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ARTICLE

Simulating urban expansion and scenario prediction using a cellular automata urban growth model, SLEUTH, through a case study of Karaj City, Iran

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Abstract Understanding, analysis, monitoring and modeling of urban growth evolution as a major driving force of land use/land cover transformation, especially in developing countries, is of great importance for land managers in the process of sustainable development. Using spatial predictive models and change detection techniques can provide an additional level of knowledge of the causes and impacts of urban growth mechanisms, which finally provide comprehensive insight into urban chronology. Karaj, the capital of Alborz province, has been experiencing a substantial increase in total area of urban environments mainly due to its socioeconomic attractions during the last three decades. The present work aims to reveal how the historical trend of the urban growth can affect its future spatial pattern. For conducting this study, the SLEUTH cellular automata urban growth model was executed via three calibration steps including coarse, fine and final. Relying on the calibrated model, dynamics of the Karaj City were predicted under its historical trend as well as two different scenarios including compact and extensive growth up to year 2040. According to the findings of the present study, while extensive growth option indicates the most consumption of the vacant lands, the compact scenario dictates infill form of the urban growth in addition to saving spaces. Finally, urban growth

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forecasting based on its historical trend illustrates that total area of the human-constructed elements will be in the middle of other two predictive scenarios.

Keywords Urban growth modeling · Urban expansion · Cellular automata · SLEUTH · Karaj · Iran

1 Introduction

Heavy pressure exerted by the process of urbanization on natural resources and limited available space signifies the importance of urban-related issues in the management and development of these complex environments (Brown 2001; Randolph 2004; Makhdum 2007; Bathrellos et al. 2008; Hasani Sangani et al. 2014). New approaches such as sustainable development and smart growth require comprehensive analysis, understanding and modeling of urban systems in which an additional level of knowledge in response to the causes, impacts and chronology of urbanization mechanism can be produced (Herold et al. 2003; Asgarian et al. 2014). Moreover, in the process of decision making, land managers need to examine the consequences brought about by the urban evolution process. Urban growth models satisfy this demand, and there has been a growing body of work in the field of urban growth modeling in the literature (Batty 1989; Knox 1994). Maybe, this interest is attributable to innovative and predictive aspects of urban growth modeling, which can support decision making in spatial systems. Regarding to the increased computing power, improved availability of spatial data sets and development of functional computer-based models, now there is a possibility in which land use managers and decision makers can evaluate the outcome of their decisions under different policy alternatives and at the minimum possible cost. Incorporation of new methodologies such as spatial multi-criteria evaluation (SMCE) and analytic hierarchy process (AHP) can further improve representation and modeling of urban dynamics, which finally provide spatial decision support systems (SDSS) for better organizing and management of urban areas. (Dai et al. 2001; Jie et al. 2010; Youssef et al. 2010; Xu et al. 2011; Pourebrahim et al. 2011; Yuechen et al. 2011; Bagheri et al. 2012; Bathrellos et al. 2012; Sheng et al. 2012; Jeong et al. 2013).

Cellular automata (CA) models can play a significant role in simulation and modeling of real-world urban processes. Relaxing from traditional urban modeling constraints (Lee 1973), CA urban growth models are of great potential for their handling of space–time dynamics, detailed level of representation of data and bottom-up modeling approach (Maithani 2010). In addition, CA-based urban growth models have a natural affinity to GIS and remotely sensed data, which makes it possible to take advantage from these techniques in an urban growth modeling practice (Sullivan and Torrens 2000). Integration of CA and GIS can provide a strong tool for exploring complex urban environments (Itami 1994). There is significant number of points on integration of GIS and CA modeling that have been documented in the literature. Couclelis (1985, 1989) argued the theoretical necessities of linking CA and GIS and their important common features as well as their complementary functionalities. Sui and Zeng (2001) acknowledged the utility of GIS-based CA modeling. They pointed out the bottom-up approach of CA in modeling, which facilitates incorporation of different local factors. In this regard, the static representation of GIS can be improved through generating realistic urban dynamics. Batty and Longley (1986, 1994) and Batty and Xie (1994, 1997) have enhanced the methodological aspects of Tobler's work (1979), for modeling complex processes. White and Engelen (1993, 1994) indicated that CA is capable of producing actual patterns of urban land use dynamics. In the same spirit and with the aim of testing general aspects of structural evolution of CA, White and Engelen (1993) employed CA to investigate spatiotemporal dynamics of urban land use. In another study, White and Engelen (1997) and White et al. (1997) utilized CA to model and predict the dynamics of the Caribbean Island of St. Lucia in USA. In both studies, transition rules were formulated based on land suitability of different land uses and neighborhood effects. Barredo et al. (2003, 2004) also developed a CA model for predicting land use change in Dublin and Lagos, Nigeria, respectively. In this research, transition rules were internalized based on four general factors of accessibility, neighborhood, suitability of a cell and zoning status. Given the long research tradition modeling of urban growth evolution through CA for spatial dynamics (Batty and Xie 1994; Engelen et al. 1997; Wu 1998; Portugali 2000; Liu and Andersson 2004; Liu et al. 2007; Stevens et al. 2007; Al-Ahmadi et al. 2008; He et al. 2008; Verburg and Overmars 2009), many CA-based models such as iCity (Stevens et al. 2007), DINAMICA (Soares-Filho et al. 2002) and CLUE-S (Verburg et al. 2002) have been developed (Singh 2003). As a central characteristic in the CA-based modeling approach, there is a tendency in the system known as *self-organizing*, which indicates that a system can spontaneously generate globally ordered patterns from local interactions among different factors and decision-making processes. This property is of great capability for producing realistic simulations of the urban growth phenomenon in responding to the defined transition rules. Maybe, the main difference among developed CA models is how the transition rules are formulated and internalized, which ultimately influences the calibration of model parameters (Straatman et al. 2004). Transition rules are one of the fundamental components of CA modeling and are calculated according to the four principles as follows:

1. Neighborhood effect (Verburg et al. 2004; Vliet et al. 2008);
2. Accessibility (Echenique 2004; Geurs and van Wee 2004);
3. Suitability (White and Engelen 1997; White et al. 1997); and
4. Zoning status (Barredo et al. 2003, 2004).

The most important CA-based models designed for exploring the urban growth mechanism include CA modeling with artificial intelligence (Al-Ahmadi et al. 2009; 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 the relevant uncertainty sources. In addition, there are macro- and micro-integrated CA models (RIKS model) (Engelen et al. 1997), fuzzy CA model (Wu 1996), ANN CA model, (Li and Yeh 2002), multi-CA model (Cecchini and Rinaldi 1999) and the SLEUTH urban growth model. SLEUTH is a probabilistic CA (Clarke et al. 1997) in which five growth parameters are calibrated through four urban growth rules (see Sect. 2.3) and has been applied in the modeling of many cities at regional and continental scales all over the world such as San Francisco (Clarke et al. 1997), Chicago, Washington–Baltimore area (Clarke and Gaydos 1998), Sioux Falls, California, Philadelphia (Varanka 2001; Herold et al. 2003; Onsted and Clarke 2013) and Chesapeake Bay watershed (Jantz et al. 2010) in USA; Lisbon and Porto (Silva and Clarke 2002, 2005) in Portugal (Europe); Porto Alegre (Leao et al. 2004) in Brazil South America; Dongguan and Shenyang-Fushun (Wu et al. 2009; Feng et al. 2012; Xi et al. 2009) in China; Mashad, Gorgan, Rasht, Karaj and Isfahan (Mahiny and Gholamalifard 2007; Rafiee et al. 2009; Mahiny and Clarke 2012, 2013; Dezhkam et al. 2014; Sakieh et al. 2014; Bihamta et al. 2014) in Iran; Sana'a (Al-shalabi et al. 2012) in Yemen; and Hyderabad (Gandhi and Suresh 2012) in India.

SLEUTH is a modified CA model, which relaxes from many CA classic models constraints (Santé et al. 2010) such as the assumption of space homogeneity, uniformity of neighborhood interactions and universal transition functions (Jantz et al. 2010). In addition, complete instruction for applying the model and a rich database of research papers on the SLEUTH model are available for download online from Gigalopolis project Web site. SLEUTH is easy to use and the program operates under C-language source code. Moreover, the model offers a flexible environment to adopt different alternative scenarios with the aim of exploring the impact of different spatial considerations in land use planning. Therefore, we adopted the SLEUTH urban growth model to meet the following specific objectives: (1) to calibrate the SLEUTH model in response to local characteristics of the Karaj City and for quantifying dominant growth modes of the targeted area and (2) to predict the evolution of urban dynamics under three policy scenarios including historical trend based, compact and extensive growth alternatives.

2 Materials and methods

2.1 Study area

Karaj City is the capital of Alborz province, Iran, spanning between latitudes 35°67′–36°14′N and longitudes 50°56′–51°42′E and covers total area of 141 km^2. Alborz Chain Mountains bound this city in the north, and elevation is descending from north to south.

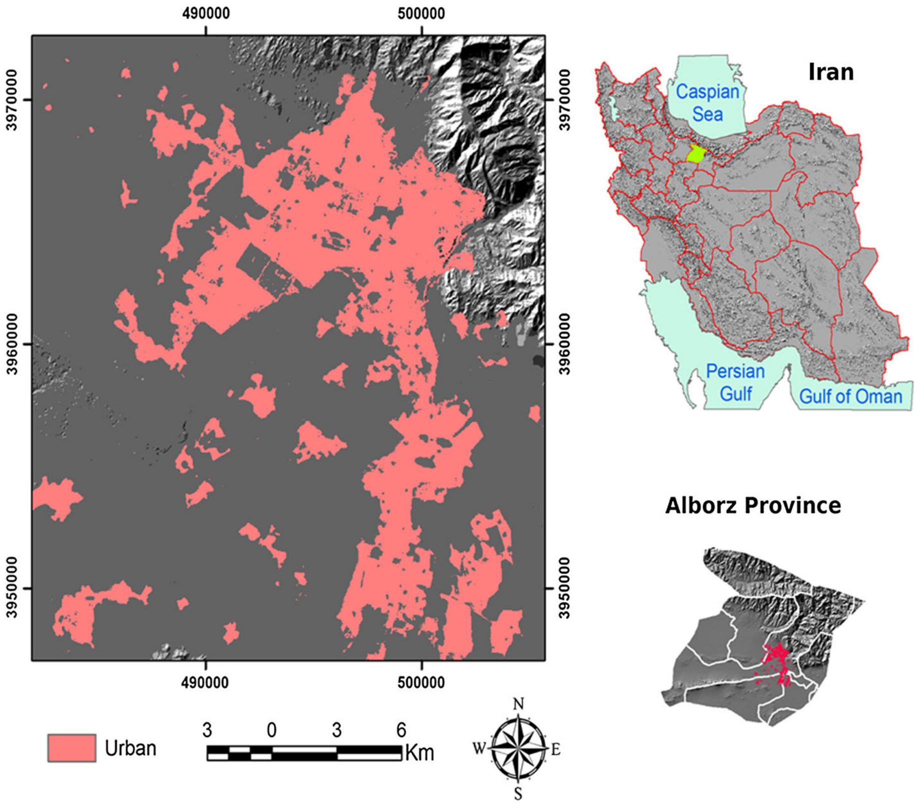

Fig. 1 Study area across Alborz province

Average elevation is 1,320 m above the sea level. Dominant wind direction is north–west and annual rainfall is 246.3 mm, with annual average temperature varying between 15 and 16 °C, and the total population of the city is 1,686,521 (Iranian Statistics Center 2012) (Fig. 1).

2.2 Urban growth modeling

2.2.1 Data preparation

All the required input data to execute the SLEUTH model were prepared by the integrated application of geographic information systems and remote sensing. In this regard, the targeted area was geometrically corrected by the source in UTM WGS 84 system. The mapping process of the urban extensions for the years 1984, 2000, 2006 and 2011 was conducted through a hybrid method including the supervised classification and visual image interpretations to Landsat TM and ETM^{+} images. The dimensions of the grids were 856 rows by 809 columns. As a model requirement, all binary urban/non-urban layers were stretched linearly and converted into GIF format with a grayscale palette. Transport layers were extracted through on-screen digitization, and the resultant vector layers were converted into raster. Using a 10-m digital elevation model (DEM), which was obtained from the National Cartographic Center (NCC) of Iran, slope percent and hill shade layers were derived. The excluded area comprised the bank river of the seasonal Karaj River that was derived from on-screen digitization (Sakieh 2013). All layers were then compiled in the same extent with 30-m resolution using the nearest neighborhood algorithm (Fig. 2). Table 1 describes the input data set and the preparation method for the SLEUTH model.

2.3 Model calibration

The name of the SLEUTH model refers to its input layers (slope, land use, excluded area, urban extension, transportation network and hillshade). As mentioned, SLEUTH is a modified CA model in which five coefficients (diffusion, breed, spread, slope and road

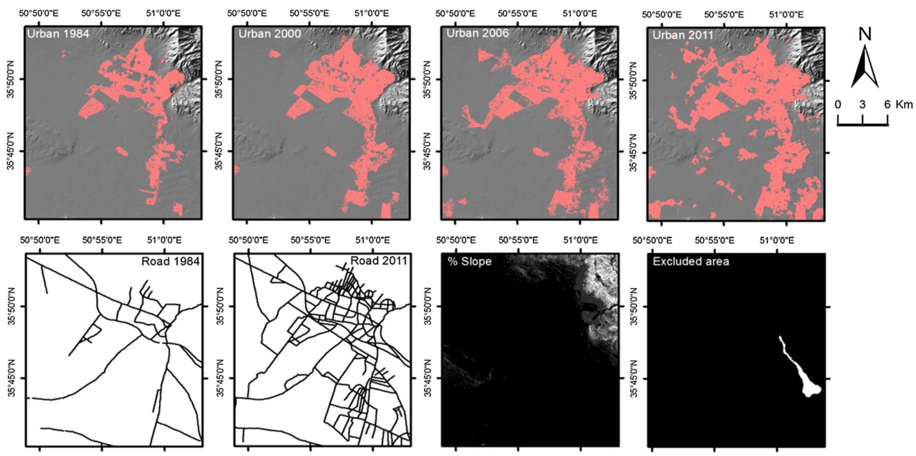

Fig. 2 Karaj City data sets to SLEUTH

Table 1 Data requirements for SLEUTH

Input layer	Prepared through	Format and year
Urban extension	Supervised classification of satellite image	Raster, 1984, 2000, 2006 and 2011
Transportation network	On-screen digitization from satellite image	Raster, 1984 and 2011
Slope	Derived from DEM	Raster
Hillshade	Derived from DEM	Raster
Excluded area	Rasterized from vector	Raster

gravity) control four types of growth rules (spontaneous growth, new spreading center growth, edge growth and road gravity growth). In addition, SLEUTH as a CA model takes advantage of a second level of rules, the so-called self-modification rules, which are properly internalized and enable the calibration mode to dynamically adopt itself to local settings over the time (Dezhkam et al. 2014). In order to show the relative importance, each coefficient has a dimensionless value ranging between 0 and 100. During the calibration process, coefficients are responsible to detect the form of urban expansion via four mentioned growth rules, and prediction of the model will be based on the best range of refined coefficients derived from the calibration mode. Table 2 shows the relationships between growth types and growth coefficients.

The main assumption of the SLEUTH model is based on the inherent pattern of urban dynamics which means that the city will witness the same scenario growth in the future based on its historical trend in the past (Clarke et al. 1997). Accordingly, during the calibration process, the model fits the simulated data to the real historical data sets of the targeted area. In this case, the model's parameters get refined through similarity comparison between the simulated urbanization against the urbanization of the control years, reflected in the various indices during growth cycles. Table 3 depicts some of the indices for evaluating the calibration results in SLEUTH modeling.

Based on each growth cycle, which is the fundamental function of the SLEUTH model, the model is able to simulate four types of urban growth rules. In addition, the self-modification rules are significantly important to dictate more accurately the typical S-curve growth rate of urban expansion (Silva and Clarke 2002). In this regard, during the first growth cycles, where there are more available cells for urbanization do exist, the coefficients are multiplied by values more than 1 and over time when growth rate levels off, the parameters values are multiplied by values less than 1 to rebate growth rate. Otherwise, the model only simulates linear or exponential trends of the growth (Silva and Clarke 2002).

Table 2 Relationship between growth types and growth coefficients

Growth types	Controlling coefficients	Summary description
Spontaneous	Diffusion	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, diffusion, breed, slope	Simulates newly urbanized cell growths along transportation networks

Source: Lu et al. (2009)

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
Lee-Salee	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)

During the calibration process, the model seeks to derive the best range of each coefficient that helps model for better simulation of the historical data set responding to the locale. Practically, the model benefits from a stochastic computation algorithm known as the Monte Carlo method. Because the SLEUTH model utilizes Monte Carlo iterations stochastically to generate multiple simulations of urban growth, parameters are standardized in a range between 0 and 100 that reflects the relative contribution of each parameter to the dynamics of urban growth in the study area. Hence, the calibration process is divided into three phases (coarse, fine and final) that in each phase the parameter space is extensively explored through sequential number of Monte Carlo iterations and possible combinations of coefficients. As it can be observed, execution of SLEUTH is computationally complex and time-consuming, mainly because of extensive automated exploration of the parameter space through selection of the different scores for each coefficient (Clarke et al. 1997). For the coarse calibration, the default values from the sample calibration–scenario file were used with the exception of critical slope, which was set at 45 % using previous knowledge of the development pattern in the study area (Sakieh 2013). The user can also define several additional forecasting parameters according to the needs of a particular study, for instance, the excluded layer, roads layer, urban extent layer, critical slope, critical high, critical low, boom, bust and random seeds (Xi et al. 2009, 2012). Accordingly, the coefficients get refined from their widest range in the coarse phase (0–100 given to breed, spread, slope, roads and diffusion) leading to narrower range that feeds the next calibration phases including fine and final stages that best describe the spatial characteristics of locale. Sensitivity of the model can be addressed by incrementing the parameters through incremental steps during the calibration stage (the bigger steps, the less model sensitivity). In addition, full spatial resolution of the input layers (30 m) in three calibration phases was applied. As mentioned before, during the calibration process, a series of indices

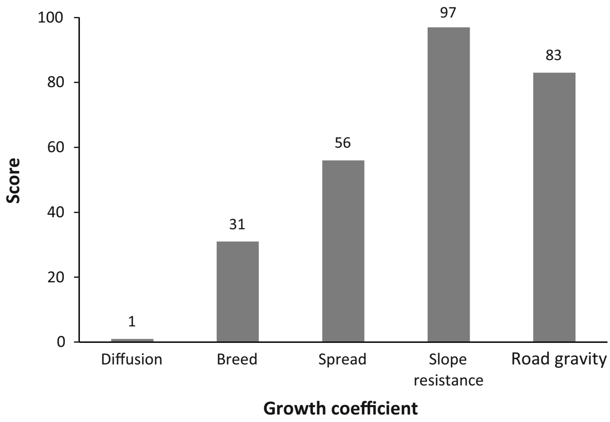

Fig. 3 Parameters averages for prediction

are calculated to assess the modeling goodness of fit. In order to select the best range of each coefficient during the calibration stages, all indices were sorted in descending order based on optimized SLEUTH metric (OSM) (Dietzel and Clarke 2007) and the top highest scoring results were selected and fed to the subsequent calibration step. Finally, by using the best set of derived coefficients from three steps of calibration, the model was executed for the simulation of historical data set. In this phase, the number of Monte Carlo iterations will support the robustness of final coefficients to run the prediction part of the model. 100 Monte Carlo iterations was applied with one step increment (Candau 2002; Jantz et al. 2003) and resulted in extraction of the final parameters averages (Fig. 3).

2.4 Model validation

To evaluate the accuracy of the SLEUTH model, we selected two separate validation indices, each varying in their technical approach and their focus on evaluation (Wu et al. 2009; Rienbow and Goetzke 2014):

- The receiving operator characteristic (ROC);
- Kappa index of agreement

The ROC is a proven measure for accuracy assessment of binary categorical probability estimations (Pontius and Schneider 2001). The ROC distributes the probability outcomes into percentile groups from high to low likelihood and compares the individual probability classes with cumulative real values. The ROC only considers the positive values approximated by the model, in this study all urban growth cells. To define the ROC, true positive and false positive rates area plotted for every percentile class. The output is a curve, where the area under the curve (AUC) is the measure that reflects the ROC statistic. If a model performs randomly, the curve will be a line through the origin a slope of 1 and the AUC of 0.5. If a model performs perfectly, the AUC is 1.

The Kappa index is a standard and widely implemented measure of accuracy assessment of remote sensing image classification (Congalton 1991). The Kappa coefficient is considered to be more robust than simple overall accuracy, because it takes into account the proportion of pixels that are classified correctly simply due to chance.

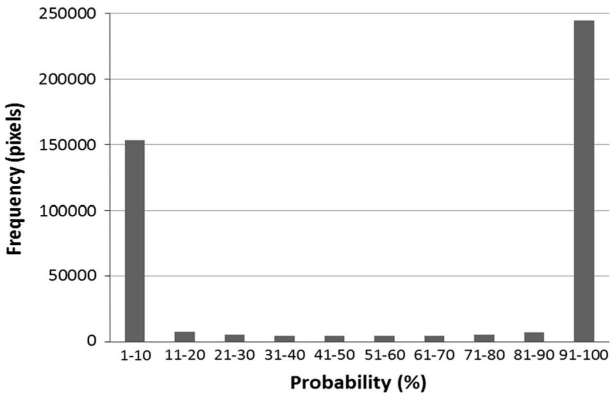

Fig. 4 Frequency histogram of probability urbanized map for the year 2040

2.5 Model prediction

After the calibration and performance evaluation of the model, the prediction mode was executed by means of full resolution of the data set in addition to 100 Monte Carlo iterations. Prediction of the model is based on the initial seed year of the present urban pattern using those refined values of coefficients. This means that the refined coefficients exert the inherent behavior of urban growth during control years, and sprawl of the city will be maintained in a similar trend, which has happened in the past. Output of the SLEUTH model is a probability image in which each cell has a probability value to become an urbanized space in the future. This map is produced for every year including first year (1984) to the last year (2040). In order to produce a crisp map, which indicates the future urbanized cells, a frequency histogram and the cutoff point method was applied. The frequency histogram reveals the frequency of each probability within the cell space. As Fig. 4 illustrates, there is a sharp increase in the number of the urbanized cells around 90 % probability value. Consequently, this threshold was selected as cutoff threshold mainly due to the following reasons (Rafiee et al. 2009; Dezhkam et al. 2014; Rienbow and Goetzke 2014):

- Pixels with 90 % of urbanization and more illustrate highly suitable as well as probable lands for urbanization in the future;
- These pixels were the most frequent values within the cumulative raster image produced by the SLEUTH model; and
- Visual interpretation of spatial patterns of the cells retaining 90 % of urbanization probability and more indicated these cells are more correlated with current urban clusters, while values under this threshold depicted a scattered distribution that could be considered as potential lands but unlikely places to experience urbanization.

There are different methods to simulate the expansion of urban area under different scenarios in the SLEUTH model. In the first method, best-fit multipliers derived from the calibration phases were altered (Leao et al. 2004; Rafiee et al. 2009) and consequently the growth rules were changed, which shows the form of urban growth. In the second method, the excluded layer is weighted through a continuous range of resistance values against urbanization to show that even cells within the excluded layer have the potential to be urbanized under different probabilities (Oguz et al. 2007; Mahiny and Clarke 2012, 2013). Finally, in the third scenario, the constraints of self-organization are modified (Yang and

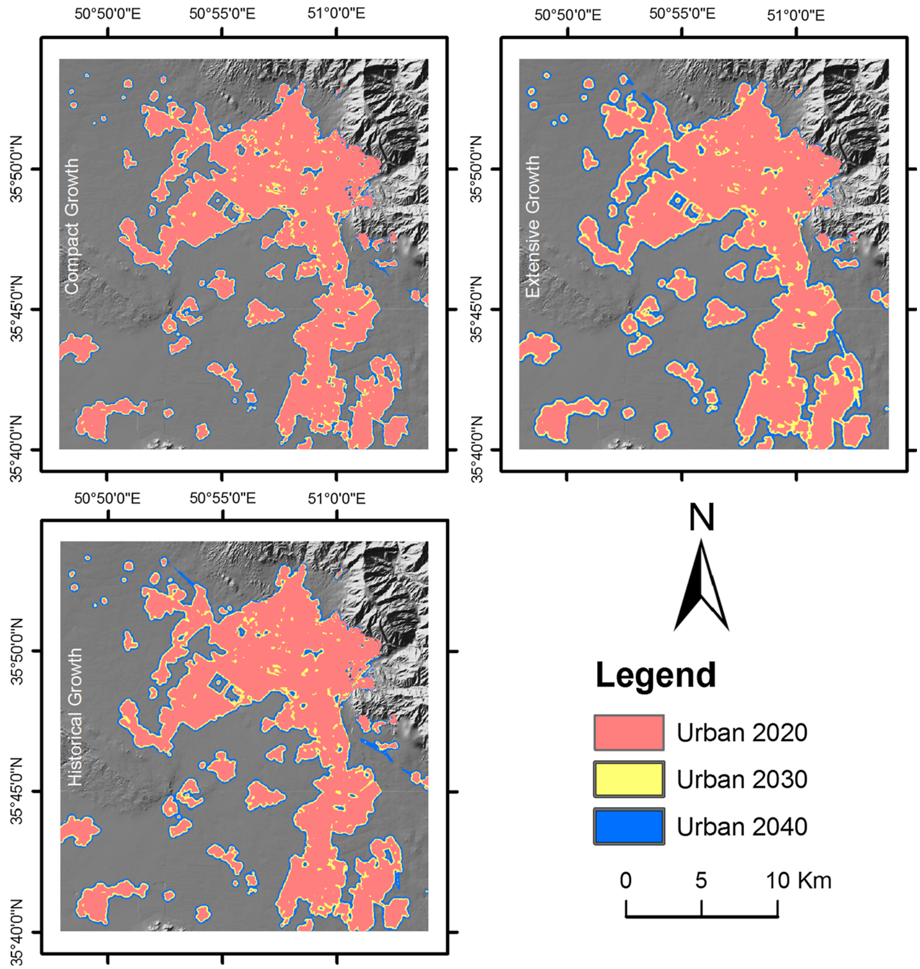

Fig. 5 Dynamics of the Karaj City under three different scenarios

Lo 2003; Xi et al. 2009). In this study, the first method was applied and the coefficients were altered in a similar way proposed by Rafiee et al. (2009). In this case, the historical trend of the urban growth and two different scenarios were forecasted, emphasizing the concepts of controlled and uncontrolled urban growth (Fig. 5).

The coefficients values derived from the calibration steps were directly fed into the prediction mode of the model based on its historical trend, which assume that the current trend of urban growth will be maintained in the future. Insisting on the concept of controlled growth, through the compact growth option, the values of the spread and breed parameters were reduced (from 31 and 56 to 21 and 46, respectively) to dictate an infill form of urban development with the aim of protecting the immediate environment of the city against urbanization. In order to investigate the role of an uncontrolled growth policy, an extensive form of urban expansion was also predicted through increasing spread and breed coefficients from 31 and 56 to 45 and 70, respectively. Finally, the prediction mode

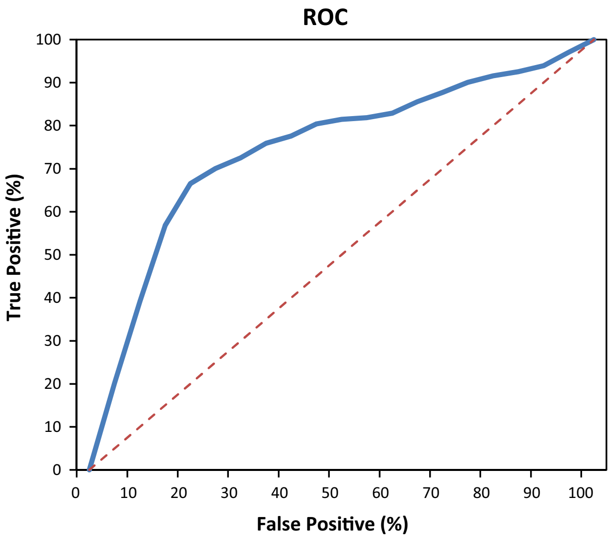

Fig. 6 ROC curve derived from the cumulative probability of urbanization of the year 2011 and the reference layer of the corresponding year

of the model was executed according to these three scenarios and different results were acquired as well.

3 Results

3.1 Model validation results

The historical trend based of urban growth profile was simulated. In this case, the 1984 map layer was set as the beginning year and the 2011 urban layer was set as prediction stop date. The accuracy of the simulated urban pattern of the year 2011 was assessed through the ROC method and the Kappa coefficient. Figure 6 presents the ROC curve (comparing the cumulative probability image of the year 2011 and the binary urban map of the corresponding year). The curve is clearly characterized by a linear increase that becomes stable at high percentile groups. The resultant AUC value confirms the validity of the calibrated model, which scored at 0.81—an acceptable performance for the AUC. In addition, the Kappa index of agreement was scored at an acceptable value as well (70 %), which indicates that the model successfully detected the local settings of the study location during the calibration mode. Finally, the OSM also gained adequate value in the final calibration stage (0.4354) that validates the calibration procedure (Dietzel and Clarke 2007).

3.2 Model calibration results

Model calibration results are presented in Tables 4, 5, 6 and 7. Each table represents the sorted top ten highest scoring values from thousands of model run.

In the coarse calibration phase, the growth multipliers were ranged between 0 and 100, the possible minimum and maximum values for a parameter. In the next step (fine), diffusion, breed, spread, slope resistance and road gravity parameters covered range of

Table 4 Coarse calibration results

Compare	r^2 population	Cluster size	Lee-Salee	Average slope r^2	% Urban	xmu r^2	ymu r^2	Rad
0.84	0.95	0.85	0.59	0.94	1.00	0.90	0.93	0.96
0.84	0.95	0.25	0.59	0.93	1.00	0.90	0.94	0.96
0.84	0.95	0.47	0.59	0.95	1.00	0.90	0.94	0.96
0.84	0.95	0.46	0.59	0.76	1.00	0.91	0.94	0.96
0.83	0.96	0.62	0.59	0.98	1.00	0.93	0.94	0.96
0.83	0.96	0.62	0.59	0.98	1.00	0.93	0.94	0.96
0.85	0.95	0.68	0.59	0.16	1.00	0.90	0.94	0.96
0.84	0.95	0.51	0.59	0.92	1.00	0.90	0.94	0.96
0.85	0.95	0.50	0.59	0.97	1.00	0.92	0.93	0.96
0.81	0.95	0.55	0.59	0.28	1.00	0.92	0.93	0.96

Table 5 Fine calibration results

Compare	r^2 population	Cluster size	Lee-Salee	Average slope r^2	% Urban	xmu r^2	ymu r^2	Rad
0.76	0.96	0.61	0.59	0.91	1.00	0.90	0.96	0.97
0.76	0.96	0.61	0.59	0.75	1.00	0.91	0.96	0.97
0.74	0.96	0.61	0.59	0.92	1.00	0.90	0.96	0.97
0.77	0.96	0.16	0.59	0.71	1.00	0.90	0.97	0.97
0.75	0.96	0.30	0.59	0.72	1.00	0.90	0.96	0.97
0.74	0.96	0.20	0.59	0.90	1.00	0.91	0.95	0.97
0.76	0.96	0.62	0.59	0.80	1.00	0.91	0.96	0.97
0.77	0.96	0.42	0.59	0.59	1.00	0.90	0.96	0.97
0.74	0.96	0.13	0.59	0.81	1.00	0.91	0.96	0.97
0.79	0.96	0.70	0.59	0.04	1.00	0.91	0.96	0.97

Table 6 Final calibration results

Compare	r^2 population	Cluster size	Lee-Salee	Average slope r^2	% Urban	xmu r^2	ymu r^2	Rad
0.75	0.96	0.18	0.59	0.84	1.00	0.91	0.96	0.97
0.75	0.96	0.18	0.59	0.84	1.00	0.91	0.96	0.97
0.76	0.96	0.34	0.59	0.82	1.00	0.90	0.96	0.97
0.76	0.96	0.34	0.59	0.82	1.00	0.90	0.96	0.97
0.77	0.96	0.25	0.59	0.74	1.00	0.90	0.96	0.97
0.77	0.96	0.25	0.59	0.74	1.00	0.90	0.96	0.97
0.77	0.96	0.25	0.59	0.74	1.00	0.90	0.96	0.97
0.77	0.96	0.25	0.59	0.74	1.00	0.90	0.96	0.97
0.76	0.96	0.53	0.59	0.92	1.00	0.89	0.95	0.97
0.76	0.96	0.53	0.59	0.92	1.00	0.89	0.95	0.97

Table 7 Summary of parameters during calibration process

Growth parameter	Coarse		Fine		Final		Result value
	Monte Carlo iterations = 4		Monte Carlo iterations = 7		Monte Carlo iterations = 9		
	Total number of simulation = 3,125		Total number of simulation = 7,776		Total number of simulation = 7,776		
	OSM = 0.2607		OSM = 0.3551		OSM = 0.4354		
	Range	Step	Range	Step	Range	Step	
Diffusion	0–100	25	0–20	4	0–5	1	1
Breed	0–100	25	25–50	5	30–35	1	31
Spread	0–100	25	50–75	5	50–60	2	56
Slope	0–100	25	75–100	5	85–100	3	97
Road gravity	0–100	25	75–100	5	80–95	3	83

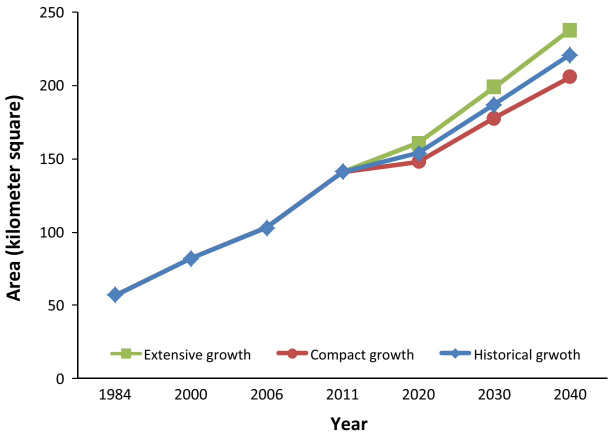

Fig. 7 Growth trend of the Karaj City under three scenarios up to year 2040

values between 0–20, 25–50, 50–75, 75–100 and 75–100, respectively. Theses range became even more narrowed through the subsequent phase (final), leading to the values between 0–5, 30–35, 50–60, 85–100 and 80–95. The importance of this multistage sequential optimization can be attributed to thousands of automated explorations within the parameter space via selection of the highest scores of the five coefficients. This process leads to coefficients with narrower range, which better reflect the local settings of the targeted area (Silva and Clarke 2002; Sakieh 2013).

To assess the simulation accuracy, the comparison between the provided indices and real data set are presented for each calibration stage. The comparison of the model final "r^2 population" (number of urban pixels) indicates a high correlation of 0.96 and for "compare" it is 0.75, making it possible to address that the prediction of model based on historical available data set using those refined values from final calibration stage is very similar to what witnessed in reality. Taking the Lee-Salee index into account, there is 0.59 spatial fit between the modeled growth and the known urban extent for the control years.

As Fig. 3 illustrates, the growth multipliers were scored at values of 1, 31, 56, 97 and 83 in the case of diffusion, breed, spread, slope resistance and road gravity coefficients, respectively. The highest value of the slope resistance parameter indicates the limiting influence of the steeper slopes on general trend of urban growth especially in the north part of the city where Alborz Chain Mountains completely stopped urban sprawl. In addition, the values of 31, 56 and 83 belonging to breed, spread and road gravity multipliers mirror that there is tendency of linear and scattered form of growth alongside of the transportation network, which results in outward urban sprawl with proximity to immediate lands from current urban boundaries. With regard to the low percentage of diffusion multiplier, it can be concluded that there is low probability for establishing new urban centers through spontaneous growth. It should be noted that small urban clusters around Karaj City will experience a rapid change in their immediate vacant lands, which can result in massive consumption of agricultural fields, surrounded those cities.

Growth prediction of the Karaj City based on extensive prediction shows the most increase in urban extent by which the total area of the city will dramatically expand from 141 km^2 in 2011 to 238 km^2 in 2040, an 80 % of expansion. The compact predictive scenario represents the least amount of increase in the total area of urbanized lands (206 km^2), mainly because of reduced score of spread and breed multipliers to dictate the compact growth. According to the historical trend-based scenario, the total area of the Karaj City has accelerated up to 221 km^2. Therefore, it can be concluded that the anticipated extent of the Karaj City under the compact scenario can lead to minimum consumption of vacant lands and agricultural fields in the immediate city fringe. Figure 7 demonstrates the urban extent of Karaj City under three scenarios.

4 Discussion

Urban expansion is a complicated phenomenon that occurs mainly because of the need for more construction rising from increasing population. Consequently, vast lands of valuable ecosystems such as forests and pastures are consumed and converted to urban areas and impervious surfaces. In this paper, the SLEUTH urban growth model was employed to investigate the role of different spatial considerations in developing policy scenarios. Findings of this paper are as follows.

First, calibration of the model depicts that the major driving force of urban growth in the study area are the coefficients of slope resistance, spread and road gravity. This combination implies that the city tends to sprawl alongside of current urban boundaries, but the expansion is largely regulated through the effect of topographic characteristics of the area. Other multipliers including diffusion and breed with less significant contribution in the overall process of urban growth denote that there is low probability for establishing new urban centers in areas without preexisting urban infrastructures. On the other hand, emergence of new urbanized lands tended to occur alongside of current urban boundaries. Maybe, this can be attributed to the sprawl features of the Karaj City. In this case, factors such as slope, relief, river and regulations are natural and human-made limitations to the development of the city. Under these constraints, the construction of transportation networks and infrastructure facilities influence any further establishment of new settlements. Considering the coefficients' values of other applications of SLEUTH in Iran (Mashad, Gorgan and Rasht), it is worthwhile to notice that spread, breed and road gravity multipliers received the highest relative importance among others, which suggest that these areas are experiencing a scattered form of urbanization. In the case of the Karaj City, the relative importance of the coefficients depicts moderate variations in which spread and road gravity multipliers are quite dominant. Therefore, similar to those cities, the area is expanding along its current boundaries and sprawls toward its immediate surroundings (Rafiee et al. 2009; Mahiny and Clarke 2012, 2013; Dezhkam et al. 2014).

In the case of the spread and breed coefficients, the findings are consistent with the work of Mahiny and Clarke (2012, 2013), where study areas showed the same characteristics. On the other hand, slope resistance parameters of the two studies are quite different. As the slope resistance coefficient scored at a high value of 97, steeper slopes completely stopped urban sprawl in the northen part of the city, which is considered as a constraining force. This is also in consistency with some other studies such as Jantz et al. (2003), Syphard et al. (2005) and Rafiee et al. (2009), in which the major growth modes were also reflected in breed, spread and road gravity parameters. In addition, the resultant model parameters show the high degree of difference between current application of the SLEUTH model and results of studies conducted by Silva and Clarke (2002) and Yang and Lo (2003). According to the work of Silva and Clarke (2002), all coefficients gained approximately similar scores in response to the local characteristics of the study area (20, 20, 40, 42 and 20 in the case of diffusion, breed, spread, slope resistance and road gravity coefficients, respectively). Based on the work of Yang and Lo (2003), coefficients were scored at quiet different combination in which most of the growth multipliers acquired significant proportion in overall trend of urbanization (92, 13, 41, 95 and 100 assigned for diffusion, breed, spread, slope resistance and road gravity coefficients, respectively). Although simple, these differences in coefficients values imply applicability of the SLEUTH model to the wide range of conditions in which model parameters during calibration can be refined and reflect the local characteristics.

Second, scenario prediction of the model reveals some interesting results. In this regard, the Karaj City has expanded from 57 km^2 in 1984 up to 141 km^2 in 2011, meaning a substantial increase in total area of manmade structures. According to the historical-based prediction of the Karaj City, it is logical to say that the city will witness the similar trend of growth in the future that denotes a substantial increase up to the year 2040 (221 km^2). Owing to the fact that there are agricultural fields close to the urban boundaries, especially in the south part of the city where steeper slopes do not pose any limitation, it is necessary to declare current trend of urban growth could not be maintained. Therefore, two alternative scenarios emphasizing on the concepts of controlled and uncontrolled growth were predicted. In this regard, in environmentally sound prediction (compact growth), score of spread and breed coefficients were reduced and rest of the multipliers remained the same. Under this prediction, the city will expand from 141 km^2 in 2011 up to 206 km^2 in 2040. Visual interpretation of the results shows that infill growth type of the city will save more vacant lands and leading to minimum conversion of agricultural fields into impervious surfaces. Finally, model outputs based on extensive urban expansion depict admonishing growth rate compared with other scenarios (238 km^2).

As a central conclusion to this study, since the Karaj City has witnessed the emergence of some urban satellite nucleus that are completely separated from each other, it is not recommended that smaller urban clusters would grow outward and join together to form much larger clusters. Because the current formation of urban clusters requires linear and scattered pattern of urban sprawl to join numerous and distant edge cities throughout the entire study area. Alternatively, each urban cluster should start its own growth cycle, especially where there is vacant land in the interior urban environment. In addition, establishment of any further new urban centers should be prohibited, which can lead to more fragmented urban landscape and more dispersed configuration of urban clusters.

According to Chaudhuri and Clarke (2013), temporal accuracy in urban growth forecasting is largely dependent on prediction date range and propinquity of the predication date from the immediate future to the distant future. The authors reported that beyond 10 years, the future prediction becomes increasingly more uncertain. In this study, the 30-year prediction time profile was decided mainly due to the following reasons:

- Functionality of the SLEUTH growth rules as well as growth multipliers in detecting suitable but uncertain lands for urbanization, which provides holistic guidelines on future sustainable directions of a city (Mahiny and Clarke 2012, 2013);
- Based on report released by municipality of the Karaj City (Municipality of the Karaj City 2012), a high degree of consistency was observed between detected locations of urban growth in this study and legislated directions by policy makers for managing the future urban environment of the Karaj City; and
- Similar studies such as Herold et al. (2003) and Dietzel et al. (2005) that implemented the SLEUTH model highlighted urban growth general patterns can be identified and measured provided that the model is furnished with enough change in urban areas to work properly.

Due to the fact that the SLEUTH model employs physical and less variant aspects of the real world, such as topographic properties of land and important socioeconomic infrastructures like transportation network as input data layers, this model is more recommended for those areas where socioeconomic data are not widely available. Since the SLEUTH model benefits from physical aspects of land, it can be effectively implemented when more robust results of prediction are needed. On the contrary, compared with the other spatial models such as CLUE-S, DINAMICA, iCity, GEOMOD and the coupled CA-Markov chain model, the SLEUTH model requires fewer number of input layers and also offers various and flexible environments for developing different growth alternatives. These characteristics of SLEUTH have made the model as most implemented land use simulation method at regional, national and even binational scales (Maithani 2010; Chaudhuri and Clarke 2012; Norman et al. 2009, 2012). Lastly, it is suggested that any further effort in application of the model should focus on the important role of the self-modification rules. Given the wide experience of urban simulation through the SLEUTH model and rich database acquired from these studies, self-modification rules can be modified to better and more accurately represent either historical growth mechanism or scenario prediction of the real-world urban processes.

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