Application of Land Use Model Combined With GIS and RS Technology in Supporting Urban Spatial Planning

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Abstract

This paper illustrates an application of the Conversion of Land Use and Its Effects at Small regional extent (CLUE-S) model, combined with GIS (Geographic Information System) and RS (Remote Sensing) technology, in simulating future land use and landscape pattern change under different land use scenarios in Xinzhuang town, Jiangsu province, China. It is based on multi-temporal high-resolution remotely sensed images. Three different scenarios are designed to simulate the future patterns of the study area. Kappa coefficients are applied to evaluate the feasibility of CLUE-S model for supporting spatial planning. The results showed that the increase of

construction land and decrease of paddy fields would be the dominant trend of future land use change. Plenty of farmlands and ecological land will be encroached by construction land in the next twenty years. The landscape pattern will be more fragmented, disaggregated and disconnected, and the landscape will become more diversified and homogenous. The prediction accuracy of CLUE-S is satisfactory; it means that this model can provide scientific support for land use planning and policy making.

1. Introduction

Land use changes are driven by the spatial-temporal interactions between biophysical and human dimensions at different scales (Veldkamp and Lambin, 2001; Verburg et al., 2004). They affect the ecological, physical, and socioeconomic processes of a region in various ways (Forman, 1995; Brookes, 2001). Thus, increased efforts have been made to understand the processes, trends and driving forces of land use change and its ecological consequences (Verburg et al., 1999; Parker et al., 2003; Turner et al., 2007). Identifying the primary causes, processes and trends of land use change are crucial for urban planning, utilization of regional resources, and environmental management (Ojima et al., 2002; Zhao et al., 2013). Land use change model is a useful tool for analyzing driving forces and processes, understanding the causes and consequences, predicting the possible futures of land use change, and assessing ecological impacts and decision-making for land use planning (Luo et al., 2010). Scenarios analysis with land use modeling can provide support for land use planning (Verburg et al., 2004) and help inform policymakers of possible future patterns under different policy restraint conditions (Koomen and Stillwell, 2007). Land use change models can support an examination of future land use change under different scenarios (Liu et al., 2011). They are helpful tools in providing reproducible data to supplement our capabilities to analyze land-use change and make better-informed decisions (Costanza and Ruth, 1998). Consequently, spatially-dependent land use models are indispensable for sustainable land use planning (Guan et al., 2011).

Land use planning has attracted increasing attention over the last decade since the growing negative impacts of urban sprawl, such as consumption of prime agricultural land and open space have been realized (Batisani and Yarnal, 2009). The conflicts between urban development and farmland preservation or ecological protection have been becoming increasingly contentious all over the world, especially in China (Zheng et al., 2012). Whether it can be handled properly will have implications for food security, ecological security and social security. It is related to important issues such as sustainable development of the economy, society, and ecology (Koomen and Ding, 2006; Clover and Eriksen, 2009). The topic has caught the attention of land-use and urban planners (Bart, 2010; Carsjens and van der Knaap, 2002; Deal and Schunk, 2004; Lee et al., 2009). Planners worldwide thus seek to steer land-use developments through a wide range of interventions that either constrain certain developments or favor them. For the formulation of adequate spatial policies, the involved parties normally make use of models that simulate possible spatial developments (Koomen et al., 2008).

Land use change modeling and simulation has increasingly become a popular tool in land use planning and policy formulation. Veldkamp and Lambin (2001) emphasized the importance of land use change modeling as a planning tool for projecting alternative land use pathways into the future. Some land use models have been successfully applied in supporting region planning. However, considering the complexity of model application and actual conditions in China, land use change models have rarely been applied in assisting spatial planning. Therefore, most spatial planning maps, especially urban planning maps, were schematically made without scientific support. The planning of future urban land use is designed by the need of economic and population growth, and the planners' experiences and topographical and geologic characteristics. Such planning processes lack scientifically quantitative approaches and models.

In the past ten years, different land use change models have been developed with various objectives and backgrounds (Verburg et al., 2004). As a typical spatial-explicit and empirical-statistical model, the CLUE-S model is well-known. It can better understand the processes that determine changes in the spatial pattern of land use and explore possible future changes in land use at the various spatial scales (Verburg et al., 2008). It can also specify the scenario conditions for future land use in detail (Verburg et al., 2002; Verburg and Veldkamp, 2004). Compared to the relatively subjective land use models based on decision-making behavior of locators (Parker et al., 2003; Berger et al., 2006), the CLUE-S model is based on land use change processes and its simulation result is more objective and persuasive. However, it lacks multi-temporal historical land use data. The advantage of this model is the explicit attention for the functioning of the land-use system as a whole, the capability to simulate different land-use types at the same time and the ability to simulate different scenarios. CLUE-S model has been successfully applied in simulating land-use changes based on different spatial and non-spatial policies (Verburg et al., 2006; Overmars et al., 2007).

In this study, three scenarios were designed to systematically describe possible alternative land use views of the future. These scenarios considered land use planning, farmland and ecological environment protection over the next twenty years. The objective of this study is to simulate a broad range of future spatial developments and offer a full overview of the potential land use change trends under different scenarios based on CLUE-S model. First, we provide a detailed account and the implementation issues of the methodology. Second, spatio-temporal changes in land use and landscape patterns under different scenarios were analyzed. Third, the predicted results of urban construction area under the three scenarios in 2020 were compared with a prospective plan map of 2020 to evaluate the feasibility of a land use change model for supporting spatial planning. Finally, we discuss the evaluation of CLUE-S model and present the conclusion. This study will be helpful for urban planners and decision-makers to better understand the complexities of land use change and make scientifically sound decisions for future land use planning and management.

2. Materials and methods

2.1. Study area

As a typically area of rapid urbanization and industrialization in the south of Jiangsu province, Xinzhuang town (120°32'—120°44'E, 31°29'—31°37'N) is located in the Changshu city (Fig.1). It is one of the two significant development central towns in the latest master plan of Suzhou city, due to its prominent location and convenient location for water and land transportation. It is in the east of Shajiabang resort district, in the west of Wuxi city, approximately 50 km from Suzhou city and Wuxi city, and 190 km from Nanjing city and Hangzhou city. The study area is about 104.26 km^2, including 2 district agencies, 20 villages, 3 neighborhood committees and a farm named South Lake. In recent years, the economy of Xinzhuang town has been growing rapidly. In 2008, the GDP of the study area was 6.058 billion CNY, and the population was about 127500, including more than 52000 adventitious workers. Urban and rural industrial and residential land has continuously expanded with economic and industrial growth in Xinzhuang, especially after 2000 (Zhou et al., 2010); Urban sprawl has occupied plenty of farmland and caused substantial change to the area’s landscape and environment in the past decades (Zhou et al., 2011).

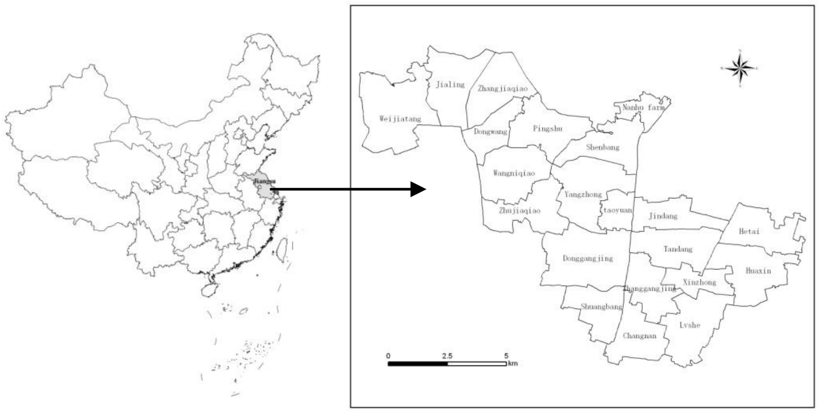


Fig. 1. Location of Xinzhuang Town in Jiangsu Province, China

2.2. Data preparation and processing

In this study, many data sets, including 1991 aerial photographs at 1:10000, 2001 IKONOS image and 2009 QUICKBIRD image, were used to acquire land use maps. The 1:10000 topographic maps and 1:10000 digital elevation model (DEM) of the study area were collected from Geographic information center of Jiangsu province. A total of 405 evenly distributed field-survey points for land use information were sampled via field surveys in 2009 with the help of a global positioning system (GPS) with ±1 m error for ground-truthing.

Other data used in this study includes: 1) Statistical yearbooks of 1991, 2001 and 2009 of Changshu city obtained from Changshu Statistical Bureau; 2) Statistical yearbooks from 2007 to 2010 of Xinzhuang town obtained from Xinzhuang Statistical Bureau; 3) The urban planning and land use maps and textbooks of Xinzhuang town obtained from Xinzhuang Planning Bureau of Land and Resources.

Firstly, the 2009 QUICKBIRD image was geometrically corrected and geo-coded to the Transverse coordinate system, using the 1:10000 topographic maps with ERDAS IMAGE 9.1 software. Secondly, the image-to-image method was applied for the geo-referenced registration of images in 1991 and 2001 with the total Root Mean Squared (RMS) error of less than 0.5 pixels. Thirdly, an image enhancement of intensifying visual distinction among features was performed to increase the amount of information. In succession, image interpretation symbols of different image elements were added accompanying by field investigations, which could be consulted in the process of artificial visual operations. Finally, visual interpretation was carried out on images of 1991, 2001 and 2009, and land use maps were acquired with the help of ancillary data including the topographic map and ground survey information. Land use types were divided into 9 classes: paddy field, dry land, forestland, water area, urban and rural construction land, aquaculture land, grassland, vegetable field, and orchard land). Because of the restriction of area percentage of each land use type in CLUE-S model, the 9 land use types were integrated into 6 categories for simulating: paddy field, dry land (including vegetable field), forestland(including grassland and orchard land), water area, aquaculture land, urban and rural construction land. The 405 field-survey points were used to examine the accuracy of the image classification. The Kappa coefficient was 95.2% in 2009, 93.5% in 2001, and 92.1% in 1991. Both ERDAS Imagine 9.1 and ARCGIS 9.0 were applied to integrate the data using standard GIS features. Due to the different resolutions of remotely-sensed images, all the results of classification were re-sampled at 20m × 20m for further analysis.

2.3. The CLUE-S model

The CLUE-S is a new version based on early CLUE model (Veldkamp and Fresco, 1996; Verburg et al., 1999). It was based on an empirical analysis of location suitability combined with the dynamic simulation of competition and interactions between the spatio-temporal dynamics of land use systems, and specifically developed for the spatially explicit simulation of land use change (Verburg et al., 2002). This version has been applied in case studies with a local to regional extent and the spatial resolution ranging from 20 to 1000 m (Verburg and Veldkamp, 2004; Overmars et al., 2007).

The model is sub-divided into two distinct modules: non-spatial demand module and 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 (Fig.2). Allocation of each land use type is based on a combination of empirical analysis, spatial analysis, and dynamic modeling. Empirical analysis is applied to determine the relationships between spatial distribution of land use and a number of proximate factors that drive or constrain land use change. Based on the competitive advantage of each land use at a location, the competition among land uses for a particular location is simulated. The schematic representation of the procedure to allocate change in land use in CLUE-S model is in Fig. 3 (Verburg et al.,

2002) (Fig.3). Verburg et al. (2006) provided its basic structure. The actual allocation process depends on the constraints and preferences defined by the user based on the characteristics of the land use type or the assumed processes and constraints relevant to the scenario.

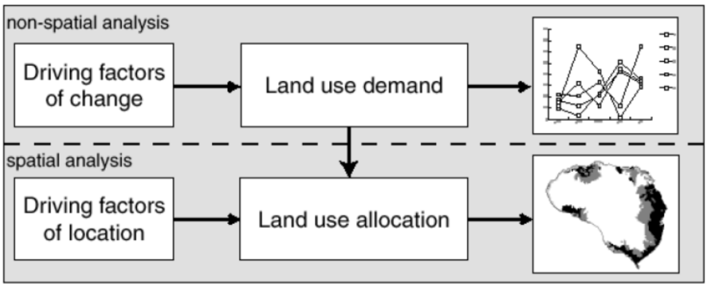


Fig. 2. Modules within the CLUE-S model (Verburg et al., 2002)

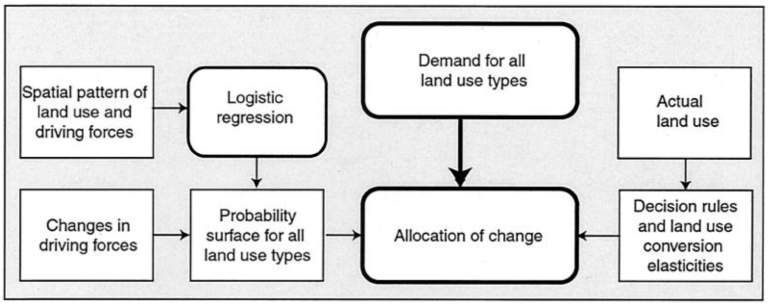


Fig. 3. Overview of the procedure to allocate changes in land use to a raster based map (Verburg et al., 2002)

2.3.1. Scenarios design and assumptions

In this study, three scenarios were designed to represent different implementations of the spatial policies and restrictions: (1) The Historical Trend (HT) scenario was formulated based on historical land use change from 1991 to 2009. Land use area demand was forecasted via the auto-regressive integrated moving average (ARIMA) approach, which employs a time series analysis based on the historical land use area changes. Besides 1991, 2001, and 2009, the land use data in this study area for the years from 1991 to 2009 were obtained from statistical yearbooks of Changshu city. (2) The Urban Planning (UP) scenario was designed based on the urban planning and land use planning schemes of Xinzhuang town, which emphasized compact urban development and basic farmland preservation. The areas which demand different land use types in the UP scenario were adjusted from the results of the HT scenario. (3) The Ecological and environmental protection (EE) scenario was designed based on related ecological and environmental protection policies in the study area over the next twenty years, the expectation of this scenario was to maintain the ecological land and improve the increasingly worsening ecological problems. The land use area demand in the EP scenario was adjusted based on the results from the UP scenario.

2.3.2. Logistic regression

The demand for land by the different land use types determines the overall competitive capacity of the different land use types, but the location suitability is also a major determinant of the competitive capacity of the different land use types at a specific location. Generally, conversions of land use are expected to take place at locations which have the highest 'preference' for a specific type of land use at a given moment. It can be calculated as a probability of a certain grid cell by logistic regression as follows (Bucini & Lambin, 2002):

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

Where P_i is the probability of a grid cell for the occurrence of the considered land use type i and the X are the driving factors; β_0, β_1, …, β_n are the beta values of logistic regression for driving factors. The value of Relative Operating Characteristics (ROC) proposed by Pontius and Schneider (2001) was used to evaluate the fit of the regression model. A completely random model gives ROC a value of 0.5 while a perfect fit results with ROC value of 1.0. If the value of ROC is below 0.7, the accuracy of the model is low; the accuracy will be preferable if an ROC value is above 0.7 (Pontius, 2000).

The driving factors of land use change taken into account as potential determinants were selected based on literatures and fieldwork in the study area, including 11 factors: distance to major road, distance to minor road, distance to river, distance to village government, distance to rural settlement, GDP, gross industrial product, gross agricultural product, grain output, population density, per capita income. The logistic regression models, based on the GIS dataset, were constructed to determine the relations between land use changes and a set of potential driving factors. The logistic regression results got through SPSS software were 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 (>0.7).

The derived regression models were used to calculate suitability maps for different land use types.

Table 1. Results of logistic regression for different land use types in 2009

Driving factor	Exp(β) construction land	Exp(β) dry land	Exp(β) paddy field	Exp(β) aquaculture land	Exp(β) forestland	Exp(β) water area
a	0.9987	0.9998	1.0002	1.0007	0.9991	1.0000
b	0.9995	1.0000	1.0001	1.0002	1.0001	1.0001
c	0.9989	0.9999	0.9955	1.0037	0.9983	1.0017
d	1.0000	1.0000	1.0000	1.0000	1.0000	0.9999
e	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
f	0.9998	1.0003	1.0003	0.9996	0.9996	1.0000
g	1.0003	0.9998	0.9997	1.0001	0.9998	0.9999
h	0.9999	0.9998	1.0000	1.0002	0.9999	1.0000
i	1.0004	1.0003	0.9993	0.9994	1.0008	1.0002
j	1.0048	0.9908	1.008	1.0063	1.0037	0.7906
k	0.9777	0.998	1.0015	1.0061	1.0029	1.0015
Constant	0.0279	0.4873	10.3249	0.0157	0.9809	8.2511
ROC	0.851	0.759	0.792	0.812	0.815	0.988

a, distance to major road; b, distance to village government; c, distance to minor road; d, GDP; e, gross industrial product; f, grain output; g, per capita income of resident; h, gross agricultural product; i, population density; j, distance to river; k, distance to rural settlement; ROC, relative operating characteristics.

2.3.3. Simulation spatial and temporal resolution setting

A series of test scenarios were set using 10-m to 50-m resolution with 10-m steps. The results showed that the highest spatial resolution in the CLUE-S model was 20 m in Xinzhuang town. Therefore, the simulation spatial resolution was set as 20 m × 20 m grid in this study, including 946 rows and 685 columns.

The land use in 2009 was simulated based on that in 1991 and 2001 with CLUE-S model to validate its applicability in the study area. The forecast periods were 18 and 8 years, respectively. The predicted land use map in 2009 was compared with the actual land use in 2009 by utilizing the Kappa coefficient. It has been applied to any model that predicts a homogenous category in each grid cell. The Kappa result was 0.75 and 0.80 for 1991 and 2001, which indicated that the two maps show a relatively high consistency with 18 years. CLUE-S was then used to predict land use change for the 18-year period beginning in 2009 with 1-year steps in the study area.

2.3.4. Land use conversion matrix and elasticity setting

There are two sets of parameters in the CLUE-S model (land use conversion matrix and elasticity) that could influence the pattern of land use change. The land use conversions restricted by land use policies, restrictions and land tenure could be reflected in a land use conversion matrix. The rows of the matrix indicate the land use type at time step t and the columns indicate the land use type at time step (t+1). Moreover, land use type specific conversion settings were defined and implemented by the relative elasticity for change (ELAS) in the model (Verburg et al., 2002). The relative elasticity ranges between 0 (easy conversion) and 1 (irreversible conversion). The value of this factor is set based on expert knowledge and can be adjusted during the calibration stage.

In this study, we assumed that the construction land would not be converted to other land use types. Based on the reference data during 1991–2009 and expert knowledge, the values of conversion elasticity for different land use types were tuned so that they were suitable for the calibration of the model. The final conversion elasticity values of paddy field, dry land, forestland, water area, aquaculture land, urban and rural construction land in the model during 2009–2027 were 0.4, 0.5, 0.6, 0.7, 0.4, and 0.9, respectively.

2.4. Landscape metrics

In order to evaluate and compare the simulated results based on CLUE-S model under the three scenarios of the strategy in the study area, four landscape-level spatial metrics were selected to reflect future landscape pattern changes based on their ecological meanings, including number of patches (NP), landscape shape index (LSI), Shannon's evenness index (SHEI), and Contagion index (CONTAG), these metrics were calculated using Fragstats 3.3 software at the landscape level.

3. Results and analysis

3.1. Spatio-temporal change of land use in future under different scenarios

Different land use types with regard to future area changes are shown in Fig. 4, which displayed different change trajectories from 2010 to 2027. The main land use types of construction land and aquaculture land showed the similar increasing trend under the three scenarios. The average annual increase rate of construction land and aquaculture land under HT scenario were 68.97 ha/a and 41.57 ha/a, which were obviously higher than the other land use types. The transfer matrix analysis showed that the increased area of construction land was mainly converted from paddy field. Unlike the other two scenarios, under the EE scenario, the forestland and water area would increase, for their higher ecological service values. In addition, the dry land under EE scenario was well protected, and its area increased slightly. The area of paddy field would decrease under all scenarios. This is particularly true for the HT scenario, which showed the area of paddy field decreased by 2088.50 ha from 2009 to 2027, while the area under UP and EE scenario decreased by 472.25 ha and 346.81 ha, respectively.

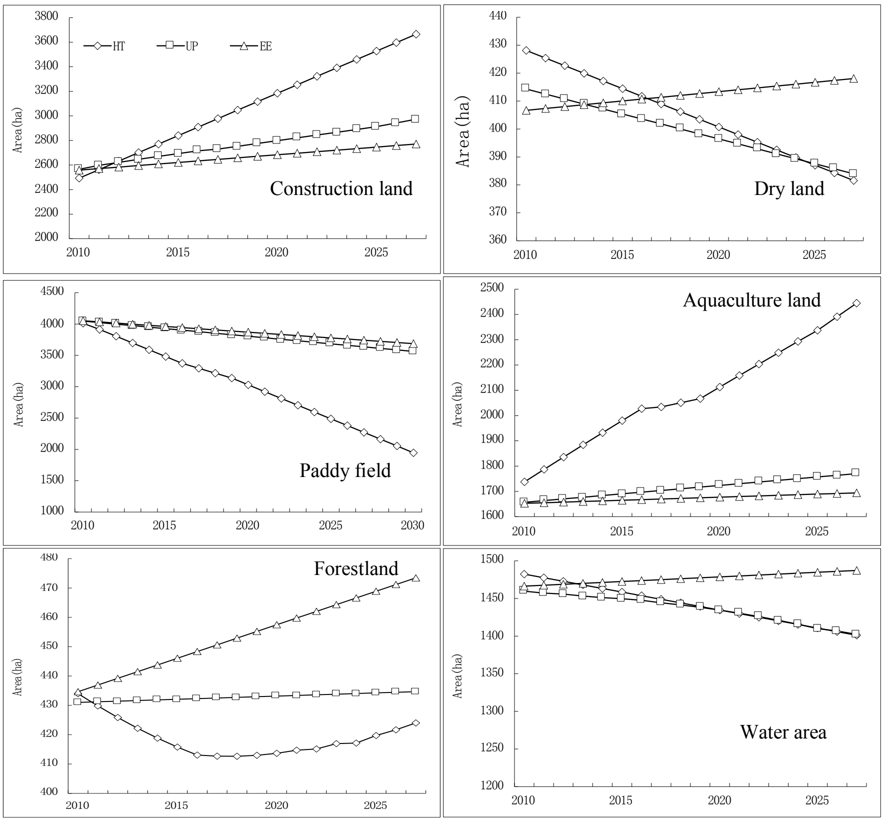
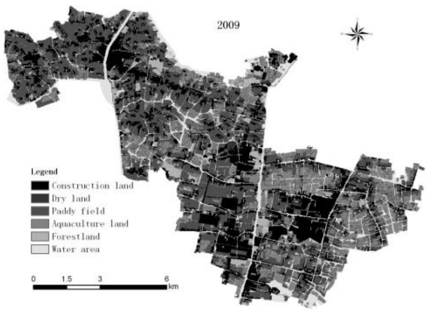
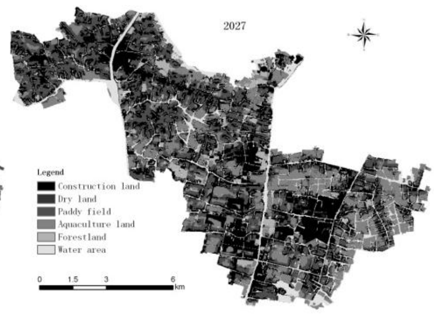


Fig. 4. Area change of different land use types in the study area under three scenarios

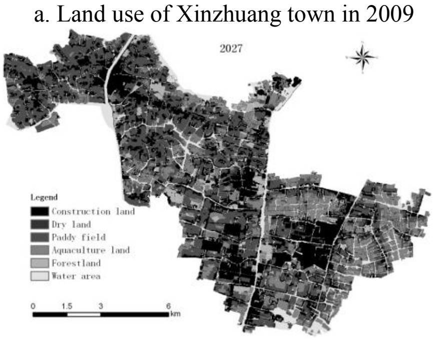
In summary, the expansion of construction land and the decrease of paddy field were the dominant changes of land use in the study area under the three scenarios (Fig. 5). Most of the increasing construction lands were due to the sprawl from the existing construction area through occupation of the surrounding paddy field, dry land, forestland, and so on. It occurs mainly at the urban-rural fringe, nearby existing construction land and around major roads and water area. The decreased paddy fields were mainly located near existing construction land, and along water area and major roads. As elsewhere, the farmland in this area was also more likely to be encroached by construction land, which means the conflicts between urban and rural development and farmland preservation will gradually increase. Consequently, in the process of plan-making, the urban planners and decision-makers in Xinzhuang town need to highlight the issues and strengthen the control of its land use by confirming the amount of urban and rural construction land scientifically, and reasonably prohibiting the unplanned sprawl of construction land, in order to realize the sustainable development of land use.



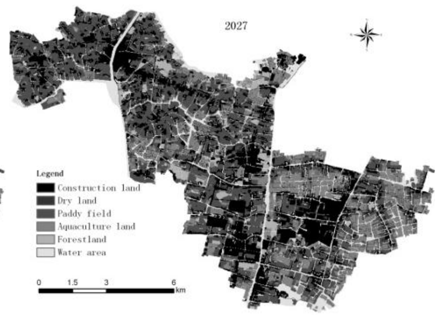
a. Land use of Xinzhuang town in 2009



b. Simulated results under HT scenario



c. Simulated results under UP scenario



d. Simulated results under EE scenario

Fig. 5. The land use map in 2009 and simulated results of land use in 2027 under different scenarios

3.2. Landscape pattern change under different scenarios

The number of patches at the landscape level over the study area increased under UP and EE scenarios from 2010 to 2027, which means that the landscape would be more fragmented, especially under UP scenario. The number of patches would increase rapidly before 2018, and then decline quickly under HT scenario. Such change may be due to the discrete construction land increasingly linked together after 2018, for the rapid growth of urban land and rural settlement area. The increasing trend of landscape shape index under each scenario from 2010 to 2027 indicates that the landscape patches would become increasingly disaggregated. Shannon's evenness index increased under UP and EE scenarios, which means the landscape pattern would be toward more diversified and homogenous. Under HT scenario, the SHEI showed a parabolic trend. Namely, the value increased first, then decreased for the construction land; it would become the dominant landscape and make the land use type patches more uneven in future. Contagion index showed a decreasing change trend under UP and EE scenarios, which means that the connectivity of future landscape would decline and the landscape would be more fragmented. (Fig. 6)

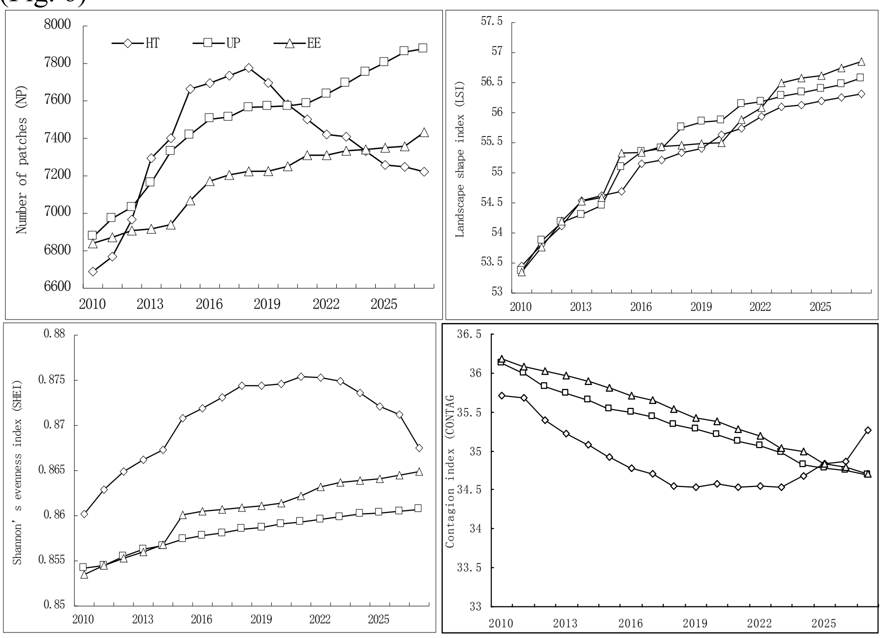


Fig. 6. Landscape metrics at landscape level under the three scenarios

3.3. Comparison analysis of simulated results with urban planning maps

Fig. 7. The simulated urban construction land under three scenarios and prospective plan map in 2020

Table 2. Results of Kappa coefficients of simulated map with plan map in 2020

Comparison	K standard	K location	K quantity
UP scenario	0.551	0.831	0.663
EE scenario	0.533	0.824	0.647
HT scenario	0.564	0.815	0.691

To evaluate the feasibility of land use change model in supporting spatial planning, a comparison analysis was made between simulated urban construction land of 2020 and perspective plan map in 2020 from Xinzhuang town urban planning (2006-2020). The simulated urban construction land in 2020 under different scenarios and the perspective plan map in 2020 are shown in Fig. 7. It is observed that the urban construction land in the planning map was regular and compact with clear boundaries, while the simulated urban construction land in 2020 under different scenarios was rather spatially dispersed with complicated boundaries. However, the simulated map may more closely reflect the real situation of urban growth pattern, while the planning map is more like subjective blueprint with few objectively and scientifically technological and methodological supports. It is well known that the Kappa coefficient can be used for measuring the consistency between two maps based on a contingency table and for accuracy assessment as a whole. The simulated results and planning map were compared by analysis of Kappa coefficient. Table 2 shows that the consistency between simulated maps and planning map was more than 0.5, especially for simulated location and quantity precision, which was more than 0.8 and 0.6, respectively. This means that the three scenarios were designed reasonably and the prediction accuracy of CLUE-S model was excellent.

4. Discussion and conclusions

Based on three periods of land use data extracted from high-resolution remote sensing images, natural and socioeconomic data, the CLUE-S land use change model was used. This was then combined with GIS and RS technology to successfully simulate future land use change trend under three scenarios. The land use modeling and prediction results showed that the increase of construction land and decrease of paddy field would still be the main trend of land use change in the study area. A good deal of farmlands and ecological land, especially around existing construction land, major roads and water areas, would be mainly transformed to urban land and rural settlement in the next twenty years. Results of landscape pattern metrics analysis showed that the landscape would be more fragmented, disaggregated and disconnected, and the landscape pattern was toward more diversified and homogenous. Therefore, a reasonable constraint and control policy should be made for urban expansion and land use change. Such a policy, or policies, would improve the current land use trends and establish an ecological safety pattern for urban and rural development. This is an effective way towards smart protection and smart growth, promoting regionally sustainable development. The prediction accuracy of CLUE-S was satisfactory, no matter the location, quantity or overall accuracy of land use change, which suggests the feasibility of land use change model for land use planning supports.

In summary, our study presented an important contribution to land use modeling for supporting spatial planning, and successfully simulated and predicted the spatio-temporal changes of future land use. The simulated future land use maps under different scenarios could serve as an early warning system for understanding the future effects of land use changes. Furthermore, the simulation results can also be considered as a strategic guide for urban land use planning. It would help local authorities better understand the complex land use system and develop the improved urban development and land use management, which can better balance urban expansion, basic farmland and ecological environment conservation. Above all, the land use change model can be a helpful and scientific tool for supporting urban land use planning and policy making. Planners and decision-makers should pay more attention to the potential consequences of land use change in the process of policy-making. Our findings and discussions will not only give decision-support for Xinzhuang town, but also for other similar areas with rapid rural urbanization in China.

Acknowledgments

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