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Extending the SLEUTH model to integrate habitat quality into urban growth simulation

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ABSTRACT

This study aims to support sustainable urban and environmental planning by using urban growth simulation models, in which environmental quality is employed as one of the inputs. We proposed an extended SLEUTH urban growth model (UGM) for the regions threatened by environmental quality degradation caused by uncontrolled urban expansion. In this model, habitat quality is assessed by the InVEST model and is used to represent environmental quality, which is utilized in urban growth simulation. The habitat quality map is used to replace the slope layer as input for the SLEUTH model's urban growth simulation for cities where relatively flat topography makes this layer of minimal explanatory value. The extended SLEUTH UGM was calibrated using data for Changzhou city, China in 1990, 2000, 2010, and 2014. The best value of the Optimal SLEUTH Metric (OSM) was calculated for both the standard SLEUTH UGM and the extended SLEUTH UGM independently. The OSM value for the latter model was much higher than that of the former model, which indicated that the extended model provided a better explanation of urban growth in the study area. The calibrated extended SLEUTH UGM was applied to predict growth in Changzhou city from 2014 to 2030. The result showed that the urban area is expected to expand about 626 km^2 by 2030. Comparison with the prediction result by using standard SLEUTH UGM showed that the area with high habitat quality could be reserved and the urban expansion could be limited by using our model. The findings demonstrate that the extended SLEUTH UGM could be a valuable tool for sustainable urban and environmental planning and management in developing regions where environmental protection should be considered as one of the major land-use objectives in their rapid urbanization process.

1. Introduction

Urban land use change is among the most significant land use change processes that shape the dynamics of the earth's surface and affect the earth's ecosystem services and environmental quality (Grimm et al., 2008; Seto et al., 2012; Ahern, 2013; Wu, 2014). These changes in turn affect the ecosystem's capacity to deliver important services for supporting human well-being. Recent reports suggest that the rapid urbanization which has characterized developing countries results in an unsustainable exploitation of resources such as land and energy (Millennium Ecosystem Assessment, 2005; UNDESA/PD, 2012; Cobbinah et al., 2015) and the generation of different types of pollution (Cui et al., 2015; Yao et al., 2015). The speed and intensity of human disturbance have exceeded the speed of ecosystem recovery, leading to substantial cumulative and even irreversible environmental damage (MA, 2005; Han et al., 2015a), which have threatened regional sustainable development.

As the largest developing country in the world, the eco-environment problem in China is one of the hotly debated topics

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worldwide, which includes fine particulate matter (PM2.5) in urban areas (Han et al., 2015c), the pollution of rivers and groundwater (Qu and Fan, 2010; Yang, 2012; Coulon et al., 2016) and the loss of natural habitats due to urban expansion (He et al., 2014), *etc.* China has undergone a massive change in urban population demographics, going from 17.92% urban population in 1978 (the beginning of the Open-Door policy) to 56.10% in 2015 (NBSC, 2016). In most Chinese cities during the past three decades, much of the farmland surrounding urban areas has been developed, with an urban land mass of $6.0 \times 10^4\,\mathrm{km}^2$ in 2010, representing a 76% change in growth from 1990 to 2010 (Kuang et al., 2016). According to Liu et al. (2015), the spatial expansion of urban and town land consumed 27664.3 ha of farmland in China during 1998–2004, which accounted for 32% of the scale of expanded urban and town land. Important ecological spaces have been greatly reduced (*e.g.*, farmland, waterbodies and forests), as areas including wetlands, forests, and grasslands are gradually being replaced by impervious surfaces. This change has triggered a series of urban environmental problems, including deteriorating water and air quality, urban heat islands, and more (Wu et al., 2014b; Huang et al., 2015). According to Yang (2012), about 40% of China's rivers were seriously polluted as of 2012. Currently, more than 80% of the water from underground wells used by farms, factories and households across the heavily populated plains of China is unfit for drinking or bathing because of contamination (Buckley and Piao, 2016). The estimation from the Chinese Academy of Sciences indicates that the economic loss from environmental pollution and ecological destruction in China accounts for 15% of GDP, while GDP growth is about 7% (He et al., 2018). This indicates that environmental problems may seriously affect sustainable development and economic development achievements in China. It is an urgent task to formulate sustainable urban and environmental plans with the aim of controlling extraordinary urban expansion.

Since 2014, the Chinese government has been promoting a new urbanization strategy to develop human-oriented, efficient, and more sustainable cities (Zeng et al., 2015). Urban development boundaries and ecological redlines have been proposed and stressed in order to restrict uncontrolled urban expansion and protect sensitive ecological environments and natural resources (Xi et al., 2013). In order to set new urban development boundaries and ecological redlines, it is imperative that an understanding of the urban growth process and a consideration of environmental quality is implemented into urban growth simulation. It is also beneficial for sustainable urban and environmental planning in developing regions to implement environment-friendly urban growth prediction. Consequently, we aim to propose an urban growth simulation model, in which environmental quality data can be embedded into urban growth simulation for supporting sustainable land use and environmental planning.

Many land-use change models have been developed to help explain the evolving process of urban growth and to predict the possible future changes of urban extent. However, most of these models still face the challenges of being case-specific and lacking in universality. Some of the land-use change models have performed relatively well on the model's universality, including the SLEUTH model proposed by Clarke et al. (1997). As a bottom-up approach, the SLEUTH model is not dependent on intensive preliminary studies regarding the general causes of urban growth in a study area or the location-specific driving forces (Clarke et al., 1997). The SLEUTH model has been applied in urban growth studies in many countries throughout the world, due to both its relatively simple simulation rules and its ability to capture the complex emergence of urban patterns (Silva and Clarke, 2005; Wu et al., 2008; Chaudhuri and Clarke, 2013). Urban growth scenario simulations are often implemented through adding a weighted excluded layer in the SLEUTH urban growth model (UGM), and possible future urban land use patterns under varying scenarios can be obtained through forecasting (*e.g.* Jantz et al., 2004; Dezhkam et al., 2014; Bihamta et al., 2015; Han et al., 2015b). Furthermore, the SLEUTH model allows policies and plans of urban development to be incorporated through variations in the excluded layer or in the set of model coefficients (*e.g.* Yang and Lo, 2003; Jantz et al., 2004; Dezhkam et al., 2014; Liang and Liu, 2014; Bihamta et al., 2015; Han et al., 2015b; Sakieh et al., 2015). Although the performance of SLEUTH is relatively high, it gives no information about the human and ecological factors affecting the local suitability of urban growth (Rienow and Goetzke, 2015).

To restrict uncontrolled urban expansion and protect environmental quality, it would be instructive to link the SLEUTH UGM with environmental quality data in urban growth simulation. Habitat quality map can be a choice for representing environmental quality. It has been widely used to describe the ability of the ecosystem to provide conditions appropriate for individual and population persistence, which depends on a habitat's proximity to human land uses and the intensity of these land uses (Nellemann et al., 2001; McKinney, 2002; Forman, 2003). The habitat quality module of the InVEST model (Integrated Valuation of Ecosystem Services and Tradeoffs; Tallis et al., 2011) was used to map habitat quality in this study. InVEST can analyze the impact of land use and land management on species habitat provision and quality and generate spatially explicit predictions of the biophysical supply of ecosystem services (Nelson et al., 2008; Bai et al., 2011; Baral et al., 2014; Terrado et al., 2015). It has been used in evaluating the impact of land-use change on ecosystem services, biodiversity, and habitat quality (*e.g.* Nelson et al., 2009; Goldstein et al., 2012; Polasky et al., 2011; Sánchez-Canales et al., 2012; Leh et al., 2013; Wu, 2012; Wu et al., 2014a), which is helpful for sustainable resources and environmental management and land-use planning. By evaluating the output from InVEST, modelers can provide information useful to managers and policy-makers weighing the tradeoffs in environmental protection and other land-use objectives.

Previous work has led us to the principal objective of this research: to employ environmental quality data into the SLEUTH urban growth model for supporting sustainable urban and environmental planning in developing regions threatened by environmental quality degradation caused by uncontrolled urban expansion. We extend the SLEUTH UGM by replacing one of its input layers - the slope layer - with an environmental quality map derived from the habitat quality module of the InVEST model. A pilot application was then implemented for the urban growth simulation in Changzhou City, China, which is characterized by rapid urbanization. This was possible because the study area is relatively flat with local slope mostly ranging from 0 to 3°, so slope is not a determinant of urban growth. The remainder of this paper is structured as follows: following the Introduction, section 2 describes our study area as well as the compilation of the various input data sets. We also detail the extended SLEUTH UGM and its calibration in section 2. Section 3 presents the validation of the extended SLEUTH UGM. An application of the model to urban growth prediction in Changzhou city during 2014–2030 was conducted and the results analyzed. In section 4, we discuss the applicability and contribution of the extended SLEUTH UGM. Finally, section 5 provides a short conclusion.

2. Study area and methods

2.1. Study area

Changzhou (31°09′ N-32°04′ N, 119°08′ E-120°12′ E) is located in eastern China in the southern part of Jiangsu Province and is one of the pilot regions for China's new urbanization strategy. Changzhou neighbors Shanghai, Nanjing and Hangzhou; together with Suzhou and Wuxi, form the Su-xi-chang Megaregion. It is one of the most rapidly expanding, newly urbanized areas in the Yangtze River Delta. As of 2014, Changzhou's total population was about 4.7 million (the urban population was 3.2 million, accounting for about 69% of all people). The population density was 1075 people/km^2, much higher than the countrywide average in the same period (143 people/km^2) (NBSC, 2015; CSB, 2015). In 2014, Changzhou's gross domestic product (GDP) per capita was RMB 104,423, which was much higher than the national average of RMB 46,531 (NBSC, 2015; CSB, 2015).

The study area is the core area of urban development in Changzhou (Fig. 1), composed of five municipal districts (Wujin, Xinbei, Tianning, Zhonglou, and Qishuyan), with a total of 58 townships and a total area of 4372 km^2 (the urban area comprises approximately 1862 km^2, accounting for 43% of the overall sector). Urban land increased from 130 km^2 in 1990 to about 680 km^2 in 2014 with an annual growth rate of about 7%. Nevertheless, while industrialization, urbanization, and modernization have accelerated in Changzhou, the city is also facing a series of obstacles related to decreasing environmental quality. These difficulties include conflicts between urban growth and the protection of farmland surrounding the urban area, the supply and demand of land, the low efficiency of conservation, intensification of land use and emerging environmental problems. These impediments have negatively affected Changzhou's sustainable development.

Land use and land cover (LULC) maps were obtained by the classification of multi-temporal remote sensing data including Landsat 5 thematic mapper (TM) images in 1990 and 2010, Landsat 7 enhanced thematic mapper plus (ETM+) images in 2000, and Landsat 8 operational land imager (OLI) images in 2014. Vector land use data (1:50,000) for 2010 and 2014, and vector land use data (1:100000) for 1990 of the study area, were used to verify the remote sensing image classification accuracy, collected from the Changzhou Land Resources Bureau. Following verification using land use survey data, the land-use classification accuracy in 1990 and 2000 was 81.7% and 83.6%, respectively. Thus, the comparisons demonstrate that these LULC maps can be effectively used as input to the SLEUTH model. The accuracy compares well as the typical overall accuracy of LULC classification is 80%–90% for cellular automata land use change modeling (Grinblat et al., 2016). Road maps for 1990, 2002, 2008, and 2012 were collected from the Changzhou Land Resources Bureau. Road layers in 1990, 2000, 2010 and 2014 were obtained by revising road maps in 1990, 2002, 2008, and 2012 with remote sensing data. The GDP and population data (raster size: 1000 m × 1000 m) were provided by the Data Center for Resources and Environmental Sciences, of the Chinese Academy of Sciences (RESDC) (http://www.resdc.cn).

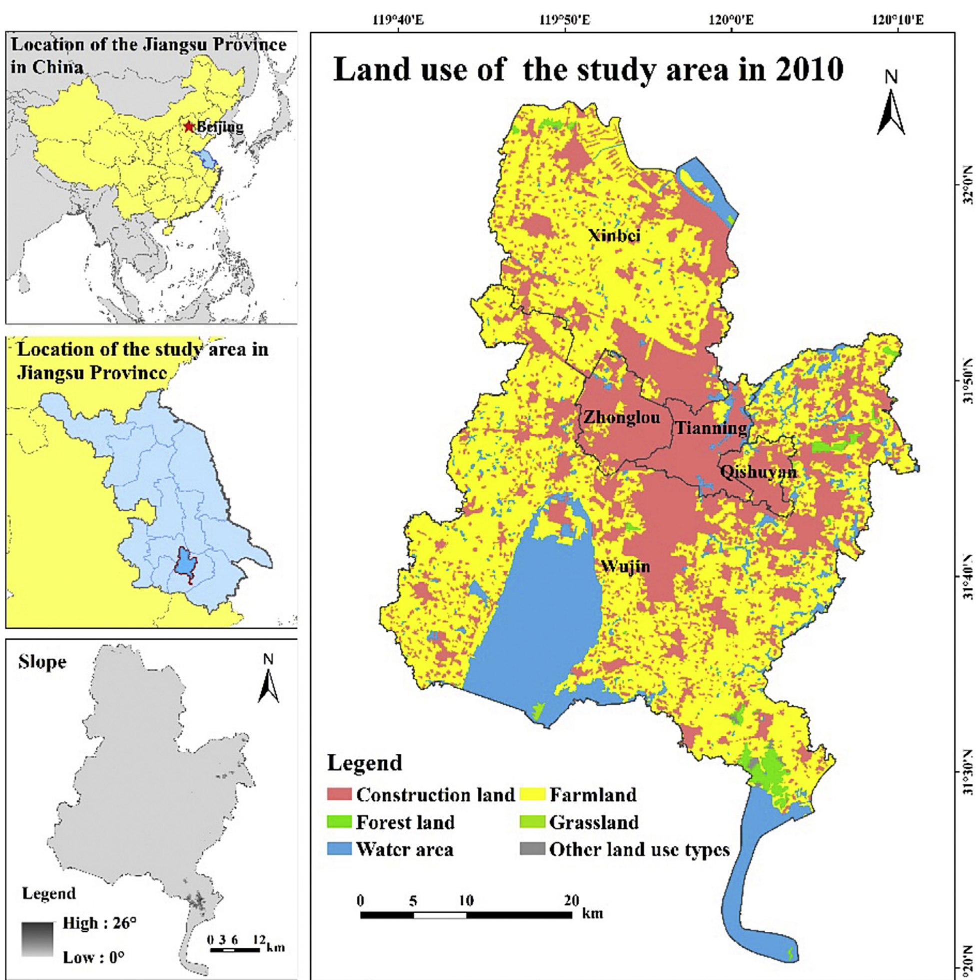

Fig. 1. Location of the study area.

2.2. Habitat quality mapping by using the InVEST model

In the habitat quality module of the InVEST model, habitat quality for each grid cell is defined as a function of the LULC within the grid cell, the LULC in surrounding grid cells, and the sensitivity of the habitat in the grid cell to the threats posed by the surrounding LULC. Data requirements for habitat quality evaluation in the InVEST model include a current LULC map, threat layers, habitat types and the sensitivity of habitat to each threat.

Human activity factors that cause habitat fragmentation and degradation are considered as threats which include population, GDP, built-up land and roads (Table 1) (see Chiang et al. (2014), Chen et al. (2016) and He et al. (2017)). Although other factors, such as biophysical factors, may act as degradation sources, we consider only those that focus on the impact of human activities on habitat quality. GDP and population data were obtained from RESDC. The built-up land layers were extracted from the corresponding LULC maps. The parameters of maximum distance of influence were set using the InVEST settings outlined in the InVEST user's guide and the existing studies, and a linear distance-decay function was chosen to describe how a threat decays over space (Table 1). Foresman (2001) found that distance at which major roads impacted wetlands in Montana varied between 8.18 km and 12.77 km. Chiang et al. (2014) and Chen et al. (2016) whose study areas were in Taiwan and Beijing set a maximum impact distance of roads on habitats as 2.0 km and 3.0 km respectively. Given these studies, we set the maximum impact distance of major roads as 2.0 km with consideration given to road width, carrying capability, and the total area of the study site. In a similar vein, the impact distance of built-up land on habitat quality was set as 5.0 km in Chiang et al. (2014) and the maximum impact distance of urban and rural residential land on habitat quality is set at 5.0 km and 10.0 km respectively in Chen et al. (2016). Burke and Selig (2002) found that distance at which towns impacted reefs in Southeast Asia ranged between 5.0 km and 10.0 km when the population was between 50,000 and 100,000. The maximum impact distances of population and built-up land on habitat quality in our study is set at 6.0 km and 5.0 km respectively according to the population and built-up land distribution in the study area which is similar to Chen et al. (2016), Chiang et al. (2014), and Burke and Selig (2002). It is assumed that the more sensitive a habitat type is to a threat, the more degraded the habitat type will be by that threat. Sensitivity scores were determined based upon empirical values outlined in the InVEST user guide (Tallis et al., 2011) and expert knowledge (Table 2).

Table 1
The threats factors and related coefficients.

Threat factor	d_{r_max} (*km*)	Weight w_r	Distance-decay function
population	6.0	0.28	Linear distance-decay
GDP	7.0	0.31	Linear distance-decay
built-up land	5.0	0.24	Linear distance-decay
roads	2.0	0.17	Linear distance-decay

The total threat level in grid cell x with LULC or habitat type j is given by D_{xj}, in Equation (1), which is used for the habitat quality calculation.

$$D_{xj} = \sum_{r=1}^{R} \sum_{y=1}^{Y_r} w_r r_y i_{rxy} S_{jr} \tag{1}$$

where, R is the number of threat factors, y indexes all grid cells on r's raster map and Y_r indicates the set of grid cells on r's raster map, w_r is the normalized influencing weight of a threat factor, i_{rxy} indicates the impact of threat r that originates in grid cell y on habitat in grid cell x represented by linear or exponential distance-decay function, $s_{jr} \in [0,1]$ indicates the relative sensitivity of LULC (habitat type) j to threat factor r where values closer to 1 indicate greater sensitivity. In this study, i_{rxy} is represented by a linear distance-decay function shown in Equation (2).

$$i_{rxy} = \begin{Bmatrix} 1 - \left(\dfrac{d_{xy}}{d_{r\_max}}\right) & d_{xy} < d_{r\_max} \\ 0, otherwise & \end{Bmatrix} \tag{2}$$

where, d_{xy} indicates the distance between pixel x and pixel y; and d_{r_max} is the maximum impact distance of threat r originated in pixel y.

Then, the habitat quality value is calculated using a half saturation function (Equation (3)).

$$Q_{xj} = \frac{H_j}{\left(\left(D_{xj}/K\right)^z + 1\right)} \tag{3}$$

where, Q_{xj} is the habitat quality of grid cell x in land type j; $H_j \in [0,1]$ represents the habitat suitability of the *jth* land type which is simplified to represent the suitability level of the *jth* land type for maintaining environmental quality in this study, where 1 indicates the highest habitat suitability; z is the scaling parameter which is normally set as 2.5; and k is the half-saturation constant, which is often set as half of the highest grid cell degradation value in the study area. To find the highest degradation value, the model needs to be run once and k is set. The habitat suitability score ranging from 0 to 1 for each land type in our study area was set according to the capability of each land-use type for maintaining habitat quality and expert knowledge, shown in Table 2.

The habitat quality maps of Changzhou city in 1990, 2000, 2010 and 2014 were obtained by using the habitat quality module in the InVEST model (Fig. 2a–d). The results indicated that the habitat quality was high around the waterbodies and the forest land. However, the habitat quality was relatively low around the existing built-up land and along the major roads. An integrated habitat quality map was obtained by averaging the multi-temporal habitat quality maps (Fig. 2e). The integrated habitat quality map showed the similar spatial distribution trend according to the analysis on the habitat quality histograms and distributions of the four habitat

Table 2
Land types and sensitivity of each land type to threats.

	Land-use type	Habitat suitability score	Sensitivity to threats			
			Population	GDP	Built-up land	Roads
1	farmland	0.4	0.6	0.7	0.5	0.2
2	forest	0.8	0.7	0.8	0.6	0.4
3	grass	0.6	0.7	0.8	0.6	0.3
4	water	0.9	0.9	0.9	0.9	0.6
5	built-up land	0.0	0.0	0.0	0.0	0.0
6	others	0.0	0.0	0.0	0.0	0.0

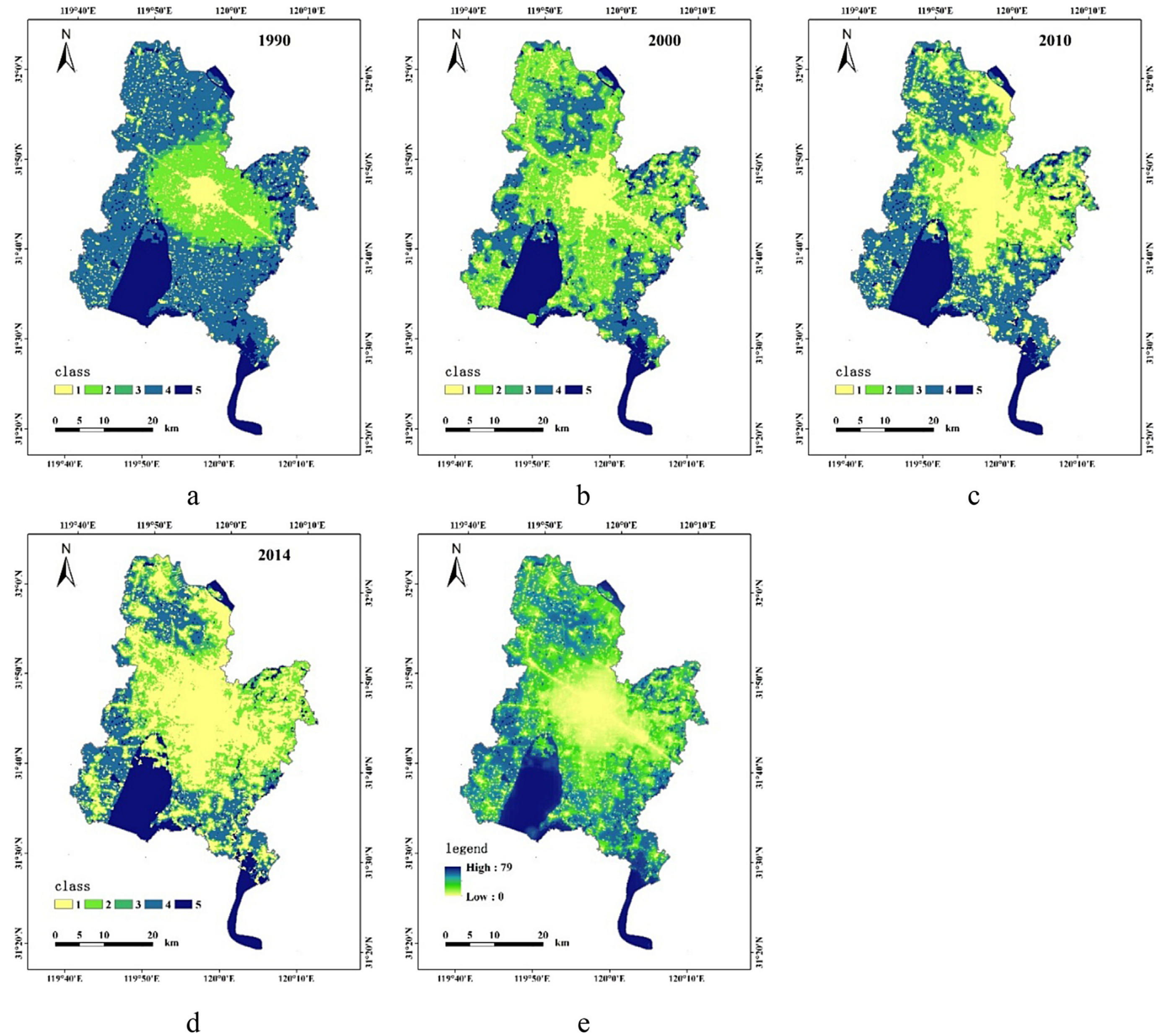

Fig. 2. Habitat quality maps of Changzhou city (class 5 is highest), Fig. 2a–d were the habitat quality maps in 1990, 2000, 2010 and 2014 respectively; Fig. 2 e was the integrated habitat quality map.

quality maps except of that of 1990. Last, the integrated habitat quality map was used as a replacement of the slope layer in the calibration of the extended SLEUTH UGM in the study area during the simulation period.

2.3. Data processing for SLEUTH model and the extended SLEUTH model

The data requirements for the SLEUTH UGM include one layer of slope percentage, at least one excluded layer, two (or more) layers of the transportation network for different time periods, and four or more layers of urban extents that provide changes in urban areas. In this study, four layers of the urban extents of Changzhou city were obtained by extracting the urban land information from the corresponding LULC maps, the excluded layer was created by extracting water bodies and core ecological protection areas that are strictly protected from development. Other input layers included road maps for 1990, 2000, 2010 and 2014, the slope and hillshade layers generated from DEM data (ASTER GDEM, 30 m) (Fig. 3).

In the extended SLEUTH UGM, the slope layer was replaced by the habitat quality layer for our study case (Fig. 3). Similar to the slope value, a higher habitat quality value, which ranges from 0 to 100, means that the land pixel is more suitable for protection rather than development. Accordingly, the coefficients related to slope were adjusted to ecology-related coefficients which included the ecology resistance (replacing the slope resistance), the ecology sensitivity (replacing slope sensitivity), and the critical ecology (replacing critical slope). The ecology resistance ranges from 0 to 100, which is self-modifying during the calibration processes. The

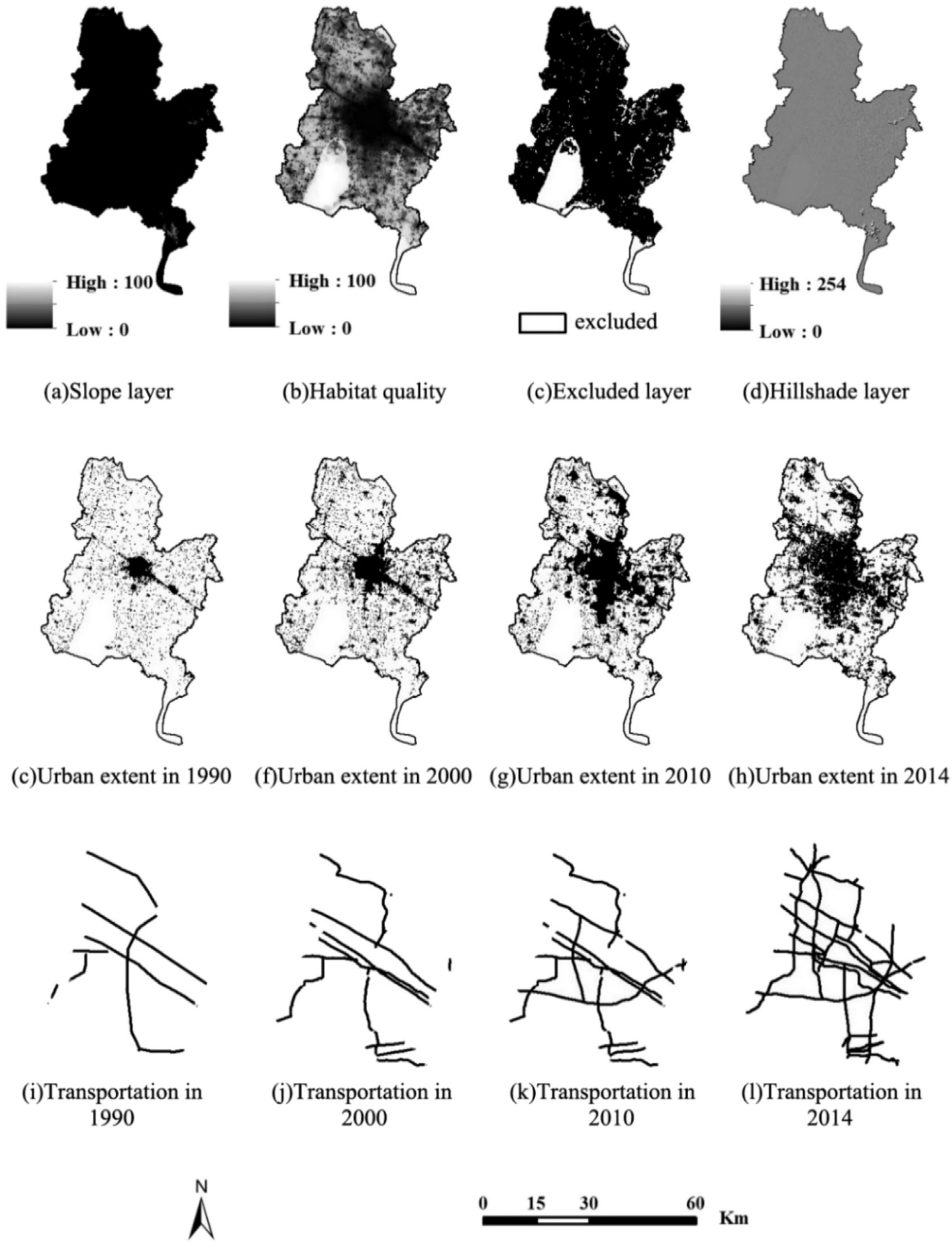

Fig. 3. The input data of SLEUTH UGM and the extended SLEUTH UGM.

ecology sensitivity is set as 0.1 which is similar to the slope sensitivity. As slope restricts urban development, the threshold slope value which is defined as the critical slope is 21 for the application of SLEUTH UGM to the plain areas in China according to *the Code for Vertical Planning on Urban Field (CJJ 83-99)* in China (Liu, 2011). The critical ecology value was set through a trial and error process. That is, an initial value of 0 was chosen and then subsequently incremented by 5 and resolved. The value that gave the best model fit was then selected as the parameter value. Finally, it was set as 60, which is nearly the median value of the habitat quality value of ecological protection area.

2.4. The models' calibration

There are three calibration processes included in the calibration of SLEUTH UGM: coarse calibration, fine calibration, and final calibration. The brute force calibration method was used in the three calibration processes of SLEUTH UGM, which sequentially narrows down the range of SLEUTH behavior parameter values, leaving the set which best replicates the historical data (Chaudhuri and Clarke, 2013). For each calibration, SLEUTH yields 13 metrics of goodness of fit of the simulated pattern with past known data. A subset of seven metrics (compare, population, edges, clusters, slope, X -mean, and Y-mean —Table 3) was used for deciding on the best performing iterations, which are multiplied together to calculate the Optimal SLEUTH Metric (OSM) (Dietzel and Clarke, 2007). The SLEUTH UGM and the extended SLEUTH UGM were calibrated separately. For our calibration analysis, we utilized the OSM value for the standard SLEUTH UGM (Equation (4)) and an extended OSM for our extended SLEUTH UGM (Equation (5)) to evaluate the goodness of fit with past data.

$$OSM = compare \times pop \times edges \times clusters \times slope \times Xmean \times Ymean \quad (4)$$

$$extended\ OSM = compare \times pop \times edges \times clusters \times ecology \times Xmean \times Ymean \quad (5)$$

3. Results analysis

3.1. Analysis on the calibration results

The calibration results showed that a high OSM was obtained by using the extended SLEUTH UGM (Fig. 4, Tables 4 and 5). The OSM values for coarse calibration, fine calibration and final calibration of the extended SLEUTH UGM were 0.7843, 0.8691, and 0.9082 respectively, showing an increasing trend (Fig. 4). They were higher than those obtained in other related studies. The OSM obtained by the extended SLEUTH model (0.9082) was 34.31% higher than that of SLEUTH model (0.6762) after the final calibration. For the parameters for calculating OSM of the extended SLEUTH model (shown in Fig. 6), compared to those in the standard SLEUTH UGM, *Compare* and *Pop* increased 16% and 2% respectively, which represent the precision of the simulated urbanization area; X_{mean} increased 2% and Y_{mean} remained at the same level depicting the precision of the simulated urbanized cells' location; *Clusters* and *Edges* increased 1% and 6% respectively, which represent the clustering and shape of simulated urban land. These results show that the extended model performs well in the fitting of urbanization area, location, clustering and shape.

Furthermore, major urban growth types can be interpreted by the analysis on the coefficients of SLEUTH UGM. In SLEUTH UGM, there are five growth coefficients that control the behavior of the four urban growth types: diffusion (that controls the overall dispersive nature of the distribution); breed (that determines the likelihood that an urbanized cell will start its own growth cycle); spread (that controls how much outward 'organic growth' expansion and infill take place within the system); slope resistance (that influences the likelihood that a cell will be urbanized on a steep slope); and road gravity (a factor that encourages growth along the road network) (Clarke et al., 1997). These urban growth types include spontaneous (growth in suitable locations for urbanization at any location randomly), diffusive (new spreading center), organic (growth in infill and edge areas) and road influenced growth (growth along the transportation network).

According to the optimal control coefficients shown in Fig. 5, new spreading center growth and in-fill and edge growth were indicated as the major urban growth types for the study area when simulating urban growth with the standard SLEUTH UGM. The breed coefficient decreased, and the road gravity coefficient increased when using the extended SLEUTH UGM. Thus, the main urban growth types were shown as in-fill and edge growth and road influenced growth, which could depict the actual urban growth better in the simulation period. Moreover, in the standard SLEUTH UGM, the slope resistance coefficient was low, which indicated that the slope was not the main obstructive factor to urban growth in the study area. In the extended SLEUTH UGM, the ecology resistance coefficient was comparatively high, which

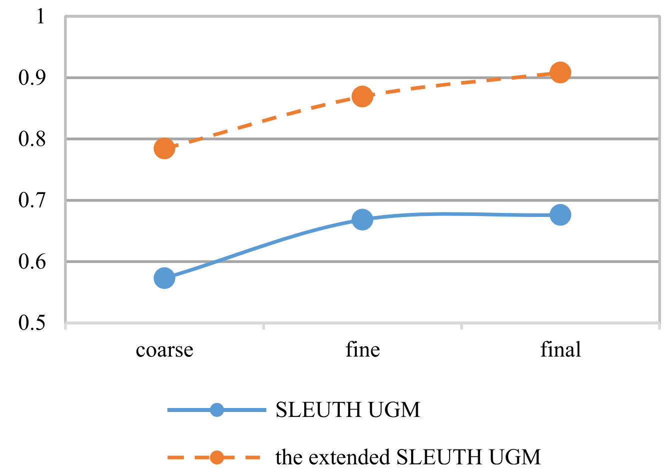

Fig. 4. OSM of three rounds calibrations.

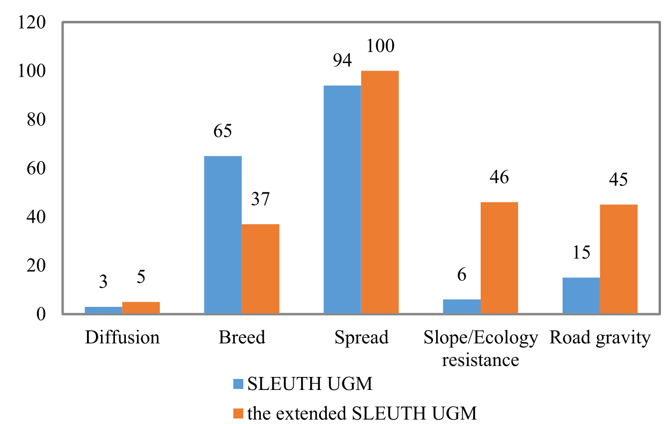

Fig. 5. Optimal control coefficients.

Table 3
OSM used to evaluate goodness of fit in SLEUTH or extended SLEUTH.

Name	Description
Compare	Modeled population for final year/actual population for final year, or IF *P*modeled > *P*actual {1 − (modeled population for final year/ actual population for final year)}
Pop	Least-squares regression score for modeled urbanization compared to actual urbanization for the control years
Edges	Least-squares regression score for modeled urban edge count compared to actual urban edge count for the control years
Clusters	Least-squares regression score for modeled urban clustering compared to known urban clustering for the control years
X_{mean}	Least-squares regression of average x_values for modeled urbanized cells compared to average x_values of known urban cells for the control years
Y_{mean}	Least-squares regression of average y_values for modeled urbanized cells compared to average y_values of known urban cells for the control years
Slope/ Ecology	Least-squares regression of average slope (habitat quality) for modeled urbanized cells compared to average slope (habitat quality) of known urban cells for the control years

Note: As excerpted from Dietzel and Clarke (2007).

Table 4
Calibration coefficients for SLEUTH UGM for our study area.

		Coarse		Fine		Final		Best fit
		Monte Carlo iterations = 4 Total # of simulation = 3125 OSM = 0.5729		Monte Carlo iterations = 7 Total # of simulation = 3750 OSM = 0.6683		Monte Carlo iterations = 8 Total # of simulation = 6480 OSM = 0.6762		
		range	step	range	step	range	step	
Coefficients of growth	Dispersion	0–100	25	0–20	5	3–8	1	3
	Breed	0–100	25	50–75	5	50–70	5	65
	Spread	0–100	25	80–100	5	85–100	3	94
	Slope resistance	0–100	25	0–20	5	0–15	3	6
	Road gravity	0–100	25	0–100	25	0–25	5	15
Self-modification parameters	Road sensitivity	0.01		0.01		0.01		
	Slope sensitivity	0.10		0.10		0.10		
	Critical low	0.97		0.97		0.97		
	Critical high	1.30		1.30		1.30		
	Critical slope	21		21		21		
	Boom	1.01		1.01		1.01		
	Bust	0.09		0.09		0.09		

Table 5
Calibration coefficients for the extended SLEUTH UGM for our study area.

		Coarse		Fine		Final		Best fit
		Monte Carlo iterations = 4 Total # of simulation = 3125 OSM = 0.7843		Monte Carlo iterations = 7 Total # of simulation = 4500 OSM = 0.8691		Monte Carlo iterations = 8 Total # of simulation = 5400 OSM = 0.9082		
		range	step	range	step	range	step	
Coefficients of growth	Dispersion	0–100	25	0–20	5	1–5	1	5
	Breed	0–100	25	25–50	5	25–40	3	37
	Spread	0–100	25	80–100	5	90–100	2	100
	Ecology resistance	0–100	25	40–60	5	45–50	1	46
	Road gravity	0–100	25	0–50	10	30–50	5	45
Self-modification parameters	Road sensitivity	0.01		0.01		0.01		
	Ecology sensitivity	0.10		0.10		0.10		
	Critical low	0.97		0.97		0.97		
	Critical high	1.30		1.30		1.30		
	Critical ecology	60		60		60		
	Boom	1.01		1.01		1.01		
	Bust	0.09		0.09		0.09		

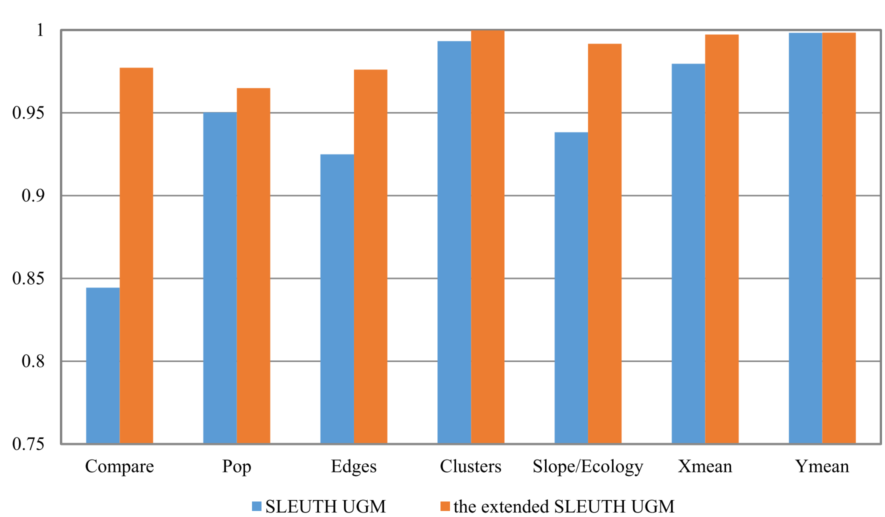

Fig. 6. Calibrated metrics in final calibration of SLEUTH model and the extended SLEUTH model.

showed that the habitat quality had restricted the urban growth of Changzhou city to a certain extent.

3.2. Validation of the extended SLEUTH urban growth model

To further verify the simulation power of the extended SLEUTH UGM, urban growth in Changzhou city was hindcast through the prediction module of the SLEUTH model. The required input layers of 1990 and the best fit coefficients (Table 5) were used as the inputs and the growth coefficients. The extended SLEUTH model was then run to predict urban growth in Changzhou city from 1990 to 2014. The simulated urban extents in 2000, 2010 and 2014 were overlaid with the actual urban extents for validation.

The total number of urban land pixels, Moran's I index and spatial fit degree were used to compare the simulation results and the actual urban growth in Changzhou city. The total number of urban land pixels reflects the overall scale of urban land. Moran's I index reflects the overall pattern of urban land. The spatial overall fit degree reflects the simulation accuracy of the overall urban scale and spatial patterns (Equation (6)), and the degree of spatial variation fit reflects the simulation accuracy of the urban land scale and patterns at different stages based on the urban land map in 1990 (Equation (7)) (Wang, 2012).

$$D = 1 - \frac{N(S_m \cup S_0 - S_m \cap S_0)}{N(S_m \cup S_0)} \tag{6}$$

$$D_{\Delta} = \frac{N(\Delta S_m \cap \Delta S_0)}{N(\Delta S_m \cup \Delta S_0)} \tag{7}$$

where, D is the spatial overall fit degree, S_m is the simulated urban land pixels, S_0 is the actual urban land pixels, $N(S_m \cup S_0)$ is the total number of the union of the simulated urban land pixels and the actual urban land pixels, $N(S_m \cap S_0)$ is the number of the interaction of the simulated urban land pixels and the actual urban land pixels, $N(S_m \cup S_0 - S_m \cap S_0)$ is the number of disagreement pixels between the simulated and actual urban lands. D_{Δ} is the spatial variation fit degree, ΔS_m is the simulated land pixels converted to urban land during a simulation period, ΔS_0 is the actual land pixels converted to urban land during a simulation period, $N(\Delta S_m \cap \Delta S_0)$ is the number of the intersection of ΔS_m and ΔS_0, and $N(\Delta S_m \cup \Delta S_0)$ is the total number of the union of ΔS_m and ΔS_0.

As shown in Figs. 7 and 8, the simulation results of the extended SLEUTH model were much closer to the actual urban growth in terms of urban scale and spatial pattern. The results indicated that the simulation power has been improved to a certain extent after

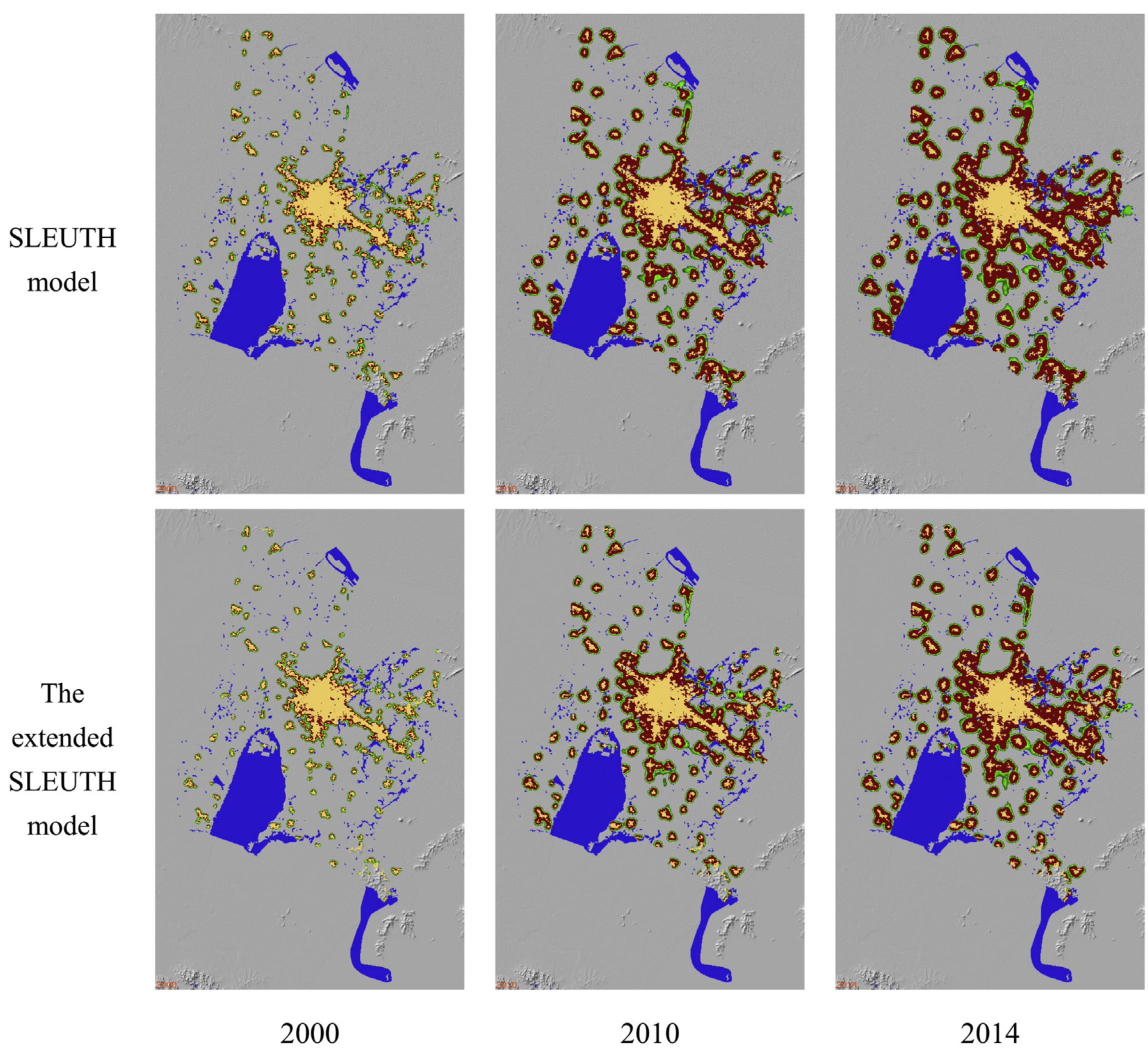

Fig. 7. Hindcasting results of SLEUTH UGM and the extended SLEUTH UGM (2000, 2010 and 2014). Tan is urban in 1990, red is 90–100% probability, and light to dark green is 50–89% probability. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

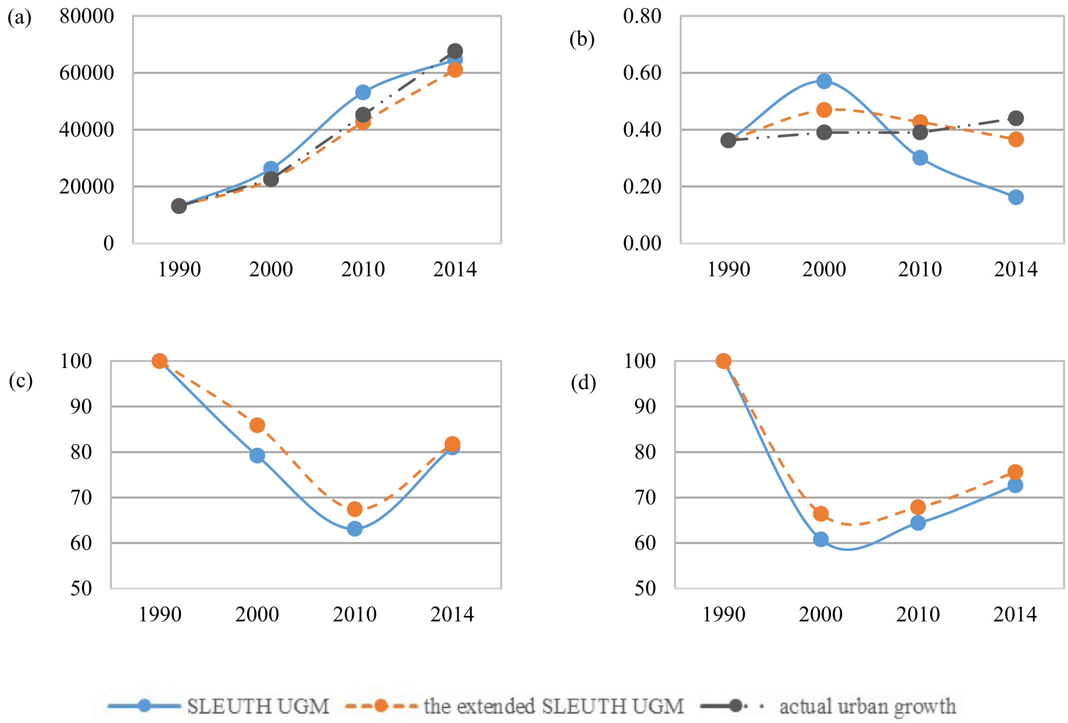

Fig. 8. (a) The total number of urban land pixels; (b) Moran's *I* index; (c) Spatial overall fit degree; (d) Spatial variation fit degree.

the SLEUTH urban growth model was extended. First, the total numbers of the simulated urban land pixels both increased for SLEUTH UGM and the extended SLEUTH UGM. Compared to the SLEUTH UGM, the simulated urban growth area by the extended SLEUTH UGM were closer to the actual urban growth area in the study area during the period from 1990 to 2010. The simulated urban areas of both models are less than, but still close to the actual urban area in 2014 in the study area (Figs. 7 and 8a). Second, the Moran's *I* index of actual urban land distribution increased during 1990–2014, which indicated that urban land tended to aggregate in space. Comparatively, the Moran's *I* indices of simulated urban land distribution by both models decreased after increasing during 1990–2014, and the simulation result by the extended SLEUTH tended to be relatively stable (Fig. 8b). The possible reason could be that edge growth is the most significant growth type during the early stage of hindcasting, whereas other growth types became more obvious during the later stage of hindcasting. The new towns emerged as new urban growth centers, and the simulated urban land scattered in space during the simulation period. In the meanwhile, the simulated new urban pixels by using the extended SLEUTH UGM showed scattering at a relatively lower degree due to employing the constraint of habitat quality. Third, the values of spatial overall fit degree and spatial variation fit degree showed a tendency of increasing after decreasing as shown in Fig. 8c and d. Both indices for the simulation result using the extended SLEUTH UGM were higher than those of SLEUTH UGM. This indicated that it has given a better explanation on urban patterns by using the extended SLEUTH UGM than by the standard model for the study area. This is probably because the environmental constraints provided more spatially explicit information to train the SLEUTH model, and so better captured the urban dynamics. However, as shown in Fig. 7, the hindcasting results showed disagreement between the actual urban growth and the simulation results in some areas, such as the north of urban center, which may be caused by the complexity and flexibility of human activities and urban development policies.

3.3. Urban growth prediction experiment

The calibrated SLEUTH UGM and the calibrated extended SLEUTH UGM were applied to predict urban growth in Changzhou from 2014 to 2030. The excluded layer was consistent with that used in the calibration process. We represented the study area using pixels with a resolution of 100 m. We set the model parameter values by using the parameters derived from the predict module of the SLEUTH model after final calibration.

The prediction results show that during the period from 2014 to 2030, the predicted urban growth area using the extended SLEUTH UGM is 626 km^2, while the predicted urban growth area using standard SLEUTH UGM is 680 km^2. The results indicate that the involvement of habitat quality in the extended SLEUTH UGM contributes to limiting the urban growth to a certain extent. Furthermore, by overlapping the urban growth prediction results by using the two models (Fig. 9), it shows that the proportion of disagreement pixels is about 9%, which is mainly distributed in the northwest, southeast and southwest of the study area where the habitat quality value is relatively high. This indicates that environmental quality constraint can be considered in urban growth simulation by using the extended SLEUTH UGM. The extended SLEUTH UGM would be a better choice than the standard SLEUTH UGM when environmental protection in the study area is one of the priorities.

4. Discussion

4.1. Employing a habitat quality map is helpful for improving simulation power of the extended SLEUTH urban growth model

In this study, we proposed an extended SLEUTH UGM by employing habitat quality map. The results of the model as applied to Changzhou City show that the new model improves the SLEUTH

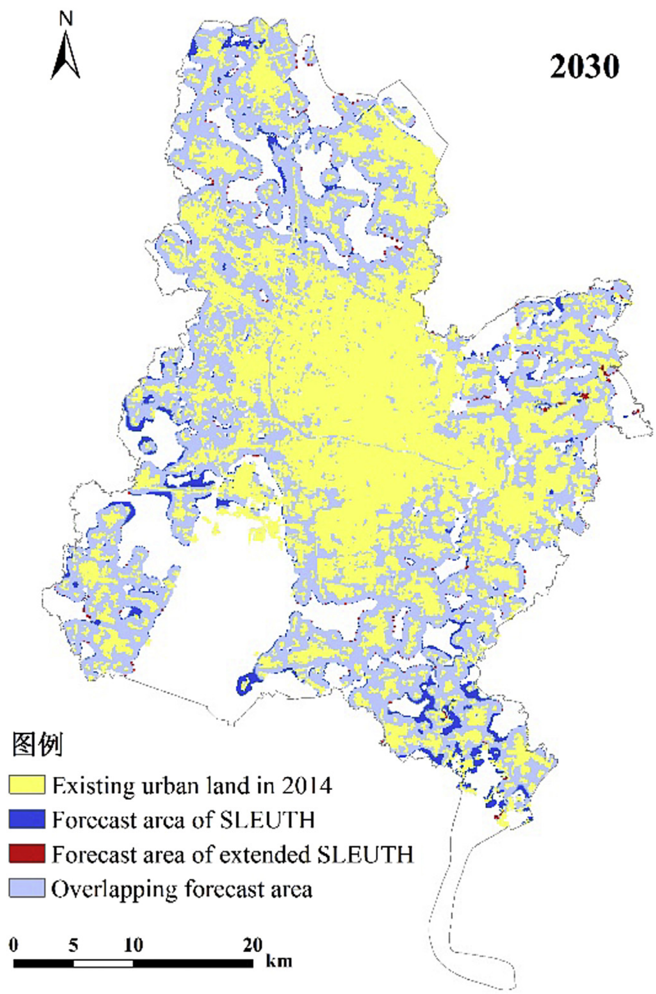

Fig. 9. Urban growth prediction results for the study area in 2030.

model's simulation power. This allows for a better interpretation and analysis as habitat quality map is incorporated into the model. After calibration, the OSM value of the extended SLEUTH UGM reached 0.9082, which showed that the extended model fits the study area very well. Moreover, new urban growth types in the study area have been interpreted by using our model. That is, in-fill & edge growth and road influenced growth were indicated as the major urban growth types during the simulation period rather than new spreading center growth and in-fill & edge growth, which were detected when using the standard SLEUTH UGM. We claim that the extended SLEUTH UGM is applicable to simulating urban growth in regions threatened by environmental quality degradation and farmland loss caused by uncontrolled urban land expansion. Furthermore, after calibration, the ecology resistance coefficient in the extended model is obtained. Analysis on the changes in the ecology resistance coefficient as well as comparison of the ecology resistance coefficient with an ecology threshold can also show the significance of environmental protection in past urbanization processes.

In the extended SLEUTH UGM, we employed a habitat quality map as one of the input layers. We argue for the use of a habitat quality map by using the habitat quality module of the InVEST model as this helps represent the environmental quality of areas under threat from human activities. The habitat quality maps for Changzhou city showed that water bodies, forest land and their surrounding areas maintain relatively high habitat quality values. In turn, the urban area and its surroundings show relatively low habitat quality values. The total area with relatively low habitat quality value increased notably as the urban expanded in our study area. These evaluation results by using the habitat quality module of the InVEST model conform to the actual environmental quality changes caused by urban growth in the study area.

4.2. The extended SLEUTH urban growth model contributes to sustainable urban and environmental planning

We advocate the importance of conducting and integrating environmental quality mapping into urban growth simulation; such models are helpful for urban and environmental planning as they aid in the coordinated development of human and environment. It is increasingly recognized that approaches which factor in environmental conditions are needed for sustainable planning and management of the environment and natural resources worldwide. This need is particularly important as urbanization levels in developing countries are expected to exceed 50% by 2020, and further increase to 64.1% in 2050 (UNDESA/PD, 2012), which will result in continued pressure on the environment and natural resources. However, analysis and coordinated planning of urban areas with respect to humans and the environment in developing urban regions are still relatively new phenomena as responses to the fragmentation and deterioration of environment systems (Panagopoulos et al., 2016). The extended SLEUTH urban growth model is helpful for sustainable urban and environmental planning and management, in which habitat quality is employed as one of the inputs that can affect and constrain urban expansion. First, the model is applicable to scenario simulations of urban growth and environmental quality patterns by urban and environment managers as a way to examine potential conflicts between the two. Second, the model can be applied to understanding the uncertainties of future urban growth and environment quality pattern under varied management policies, industrial planning, and local climate change coping strategies, *etc.* As Shearer et al. (2006) mentioned, significant attention should be given to futures that include 'critical uncertainties': those aspects of the future that are most difficult to predict, but should they come to pass, may have the greatest impact on goals and plans. Third, the model is also applicable to understanding the potential environmental consequences or impacts that each urban growth alternative might bear. Thus, the results can be referenced by decision-makers when setting urban growth boundaries and ecological redlines for controlling urban expansion and conserving environmental quality, which were promoted in the new urbanization strategy in China. Finally, the model is not dependent on intensive preliminary studies regarding the general causes of urban development in a study area or the location-specific driving forces. Thus, it has the advantage of universality and ease-of-use, compared to other urban growth models that are usually case-specific.

The extended SLEUTH model is a valuable tool for decision-makers to form environmental planning and management policies, as urban growth increasingly poses serious challenges to sustainable environmental management (Llausàs et al., 2016; Rudolf et al., 2018). By varying model parameters which represent environmental quality thresholds, the model can be applied to studying the formulation of environmental planning and management policies (such as environmental functional zoning) and testing the response of urban expansion to these policies. It is also helpful for understanding the past urban expansion and environment conservation trajectory, given that more information can be incorporated into the simulation. Furthermore, the excluded layer in our model can be designed by modelers to depict varied social, economic and climate change coping policies, and the model, by a form of loose coupling between the SLEUTH model and the InVEST model, is also applicable to studying the interactions between urban environmental quality change and urban land expansion.

We further suggest that the application of the model may result in an increased sense of responsibility and more consideration given to environmental sustainability. This will aid in a shift from planning focused solely on economic growth to planning which incorporates natural assets and environmental sustainability. This is particularly important as it may aid in a shift in government regulators' perceptions in developing countries. The results of applying the model can show the changes in environmental quality patterns and processes and environmental quality conditions that have occurred during recent decades to the present, which can cause reactions and changes related to environmental conservation in the attitudes of the city residents and decision-makers (Yli-Pelkonen, 2008). Compared to conventional socio-economic development planning that focuses more on economic growth rather than on natural assets and environmental sustainability (Wang, 2009), environmental conservation and natural resources management will be the persistent topics for sustainable socio-economic development planning in developing countries. Our model can provide decision-makers a more fundamental understanding of the interaction process between environmental quality patterns and urban expansion. As a result, they are willing to make trade-offs between the two.

5. Conclusions

This paper outlines an extended SLEUTH UGM for urban growth simulation by replacing the slope layer by a habitat quality layer, which is applicable to the cities with a relatively flat topography. This represents a form of loose coupling between the SLEUTH model and the InVEST model, i.e. a linkage through input data. With setting GDP, population, built-up land and roads as major threat factors to represent the impact of human activities on habitat quality, the habitat quality was evaluated by using the habitat quality module of the InVEST model, which was employed as one of the input layers to replace the slope layer for the study area. Then, the model we proposed was applied to an urban growth simulation in Changzhou city after calibration, which is threatened by environmental quality degradation caused by uncontrolled urban land expansion. The results of the experiment showed that the SLEUTH model's simulation power was improved by employing habitat quality map as one of the input layers in the new model.

The extended SLEUTH model is applicable to the development of sustainable urban and environmental plans as it can provide a way to examine interactions between urban environmental quality pattern and urban land expansion. The extended SLEUTH model can be used by decision-makers in Chinese cities when setting urban growth boundaries and ecological redlines for balancing urban expansion and environment conservation. It is also a useful innovation to support sustainable urban land-use planning and environmental functional zoning for cities in developing countries where rapid land urbanization is the prominent characteristic of land-use change, as it can generate land-use allocation patterns and environmental quality patterns and test the response of urban expansion to different environmental policies. In the meanwhile, the model can provide decision-makers a fundamental information of the past urban growth and environment conservation trajectory, thus it contributes to understanding the uncertainties of urban growth and environmental quality patterns under varied polies, planning and climate change coping strategies.

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