GeoJournal
DOI 10.1007/s10708-013-9515-9

Simulating the urban growth dimensions and scenario prediction through sleuth model: a case study of Rasht County, Guilan, Iran

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Abstract Urban growth models (UGM) as regional planning tools are of great interest for quantitative analysis of urban complex systems. In this study, the SLEUTH UGM has been calibrated through a sequential multistage automated method to derive the pattern of urban growth in Rasht County from 1975 up to year 2011. Evaluation of model goodness of fit confirms that the model is adjusted properly to the area under investigation. Four growth rules of spontaneous, new spreading center, edge and road influenced growth as well as five coefficients of diffusion, breed, spread, road gravity and slope resistance are responsible to detect quantitative aspects of urban dynamics from control years. According to the results, successive improvement of the model parameters during the calibration mode indicates applicability of the model for forecasting of future urban growth mechanism until the year 2050. Accordingly, two growth scenarios were developed mainly with the aim of investigating the coefficients' role in controlling the nature of urban dynamics. In this concern, the spread and road gravity coefficients' value, as two major driving forces of urban sprawl in the study area were reduced to dictate compact and infill growth, compared to their original values derived from calibration for historical prediction. Comparison between two forecasted scenarios indicates insignificant difference in total amount of the urban area, which denotes there is a threshold to urbanization and the current trend of urban growth could not be maintained. Finally, we conclude that Rasht County with considerable industrial and agricultural attractions, will witness noticeable expansion from 20,310 ha in 2011, up to 34,745 ha in 2050, accounting to 71 % increase in total area of manmade surfaces.

Keywords Simulation · Modeling · Urban growth · SLEUTH · Rasht County

Introduction

As a social and economic phenomenon, urbanization is taking place at an astonishing rate and unprecedented scale all over the world. Urbanization is considered as the most drastic form of land use and land cover (LULC) transformation, which influences environment through harmful and irreversible outcomes (Bathrellos et al. 2008). The dynamic nature of urban growth process has resulted in fundamental impacts on the structure, functions and services of ecological systems at a wide range of scales (Ewing 1997; Charles et al. 2005; Ma et al. 2008). Although urbanized areas cover 3 % of the whole earth's land surface, they are responsible for more than 78 % of

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Published online: 24 December 2013

carbon emission, 60 % of residential water use, and 76 % of the wood used for industrial purposes (Brown 2001). In the literature, different types of urban growth and evidence of the environmental impacts of urban sprawl has been well-documented (Ewing 1997; Hasse and Lathrop 2003; Sun et al. 2012), which clearly address the importance of urban areas and their relevant issues for sustainable management of these complex environments. For managing and mitigating, quantitative results derived from different aspects of urban growth dimensions can provide a comparative basis for understanding, analysis and management of urban areas and it offers a decision support system and planning tool for developing alternative scenarios.

During last two decades, a considerable number of studies has been conducted on spatial modeling mainly because of increased computing power, improved availability of spatial data and the need for innovative planning tools to construct spatial decision support systems for management of urban areas (Dai et al. 2001; Bathrellos et al. 2012; Xu et al. 2011; Bagheri et al. 2012; Sheng et al. 2012; Jie et al. 2010; Pourebrahim et al. 2011; Jeong et al. 2013; Yuechen et al. 2011; Youssef et al. 2010). Spatial predictive urban growth models (UGM) offer significant potential for analysis, understanding and modeling of urban growth evolution by the aim of improving efficacy of LULC management plans, which ultimately can result in saving and providing suitable and safe environment for humankind. UGMs as an effective regional planning tools, are of great capability for analytical and the forecasting of the dynamics of urban growth. In this regard, integration of GIS spatial analysis techniques with spatial dynamic models such as cellular automata (CA) provides a robust methodology for exploring urban complex systems (Tobler 1979). Integration of GIS and CA-based models relaxes many traditional UGMs constraints such as poor handling of space–time dynamics, coarse representation of data and top down approach, which ultimately fail to reproduce realistic simulations of urban systems (Maithani 2010). Thus towards the mid 1980s, CA-based models were proposed as an alternative to traditional models largely because of following reasons (Sullivan and Torrens 2000a):

- Simplicity;
- Capability of dynamic spatial simulation;
- Potential to high resolution modeling; and
- Natural compatibility to GIS and remotely sensed data.

The linkage between CA and GIS opens up new insight to the modeling of urban complex environments. In this regard, there has been a noticeable number of studies in the literature on integrated application of CA modeling with artificial intelligence (Al-ahmadi et al. 2008, Yang et al. 2008, Singh 2003) and optimization algorithms (Feng et al. 2011) as well as simulation methods (Wang et al. 2012). The focal core of these studies was to calculate transition rules regarding to relevant uncertainty sources. Moreover, some specific CA-based softwares for investigating the process of land use change have been developed, such as iCity (Stevens and Dragicevic 2007), DINAMICA (Soares-Filho et al. 2002), CLUE-S (Verburg et al. 2002) and SLEUTH UGM, which the later one has been widely applied in the study of many planned cities all over the world such as San Francisco (Clarke et al. 1997), Chicago, Washington-Baltimore area (Clarke and Gaydos 1998), Sioux Falls, California, and Philadelphia (Varanka 2001; Herold et al. 2003; Onsted and Clarke 2012); Chesapeake Bay watershed (Jantz et al. 2010) in USA; Lisbon and Porto (Silva and Clarke 2002, 2005) in Portugal (Europe); Porto Alegre (Leao 2002) in Brazil South America; Dongguan and Shenyang-Fushun (Fengming et al. 2010; Feng et al. 2012; Wu et al. 2009) in China; Mashad (Rafiee et al. 2009; Mahiny and Clarke 2012) in Iran; Sana'a (Al-shalabi et al. 2012) in Yemen; and Hyderabad (Gandhi and Suresh 2012) in India. In addition, different methodologies like Spatial Multi Criteria Evaluation (SMCE) and analytical hierarchy process have been applied to further improve the quality of urban growth modeling.

Given its success in regional urban modeling and relative ease of implementation as well as robust computation and processing methodology we adopted SLEUTH UGM. (Clarke et al. 1997; Clarke and Gaydos 1998). The software is public domain package and comprehensive instruction on model implementation is provided by Gigalopolis project website (http://www.ncgia.ucsb.edu/projects/gig/2012).
SLEUTH as a modified CA model relaxes from many classic CA model limitations (Santé et al. 2010) such as assumption of space homogeneity, uniformity of neighborhood interactions, and universal transition functions (Jantz et al. 2010). Urban growth types are

measured through four modes of growth behavior including spontaneous, diffusive, organic and road-influenced in the SLEUTH model, which shows the high degree of similarity with historical trend based growth of the study area (Rasht County). Therefore, the SLEUTH model have calibrated in response to the locale characteristic of the study area by the aim of providing scientific understanding of urban growth impacts at regional scale. In addition, predicted scenarios in this study offer a comparative basis, which facilitates evaluation of spatial decisions made by land use planners and policy makers. Specifically, the objectives of this paper are: (1) to calibrate the SLEUTH UGM in response to locale characteristic of Rasht County; and (2) to forecast the urban dynamics according to the historical circumstances and environmental considerations as two scenarios, insisting on the concepts of uncontrolled and controlled growth, respectively.

Materials and methods

Study area

The study area comprises administrative boundary of Rasht County in Guilan province, spanned over a region of 1,215 km^2 (Fig. 1). According to the report

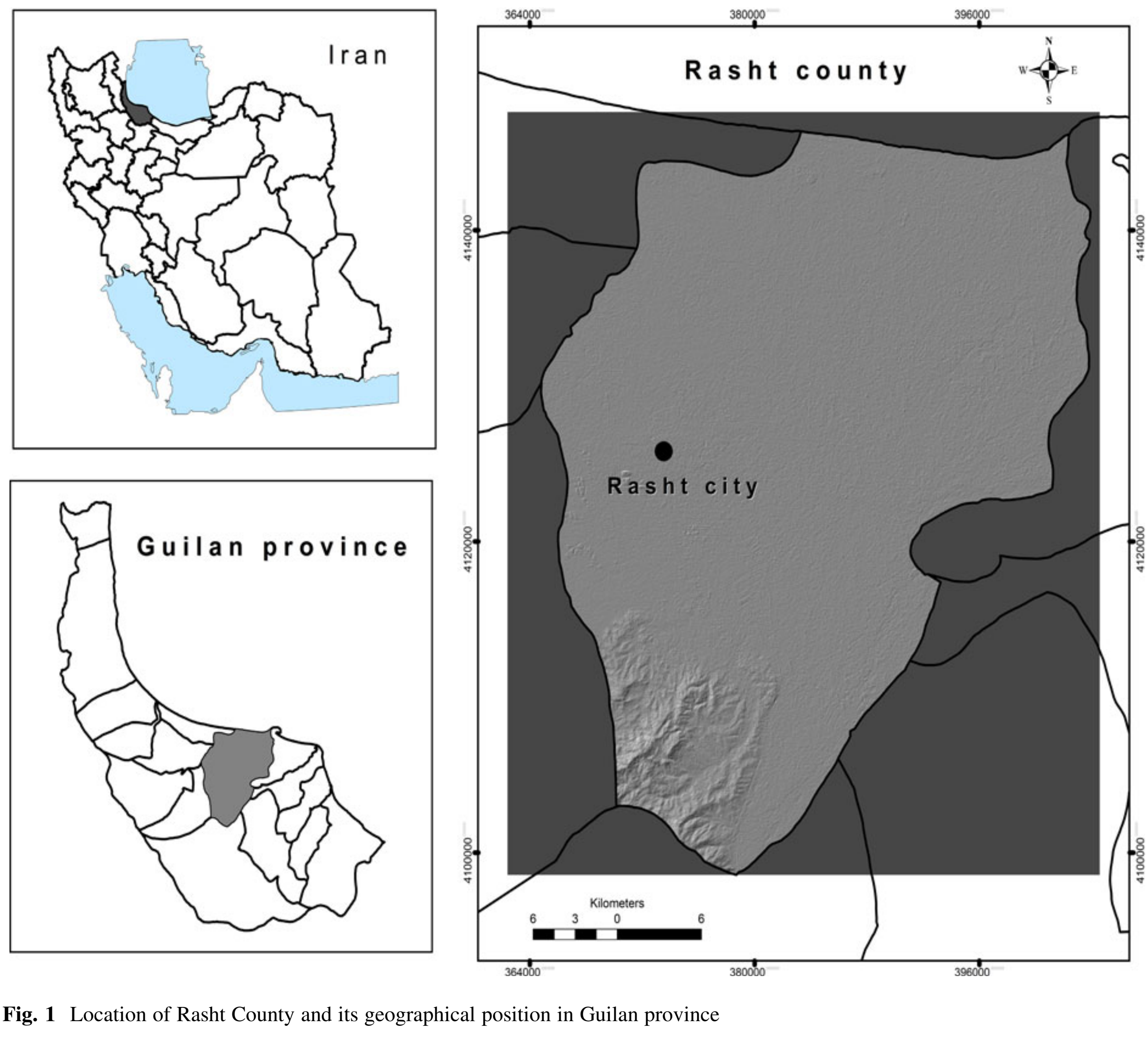

Fig. 1 Location of Rasht County and its geographical position in Guilan province

of Statistical Center of Iran, Rasht County has a population of 0.9 million and since 1989, number of residents in urban environments has sharply increased from 53.02 % up to 76 % in 2013. Rasht County is characterized with 1,500 mm of average annual rainfall and monthly average temperature of 15.8 Celsius as well as 81 % of annual relative moisture of the weather. Because of massive available lands and soil fertility, this County has been reputed as one of the most suitable areas for rice cultivation during last decades. Moreover, as capital of Guilan province and being located in the main route of Tehran, Ghazvin, Anzali and Astara on the one hand and Guilan to Mazandaran province on the other hand, Rasht County is one of the most active industrial and agricultural regions in Iran (Statistical center of Iran 2012).

Urban growth modeling

As noted SLEUTH is a modified CA model for urban growth modeling. The name of the model is a moniker for the input data required to use the model: Slope, Land use, Excluded area, Urban extent, Transportation network and Hillshade graphic. The model executes under UNIX operating system and incorporates two sub models: the UGM and the land cover deltatron model, which the later one is optional. Urban growth patterns are demonstrated through four internalized rules in SLEUTH model: spontaneous, new spreading center (diffusive), edge (organic) and road influenced growth (Candau 2002). Spontaneous growth rule is responsible to simulate emergence of new urban centers in areas with suitable slope and with no pre-existing infrastructure. New spreading center growth is in charge of controlling the probability of spontaneous growth to become the center of continued urban growth. Edge growth replicates sprawl of the city along with its boundaries in both outward and infill directions. Road-influenced growth determines the likelihood of new urban settlements attracted by road infrastructures, which encourage urban cells to be developed along side of the road networks (Candau 2002; Silva and Clarke 2002).

Five growth parameters consisted of diffusion, breed, spread, road gravity and slope resistance control four types of urban growth rules. To indicate relative importance, each parameter has a dimensionless value, ranging from 0 to 100.

The diffusion multiplier controls the number of times a pixel will be randomly selected for possible urbanization during spontaneous growth; a breed coefficient determines the probability of a pixel urbanized by spontaneous growth becoming a new spreading center and starts its own growth cycle; a spread multiplier determines the probability that any pixel that is part of a spreading center (a cluster of pixels of three or more in a nine cell neighborhood) will generate an additional urban pixel in its neighborhood; a slope resistance coefficient affects all growth rules in the same way. When a location is being tested for suitability of urbanization, the slope at that location is considered and road gravity parameter demonstrates the attraction of urbanization toward and along road networks. Table 1 depicts the relationship between urban growth rules with five growth parameters.

The model was implemented through five following steps: model test and compilation, preparation of required input data, model calibration, model prediction and finally evaluation of output results (followed as Yang and Lo 2003; Rafiee et al. 2009).

The test mode of the model was executed to verify input data and their initial reactions are conformed to input specifications. This indicates that model is properly applicable for calibration mode.

SLEUTH required data preparation

A minimum set of four urban extent years, two road years, at least one excluded layer from urbanization, one slope layer and one hillshade image for graphical background are required. All the required data for model calibration were prepared through an integrated

Table 1 Relationship between growth types and growth coefficients

Growth types	Controlling coefficients	Summary description
Spontaneous	Dispersion	Simulates the random urbanization of land
New spreading center	Breed	Simulates establishment of new urban centers
Edge	Spread-slope	Simulates old or new urban centers spawn additional growth
Road Influenced	Road-gravity, dispersion, breed, slope	Simulates newly urbanized cell growths along transportation networks

Source Lu et al. (2009)

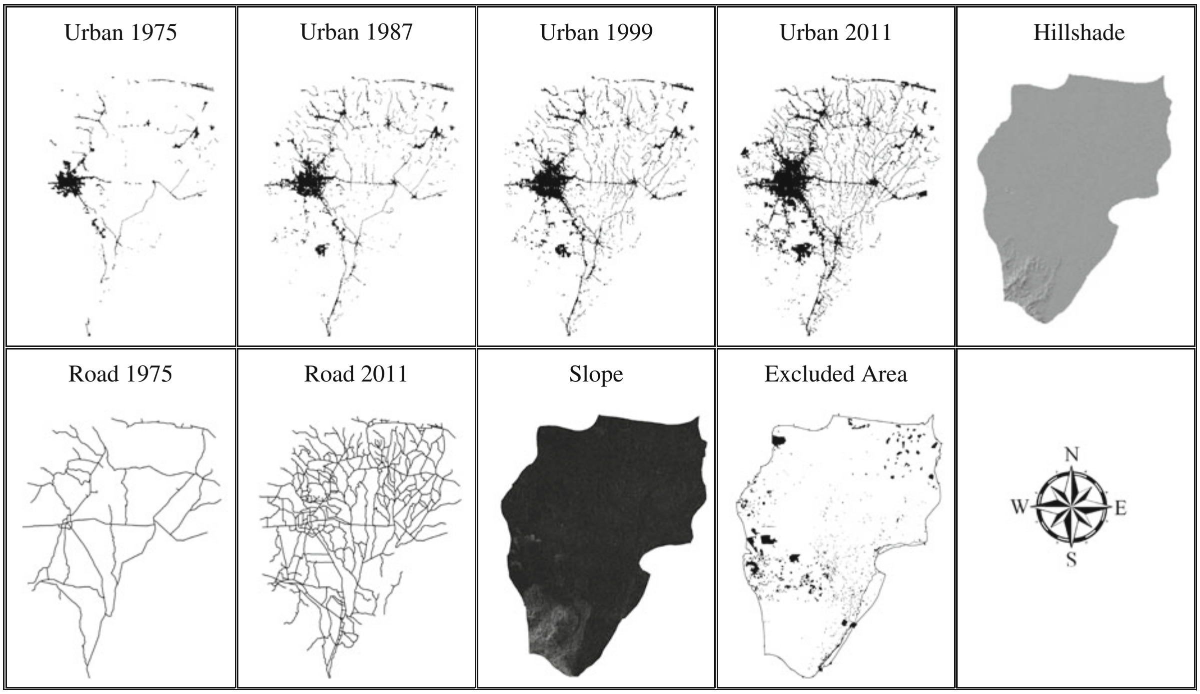

Fig. 2 Input information layers for SLEUTH model

application of remote sensing and geographic information system. The data were co-registered by the source in UTM WGS 84 system and compiled in the similar extend with 30 m of spatial resolution. The dimensions of resultant grid were 1,405 columns and 1,633 rows. By the aim of standardization, all the input data were stretched linearly and exported into the 8-bit grayscale GIF format, illustrating urban and nonurban areas.

Urban layers were created through an extensive effort of visual interpretation on computer display using Landsat MSS and TM images of the years 1975, 1987, 1999 and 2011 to present the profile of Rasht County dynamics since 1975. Road transportation networks were also extracted using the same method only for the years of 1975 and 2011. The resultant vector layers were converted into raster. Percent slope and hillshade layers were generated from 30 m digital elevation model, which was derived from topographic maps of the year 1994 with the scale of 1:25,000, obtained from National Cartographic Center of Iran. Finally, wetland and water bodies were determined to be completely excluded from urbanization (Dezhkam 2013) (Fig. 2). Table 2 shows the required input data layers for the SLEUTH model.

Table 2 Data requirements for SLEUTH

Input layer	Prepared through	Format and year
Urban extension	Visual interpretation	Raster 1975, 1987, 1999 and 2011
Transportation networks	On screen digitization from satellite image	Raster 1975 and 2011
Slope	Derived from DEM	Raster
Hillshade	Derived from DEM	Raster
Excluded area	Rasterized from vector	Raster

Model calibration

The straightforward calibration method applied by the SLEUTH makes it possible to state that the model is able to adopt itself to any particular geographic area over time even with distinct locale settings (Clarke et al. 1996). Consequently, the problem of model specificity to the city to which it was applied (Lee 1973) is not a concern in the SLEUTH model. Taking into account that SLEUTH is a global model, for reflection of local characteristics, the model takes advantage from quite robust calibration method. In calibration mode, SLEUTH parameters are

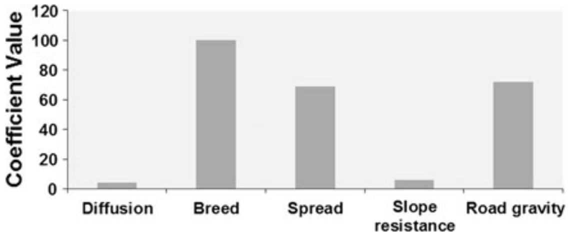

Fig. 3 Coefficients average values for forecasting the urban growth scenarios

determined to learn about global properties from local performance of parameters (Silva and Clarke 2002).

Calibration process includes coarse, fine and final stages and after that, the model will be ready to be applied in prediction mode, which provides a flexible environment to adopt various scenarios with different considerations.

During the model calibration, it tries to detect the inherent pattern of urban growth. Accordingly, the SLEUTH utilizes set of basic simulations, which is a step up in complexity from urban growth cycle. In fact, simulation is series of growth cycles that starts from the first control year up to the stop date and in each simulation, model attempts to regenerate the witnessed pattern of urban growth via different combinations of model parameters. Finally, when the total number of the growth cycles has been executed, the simulation concludes. Simulations are conducted through three stages of calibration mode in order to make model able to adjust itself to locale characteristics, which is reflected in the best range of model's parameters (Fig. 3).

Growth cycle is the fundament unit of SLEUTH run. In the first step, an initial unique combination of coefficients is set. Afterward, growth rules are executed and model goodness of fit is evaluated via various indexes provided by the model. Table 3 provides a general overview of SLEUTH indexes, used in calibration.

Owing to the fact that self-modification rules in the SLEUTH model are properly internalized, the model can prevent producing only linear or exponential simulations. In this regard, if the growth rate exceeds the critical high value, self-modification rules are employed and growth parameters will be multiplied by values more than 1 (boom condition). This occurs mainly because there are more free cells available to urbanization at the beginning years of growth. On the other hand, when there is less free cells to be

Table 3 SLEUTH indices for evaluating accuracy of simulated output of model during calibration phases

Index	Summary description
Product	A composite index, resulted from all indices scores multiplied together
Compare	Comparison between modeled final urban extent to real final urban extent
r^2 population	Least square regression score of modeled urbanization compared with actual urbanization for control years
Edge r^2	Least square regression score of modeled urban edges against the urban edges of control years
R^2 cluster	Least square regression score of modeled urban clustering against real final urban clustering
Leesalee	A shape index, a measurement of spatial fit between the modeled growth and the known urban extent for control years
Average slope r^2	Least square regression of average slope for modeled urbanized cells compared with average slope of known urban cells for control years
X-r^2	Center of gravity[x]: Least square regression of average x values for modeled urbanized cells compared with average X values of known urban cells for control years
Y-r^2	Center of gravity[y]: Least square regression of average y values for modeled urbanized cells compared with average y values of known urban cells for control years

Source Silva and Clarke (2002)

urbanized, growth coefficients will be multiplied by values lower than 1 to indicate depressed growth (bust condition) (Silva and Clarke 2002). Figure 4 represents general structure of the self-modifying characteristic of SLEUTH UGM.

Calibration of the model is quite computationally complex and time consuming. The same computation algorithm will be carried out in each calibration phase. In this regard, each coefficient set combination created by the coefficient START, STOP and STEP values begins a run. Furthermore, each run executes Monte Carlo iterations and several statistics and image files will be produced and stored. In fact, in each calibration phase (coarse, fine and final), the model performs thousands of runs by which during each model run, simulation of urban growth based on actual derived pattern is regenerated. Then, simulation accuracy is assessed by SLEUTH indices.

To derive the best set of coefficients in each calibration phase, model parameters were sorted based

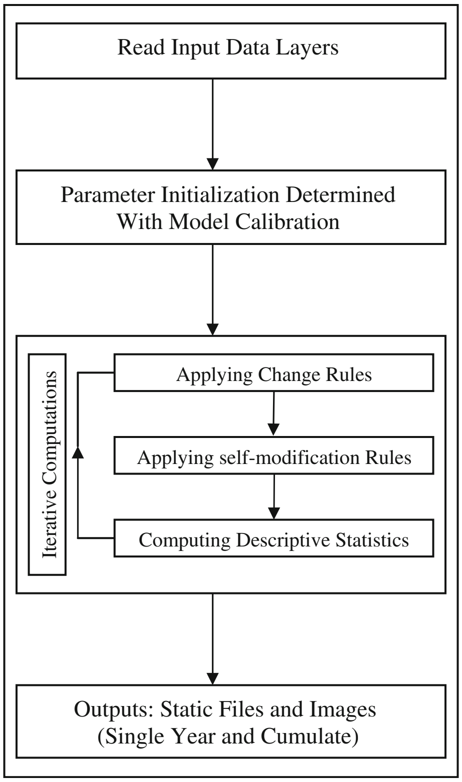

Fig. 4 Self-modification structure of SLEUTH UGM (*Source* Yang and Lo 2003)

on Leesalee metric (Silva and Clarke 2002) and top ten highest scores were selected to feed into the next step. Consequently, model parameters were refined and narrowed down in range, which indicates adoption of model parameters to the locale properties of targeted area.

During each step of model calibration, parameter space is heavily explored through an automated exploration process. To reduce computational complexity as well as increasing the efficiency of model performance, exploration of parameter space is accomplished through Monte Carlo stochastic method, which can reduce cost and time expenses.

Model prediction

There are different methods to utilize SLEUTH model in prediction mode. In the first method, different values of protection are assigned to excluded areas to indicate different levels of cells potential for urbanization (e.g. Oguz et al. 2007; Jantz et al. 2010; Mahiny and Clarke 2012). In the second method, self-organization constraints are manipulated (e.g. Yang and Lo 2003) and the third method concerns changing parameter values, which dictates the form of urban growth and affect urban growth rules (e.g. Leao et al. 2004; Rafiee et al. 2009). In order to benefit from its flexible environment and ease of implementation, we applied the third method of model prediction. Herein, two scenarios with different considerations were forecasted up to year 2050, including historical and environmentally sound predicted growth scenarios. There are different standards for definition and application of scenarios, which has been partly discussed by Xiang and Clarke (2003). Three criteria consisting of plausible unexpectedness, informational vividness, and cognitively ergonomic design have been recommended by them for every suitable set of scenarios. The adopted scenarios in this study, although simple, are mainly enriched with some facts of the study area and its development in the past as well as considering the fact that land use planning programs are mostly controlled by master plans of the cities derived from regional land use planning (Makhdum 1993). Hence, the adopted scenarios were set up according to assumptions of the controlled and uncontrolled growth, which allows decision makers to construct a quantitative comparative basis for evaluation of different growth alternatives. Taking Rasht County into consideration, this area includes quite valuable ecosystems such as Anzali international wetland (http://www.ramsar.org/2012) and highly dense forests, which offer important ecosystem services like providing wildlife habitats and conservation of water and soil resources. Consequently, the importance of environmental considerations to prevent irreversible changes in structures and processes of these natural ecosystems in land use planning is crucially necessary to be considered.

After calibration of the model, in the first scenario the historical trend of the urban growth was forecasted applying the average values of the parameters derived from the calibration, which maintains the assumption that the area will witness the same growth pattern similar to its historical trend. Prediction mode was conducted by means of full resolution data and 100 Monte Carlos iterations. Output of SLEUTH model is a probability map image, which demonstrates probability of each single pixel for urbanization. In order to produce a crisp map that indicates future urbanized areas, frequency histogram method with cutoff point

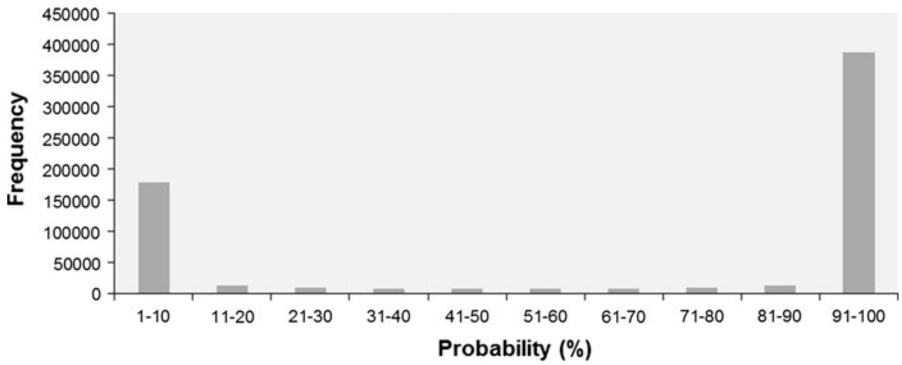

Fig. 5 Frequency histogram of probability urbanization map of the year 2050

Table 4 Results of coarse calibration step

Compare	r^2 population	Edge r^2	r^2 clusters	Leesalee	Average slope r^2	xmu r^2	ymu r^2	Diff	Brd	Sprd	SLP	RG
0.37	0.93	0.97	1.00	0.37	0.70	0.10	0.99	1	100	50	25	100
0.38	0.95	0.98	1.00	0.37	0.72	0.09	0.99	1	100	50	25	25
0.37	0.93	0.96	1.00	0.37	0.70	0.09	1.00	1	75	50	25	50
0.38	0.94	0.97	0.99	0.37	0.71	0.09	0.98	1	100	50	25	75
0.37	0.92	0.96	1.00	0.37	0.69	0.10	1.00	1	75	50	25	75
0.37	0.94	0.97	1.00	0.37	0.71	0.11	1.00	1	100	50	25	50
0.36	0.89	0.94	0.98	0.37	0.65	0.12	1.00	1	50	50	25	50
0.37	0.93	0.97	1.00	0.37	0.71	0.09	0.99	1	75	50	25	100
0.36	0.89	0.94	0.98	0.37	0.65	0.12	1.00	1	75	50	25	1
0.36	0.89	0.93	0.98	0.37	0.65	0.13	1.00	1	75	50	25	25

was used. Figure 5 illustrates the frequency of each specific probability value within the output probabilistic image. As it is obvious, there is sharp increase somewhere around 90 % for urbanized cells. Therefore, this value was selected as cut off point. On the other word, 90 % value was taken as a threshold to depict that which cells are the most probable ones to become urbanized during 40 years ahead.

Results

Model calibration results are presented in Tables 4, 5, 6 and 7. Each table demonstrates top ten highest score from thousands of runs for each coefficient based on Leesalee metric. During each calibration step, possible combination of the coefficients in the parameter space is heavily explored, leading to successive improvement of the model parameters.

In the coarse phase, the parameter values ranging between possible minimum and maximum of 0–100. Subsequently, in the fine stage, they have been narrowed down to values of 0–20, 50–100, 50–75, 25–50 and 0–100 accounting for the dispersion, breed, spread, slope resistance and road gravity coefficients, respectively. These parameter values fed into next step of the final calibration and the model became even more sensitive to locale characteristics of the study area, reflecting in values of: 1–3, 88–100, 50–53, 25–28 and 55–100 specified to the model parameters' values.

The comparison between the model final "population" (number of urban pixels) and the actual urbanization of control years indicates high correlation of 0.98, which means prediction of the model using refined parameter values is quite similar to what happened in reality. According to the values of r^2-edges (1.00) and r^2-clusters (0.99), it is feasible to state

Table 5 Results of fine calibration step

Compare	r^2 population	Edge r^2	r^2 clusters	Leesalee	Average slope r^2	xmu r^2	ymu r^2	Diff	Brd	Sprd	Slp	RG
0.38	0.95	0.98	1.00	0.37	0.73	0.09	0.99	1	90	50	25	50
0.40	0.97	0.99	1.00	0.37	0.77	0.07	0.97	1	90	55	25	75
0.38	0.94	0.97	1.00	0.37	0.72	0.10	0.99	1	100	50	25	100
0.37	0.94	0.97	1.00	0.37	0.71	0.10	0.99	1	90	50	25	100
0.38	0.96	0.98	1.00	0.37	0.74	0.08	0.97	1	90	55	30	75
0.40	0.97	0.99	1.00	0.37	0.77	0.07	0.98	1	100	55	25	50
0.39	0.98	1.00	1.00	0.37	0.79	0.10	0.95	5	70	50	30	75
0.37	0.92	0.96	0.99	0.37	0.69	0.10	0.99	1	80	50	25	25
0.40	0.97	0.99	1.00	0.37	0.76	0.08	0.97	1	100	55	25	75
0.37	0.94	0.97	1.00	0.37	0.71	0.08	0.99	1	90	50	25	25

Table 6 Results of final calibration step

Compare	r^2 population	Edge r^2	r^2 clusters	Leesalee	Average slope r^2	xmu r^2	ymu r^2	Diff	Brd	Sprd	Slp	RG
0.45	0.98	1.00	0.99	0.37	0.73	0.09	0.98	3	94	50	27	70
0.38	0.97	0.99	1.00	0.37	0.77	0.10	0.98	2	100	50	28	100
0.39	0.97	0.99	1.00	0.37	0.72	0.10	0.98	2	100	50	26	85
0.40	0.98	0.99	1.00	0.37	0.71	0.08	0.97	2	100	51	26	70
0.38	0.97	0.99	1.00	0.37	0.74	0.08	0.98	2	88	51	28	70
0.40	0.98	0.99	1.00	0.37	0.77	0.10	0.97	2	94	53	28	55
0.39	0.97	0.99	1.00	0.37	0.79	0.10	0.97	2	88	51	27	70
0.38	0.95	0.98	1.00	0.37	0.69	0.09	0.98	1	88	51	25	100
0.38	0.94	0.97	1.00	0.37	0.76	0.09	0.98	1	88	51	26	100
0.40	0.98	0.99	1.00	0.37	0.71	0.09	0.97	2	100	51	26	100

Table 7 Summary of parameters during calibration process

Growth parameter	Coarse		Fine		Final		Result value
	Monte Carlo iterations = 5		Monte Carlo iterations = 8		Monte Carlo iterations = 10		
	Total number of simulation = 3,125		Total number of simulation = 5,400		Total number of simulation = 6,480		
	Leesalee = 0.37		Leesalee = 0.37		Leesalee = 0.37		
	Range	Step	Range	Step	Range	Step	
Dispersion	0–100	25	0–20	5	1–3	1	4
Spread	0–100	25	50–100	10	88–100	2	69
Breed	0–100	25	50–75	5	50–53	1	100
Slope	0–100	25	25–50	5	25–28	1	6
Road Gravity	0–100	25	0–100	25	55–100	1	72

that the model parameters are adjusted properly to simulate the shape and form of urbanization against the control years. In addition, the model performance along side of Y axis (ymu r^2) seems completely close to the reality, presenting the high correlation value of 0.98. On the contrary, the low value of 0.09 in the case

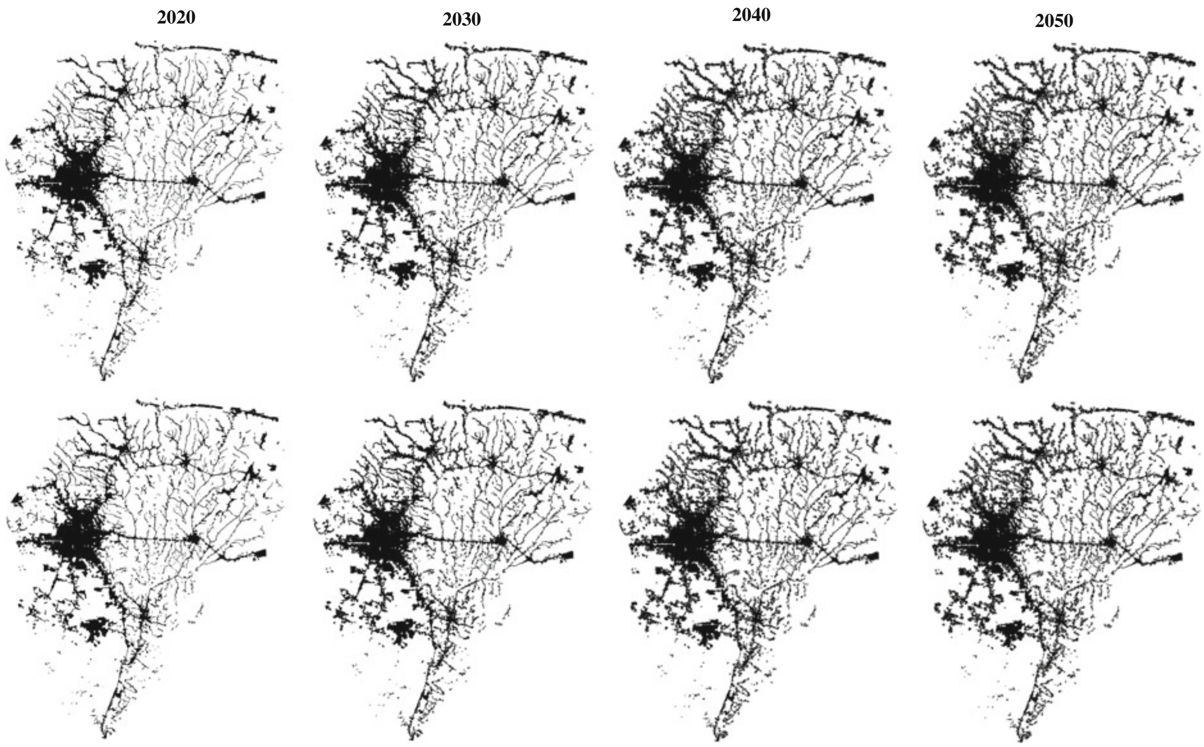

Fig. 6 Urban growth trend of Rash County up to the year 2050. The *first row* shows historical scenario and the *second row* shows environmental scenario

of "xmu r^2" reflects low level functionality of model simulation along X axis compared to known urban cells. Finally, the value of 0.73 specified to "Average Slope r^2" means the model simulation in flat ground is similar to the witnessed pattern derived from the control years.

Taking into account that study area has witnessed massive amount of urbanization with considerable proportion of 334 % expansion in total area of man-built structures (4,680 ha in 1975 increased up to 20,310 ha in 2011). It is logical to address that the County will experience heavy pressure on available free lands during four decades ahead. Accordingly, output evaluation of the historical prediction scenario indicates 71 % increase in total area of the impervious surfaces taking up 34,745 ha in 2050. As it is observed, although the rate of growth is depressed, there is still considerable amount of urbanization. On the other word, because there is less available space than before, generation of new urban centers will significantly level off and each specific urban area will start its own growth cycle. With regard to the high value of road gravity coefficient (72) new establishment of urban centers and sprawl of already urban areas will be sharply influenced by road infrastructures leading to connection of departed urban centers to form more continuous impervious surfaces.

In the second scenario, parameters were manipulated. Spread and road gravity coefficients were reduced to 40 and 30, respectively (Rafiee et al. 2009). These modifications were carried out by the aim of environment conservation and to dictate the compact and infill growth of the city, which can result in consumption of interior vacant lands in urban context. According to the result of second scenario prediction, Rasht County will experience quite similar pattern of growth to its historical trend even with its manipulated growth coefficients. As both Figs. 6, 7 illustrate, there is no discrepancy between two predictive scenarios of Rasht County up to year 2050. Both policy alternatives reveal the same pattern of growth and approximately similar area for urban land use within the administrative boundary. The study area will witness the same rate of growth in both scenarios (71 %) up to year 2050, mainly because of

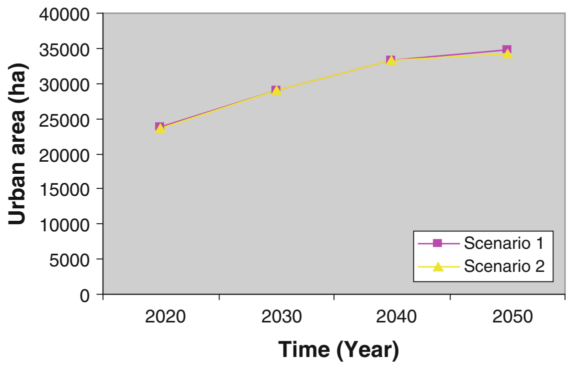

Fig. 7 The urban extend of Rash County up to the year 2050 under two scenarios

reduced amount of vacant lands for urbanization, which leads to constrained form of urban dynamics. As the most important conclusion of this study, there is a threshold for area under investigation to the sprawl of urban areas and after experiencing an exponential growth rate, there is a peak in which the growth can not be maintained as before mainly due to unavailability of land. Therefore, growth rate of new urban center establishment will reduced and urban centers will start their own growth cycles.

Discussion and conclusion

This research applied SLEUH model to investigate urban growth evolution in Rasht County, Iran and evaluate two alternative scenarios. The results reveal some interesting findings.

(1) Calibration of the model demonstrated that major growth modes in the targeted area were "breed", "road gravity" and "spread" coefficients, which is consistent with the results of other applications of SLEUTH model in Iran (Rafiee et al. 2009; Mahiny and Clarke 2012). In other word, the comparison between relative importance of growth coefficients indicates that new developments have occurred where there are no pre-existing urban centers and infrastructure facilities (such as drainage systems and disposal management systems). In this matter, establishment of new urban areas is highly influenced by transportation network within the administrative boundary of the study area (Fengming et al. 2010; Yang and Lo 2003). In contrast, the effect of topography was insignificant, which implies that steeper slopes are not determined as limiting factors to urbanization. According to the value of slope resistance coefficient, this study shows high degree of consistency to other cities with the same topographic characteristics where SLEUTH model is implemented. These studies include Jantz et al. (2003), Syphard et al. (2005) and Rafiee et al. (2009). In addition, the low value of "diffusion coefficient" implies that low probability of spontaneous growth in the study area, which is in accordance with the study carried out by Gandhi and Suresh (2012) due to the same characteristic of the study sites. This may explain by the factors of urban development where there are massive available lands with suitable ecological and physical conditions. Consequently, the study area has witnessed substantial increase in total area of impervious surfaces, resulting in the same growth modes with similar study sites in terms of relative importance of growth coefficients. With the time, the urban landscape became more scattered and dispersed, especially where there are no conditions posed by regional planning and environmental protection, then construction was happened at places where it is cheapest (Jaeger et al. 2010).

(2) According to the two predictive scenarios, there is no noticeable difference in the area of urban structures derived from two scenarios. Historical trend based prediction of the Rasht County and the scenario with environmental considerations reflect a central characteristic of urban growth mechanism. In this regard, *self-organizing* behavior of the urban complex system plays an important role in controlling the overall process of urban growth. Accordingly, at the beginning of growth cycle where there many available cells to urbanization exist, the growth rate shows an exponential pattern and then, with the time, the parameters are decreased as growth rate levels off and falls below the critical low mainly due to fewer available lands to be urbanized (Silva and Clarke 2002). In the same spirit, *self-modification* rules of the model reflected accurately this cybernetic behavior of a real urban ecosystem. Namely, applying self-modification rules generates new organizational level of adoption to urban growth process. The new organizational level of adoption is also influenced by spatio-temporal dynamic nature of new conditions of urban growth derived from current growth pattern. Consequently, it is possible to state that the model adopts itself dynamically to growth trend as it alters. This claim was further strengthen when both predictive

scenarios showed the same results, indicating that there is a threshold for urbanization in the study site. Thus, it can be claimed that Rasht County has experienced its peak in the process of urban sprawl, which may alarm decision makers and policy makers for any further establishment of new urban centers. The inherent property of urban growth, suggests that the subsequent settlements should be conducted to agglomerate around existing urban centers for better organization and service delivery (Krugman 1991). New developments thus should be guided contiguous with existing area and newly urbanized patches should start their own growth cycles.

Finally, this research shows the utility of urban growth modeling in regional land use planning via an integrated application of remote sensing, geographic information system and CA modeling subsystems for better handling of spatiotemporal aspects of real-world urban processes. The model also serves as a decision support tool and helps city managers realize the outcome of possible actions they might take.

Acknowledgments The authors are grateful to Reza Rafiee who kindly associated in all parts of model execution and to the anonymous reviewers for their valuable comments to improve this paper.

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