# Assessing Growth Scenarios for their Landscape Ecological Security Impact, using the SLEUTH Urban Growth Model

Haiwei YIN [1], Fanhua KONG [2,*], Yuanman HU[3], Philip JAMES[4], Feng XU[1], Lanjun YU[5]

[1] Haiwei YIN, Associate Professor

Department of Urban Planning and Design, Nanjing University, No. 22, Hankou Road, 210093, Nanjing, China

[2] Fanhua KONG (Corresponding author), Associate Professor

International Institute for Earth System Science (ESSI), Nanjing University, 163 Xian lin Ave., Road, 210023, Nanjing, China;

E-mail: fanhuakong@163.com

Phone: +86-25-89681033; Fax: +86-25-83316892

[3] Yuanman HU, Professor

State Key Laboratory of Forest and Soil Ecology, Institute of Applied Ecology, Chinese Academy of Sciences, Shenyang 110164, China

[4] Philip JAMES, Professor

School of Environment and Life Sciences, University of Salford, Salford, M5 4WT, UK

[1]Feng XU, Postgraduate student

International Institute for Earth System Science (ESSI), Nanjing University, 163 Xian lin Ave., Road, 210023, Nanjing, China

[5]Lanjun YU, Urban Planner

Shandong urban and rural planning design institute，Jinan 250013，China

**Abstract:** Rapid urban population growth and the associated expansion of urban areas in China (as elsewhere) present significant environmental challenges, and threaten urban and regional ecological security. Modeling land use changes is one way to aid the management of cities. Using remote sensing and geographic information system (GIS) software platforms, land use data for the years 1989, 1996, 2004, and 2010 for the area inside the Jinan third ring-road were interpreted. An urban green space network was developed, as a core strategy to ensure landscape ecological security, and subjected to ecological sensitivity analysis. The green space network and the result of the ecological sensitivity analysis were integrated into the exclusion/attraction layer of an existing cellular automaton model, SLEUTH (Slope, Land use, Exclusion/attraction, Urban extent, Transportation, and Hillshade). A development scenario for land use change was constructed that integrates these Landscape Ecological Security Development (LESD) strategies and reveals trends in urban growth for the different development scenarios between 2011 and 2040. The results of the LESD scenario were compared with those from two other development scenarios: the Historical Trend Development (HTD) and the Transit-Oriented Development (TOD). The study revealed three significant findings. First, change in the urban area in the study will be dominated by urban edge growth and transit-oriented development, while spontaneous and cluster growth were not obvious. Second, the growth rate of built-up land in the urban area in all three scenarios exhibits emerging trends. The growth rate, according to the LESD scenario, is significantly lower than that for the HTD and TOD scenarios, and encroachment into natural ecological space (such as woodlands, water, and agricultural land) is less than that in the other two scenarios. This result indicates that the LESD scenario can protect natural ecological spaces effectively and can significantly reduce the ecological security risk. This aligns with the integration of smart growth and smart conservation. Third, integrating LESD into the SLEUTH model results in the ability to evaluate urban development policies and can help characterize development strategies for urban landscape ecological security. The results of this study provide reference data and a basis for decision-making for the future management of urban growth, urban planning, and land use planning.

**Keywords:** Landscape ecological security; scenario analysis; SLEUTH urban growth model; smart growth; urban growth

## Introduction

Since 1978, China has experienced rapid urbanization. The urban population in Chinese cities rose from 17.9% in 1978 to 52.6% in 2012, and the area of built-up land increased from 6,720 $km^2$ to 39,758 $km^2$ (The Yearbook of China's Cities, 2012). Such rapid urban expansion has been, and it appears will be for the foreseeable future, the main driving force of land use change in China. Such land use change will affect environmental conditions: the conversion of open, natural ecological space to urban built-up land will result in unprecedented pressure on natural resources, and present challenges for ecological environmental management (Lin, 2004; Ma, 2004). Urban green space loss or fragmentation can entail a consequential series of negative eco-environmental problems, such as the urban heat island effect, soil erosion, water pollution, and loss of biodiversity (Kong et al., 2014; Hansen and Pauleit, 2014). Rapid structural and functional change in the urban landscape weakens the ecological functionality of the green infrastructure, reduces the ecosystem service provision, and threatens urban ecological security and sustainable development (Lovell and Taylor, 2013; Sperandelli et al., 2013).

Ecological security is the term commonly used in relation to safeguarding sustainable ecological resources (Dabelko et al., 1995; Rogers, 1997; Pirages and DeGeest, 2003). However, there is not a universally accepted definition of the term. Concerns over urban ecological security are now giving rise to strategies to reconfigure cities and their infrastructures in ways that help secure the natural resources necessary for their ecological and material well-being (Hodson and Marvin, 2009).

The concept of landscape ecological security has developed from that of urban ecological security and is based on landscape ecological theory. This is an accepted strategy to safeguard urban natural resources that involves considering the spatial pattern and function of these resources and that aims to improve urban ecological resilience (Yu, 1996; Ma et al., 2004; Colding, 2007). However, few studies have integrated landscape ecological security development (LESD) strategies with modeling to identify sustainable land use development scenarios: ones that can integrate smart growth and smart conservation to guarantee the long-term well-being of a city and its inhabitants (Silva et al., 2008; Rafiee et al., 2009; Mitsova et al., 2011). Ways to model and assess urban growth scenarios as well as forecast the resultant effect on urban ecological security are required to inform decisions on urban sustainable development.

Strategically, landscape ecological security is oriented towards urban sustainable development in the context of a rapidly growing population and of expanding urbanization. Dynamic land use models can be used to analyze and predict future land use change and to understand the influence of the relevant driving forces. The models can help urban planners and administrators analyze different scenarios for land use change, and identify the characteristics of land use conversion and the influence that this change will have on urban ecosystems. This analysis provides scientific support to policy-making related to sustainable land management and urban development (Xiang et al., 2003; Barredo et al., 2003; He et al., 2008; Liu et al., 2008). Of these models, the cellular automaton (CA) models are renowned for their flexibility, openness, non-linearity, and self-adaptiveness, and since the 1980s, they have been applied widely to simulate urban growth and land use change (Couclelis, 1997; Clarke et al., 1997; Clarke and Gaydos, 1998; Yeh and Li, 2003; Liu et al., 2008; Yang et al., 2008; Al-shalabi et al., 2012; Akin et al., 2014). With the support of GIS (geographic information system) and Remote Sensing, CA models can simulate the complicated dynamics in urban spatial patterns through simple regional transfer rules (Clarke et al., 1997; Clarke and Gaydos, 1998; Silva and Clarke, 2002; Torrens, 2003; José et al., 2003; Berling-Wolff and Wu, 2004; Leao et al., 2004; Li et al., 2007; van Vliet et al., 2012). SLEUTH (Slope, Land use, Exclusion/attraction, Urban extent, Transportation, and Hillshade) urban growth model, developed by Clarke et al. (1997), has been widely applied to simulate urban growth and land use change (Jantz et al., 2003, 2010; Li et al., 2007; Mahiny and Clarke, 2012；Onsted and Chowdhury, 2014). SLEUTH, by integrating an urban growth model and a land use model, can successfully simulate the spatial expansion process of a city (Clarke et al., 1997; Clarke and Gaydos, 1998; Peiman and Clarke, 2014; Rienow and Goetzke, 2015). In the SLEUTH model, an area is divided into cells and the development possibility of each cell is determined by constraints such as transportation, terrain, and urbanization, and the characteristics of nearby cells: an urbanized cell will be the main driver affecting the development of an entire area as its influence spreads out (Jantz et al., 2003, 2010; Li et al., 2007; Onsted and Chowdhury, 2014). The SLEUTH model can predict the dynamics of urban land use at temporal scales ranging from decades to centuries. It has frequently been applied to the simulation and the long-term prediction of urban growth (Clarke et al., 1997; Silva and Clarke, 2002; Herold et al., 2003; Jantz et al., 2010; Vermeiren et al., 2012; Badwi et al., 2014). The SLEUTH model has also been used in China to simulate urban expansion (e.g., Wu et al., 2009; Liang and Liu, 2014). However, some scholars noted the difficulty in integrating urban development policies into the model's transfer rules (Torrens and O'Sullivan, 2001). Characterizing the impact of policies on urban expansion remains a challenge for the model's users (Lemp et al., 2008). Jantz et al. (2003) suggested that the effects of policies on urban growth could be addressed by using different scenarios or reconstructing the exclusion/attraction layers in the model. Comparison of different scenarios can forecast possible ecological security problems resulting from future developments or can assess the health of an urban system.

Consequently, the main aims of this study are: (1) to construct and test three scenarios based on different development strategies using the SLEUTH model; (2) to give a perspective on the effects of the different scenarios on urban land use pattern to 2040 (a 30-year time scale); and (3) to seek an ecologically sustainable development pattern for

Jinan City by considering landscape ecological security. The coupling of landscape ecological security development with the SLEUTH model will provide an auxiliary planning decision-support tool that will assist understanding of the urban eco-environment and the relationship between urban expansion and eco-environmental change.

**The study area**

Jinan, the capital city of Shandong Province, is located in the eastern coastal region of China (latitude 36°32′–36°51′N, longitude 116°49′–117°14′E) (Fig. 1). In the past few decades, Jinan has seen rapid economic growth. The city's gross domestic product (GDP) increased from 2 billion RMB (US$0.3 billion) in 1978 to 480 billion RMB (US$76 billion) in 2012 (Jinan Statistics Bureau, 2013). Alongside this dramatic economic growth, Jinan, as with other Chinese cities, has also experienced intense rural migration to the city: the main driver of rapid urban sprawl. The urban population has increased from about 0.6 million in 1952 to 3.5 million in 2012 (Jinan Statistics Bureau, 2013) (Fig. 2). The area of urban built-up land in Jinan City has expanded from 25 $km^2$ in 1949 to 315 $km^2$ in 2011 (Statistical Yearbook of Jinan, 2012). The development of Jinan City has occurred despite several physical constraints. Growth to the south is restricted by a hilly topography and to the north by the Yellow River (Fig. 1). In the Jinan Planning Bureau's 2006–2020 Master Plan, it is proposed to expand further eastward and westward, with the urban area within the third ring road growing to 400km$^2$, and the population living in Jinan City increasing to 4 million (Kong et al., 2010).

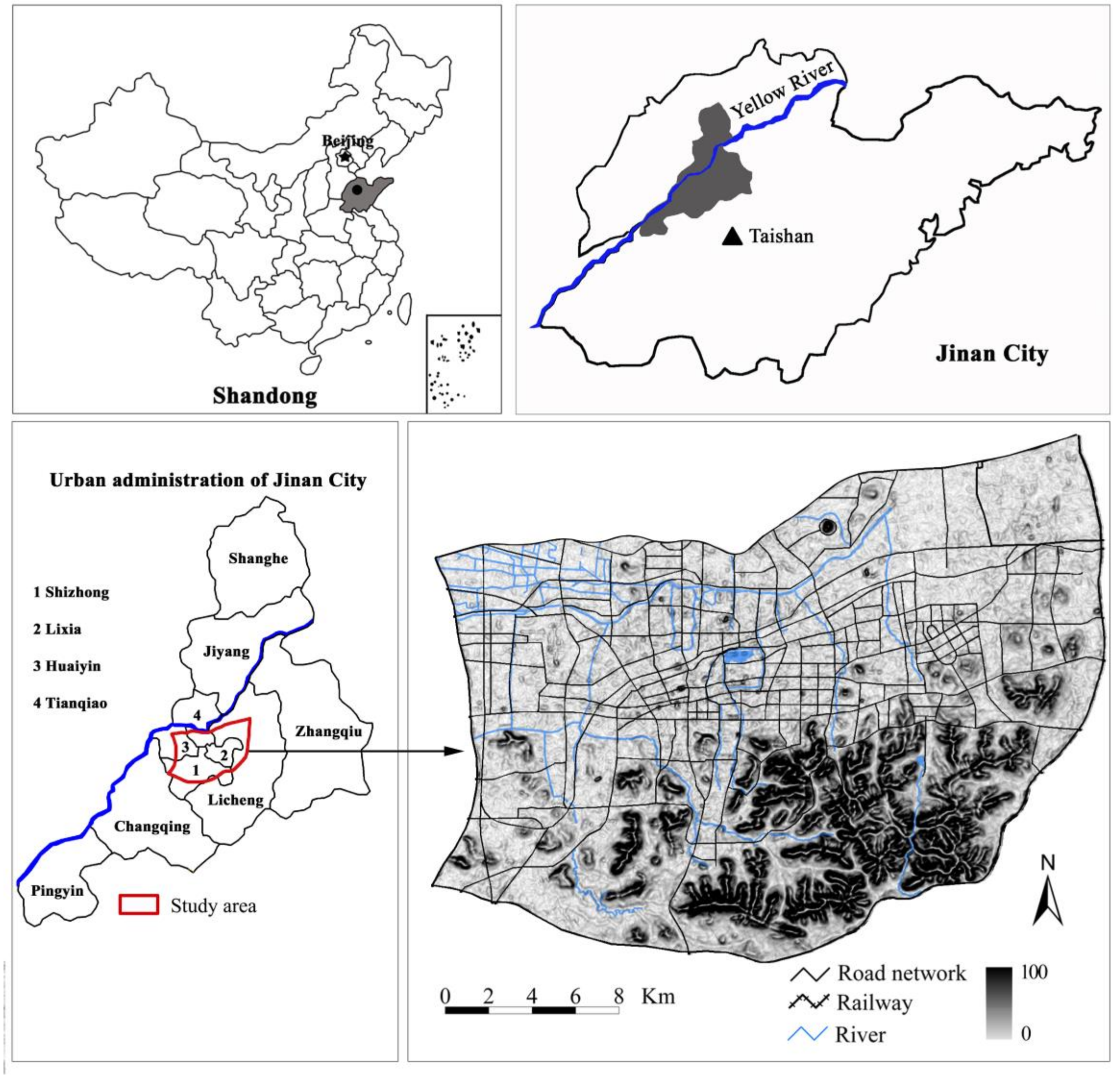


Fig. 1. Location of the study area

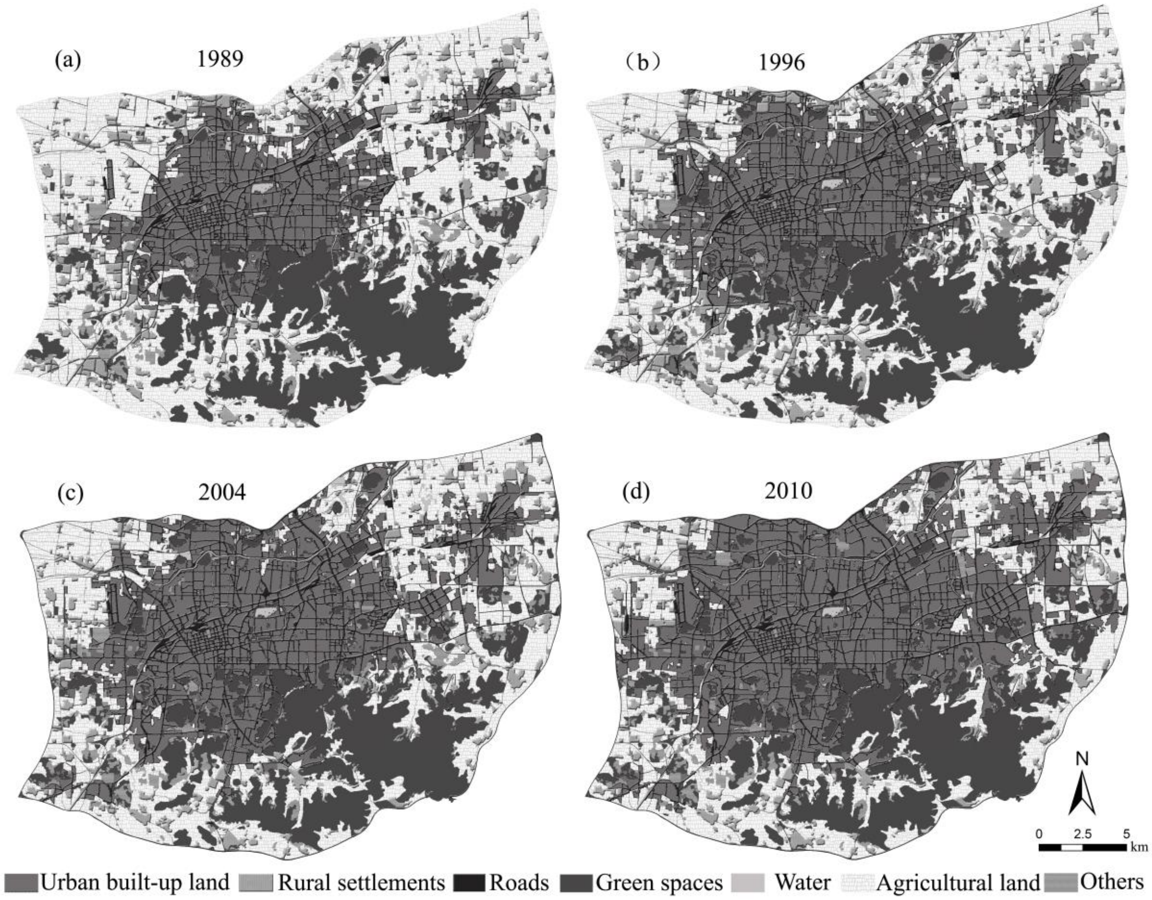


Fig. 2. Gross domestic product and population growth of Jinan City (Source: Jinan Statistic Bureau, 2013)

## Data and methods

The SLEUTH Urban Growth Model procedure is shown in Fig. 3. Data from remote sensing (SPOT (Landsat Satellite Systeme Probatoire d'Observation de la Terre), TM (Landsat Satellite Thematic Mapper), and ALOS (Advanced Land Observation Satellite)) and GIS techniques were employed to identify and integrate an urban green space network into the SLEUTH model. The three future scenarios: LESD (Landscape Ecological Security

Development), HTD (Historical Trend Development), and TOD (Transit-Oriented Development) were then designed and set in the exclusion/attraction layers of the SLEUTH model. After the model was calibrated, the impact of urban spatial expansion on landscape ecological security was assessed for the three scenarios. The data processing and key technologies in running the SLEUTH model are explained in detail in the following sections.

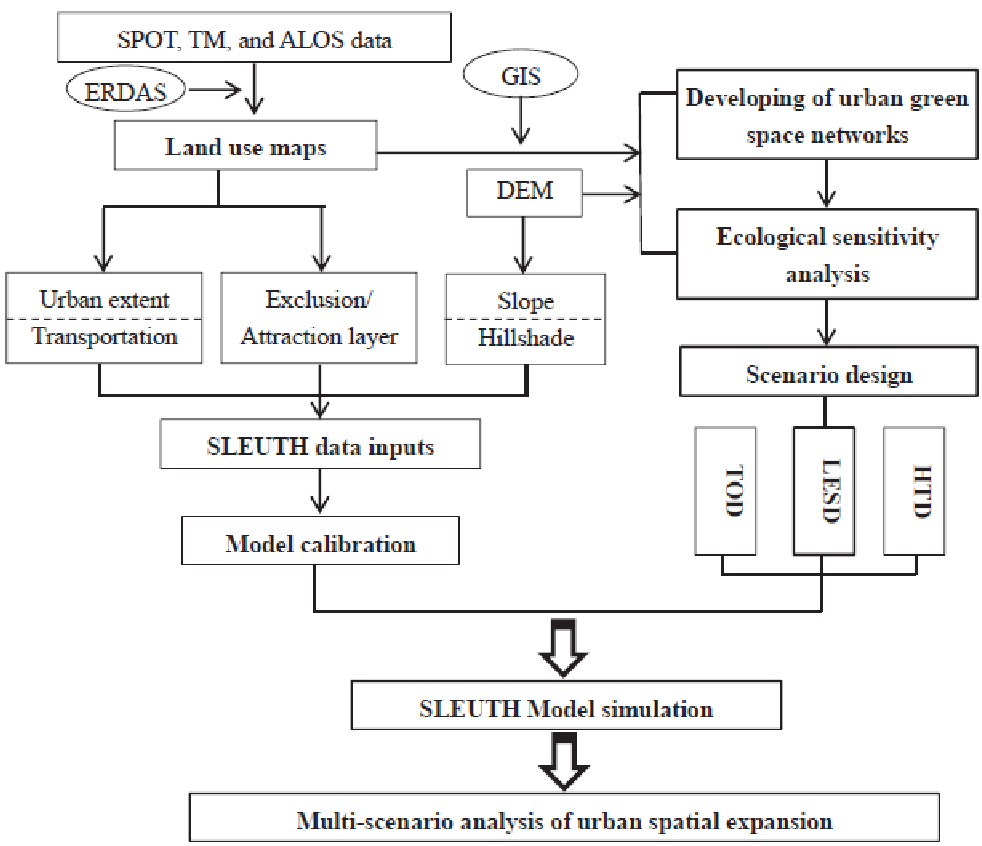


Fig. 3. The process followed in using the SLEUTH Urban Growth Model

**Data sources and data pre-processing**

In this study, SPOT images from 1989 (panchromatic band, 20 m), 1996 and 2004 (panchromatic band, 10 m; multi-spectral bands, 20 m); TM data (bands 1–5, 7; 30 m resolution); and ALOS data from 2010 (panchromatic band, 2.5 m; multi-spectral band, 10 m) were used. First, geometric correction of the remote sensing images (RMS (Root Mean Square) smaller than 1 pixel) was implemented by using the Earth Resources Data Analysis System (ERDAS 9.2 version) with the quadratic polynomial model as the correction function and uniformly distributed ground control points (GCP) on the images. The self-test error of each GCP was controlled by no more than 1. The coordinate system was adjusted to WGS_1984 with UTM (World Geodetic System 1984 with Universal Transverse Mercator) projection. Then, the SPOT, TM, and ALOS remote sensing images were corrected to the same resolution and clipped to the study area boundary. Finally, land use maps at four dates (1989, 1996, 2004 and 2010) were developed by visual interpretation based on field survey, and seven land use types were mapped: urban built-up land, rural settlements, roads, green space, agricultural land, water, and others (Fig. 4).

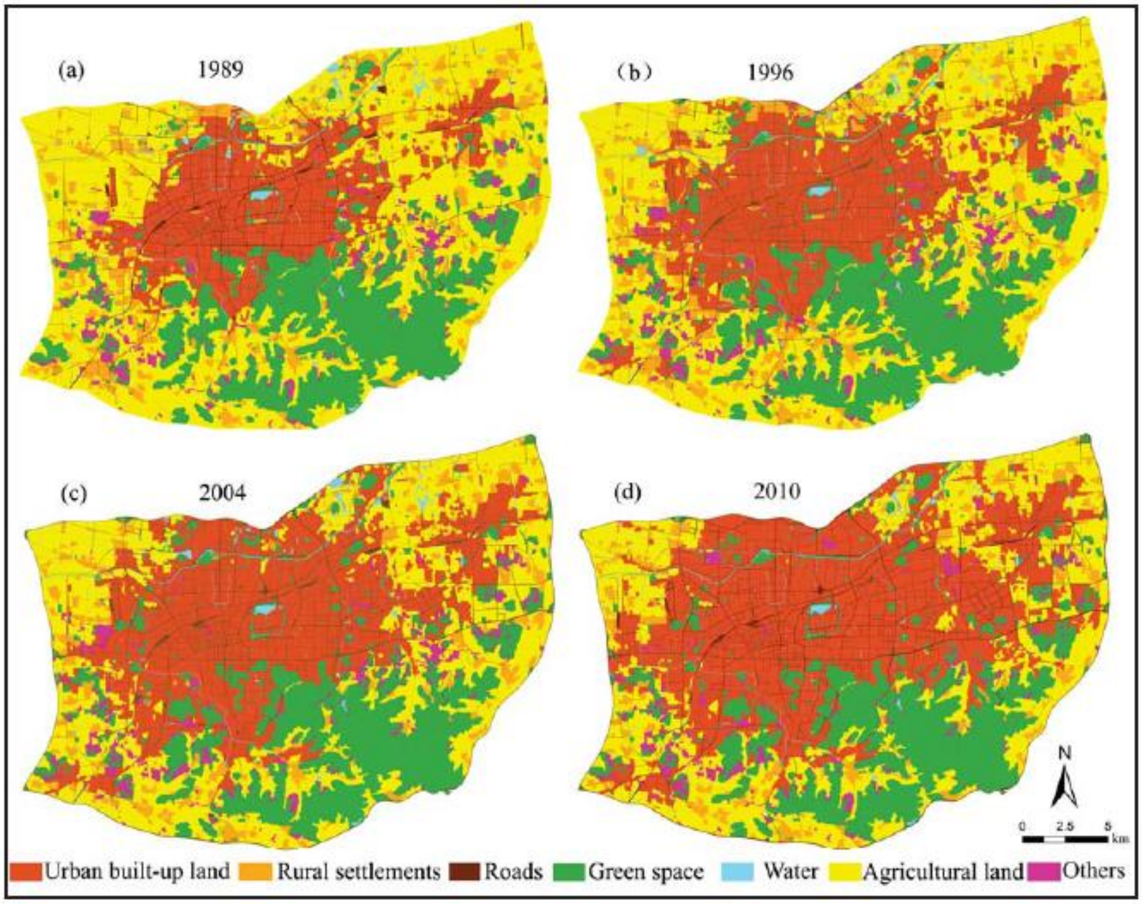


Fig. 4. Land use maps of the study area in (a) 1989, (b) 1996, (c) 2004, and (d) 2010

**The SLEUTH model**

The SLEUTH model simulates and predicts future urban expansion based on the assumption that historical urban growth trends will continue. In the model, each cell can be converted into either urban or non-urban use. The cellular state is primarily controlled by the interaction between five growth coefficients, i.e., dispersion (the probability of random growth), breed (the probability of spontaneous growth), spread (the probability that growth will occur adjacent to an already developed area), slope (the effect of topography – flat versus sloping land – on the probability of development), and road gravity (the effect of a road on the location of development), and four types of urban land use change: spontaneous growth, edge growth, road-influenced growth, and new center spreading (Clarke and Gaydos, 1998; Yang and Lo, 2003; Jantz et al., 2010). The exclusion/attraction layers of the model also affect predicted urban growth. Exclusion/attraction layers are defined according to users' needs by giving a probability of future urbanization to each region of the city. Exclusion/attraction layers reflect the intention of policy-makers, and the five growth coefficients determine the probability that any given location will be urbanized (Clarke et al., 1997; Jantz et al., 2003).

**Data input preparation**

In this study, the five grayscale raster data layers in GIF (Graphics Interchange Format) format were used as input into the SLEUTH model (i.e., urban extent, transportation, slope, hillshade, and exclusion/attraction layer). The urban extent, transportation, and exclusion/attraction layers were generated from the vector maps of land use at four dates (1989, 1996, 2004, and 2010). The urban extent layer was in binary format: urban or non-urban land use. The transportation layer was assigned a value of 100, 75, or 50, based on the category of the road: main road, subsidiary main road, or branch road, respectively

(Sangawongse et al., 2005; Myint et al., 2010). The slope and hillshade layers were generated from a DEM (Digital Elevation Model) and all slope values above 100% were redefined as 100%. Finally, all data were converted to raster maps (raster size 30 m × 30 m) in GIF format for the model use (Fig. 5). The exclusion/attraction layer was defined according to development strategies and will be explained in each design of the scenario in this study.

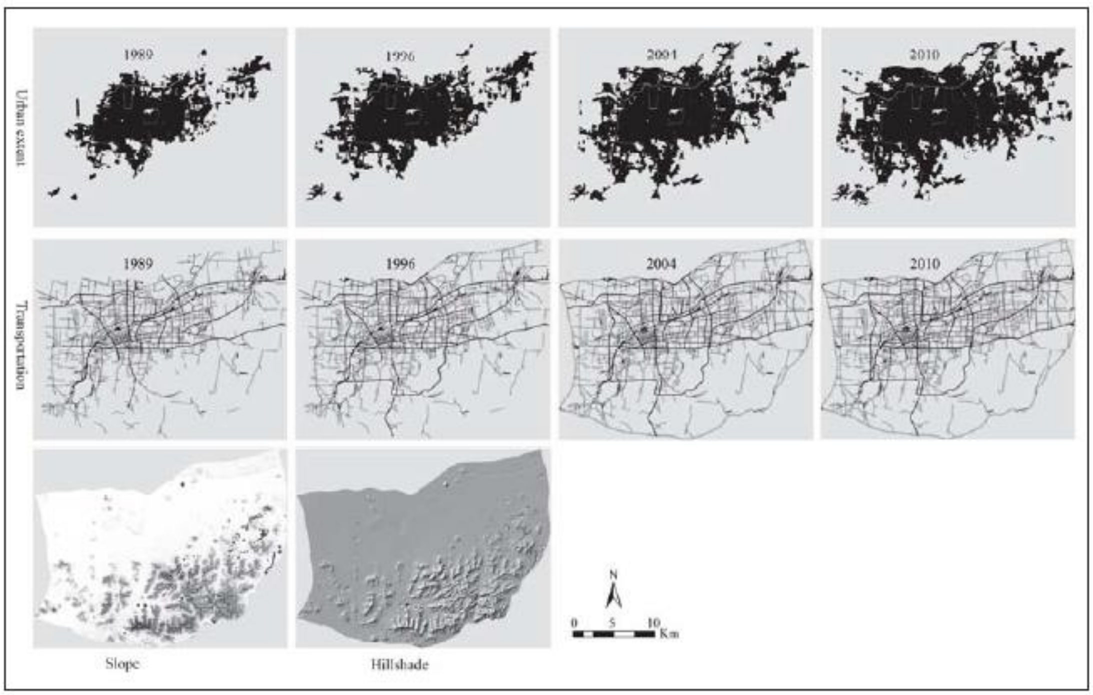


Fig. 5. The main input layer data required by the SLEUTH model

## Model calibration

The aim of calibrating the SLEUTH model is to find a set of growth parameters (i.e. the value of the five growth coefficients) that simulate future urban growth. The brute force Monte Carlo method was adopted for model calibration (Jantz et al., 2003). This involved three stages: coarse, fine, and final calibration (the derive stage). In each stage, the model is calibrated by fitting simulated data to historical data collected in the study area. A set of metrics is derived that can be used to evaluate the accuracy of the simulation results and to narrow down the range of the coefficient values. The growth parameters derived at each stage were used for the subsequent stage (Clarke and Gaydos, 1998; Silva and Clarke, 2002; Jantz et al., 2003; Dietzel and Clarke, 2007).

Data from 1989 were used as the initial layer for model calibration with data from 1996, 2004, and 2010 used as the correction layers for parameter calibration (Table 1). The exclusion/attraction layer used in the model calibration stage set only water and urban green space as having a 100% probability of not being urbanized. In the coarse and fine calibration stages, the raster maps were re-sampled to 120 m × 120 m and 60 m × 60 m, respectively.

Table 1. Comparison of metrics for each of the SLEUTH model's calibration stages

| Calibration stages / Metrics | Coarse calibration | Fine calibration | Final calibration | Derive |
|---|---|---|---|---|
| Number of Monte Carlo iterations | 5 | 7 | 9 | 100 |
| Total number of simulations | 3,124 | 6,479 | 7,775 | |
| Compare | 0.95 | 0.99 | 0.89 | |
| $r^2$ population | 0.99 | 0.99 | 0.99 | |
| Edges | 0.97 | 0.93 | 0.94 | |
| Cluster | 0.93 | 0.97 | 0.99 | |
| Lee-Salee | 0.67 | 0.68 | 0.68 | |

The model calibration stage generated a series of metrics to describe the model's accuracy. It is debated which of these metrics best represents the accuracy of models (Clarke et al., 1997; Jantz et al., 2003; Herold et al., 2003). Clarke et al. (1997) relied primarily on four metrics: $r^2$ population, Edges, Cluster, and Lee-Salee. Silva and Clarke (2002) used the un-weighted product score (multiplied together) of ten metrics. Yang and Lo (2003) relied on a weighted sum of all the metrics. In the study reported here, five metrics were used as the main criteria for model calibration and reduction of the parameter interval: Lee-Salee, Compare, $r^2$ population, Edges, and Cluster. These five metrics were selected because many studies have indicated that the correlation among them is small, and they will therefore reflect the accuracy of model simulation (Silva and Clarke, 2002; Dietzel and Clarke, 2007; Onsted and Chowdhury, 2014).

At each calibration stage, the five metrics were used to seek the optimum combination of parameters and the range of the five coefficients was reduced to generate five new coefficient intervals. The final values of the five coefficients were: diffusion = 22, breed = 85, spread = 92, slope = 25, and road gravity = 74 (Table 2). Using these coefficients, the model calibration was run at a step of 1 and 100 Monte Carlo iterations were run. Urban expansion in 2010 was simulated and a threshold of 60% was applied to the resultant 2010 probability map to create a binary image of urban extent, and this was then compared with the actual urban extent at the pixel scale to evaluate quantitatively the model simulation's accuracy (Table 3).

Table 2. Comparison of coefficients for each of the SLEUTH model's calibration stages

| Calibration stages / Growth coefficients | Coarse calibration | | Fine calibration | | Final calibration | | Derive | |
|---|---|---|---|---|---|---|---|---|
| | Range | Step size | Range | Step size | Range | Step size | Final coefficient | Step size |
| Diffusion coefficient | 1~100 | 25 | 1~25 | 5 | 10~20 | 2 | 22 | 1 |
| Breed coefficient | 1~100 | 25 | 50~75 | 5 | 55~70 | 3 | 85 | 1 |
| Spread coefficient | 1~100 | 25 | 25~75 | 10 | 65~75 | 2 | 92 | 1 |
| Slope coefficient | 1~100 | 25 | 50~100 | 10 | 50~70 | 4 | 25 | 1 |
| Road gravity coefficient | 1~100 | 25 | 25~75 | 10 | 45~65 | 4 | 74 | 1 |
| Self-modifying rules | ROAD_GRAV_SENSITIVITY = 0.01 SLOPE_SENSITIVITY = 0.1 CRITICAL_LOW = 0.97 CRITICAL_HIGH = 1.3 CRITICAL_SLOPE = 21.0 BOOM = 1.01 BUST = 0.09 | | | | | | | |

Table 3. Accuracy evaluation of SLEUTH model at the pixel scale

| Evaluation index | Nonurban | Urban | New urban | Overall accuracy (%) |
|---|---|---|---|---|
| Status of 2010 | 581,369 | 259,051 | 124,786 | - |
| Modeled pixel | 620,993 | 219,427 | 85,162 | - |
| Number correct | 551,999 | 192,086 | 57,821 | 88.54 |
| Producer's accuracy (%) | 94.95 | 74.15 | 46.34 | - |
| User's accuracy (%) | 88.89 | 87.54 | 67.90 | - |

## Scenario design and model simulation

The SLEUTH model can pre-set different scenarios of future urban development by adjusting coefficient values and designating the exclusion/attraction layers (Jantz et al., 2003). Based on the current situation and the future plan, three development scenarios were produced: LESD (Landscape Ecological Security Development), HTD (Historical Trend Development), and TOD (Transit-Oriented Development).

### The LESD (Landscape Ecological Security Development) scenario

In the LESD scenario, an urban green space network is defined and its ecological sensitivity is identified to determine the critical green spaces in the study area. The urban green space network and ecological sensitivity are integrated into the LESD scenario by defining the exclusion/attraction layer in the SLEUTH model.

The development of an urban green space network is increasingly being considered a suitable approach to increase habitat connectivity and hence ensure the viability of species populations by maintaining gene flow, and to facilitate regular migration, dispersal, and recolonization (Cook, 2000; Hargrove et al., 2004; Kong et al., 2010). Developing an urban green space network includes protecting and maintaining existing green space, creating new green spaces, and restoring lost connectivity between urban green spaces.

The identification of an urban green space network for the study area was done in the least cost patch function (a raster format using ESRI's grid module) of the ARC/Info software package. The first step was to identify the core areas that act as sources of wildlife. In this study, 12 green space patches were identified as sources (for details, see Kong et al., 2010, Fig. 4). The second step was to evaluate habitat suitability or the obstacles to wildlife dispersal through the different land uses. As plant communities are the major determinant of the dispersal of wildlife and habitat suitability (Burley, 1989), obstacles in this study were mainly weighted according to vegetative coverage rate, vegetation type, the age of the urban green space, and the degree of anthropogenic disturbance. Finally, the distance between different green space patches and landscape resistance was considered and the minimum cumulative cost path was employed to extract potential ecological corridors which, based on a gravity model, would be protected in the study area (for details, see Kong et al., 2010, Fig. 4). Ecological sensitivity analysis can be used to evaluate the ecological risks and security of ecological resources. This method involves mapping eco-sensitive areas and identifying an eco-sensitive resource pattern. In this study, the urban green space network was used as a sensitivity factor (extremely high sensitivity) which was combined with terrain, water, vegetation, and agricultural factors to construct the graded evaluation system for the ecological sensitivity analysis (Table 4). The maximum value method in GIS spatial analysis for the multi-factor comprehensive evaluation was applied and an ecological sensitivity zonation was obtained (Gadgil et al., 2011). Finally, the probability of a cell not being urbanized was scored as 0%, 10%, 40%, 70%, or 100%, according to the degree of ecological sensitivity, and the exclusion/attraction layer was derived for the integrated LESD scenario (Fig. 6a). The LESD scenario is suitable for preserving the integrity of the green space network and the associated ecosystem services while achieving the integration of smart conservation and smart growth.

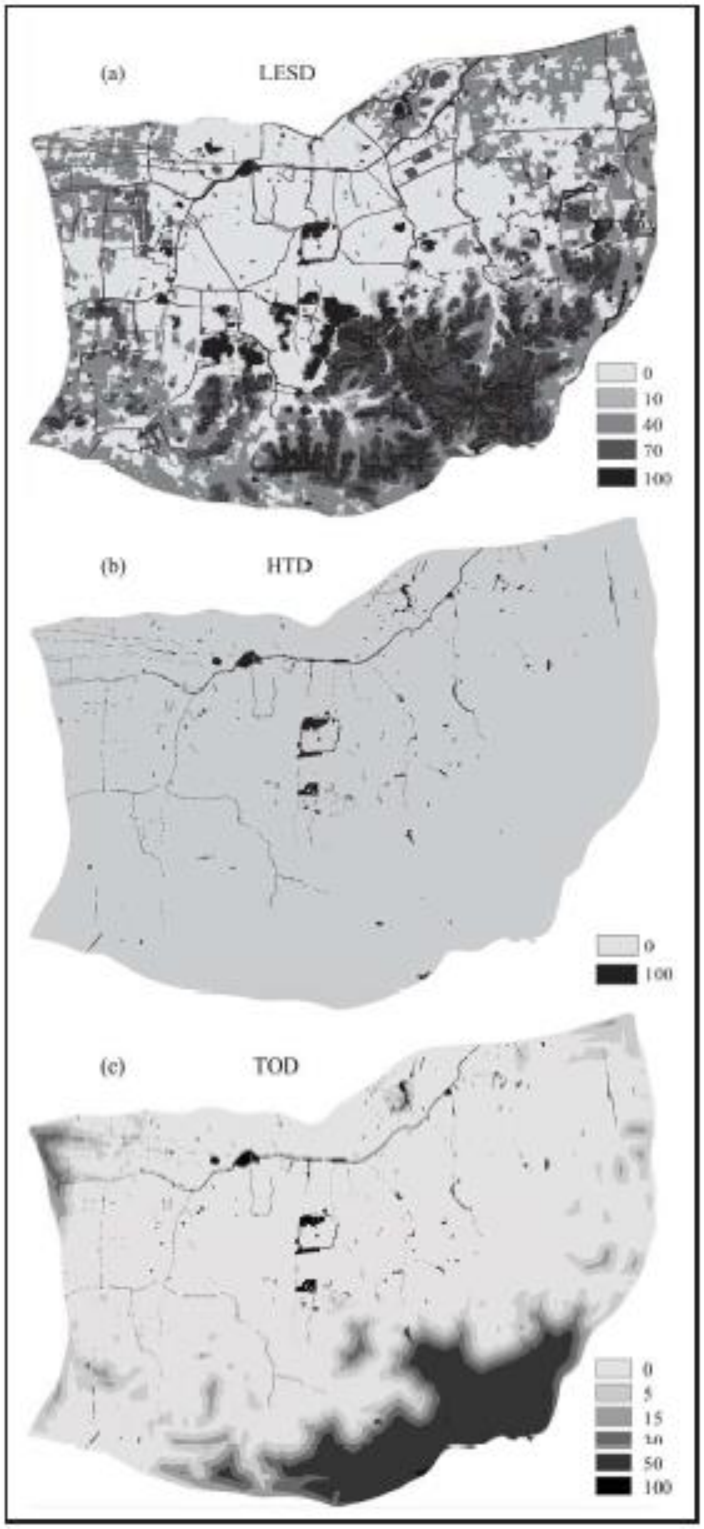


Fig. 6. Exclusion/attraction input layers of three scenarios: (a) LESD, (b) TOD, and (c) HTD

Table 4. Sensitivity grade and values of ecological sensitivity factors

| Sensitivity factor | | Classification (buffer) | Value | Ecological sensitivity grade |
|---|---|---|---|---|
| Urban green space network | Source area and ecological corridor | | 9 | Extremely high sensitivity |
| Terrain | Relief amplitude | >50 m | 9 | Extremely high sensitivity |
| | | 20–50 m | 7 | High sensitivity |
| | | 10–20 m | 5 | Moderate sensitivity |
| | | 5–10 m | 3 | Low sensitivity |
| | | <5 m | 1 | Non-sensitivity |
| | Slope | >25° | 9 | Extremely high sensitivity |
| | | 15–25° | 7 | High sensitivity |
| | | 10–15° | 5 | Moderate sensitivity |
| | | 5–10° | 3 | Low sensitivity |
| | | 0–5° | 1 | Non-sensitivity |
| Water | | Water area | 9 | Extremely high sensitivity |
| | | <15 m buffer area | 7 | High sensitivity |
| | | 15–25 m buffer area | 5 | Moderate sensitivity |
| Agricultural land | | | 5 | Moderate sensitivity |
| Green space | City park | | 9 | Extremely high sensitivity |
| | Woodlands | | 7 | High sensitivity |

### The HTD (Historical Trend Development) scenario

In the HTD scenario, only the water and green space of the study area are defined as the exclusion/attraction layer (by assigning a 100% probability of them not being urbanized); agricultural land and woodlands surrounding the city are likely to be occupied during urban expansion (Fig. 6b).

### The TOD (Transit-Orientated Development) scenario

The planned road network in 2020 was used as the initial layer in the TOD scenario (Fig. 7a). The planned new urban development area near Jinan's western high-speed railway station was incorporated into this scenario (i.e., the region circled in the urban area of Fig. 7b). The road gravity coefficient was increased from 74 to 85 to highlight the importance of roads. Based on the planned road network in 2020, the cost distance analysis method was applied to calculate accessibility (Zetterberg et al., 2010; Kong et al., 2012). The probability of a given parcel of land not becoming urbanized was assigned to one of five percentage values, i.e., 0%, 5%, 15%, 30%, and 50%, based on the accessibility level from low to high, and then the exclusion/attraction layer for the TOD scenario was built (Fig. 6c).

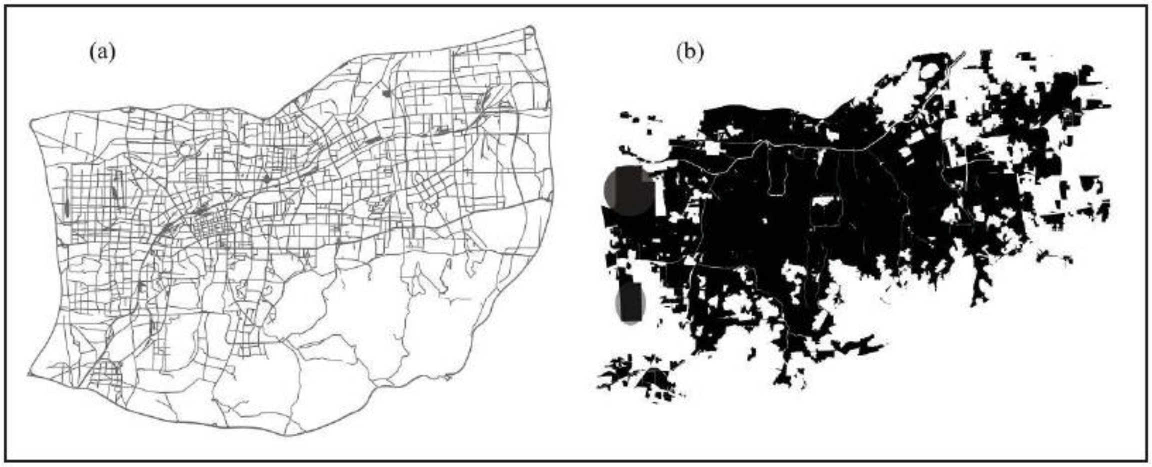


Fig.7. (a) Planned road network in 2020 and (b) urban extent considering the urban planning development zone in 2020

The images of the slope, hillshade, transportation, urban extent, and exclusion/attraction layer for different scenarios were used as the initialization input data of 2010, and 100 Monte Carlo iterations were run in the simulation. The growth of urban built-up land in the study area of the three scenarios from 2011 to 2040 was predicted by using the final year's probability map with a 60% threshold (Table 5, Figs 8 and 9).

Table 5. Predicted statistics on built-up land and other land uses in 2040 for the three scenarios

| Variation in land use type | LESD -2040 in $km^2$ (%) | HTD -2040 in $km^2$ (%) | TOD -2040 in $km^2$ (%) |
|---|---|---|---|
| Urban built-up land | +85.10 (1.11)* | +133.07 (1.62)* | +139.86 (1.68) |
| Green space | -9.59 | -26.99 | -29.26 |
| Agricultural land | -39.74 | -63.01 | -66.28 |
| Water | -1.41 | -1.88 | -2.17 |
| Other | -34.49 | -41.48 | -42.80 |

* The urban growth rate from 2010 to 2040.

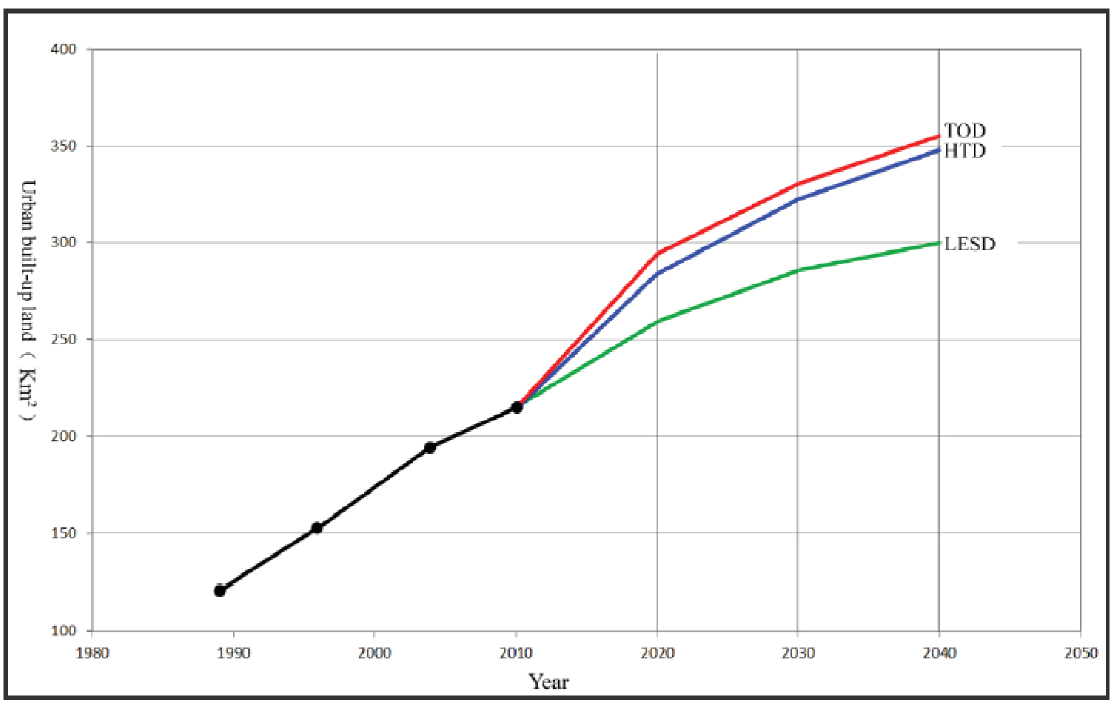


Fig. 8. Growth of urban built-up land in three scenarios: LESD, TOD, and HTD

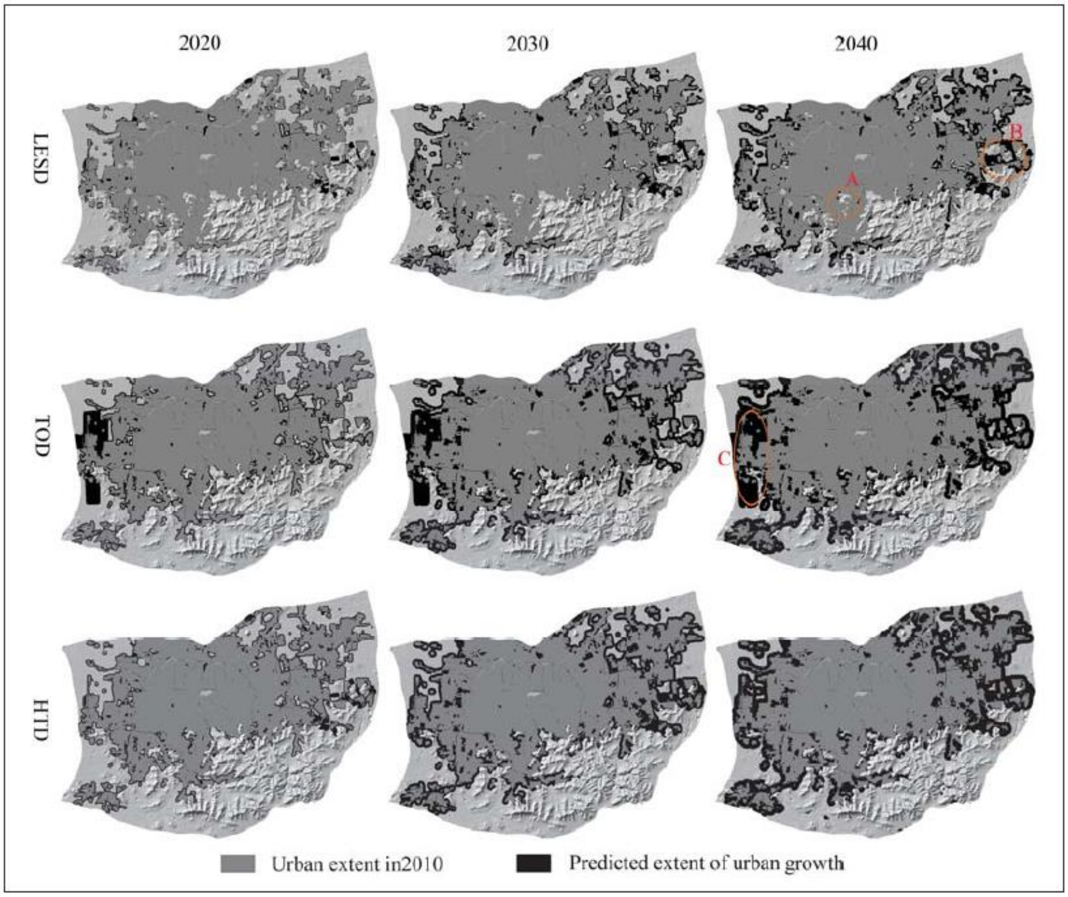

Fig. 9. Simulation of urban expansion based on the SLEUTH model under the LESD, TOD and HTD scenarios

## Results

### Model calibration and simulation accuracy

The parameters of the five metrics at the different calibration stages indicate that the simulation accuracy of the SLEUTH model is satisfactory (Table 1). The model was able to capture the amount of growth, as evidenced by the high value (0.89) for the Compare metric, and was also able to simulate urban form successfully, as evidenced by the high value (0.68) for the Lee-Salee metric (Table 1). However, the results of the spatial accuracy assessment at the pixel scale reveal some of the limitations of the SLEUTH model in simulating local urban growth patterns in 2010 (Table 3). The overall accuracy (i.e., the ratio between correct pixels and the total pixels) and the accuracy of urban pixels (i.e., the ratio between actual urban pixels and the modeled urban pixels) were high (88.54% and 87.54% respectively). However, looking at only those areas where new areas of urbanization developed (about 14.85% of the study area), the accuracy of predicting new urban pixels was low (46.34%). At the pixel scale, simulation errors come in two types: a pixel was urban in 2010 but the simulation result suggested it would be non-urban, or a pixel was non-urban in 2010 but the simulation result suggested it would be urban. Furthermore, the simulation results did not accurately capture the development of Jinan's new eastern city and western high-speed railway areas. This indicates that the model has difficulty in accurately capturing new urban growth centers resulting from urban development policies. This is probably because the current urban area can easily expand outward but a new urban center cannot grow easily (Jantz et al., 2003, 2010; Akın et al., 2014). The failure of the SLEUTH model to capture accurately the exact spatial location of urban growth is not surprising, and accuracy at the pixel scale is not crucial for a regional assessment (Jantz et al., 2003).

At the end of the calibration process, the spread coefficient was the largest (92) of the five coefficients calculated (Table 2). This indicates that urban growth is dominated by urban edge growth. The breed coefficient is 85, indicating a high possibility of a new city center developing. The diffusion coefficient is the smallest (22), which indicates that spontaneous growth is not evident. This all suggests that edge growth is the overwhelming direction for growth in the study area, and that spontaneous growth will be a relatively minor factor (Fig. 9). The road gravity coefficient is also very high (74), which indicates that the road network density has a significant impact on urban growth in the study area. The slope coefficient is 25, indicating that terrain conditions have an inhibitory role on urban growth. In summary, urban expansion in the study area is primarily affected by the spread and road gravity coefficients, and it occurs mainly on the fringe of the city and in areas of the city with high road network density.

**Multi-scenario analysis of urban spatial expansion in Jinan**

According to the simulation results (Table 5 and Fig. 8), in the next 30 years the urban area is predicted to grow quickly in all three scenarios tested. However, the LESD scenario was the one that resulted in the least urban growth. In this scenario, the urbanized area will increase by 85.10 km$^2$ at an annual growth rate of 1.11%. Natural, ecological space such as woodland and agricultural land will be reduced by only 9.59 km$^2$ and 39.74 km$^2$, respectively. In comparison, the TOD scenario resulted in the greatest urban growth: the urbanized area will increase by 139.86 $km^2$ at an annual growth rate of 1.68% and woodland and agricultural land will decrease by 29.26 $km^2$ and 66.28 $km^2$, respectively. The area of urban growth suggested in the HTD scenario, 133.07 $km^2$, an increase of 1.62%, is slightly lower than in the TOD scenario. The rate of and woodland and agricultural land are correspondingly reduced by 26.99 $km^2$ and 63.01 $km^2$. Therefore, the LESD scenario would be the preferred option if the aim is to control the increase of built-up land and avoid the loss of natural, ecological space.

As indicated by the data presented in Fig. 9, urban growth in the three scenarios is primarily dominated by the edge proliferation and interior-filling patterns. The appearance of built-up areas along the urban road network is also significant, whereas its development in the new urban center is not remarkable. In the LESD scenario urbanization is effectively restricted to those areas with low ecological sensitivity. Hence the woodlands and urban green space in the southern mountain region are protected from urbanization. This implies that this scenario is capable of sustaining ecologically friendly urban development in the long term, and protecting both the southern mountain region and urban green spaces. For example, Regions A (the peripheral portion of the scenic area of the Ying Xiongshan Mountains) and B (the peripheral portion of the Feng Huangshan Mountains) (Figs. 9 and 10) are both gradually occupied in the other two scenarios, but the woodlands in these areas are preserved in the LESD scenario. Meanwhile, the increase of built-up land in the southern mountain region is better controlled. Therefore, the incorporation of the urban green space network and ecological sensitivity into the LESD scenario by the exclusion/attraction layer can be seen to have effectively protected the integrity of the green space network and the associated ecosystem services. This protection may offer sufficient green space for future urban development and achieve the integration of smart growth and smart conservation, which accords with sustainable land use.

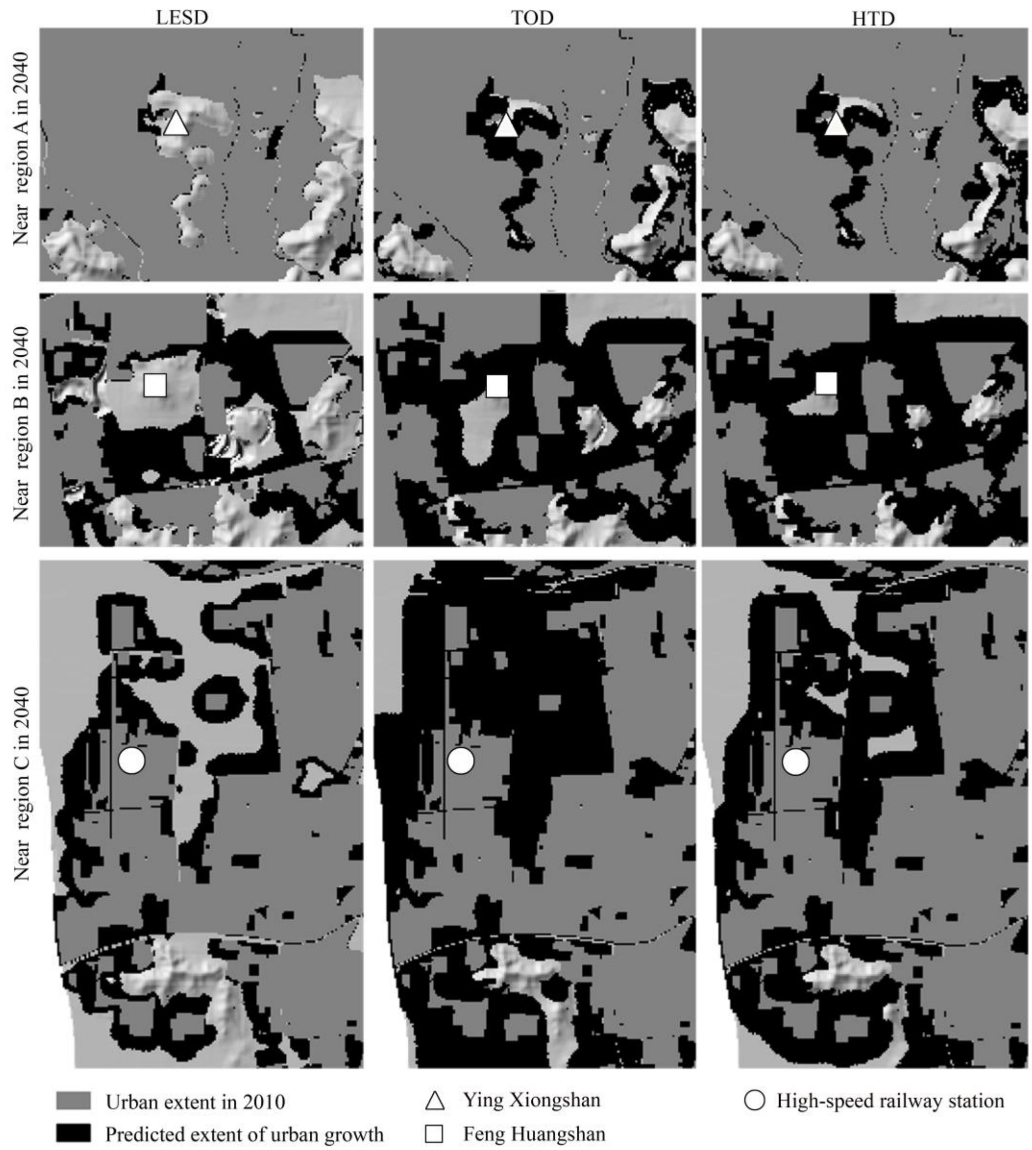


Fig. 10. Specifying the different outcomes of the urban growth under the LESD, TOD and HTD scenarios

Compared to the HTD scenario, the edge proliferation growth pattern of built-up land is controlled in the TOD scenario. New urban areas are concentrated where there is good road accessibility, or in new urban centers. This indicates that highlighting the road gravity coefficient and the transportation accessibility in the exclusion/attraction layer allows the model to capture the highly accessible urban growth areas. Meanwhile, incorporating planned urban development areas into the initial urban extent layer also helps predict the future urban structure and the new city construction pattern in the study area (Region C in Figs. 9 and 10). Basically, the embryonic form of the new city in the study area is emerging in the first five-year plan, and the new city will be completely constructed within the next two or three five-year plans. In this scenario, the plan and expectations of the new city center around the western high-speed railway are reflected more accurately than in the other two scenarios. However, edge proliferation still dominates the simulated growth in this area rather than the development of new urban centers, indicating that it is difficult for the model to capture this feature based on the historical data.

## Discussion

### Landscape ecological security in response to urban growth

Urban areas in China are expanding rapidly, a process which brings significant threats to natural resource use and environmental sustainability. Seeking a smart and sustainable route regarding urbanization is a priority of the Chinese government (China's National Report on Sustainable Development, 2012), as well as of the urban planners. By using the LESD, HTD, and TOD scenarios, urban growth patterns to 2040 were revealed and landscape ecological security was assessed for each scenario.

We found that the HTD and TOD scenarios resulted in rapid urban growth (1.62% and 1.68% per year) with an associated loss of agricultural lands and woodland (90 $km^2$ and 96 $km^2$, respectively) (Table 5, Figs. 8 and 9). Such urban growth threatens the security of the urban ecological space, which is not conducive to realizing a sustainable and healthy city. The LESD scenario, which integrated ecological sensitivity and a green space network, resulted in the smallest urban growth (1.11% per year) (Table 5) and effectively conserved natural, ecological space. The LESD scenario results indicate that the development strategies and the urban green space conservation policies in this scenario will help to sustain ecologically friendly urban development. The results also imply that the SLEUTH model can provide reference data and support decision-making regarding the management of urban land use growth and urban planning, and can effectively protect the natural ecological space as part of sustainable development.

**The model's ability to capture the impact of development policies**

Rapid growth of the new urban center is one of the main features of urban expansion in the study area (Fig. 4). However, none of the three scenarios successfully captured this urban growth pattern well (Fig. 9). This outcome is related, in part, to the priority given to edge growth in the model encoding (Clarke et al., 1997; Jantz et al., 2003) and is most likely also to be due to insufficient usable land resources in the study area (Onsted and Chowdhury, 2014).

In addition to the above reasons, these new urban centers were mainly the result of the urban development policies. Due to non-integration of data on these policies, the SLEUTH model cannot accurately capture the impact of urban development policies on the area of urban expansion or the direction of that expansion. Urban development policies in China, particularly the adjustment of the development direction and the construction of new cities, often result in unexpected and abrupt city development. For example, in this study area, the construction of the new eastern city and western high-speed railway areas in Jinan City converted the urban development direction from eastward only to both eastward and westward (Fig. 7b). Correctly acquiring the conversion rule parameter values from the historical data before and after unexpected development, therefore, becomes important. Urban development policies have zoning characteristics (e.g., the western high-speed railway areas) (Fig. 7b). Some previous studies have recognized that zoning may have implications for the urban expansion simulation (Clarke et al., 1997; Onsted and Chowdhury, 2014). Appropriate use of zoning information incorporated into the model simulation in this study would improve the model's simulation accuracy.

## Conclusion

With the aim of creating ecological security in a typical area that faces resource and ecological constraints, remote sensing data and GIS techniques were employed to integrate an urban green space network and an ecological sensitivity analysis into the exclusion/attraction layers of the SLEUTH model. By comparing three urban growth scenarios (LESD, HTD and TOD) over the next 30 years, it was found that the LESD scenario, which reflects development strategies and urban green space conservation policies, leads to a sustainable and healthy urban development more accurately than the other two. Both the HTD and TOD scenarios result in a loss of green space that is not conducive to realizing a healthy city.

Based on historical data, the SLEUTH model can accurately predict the future growth of urban land use by modifying the prediction parameters or by setting the exclusion/attraction image layers, and it has become a powerful tool for urban planning (Clarke et al., 1997; Clarke and Gaydos, 1998; Silva and Clarke, 2002; Jantz et al., 2003; Rafiee et al., 2009). However, the SLEUTH model currently cannot accurately simulate the potential impact of government policies on urban land use (Clarke et al., 1997). Our study indicated that development strategies and policies can be incorporated into the SLEUTH model by reconstructing the exclusion/attraction layers. Hence, improving the acquisition of data to set the parameters, and the exploration and study of modifications must be the direction for future research efforts in the simulation of urban expansion to integrate urban development policies (or zoning information) into the SLEUTH model, to improve the simulation accuracy of the model, and to increase the model's capability to account for auxiliary planning decisions.

## Acknowledgements

This research was supported by the National Natural Science Foundation of China (No. 51478217, 41440006) and the open fund from the State Key Laboratory of Urban and Regional Ecology (SKLURE).

**References**

Akin, A., Clarke, K. C., Berberoglu, S., 2014. The impact of historical exclusion on the calibration of the SLEUTH urban growth model. International Journal of Applied Earth Observation and Geoinformation, 27: 156-168.

Al-shalabi, M., Billa, L., Pradhan, B., Mansor, S., Al-Sharif, A. A. A., 2012. Modeling urban growth evolution and land-use changes using GIS based cellular automata and SLEUTH models: The case of Sana'a metropolitan city, Yemen. Environmental Earth Sciences, 70: 425-437.

Badwi, I. M., El-Barmelgy, M. M., Ouf, A. S. E. D., 2014. Modeling and Simulation of Greater Cairo Region Urban Dynamics Using SLEUTH. Journal of Urban Planning and Development, 10.1061/(ASCE)UP.1943-5444.0000193 , 04014032.

Barredo, J. I., Kasanko, M., McCormick, N., Lavalle, C., 2003. Modeling dynamic spatial processes: The simulation of urban future scenarios through cellular automata. Landscape and Urban Planning, 64: 145–160.

Berling-Wolff, S., Wu, J., 2004. Modeling urban landscape dynamics: A review. Ecological Research, 19 (1): 119–129.

Burley, J. B., 1989. Habitat suitability models: a tool for designing landscape for wildlife. Landscape Research, 14(3), 23-26.

China's National Report on Sustainable Development, 2012. Available at the following website: http://www.china-un.org/eng/zt/sdreng/

Clarke, K. C., Gaydos, L. J., 1998. Loose-coupling a cellular automaton model and GIS: long-term urban growth prediction for San Francisco and Washington/Baltimore. International Journal of Geographical Information Science, 12: 699-714.

Clarke, K. C., Hoppen, S., Gaydos, L., 1997. A self-modifying cellular automaton model of historical urbanization in the San Francisco Bay area. Environment and Planning B: Planning and Design, 24: 247-261.

Colding, J., 2007. 'Ecological land-use complementation' for building resilience in urban ecosystems. Landscape and Urban Planning, 81(1-2): 46-55.

Cook, E.A., 2000. Ecological networks in urban landscapes. Wageningen University, the Netherlands, ISBN 90-5808-271-7.

Couclelis, H., 1997. From cellular automata to urban models: New principles for model development and implementation. Environment and Planning B, 24: 165-174.

Dabelko, Geoffrey D., and David D. Dabelko, 1995. "Environmental security: issues of conflict and redefinition." Environmental change and security project report 1.1: 3-13.

Dietzel, C., Clarke, K. C., 2007. Toward optimal calibration of the SLEUTH land use change model. Transactions in GIS, 11: 29–45.

Gadgil, M., Daniels, R. R., Ganeshaiah, K. N., Prasad, S. N., Murthy, M. S. R., Jha, C. S., Ramesh, B.R., Subramanian, K. A., 2011. Mapping ecologically sensitive, significant and salient areas of Western Ghats: proposed protocols and methodology. Current Science, 100(2): 175-182.

Hansen, R., Pauleit, S., 2014. From multifunctionality to multiple ecosystem services? A conceptual framework for multifunctionality in green infrastructure planning for urban areas. Ambio, 43(4), 516-529.

Hargrove, W.W., Hoffman, F.M., Efroymson, R.A., 2004. A practical map-analysis tool for detecting potential dispersal corridors. Landscape Ecology, 20: 361-373.

He, C., Okada, N., Zhang, Q., Shi, P., Li, J., 2008. Modeling dynamic urban expansion processes incorporating a potential model with cellular automata. Landscape and Urban Planning, 86: 79–91.

Herold, M., Goldstein, N. C., Clarke, K. C., 2003. The spatiotemporal form of urban growth: measurement, analysis, and modeling. Remote sensing of the Environment, 86: 286-302.

Hodson, M., Marvin, S., 2009. ‘Urban ecological security’: a new urban paradigm?. International Journal of Urban and Regional Research, 33(1): 193-215.

Jantz, C. A., Goetz, S. J., Donato, D., Claggett, P., 2010. Designing and implementing a regional urban modeling system using the SLEUTH cellular urban model. Computers, Environment and Urban Systems, 34(1): 1-16.

Jantz, C. A., Goetz, S. J., Shelley, M. K., 2003. Using the SLEUTH urban growth model to simulate the impacts of future policy scenarios on urban land use in the Baltimore-Washington metropolitan area. Environment and Planning B: Planning and Design, 30: 251-271.

Jinan Statistics Bureau, 2013. Jinan Statistical Yearbook. China Statistics Press, Beijing (in Chinese).

José, I. B., Marjo, K., Niall, M., Carlo, L., 2003. Modeling dynamic spatial processes: The simulation of urban future scenarios through cellular automata. Landscape and Urban Planning, 64: 145-160.

Kong, F. H., Yin, H. W., Nakagoshi, N., Zong, Y. G., 2010. Urban Green Space Network Development for Biodiversity Conservation: Identification Based on Graph Theory and Gravity Modeling. Landscape and Urban Planning, 95: 16-27.

Kong, F., Yin, H., James, P., Hutyra, L. R., He, H. S., 2014. Effects of spatial pattern of greenspace on urban cooling in a large metropolitan area of eastern China. Landscape and Urban Planning, 128: 35-47.

Kong, F., Yin, H., Nakagoshi, N., James, P., 2012. Simulating urban growth processes incorporating a potential model with spatial metrics. Ecological Indicators, 20, 82-91.

Leao, S., Bishop, I., Evans, D., 2004. Simulating urban growth in a developing nation's region using a cellular automata-based model. Journal of Urban Planning and Development, 130: 3(145): 145-158.

Lemp, J., Zhou, B., Kockelman, K., Parmenter, B., 2008. Visioning versus Modeling: Analyzing the Land-Use-Transportation Futures of Urban Regions. Journal of Urban Planning and Development, 134(3): 97-109.

Li, X., Yang, Q. S., Liu, X. P., 2007. CA-based knowledge mining and planning scenario simulation of urban evolution. Science in China (Series D): Earth Science, 37: 1242-1251.

Liang, Y., Liu, L. (2014). Modeling urban growth in the middle basin of the Heihe River, northwest China. Landscape Ecology, 29(10):1725-1739.

Lin, G. C. S., 2004. The Chinese globalizing cities: national centers of globalization and urban transformation. Progress in Planning, 61: 143-157.

Liu, X., Li, X., Shi, X., Wu, S. K., Liu, T., 2008. Simulating complex urban development using kernel-based non-linear cellular automata. Ecological Modelling, 211: 169-181.

Lovell, S. T., Taylor, J. R., 2013. Supplying urban ecosystem services through multifunctional green infrastructure in the United States. Landscape ecology, 28(8), 1447-1463.

Ma, K. M., Fu, B. J., Li, X. Y., Guan, W. B., 2004. The regional pattern for ecological security (RPES): the concept and theoretical basis. Acta Ecologica Sinica. 24 (4): 761-768 (in Chinese).

Ma, L.J.C., 2004. Economic reforms, urban spatial restructuring, and planning in China. Progress in Planning, 61: 237-260.

Mahiny, A. S., Clarke, K. C., 2012. Guiding SLEUTH land-use/land-cover change modeling using multicriteria evaluation: towards dynamic sustainable land-use planning. Environment and Planning-Part B, 39(5): 925.

Mitsova, D., Shuster, W., Wang, X. H., 2011. A cellular automata model of land cover change to integrate urban growth with open space conservation. Landscape and Urban Planning, 99: 141-153.

Myint, S. W., Jain, J., Lukinbeal, C., Lara-Valencia, F., 2010. Simulating urban growth on the US-Mexico border: Nogales, Arizona, and Nogales, Sonora. Canadian Journal of Remote Sensing, 36(3): 166-184.

Onsted, J. A., Chowdhury, R. R., 2014. Does zoning matter? A comparative analysis of landscape change in Redland, Florida using cellular automata. Landscape and Urban Planning, 121: 1-18.

Peiman, R., Clarke, K., 2014. The Impact of Data Time Span on Forecast Accuracy through Calibrating the SLEUTH Urban Growth Model. International Journal of Applied Geospatial Research (IJAGR), 5(3): 21-35.

Pirages, D. C., DeGeest, T. M., 2003. Ecological security: an evolutionary perspective on globalization. Rowman and Littlefield Publishers.

Rafiee, R., Mahiny, A. S., Khorasanic, N., Darvishsefatc, A. A., Danekarc, A., 2009. Simulating urban growth in Mashad City, Iran through the SLEUTH model (UGM). Cities, 26: 19-26.

Rienow, A., Goetzke, R., 2015. Supporting SLEUTH–Enhancing a cellular automaton with support vector machines for urban growth modeling. Computers, Environment and Urban Systems, 49, 66-81.

Rogers, K. S., 1997. Ecological security and multinational corporations. Environmental Change and Security Project Report, 3: 29-36.

Sangawongse, S., Sun, C. H., Tsai, B. W., 2005. Urban growth and land cover change in Chiang Mai and Taipei: results from the SLEUTH model. Proceedings of MODSIM

2005, the International Congress on Modeling and Simulation on Australia and New Zealand, Melbourne, Australia.

Silva, E. A., Ahern, J., Wileden, J., 2008. Strategies for landscape ecology: An application using cellular automata models. Process in Planning, 70: 133-177.

Silva, E. A., Clarke, K. C., 2002. Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal. Computers, Environment and Urban Systems, 26: 525-552.

Sperandelli, D. I., Dupas, F. A., Dias Pons, N. A., 2013. Dynamics of urban sprawl, vacant land, and green spaces on the metropolitan fringe of São Paulo, Brazil. Journal of Urban Planning and Development, 139(4): 274-279.

Statistical Year Book of Jinan, 2012. Beijing: China Statistics Press (in Chinese).

The Yearbook of China's Cities, 2012. Beijing: China Statistics Press (in Chinese).

Torrens, P. M., 2003. SprawlSim: Modeling sprawling urban growth using automata-based models. In: Parker D, Berger T, Manson S, eds. Agent-based models of land-use and land-cover change, Belgium, LUCC International Project Office, 72-79.

Torrens, P. M., O'Sullivan, D., 2001. Cellular automata and urban simulation: where do we go from here? Environment and Planning B: Planning and Design, 28(2): 163-168.

van Vliet, J., Hurkens, J., White, R., van Delden, H., 2012. An activity-based cellular automaton model to simulate land-use dynamics. Environment and Planning-Part B, 39(2): 198.

Vermeiren, K., Van Rompaey, A., Loopmans, M., Serwajjab, E., Mukwayab, P., 2012. Urban growth of Kampala, Uganda: Pattern analysis and scenario development. Landscape and Urban Planning, 106: 199-206.

Wu, X., Hu, Y., He, H. S., Bu, R., Onsted, J., Xi, F., 2009. Performance evaluation of the SLEUTH model in the Shenyang metropolitan area of northeastern China. Environmental modeling and assessment, 14(2): 221-230.

Xiang, W. N., Clarke, K, C., 2003. The use of scenario in land-use planning. Environment and Planning B: Planning and Design, 30: 885-909.

Yang, Q., Li, X., Shi, X., 2008. Cellular automata for simulating land use changes based on support vector machines. Computers and Geosciences, 34: 592–602.

Yang, X., Lo, C. P., 2003. Modeling urban growth and landscape changes in the Atlanta metropolitan area. International Journal of Geographical Information Science, 17: 463-488.

Yeh, A. G., Li, X., 2003. Simulation of development alternatives using neural networks, cellular automata, and GIS for urban planning. Photogrammetric Engineering and Remote Sensing, 69: 1043-1052.

Yu, K. J., 1996. Security patterns and surface model in landscape ecological planning, Landscape and Urban Planning, 36: l-17

Zetterberg, A., Mörtberg, U. M., Balfors, B., 2010. Making graph theory operational for landscape ecological assessments, planning, and design. Landscape and Urban Planning, 95(4), 181-191.