1.023
s_{15}	1.000	1.001	1.000	1.000	1.000	0.982	1.003	1.001
Constant	–2.842	–15.712	–7.671	2.073	14.759	10.251	–9.317	–11.330
ROC	0.873	0.806	0.776	0.796	0.785	0.864	0.845	0.824

Notes: s_0, digital elevation model; s_1, slope; s_2, aspect; s_3, distance to river; s_4, distance to road; s_5, distance to city; s_6, distance to rural settlement; s_7, average annual precipitation; s_8, soil organic matter; s_9, soil total nitrogen; s_{10}, population; s_{11}, rural population; s_{12}, gross agricultural product; s_{13}, gross industrial production; s_{14}, gross domestic product; s_{15}, residential consumption; ROC, relative operating characteristic

Table 2 Ecological meanings of four landscape metrics

	Ecological meanings
NP	NP reflects patch density or mean patch size, indicates the fragmentation level of a landscape
LSI	LSI reflects total edge, edge density and patch aggregation, describes fragmentation level of a landscape
SHDI	SHDI reflects patch diversity, range of patch area and landscape fragment, describes the heterogeneity of landscape pattern
CONTAG	CONTAG reflects a single class occupies percentage of the landscape, quantifies the degree of clumping of the landscape

type, accounting for about 30% of the total area. Forest land is mainly distributed in the eastern part of the study area. Forest land and shrub land remained relatively stable. From 1988 to 2004, paddy, dry farmland, and grassland area declined, while water area, rural settlement and urban area increased. The urban area increased 29.92%, while the rural settlement area increased 21.07% from 1988 to 2004. The increased area mainly came from paddy and dry farmland lands.

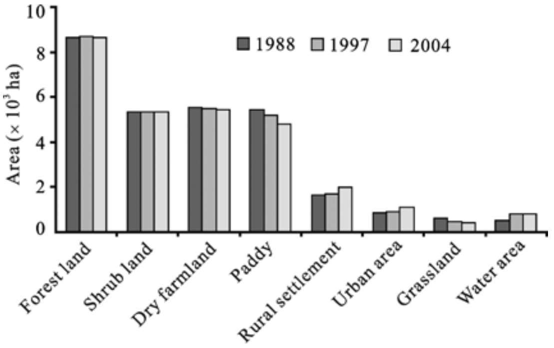

Fig. 2 Change of land-use area in different years

3.2 Land-use area change under three scenarios

The four main land-use types with regard to future area change are shown in Fig. 3 to display different change trajectories for 2004 to 2024. Under the HT scenario, urban area, rural settlement, and water area will increase (Fig. 4). The increased area will mainly come from dry farmland and paddy areas, partly from shrub land, forest land, and grassland. Under the UP scenario, the seven land-use types show the same change trend as in the HT scenario except for the rural settlement and paddy. The rural settlement area will decrease because the rural population will move to cities, and the urban area will increase more rapidly under the UP scenario, resulting in dry farmland and grassland loss. Unlike the other two scenarios, under the EP scenario forest land and water area will increase because of their high ecological value. The increased area will mainly come from dry farmland and paddy. The increasing rate of urban area and rural settlement under EP scenario will be lower than that under the other two scenarios. Area of water area will increase under three scenarios due to water conservancy engineering.

3.3 Landscape pattern change under three scenarios

NP and LSI (Fig. 5) show an increase under the HT and UP scenarios, which indicates that the landscape will be more fragmented. In contrast, NP will remain stable and

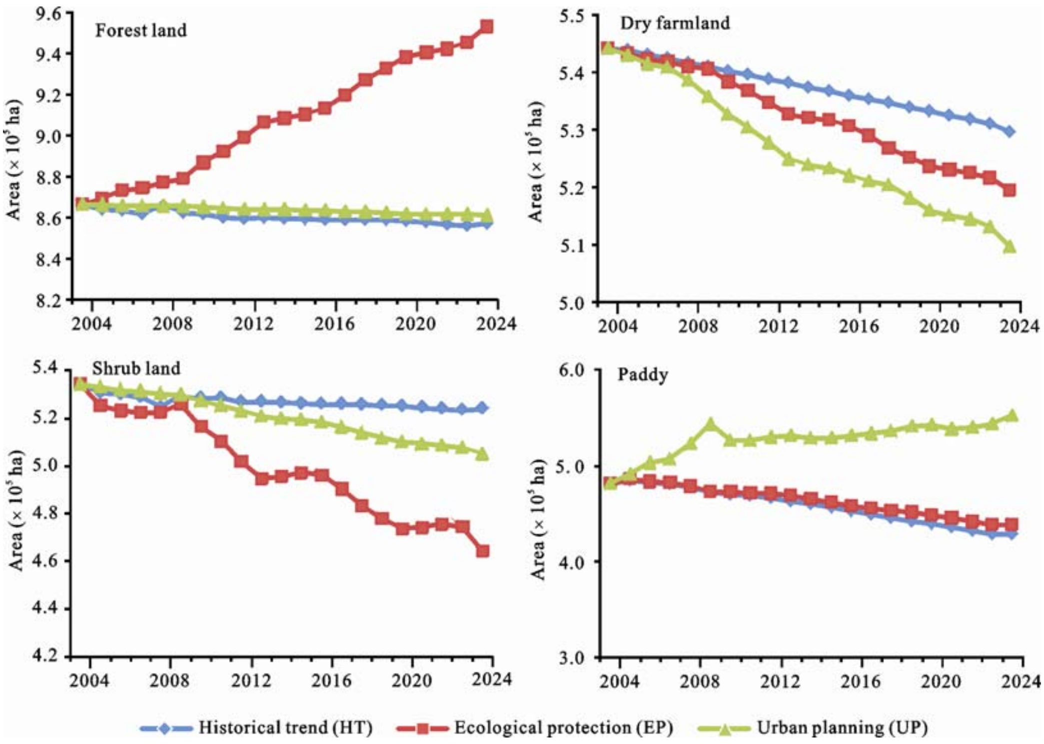

Fig. 3 Area of four main land-use types under three scenarios

LSI will decline under the EP scenario. Landscape diversity (SHDI) is the greatest under the HT scenario (Fig. 5), since the NP will increase and the gaps between the patches will be reduced. CONTAG is inversely related to edge density. The edge density will be more complex under the HT scenario than under the other

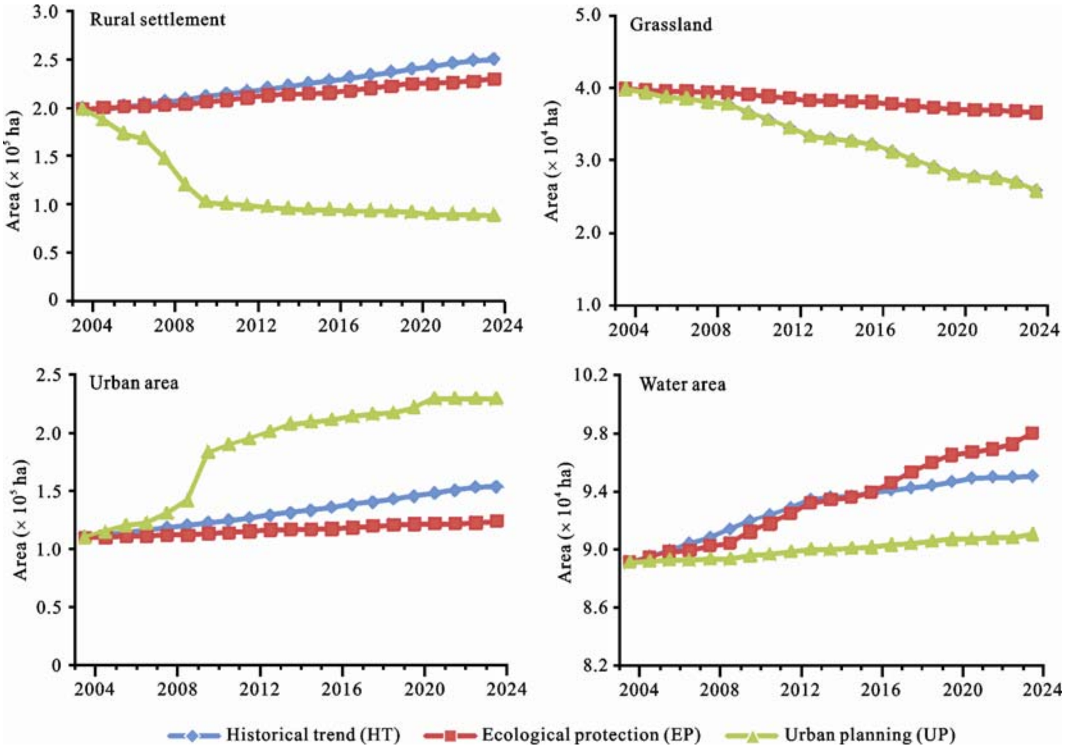

Fig. 4 Area of four minor land-use types under three scenarios

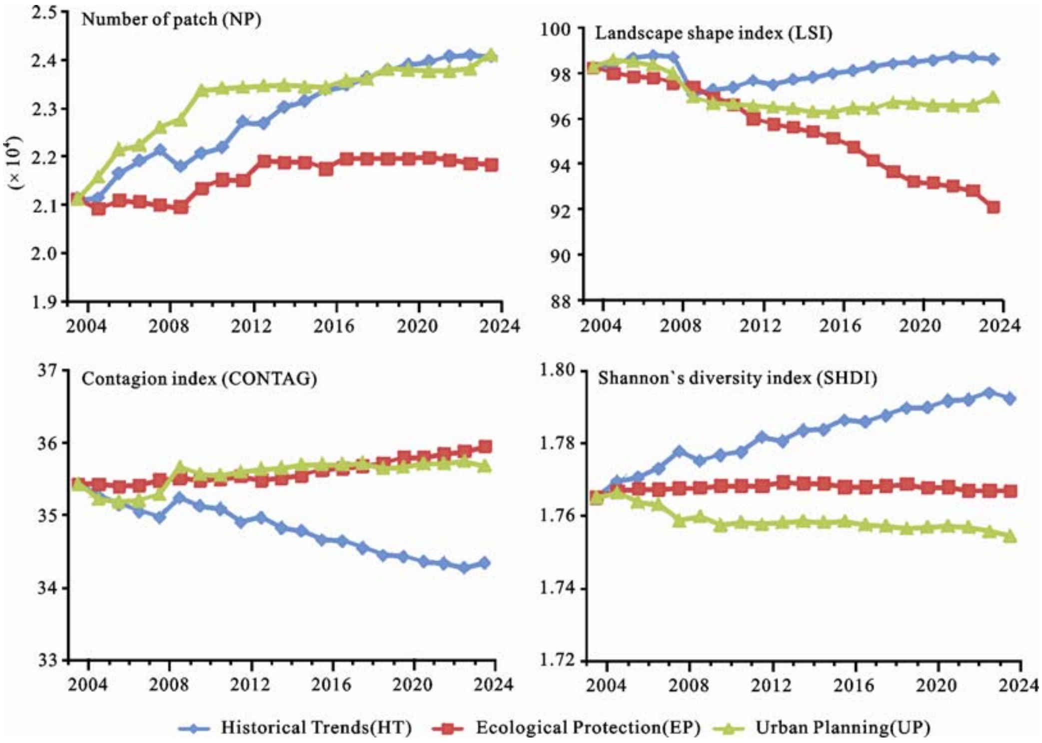

Fig. 5 Landscape metrics under three scenarios

two scenarios (Fig. 5).

Through an analysis of the landscape metrics, the landscape of the study area will become increasingly fragmented under the HT scenario. Both UP and EP could impede the landscape fragmentation trend. UP will cause greater fragmentation over a period of several years because of construction, but the landscape patches will be more regular after about 7–10 years. EP will boost the forest proportion and make the patches regular.

4 Discussion

To assess the rationality of planning, we compared the simulated future urban area with the planning urban area in 2020 from Central Liaoning Urban Agglomeration planning. The urban area in 2004, the planning map for 2020, and simulated result under UP scenario for 2020 are shown in Fig. 6. The area of urban area would amount to 221 500 ha in 2020 according to the planning text. The parameter of urban area in CLUE-S model under UP scenario was set based on the urban area in planning text. The simulated area of urban area based on the CLUE-S model would be 229 968 ha in 2020, which is only 3.82% higher than that in the planning text, reflecting the good consistency between simulated map and planning text.

However, the area of urban area in the planning map is 283 718 ha, which is 28.08% higher than that in the planning text, reflecting the poor consistency between planning map and text. The planning map and simulated urban area map in 2020 was compared with Kappa index. The result is only 0.272, which means the considerably poor consistency of two maps. The urban area distribution in the planning map is aggregated, and the boundary is clear. However, the simulated result in 2020 shows no clear boundary and a scattered pattern around the central urban area, which accords with reality. The simulated result more closely reflects the real situation, whereas the planning map is more like a broad schematic picture without scientific technological and methodological support.

The area and location of Chinese land-use change is greatly driven by land-use policy, which is reflected in regional planning. Different future land use can be simulated based on scenarios setting, such as the scenarios HT, EP and UP in our study. The scenario-simulation function of land-use change model will help po-

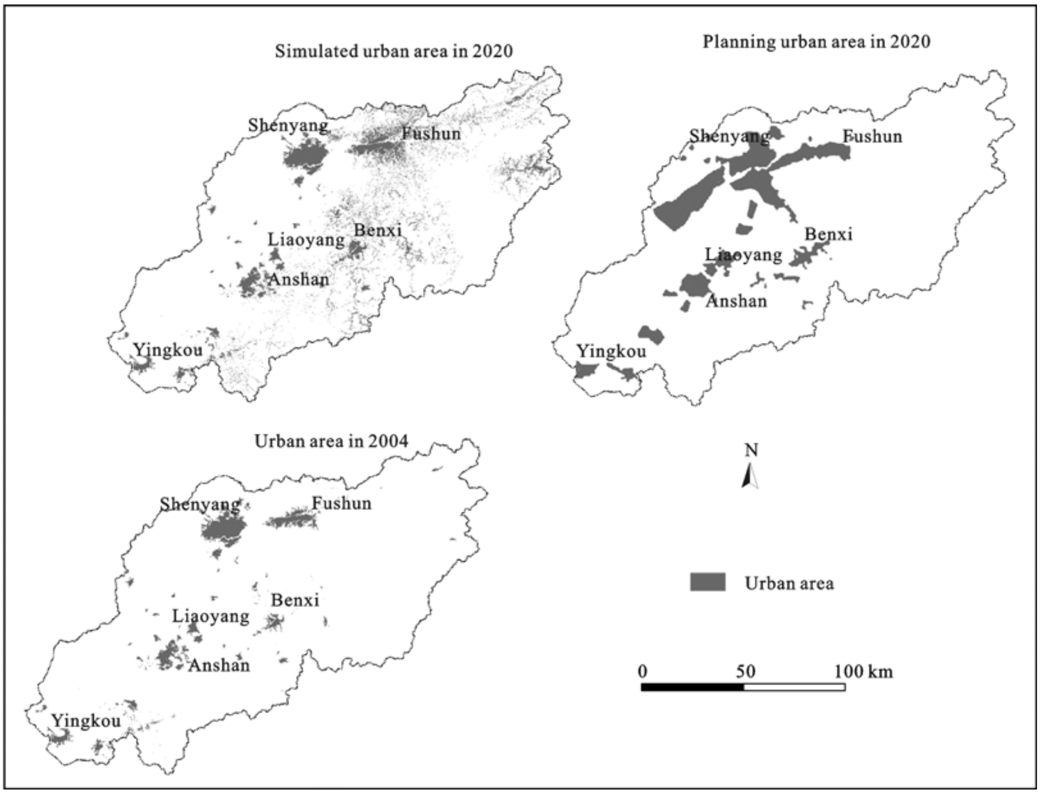

Fig. 6 Comparison of urban area in 2004, planning and simulated urban area maps in 2020

lice maker understand the consequences caused by different polices or planning schemes. Population and economic developments change the demand for different land-use types at the aggregate levels, whereas the actual allocation of change is determined by regional and local conditions. The future land-use change regions will be mainly determined by driving forces and historic land use change. The land-use change hotpot regions can be indentified through model for better management. Above all, land-use change model is useful and scientific tool for regional planning and policy-making.

5 Conclusions

Results of this study conducted in the Hun-Taizi River watershed indicate that the landscape of the study area was dominated by forest land, paddy, and dry farmland. Urban and rural settlement areas increased rapidly from 1988 to 2004. According to the scenarios in the simulated results with CLUE-S, different polices will change the land use and landscape patterns. EP scenarios can decrease the landscape fragmentation. Comparing the urban area in the planning map with simulated result, the latter one is more scientific. Land-use model is powerful and scientific tool for regional planning.

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