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RESEARCH ARTICLE

Using the SLEUTH Urban Growth Model to Simulate Future Urban Expansion of the Isfahan Metropolitan Area, Iran

Neda Bihamta · Alireza Soffianian · Sima Fakheran · Mehdi Gholamalifard

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ABSTRACT Accelerating urban growth and land use/cover changes places increasingly pressure on the natural environment and human welfare and have become a global concern. Iran, as a developing country, is also experiencing growth of its urban areas during the last decades by high rate of rural–urban migration along with rapid socio-economic and political changes that has resulted in degrading environmental quality in many parts of Iran, particularly in the metropolitan areas such as Isfahan. Therefore, developing methods for assessing different urban growth planning scenarios and simulating urban expansion is critically important. The main goal of this study was simulating future urban expansion of Isfahan Metropolitan area from 2010 to 2050, by making use of cellular automata methodology in the SLEUTH modelling. The model was calibrated using historical data extracted from a time series of satellite images. The input data required by the model including Slope, Land use, Exclusion, Urban extent, Transportation and Hillshade were obtained from satellite images based on supervised classification. This research used the four images of Landsat Multispectral Scanner (MSS) and Thematic Mapper (TM) acquired 1976, 1990, 2001, and 2010. Two scenarios were planned to simulate the spatial pattern of urban growth. The first scenario was historical urban growth, which permitted urban development maintenance of the historical trend and the second scenario was a more compact growth as an answer to hypothetical policies and the lack of land to decrease urban spreading. Calibration of the SLEUTH model for Isfahan metropolitan area showed a high spread coefficient, which means that the predicted mode of growth in Isfahan is "organic" or edge growth. In Isfahan metropolitan area, topography was also shown to have an enormous effect in controlling the urban development. The results of this study invites many opportunities for further studies in many other regions which are experiencing growth of their urban areas and can be useful for planners, and policy makers to implement preventative or controlling factors in advance and make more informed strategic decisions.

Keywords Land use · Urban growth · Simulation · SLEUTH · Isfahan

N. Bihamta (✉) · A. Soffianian · S. Fakheran
Department of Natural Resources, Isfahan University of Technology, Isfahan 84156-83111, Iran
e-mail: nbihamta2010@gmail.com

M. Gholamalifard
Tarbiat Modares University, Noor, Iran

Introduction

Accelerating urban growth and land use/cover changes places increasingly pressure on the natural environment and have become a global concern (Turner and Meyer 1994), as these are believed to be responsible for the ecological degradation such as habitat fragmentation and biodiversity loss.

Currently about 3.3 billion humans reside in cities, and this figure is estimated to increase about 5.0 billion by 2030 (United Nations 2008). With the increasing world city population particularly in developing countries and enhanced demand on land resource, urban development, the most intensive and dynamic human development activity, has become the leading forces behind these changes (Randolph 2004).

As a developing country, Iran is experiencing growth of its urban areas. The urbanization trends in Iran during last decades had been accelerated by high rate of rural–urban migration along with rapid socio-economic and political changes that formed unbalanced urban growth in Iran. The percentage of urban population to total population of Iran in 1976 was

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47 % and this ratio reached 61 % in 1996 (Fanni 2006). According to general censuses, during last 50 years, population of Iran has experienced a three-fold increase, while population of cities has undergone a six-fold growth which has resulted in degrading environmental quality in many parts of Iran, particularly in the metropolitan areas such as Isfahan. Therefore, developing methods for assessing different urban growth planning scenarios and simulating urban expansion, regarding the future consequences for land use and the progress of current spatial plans and policies is critically important for urban and regional planners and decision makers.

Urban extension models are consequently attractive and have been documented as a useful tool to help predicting the development of urban growth, supporting urban planning and policy makers, and assessing the environmental or ecological property of urbanization (Verburg et al. 1999; Berling-wolff and Wu 2004).

Many efforts have been made to model urban growth using different models and algorithms, demonstrating the helpfulness of cellular automata (CA) coupling with fuzzy logic (Liu 2009), artificial neural network (Almeida et al. 2008), Markov chain with modified genetic algorithm (Tang et al. 2007), weight of evidence (Soares-Filho et al. 2004), non-ordinal and multi-nominal logitestimators (Landis, j. 2001), SLEUTH (Clarke et al. 1997) and others (Batty et al. 1997). Amongst all, the cellular automata models have proved rather popular as frameworks for modelling and simulating the physical growth of cities. The simulation of urban growth through cellular automata models brings improved understanding of the complex dynamic process of land use change, which cannot be achieve through conventional models (Batty et al. 1997). Many studies show that the cellular automata (CA)-based spatial model is capable to competently simulate and forecast the spatial process of urban development (Silva and Clarke 2002; Ding and Zhang 2007; Oguz et al. 2007; Liu 2009). CA models involve space that should be represented as a grid of cells that can alteration condition as the model iterates. These changes are regulated by rules to specify a set of neighbourhood situation to be met before an alter in situation can occur (Webster and Wu 2001; Oguz et al. 2007). Some advances have been accomplished in expanding hybrid CA that can incorporate process-based factors (White and Engelen 2000; Oguz et al. 2007). As scheming tools, CA urban models have results that can be visualized, as well as quantified (Oguz et al. 2007).

This paper makes use of a CA program known as SLEUTH (Candau 2002). SLEUTH is an acronym for the spatial datasets required as inputs from the user to run the model. These datasets are, in order, Slope gradient, Land use, Exclusion, Urban extent, Transportation, and Hillshade. SLEUTH is one of the popular urban growth models which can be used as a significant planning tool with combining dissimilar human perceptions into the data used for predicting the future of a metropolis (ŞEVİK, Ö 2006, and because of its size autonomy, active and future oriented constitution, transportability, use of under diverse conditions by modifying some primary situation and changing input data layers and purpose of all regions with distinguishing data sets, SLEUTH has occur to a expected tool in modelling urban distribution extent over time or forecasting expansion into the potential (Yang and Lo 2003; Goldstein 2004). SLEUTH has been used to model a growing number of geographical regions such as Chester County (Arthur 2001), Washington-Baltimore metropolitan region, Porto and Lisbon, Portugal (Silva and Clarke 2002), and San Francisco (Clarke et al. 1997).

The main goal of this study was simulating future urban expansion of Isfahan Metropolitan area in central Iran, from 2010 to 2050, by making use of cellular automata methodology in the SLEUTH modelling.

Materials and Methods

Study Area

Isfahan is located in central Iran, equidistant from the Persian Gulf and the Caspian Sea, and covers 340 km^2 (Fig. 1). The city is located in the lush plain of the Zayanderood River ("The life-giving river"), at the foothills of the Zagros mountain range. Zayanderood River divides Isfahan city into north and south parts. Certainly, one of th e main factors for the growth of this city, comparing to its neighbor cities, is the existence of this river. Isfahan is one of the most important cities of Iran and attracts a large number of tourists each year because of its historical and economic values.

The Isfahan metropolitan area had a population of 1,791,069 in the 2010, the second most populous metropolitan area in Iran after Tehran. According to national censuses, Isfahan's population has increased from 255,000 in 1956 to 1,791,069 in 2010 (Statistical Centre of Iran (SCI), Accessed 2011). Isfahan has experienced unprecedented urbanization since the economic growth; the urbanization ratio increased from 44.2 to 83.5 in 1956 and 2006, respectively (Statistical Centre of Iran, Accessed 2007).

Urban expansion, population growth, in addition to industrial development, has resulted in degrading environmental quality in the Isfahan metropolitan area.

SLEUTH Model

The SLEUTH urban growth model is an open source package NCGIA 2011). The SLEUTH model developed by Clarke, based on the CA city expansion development theory, which can be applied to city development simulation in metropolitan areas (Clarke et al. 1997). The initial application of SLEUTH was to the San Francisco Bay area (Clarke, K.C.& Gaydos, J.

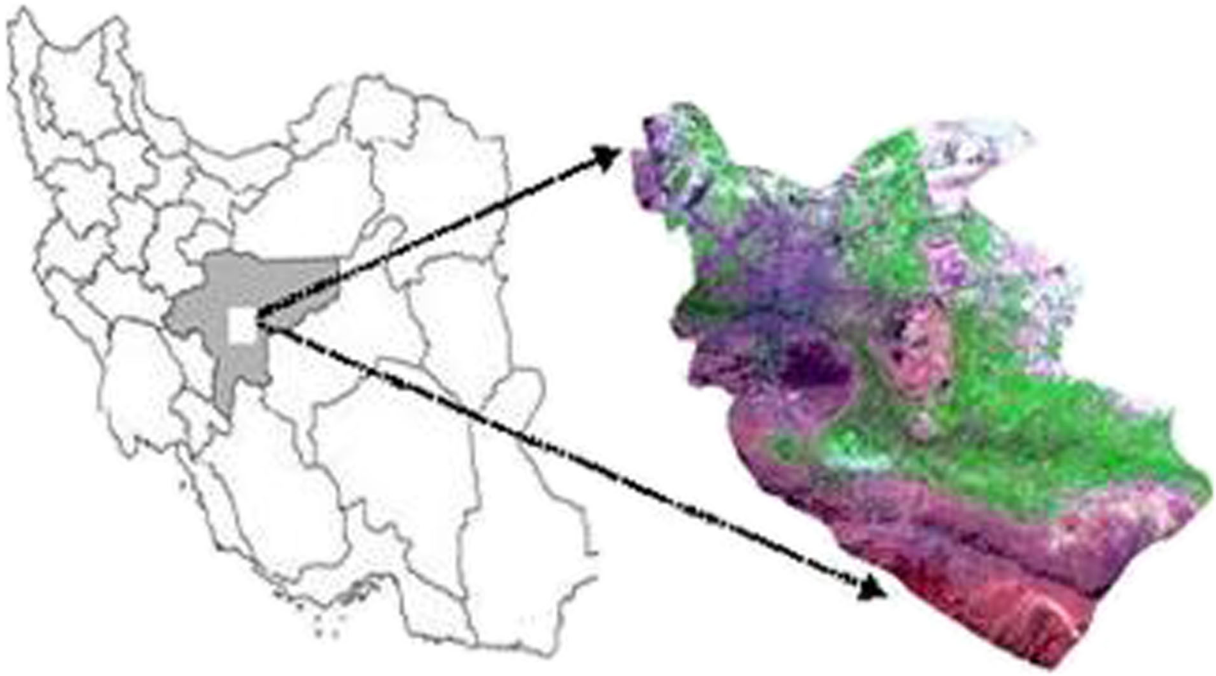

Fig. 1 Location of Isfahan Province which is in the center of Iran (left) and Isfahan city extent (right)

1998), and the name comes from the contraction of its data input necessities which are Slope, Land use, Excluded, Urban, Transportation and Hillshade (Clarke 2008). SLEUTH, which was written in C programming language and working under UNIX or LINUX operating system, has two components; urban growth model (UGM) and land cover deltatron model (LDM). The UGM uses the standard gnu C compiler (gcc) and the LDM is inserted in the code and driven by the UGM (Candau 2002). The dynamic urban growth, in SLEUTH, is described by four rules: spreading centre; edge growth; and road influenced growth (Clarke et al. 1997). Spontaneous new growth acts much the same as exurban raise at present, because it is located outside of the existing urban centres in rural hinterlands. An instance of new spreading centre growth is the institution and development of a new housing expansion or shopping mall. Edge growth is simply the sustained expansion of existing centres of urban development, and road affected growth is that which happens in immediacy to existing transportation networks (Clarke, K.C.& Gaydos, J. 1998 The aforesaid growth rules or types correspond to a set of coefficients that range in value from 0 to 100, and show how much of a persuade the different growth models have across the study area (Silva and Clarke 2002). There are five factors which control the behaviour of the model: diffusion factor, breed coefficient, spread coefficient, slope coefficient, and road-gravity factor (Ding and Zhang 2007). The relationship between these five factors and four possible types of growth is shown in Table 1.

The diffusion factor determines the overall outward dispersive nature of the distribution. The breed coefficient specifies how estimated a recently created separate settlement is to commence its own growth cycle (Clarke et al. 1997). The spread coefficient controls how much dispersion development occurs from existing settlements. The slope disagreement factor impacts the probability of settlement extending up steeper slopes. The road gravity factor attracts new settlements toward and along roads (Ding and Zhang 2007). For implementation of SLEUTH for urban growth simulation of Isfahan Metropolitan area the following five steps including model compilation, input data preparation, calibration, prediction and result output were done (adapted from (Yang and Lo 2003)). In this study, the model was compiled under Linux operator system.

Data Preparation

For this study input data were prepared and analysed using ArcGIS 9.3, Erdas and SLEUTH3.0_beta. The input data required by the model including Slope, Land use, Exclusion, Urban extent, Transportation and Hillshade were obtained from satellite images based on supervised classification

Table 1 Growth Rules and Coefficient

Growth Rules	Growth Coefficients
Spontaneous Growth	Dispersion, Slope
New Spreading Center	Breed, Slope
Edge Growth	Spread, Slope
Road Influenced Growth	Breed, Road Gravity, Slope, Spread

(Gigalopolis, Project Gigalopolis: Urban and land cover modeling 2007). This research used the four images of Landsat Multispectral Scanner (MSS) and Thematic Mapper (TM) acquired 1976, 1990, 2001 and 2010 in the Isfahan metropolitan area. The images were classified using the supervised maximum likelihood classification method. Urban layers were derived from reclassification of detailed land cover classified maps. Transport layers were resulted from visual image explanation and on screen digitization of the same satellite data and the substantial vector layers were changed into raster (Fig. 2). Slope layer was extracted from 28 m DEM which was obtained from United States Geological Survey (USGS). This layer was changed to percent slope. Also, from the same DEM, the Hillshade layer was created for the study area which was used as the background for model image output. Excluded layer consist of airport, railway station and river were digitized on the 2010 Landsat satellite image. In this Study the input layers were resembled to the three spatial resolutions i.e., 200 m coarse, 100 m fine and 50 m final resolutions which corresponds to the image size for the purpose of model calibration. All input layers have been enhanced into GIF format for applying in the SLEUTH model (Gigalopolis, Project Gigalopolis: Urban and land cover modeling 2007). The input data set for the SLEUTH have been shown in Tables 2.

Model Calibration

The calibration of SLEUTH is the most important phase for the capture of urban growth distinctiveness and to achievement of model forecasting (KantaKumar et al. 2011). The reason of the model calibration phase is choosing the best-fit values for the five growth control parameters, including coefficients of diffusion, breed and spread, slope resistance and road gravity with historical urban extent data (Clarke et al. 1997). All of the five calibration coefficients are integrated together and ranged from 1 to 100. The mainly popular calibration technique for SLEUTH is "Brute Force" calibration (Silva and Clarke 2002; Xi et al. 2009), where the user shows a range of values and the model iterates using every achievable joining of parameters. Calibration relies on statistical measures of historical fit. It is the key factor of the modelling practice by which statistical values are assigned to the model parameters in such a way that the model perfectly reproduces the actual patterns (Clarke et al. 1996; Clarke et al. 1997; Yang and Lo 2003).

Usually the calibration of SLEUTH has three-step process. In the first step, input data were resampled to four times of their initial resolution (50 m resolution data was resampled to 200 m). In the fine calibration step, the input data were resampled to twice of their original resolution (50 m resolution data was resampled to 100 m). Finally, in the final calibration step, the input data were used in ten Monte Carlo iterations with full resolution for inputs. The first year supplies a seed for the set of parameters experienced, which then simulate urban growth and then determine it compared to the actual control data (Dietzel and Clarke 2004; ŞEVİK, Ö 2006).

In these calibration consequences for Isfahan metropolitan area, the set of primary control parameter values were ranging from 1 (in the case of the diffusion coefficient) to 100 as the highest values for each of diffusion, breed, spread, slope resistance and road gravity.

At the end of each calibration run, the model produced 13 least squares regression metrics, such as compare (modeled final population), population (number of urban pixels), cluster (urban cluster edge pixels), edges (urban perimeter), Lee Sallee metric (a shape index), average slope, Xmean (average X values), and Ymean (average Y values) (Dietzel and Clarke 2004; KantaKumar et al. 2011) . Each metric represents the goodness fit between the simulated growth and the actual growth for the control years. All of these are described in Following phase of calibration was established on the 13

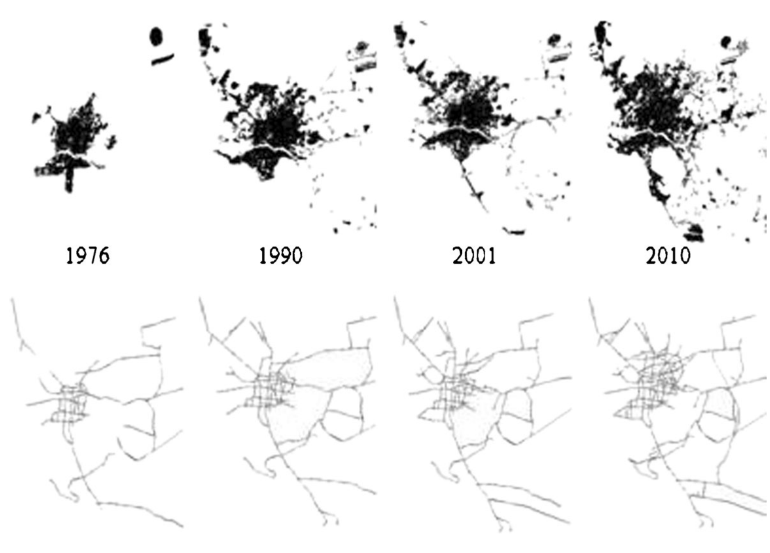

Fig 2 The extent of Isfahan city and the associated road networks since 1976

Table 2 Input data set for SLEUTH

Input layer	Source	Format and year
Land use	Classified from satellite image	Raster, 1976, 2010
Urban	Classified from satellite image	Raster, 1976, 1990, 2001,2010
Transport	Digitized on satellite image	Rasterized from vector, 1976, 1990, 2001, 2010
Slope	DEM generated by USGS	Raster
Hillshade	DEM generated by NCC	Raster
Excluded	On screen digitization	Rasterized from vector

metrics. Some approaches applied to narrow down the coefficient space consist of: arrangement on all metrics regularly, weighting some metrics, and sorting only on one metric (NCGIA 2011).

In this study, Optimum SLEUTH Metric (OSM) was used (Dietzel and Clarke 2004NCGIA 2011) and has been adopted to narrow down the coefficient ranges. OSM is the product of compare, population, edges, clusters, slope, X mean and Y mean metrics (Table 3). The calibration mode is followed by the prediction mode.

Due to the self-modification of the SLEUTH model, parameters values are persistently changed through a run from the first date to the last date and the best calibrated parameters of the stop date are chosen. Thus, utilize of the best parameters resulting from calibration and procedure of the SLEUTH for the historical time period will create a single set of stop date parameters to initialize forecasting (Rafiee et al. 2009a). However, we used the best parameter values in 100 Monte Carlo iterations with OSM metric. The result of the calibration phases for modelling Isfahan City growth is given in Table 4. For Isfahan City, the diffusion coefficient was low, which reflects a low likelihood of dispersive growth.

The very low value for the breed coefficient supports it, identified low probability of growth of new separated urban settlements. The spread coefficient stimulates growth outwards of existing and consolidated urban areas. The medium value of the road gravity coefficient denotes that the growth was affected with the transportation network only along the main roads. the score for slope resistance was high revealing that topography was a limiting factor for urban sprawl.

Model Prediction

The last step in modelling is the predictive state. Utilizing the historic trends and values from growth rules a surface representing the future distributions of urban and non-urban coverage can be generated across the study area (Rafiee et al. 2009b) . For the programmed urban layers, 100 Monte Carlo simulations was certain, and over 70 % likelihood was used to deicide a no urban grid cell as possible to happen to urbanized. The SLEUTH provides a simulation environment to investigate the consequences of policies taken by choice makers. In this study, we planned simulated Isfahan City under two scenarios; historical urban growth which permitted urban development a maintenance of the historical trend and the second scenario was a more compact growth which as an answer to hypothetical policies and the lack of land to decrease urban spreading (Mahiny 2003; Mahiny and Gholamalifard 2007). We then used the method of changing the parameter values to good fit from its flexibility. For the historical growth scenario, we set 30, 5, 50, 91 and 34 for diffusion, breed, spread, slope resistance and road gravity,

Table 3 Some of the indices for evaluation of the calibration results in the SLEUTH modelling (from Silva and Clarke 2002)

Index	
Compare	Comparison of 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 edge count compared with actual urban edge count for control years.
R^2 cluster	Least square regression score of modeled urban clustering compared with known urban clustering for control years
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 slop of known urban cells for control years
% Urban	The percent of available pixels urbanized during simulation compared to the actual urbanized pixels for each control year
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
Radius	Average radius of the circle that encloses the simulated urban pixels compared to the actual urban pixels for each control year

Table 4 The best results of the calibration trough the phases

Index\Step	Coarse	Fine	Final
Compare	0.958	0.997	0.987
r^2 Population	0.874	0.898	0.937
Edge r^2	0.962	0.973	0.994
R^2 cluster	0.969	0.984	0.998
Leesalee	0.342	0.365	0.347
Average slope r^2	0.705	0.736	0.718
% Urban	0.357	0.354	0.346
X_r^2	0.992	1	0.999
Y_r^2	0.989	0.987	0.994
Radius	0.86	0.88	0.91
Diffusion	25	30	34
Breed	1	1	4
Spread	25	50	50
Slope	75	85	94
Road gravity	25	30	52

respectively. This combination assumed that the current status would be maintained and the future growth would occur according to the historical trend. In the second scenario, we reduced the spread and road-gravity coefficients to half. These parameters generally explain the trend of urban sprawl and the effect of road gravity on institution of urban settlements near the road networks. The prediction best fit values have been derived from 50 top log file, which was produced during the final calibration that sorting only on the OSM; the values for prediction best fit are presented in Fig. 3. The results of the urban future extents modelled and predicted through the SLEUTH are indicated in Fig. 4.

Results & Discussion

We conducted 5 Monte Carlo iterations for the coarse calibration of the model in 3124 runs. For fine calibration, 8 iterations in 4355 runs were conducted and the final calibration

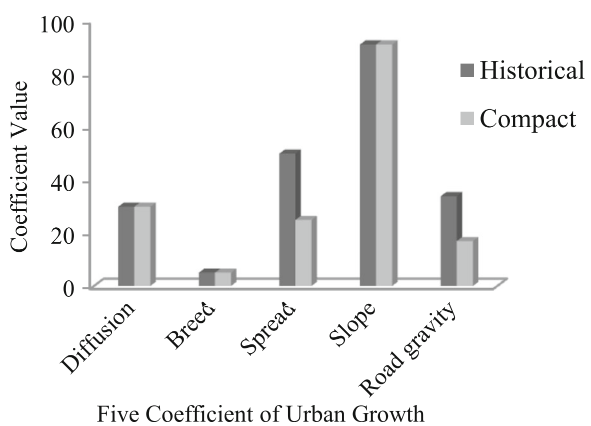

Fig 3 Best fit parameters for forecasting

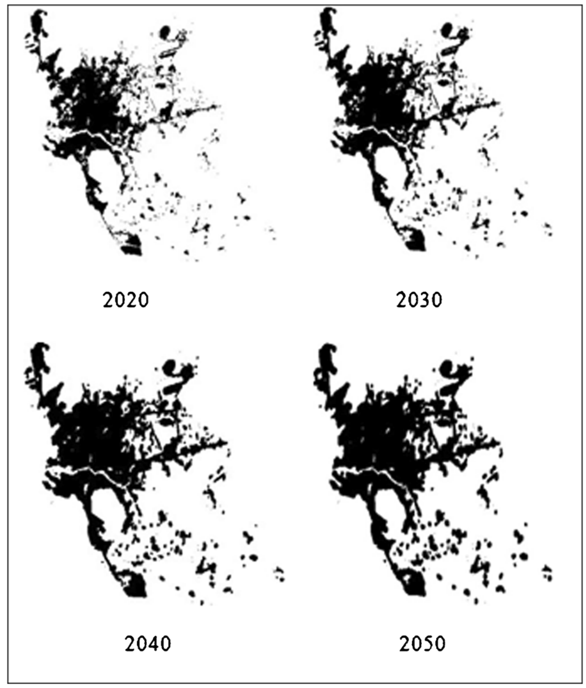

Fig 4 Simulated urban growth of Isfahan in compact scenario

was done using 10 iterations in 6479 runs. The final growth parameters derived through the calibration process were applied in the predict function. After the calibration mode, the best fit value of five growth coefficients computed as shown in Fig. 3. For Isfahan City, the diffusion coefficient is middle, which reflects an average likelihood of dispersive growth. The very low value for the breed coefficient reinforces it, given low probability of growth of new detached urban settlements. The spread coefficient stimulates growth outwards of existing and consolidated urban areas. The middle value of the road gravity coefficient denotes that the growth is also average influenced by the transportation network, occurring along the main roads. Slope resistance affects the influence of slope to urbanization. In Isfahan area, topography was shown to have a very enormous effect in controlling the urban development.

For this study the prediction was run from 2010 to 2050. SLEUTH generated urbanization map for the year 2050 in the GIF format and ESRI Arc GIS functionality was applied to

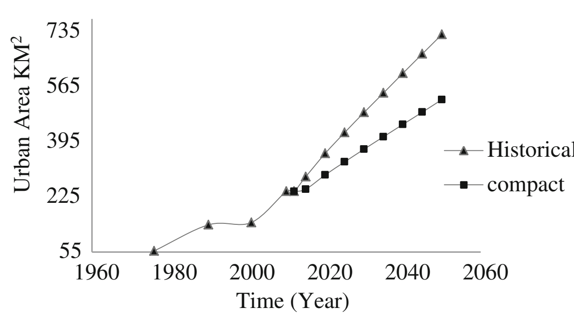

Fig 5 The area of city expansion for two scenarios

calculate the extant of each pixel category in hectares. A calculation of the total developed urban extant for 2010 produces a figure of 24261.7 ha, and 40 years later the simulated total extant has increased to 72699.25 ha by historical growth scenario and 52574.75 ha by compact city scenario. Fig 5 represents the values derived from SLEUTH output. The results of predict the growth of the city toward north and east. By expansion of urban area, the pressure of development area on agriculture land surrounding the urban area will be increased and the percent of agricultural land will decreased. Fig 4 shows the locations where the city may increase. The historical scenario predicts a greater increase for the future comparing the compact city scenario. However, the options are open to the users to construct special scenarios and immediately evaluate their effects on the fortune of the city. Alteration of the driving parameters of city change, as distinct in this study, can facilitate defining the best technique for protective measure in terms of feasibility and economy.

Conclusion

Increasing urban growth through the world has aroused global concerns over the degradation of our environment. As a result, assessing and evaluating the dynamics of urban systems and impacts of urban expansion on environmental parameters are required . Urban extension models are consequently attractive and have been documented as a useful tool to help predicting the development of urban growth, and supporting urban planning and policy makers (Oguz et al. 2007).

Models allow the user to predict options and comparable future states, and thus comprise an implement to investigate the probability of a preferred situation through testing (Mahiny and Gholamalifard 2007) . CA models represent a possible approach for regional scale modelling. Furthermore, consistent, regional data sets derived from satellite imagery and other sources can be readily integrated into the CA modelling environment.

Our research explored the suitability of utilizing a CA, the SLEUTH model, for simulating future urban expansion and local planning applications in Isfahan metropolitan area.

The study implied the helpfulness of cellular modelling and geographical information systems for urban scenario planning. Two scenarios have been planned and simulated in this research. The first scenario simulated the constant growth trend of the urban sprawl is allowed to continue and the second scenario estimated the compact growth. SLEUTH provides key functionalities like interactive scenario development and the capacity to visualize and measure outcomes spatially.

Calibration of the SLEUTH model for Isfahan metropolitan area showed a high spread coefficient, which means that the predicted mode of growth in Isfahan is “organic” or edge growth. In Isfahan metropolitan area, topography was also shown to have an enormous effect in controlling the urban development. A calculation of the total developed urban extant for 2010 produces a figure of 24261.7 ha, and for 40 years later in 2050 the simulated total extant has simulated to be increased to 72699.25 ha by historical growth scenario and 52574.75 ha by compact city scenario.

We found SLEUTH to be a practical tool for assessing the impacts of unusual policy scenarios. Although, model output is forecast of urban/non urban based on factors such as slope, and road gravity and dose not considered the socio-economic and political factors. It is also important to continue to try to advance the model both in the data provided to it and in the methodology by which it operates. The results of this study invites many opportunities for further studies in many other regions of Iran which are experiencing growth of their urban areas and can be useful for planners, city managers and policy makers to implement preventative or controlling factors in advance and make more informed strategic decisions.

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References

Almeida, C.M., Gleriani, J.M., Castejon, E.F., Soares-Filho, B.S. (2008). Using neural networks and cellular automata for modeling intra-urban land-use dynamics. international journal af geographical Information Science, 22, 943–963

Arthur, S.T. (2001). A Satellite Based Scheme for Predicting the Effects of Land Cover Change on Local Microclimate and Surface Hydrology. Penn State College

Batty, M., Couclelis, H., & Eichen, M. (1997). Urban systems as cellular automata. *Environmental and Planning, 24*, 175–192.

Berling-wolff, S., & Wu, J. (2004). Modeling urban landscape dynamics: a review. *EcolRes, 19*, 119–129.

Candau, J.T. (2002). Temporal Calibration Sensitivity of the SLEUTH Urban Growth Model, M.Sc. Theses Santa Barbara University

Clarke, K.C. (2008). A Decade of Cellular Urban Modeling with SLEUTH: Unresolved Issues and Problems, Ch. 3 in Planning Support Systems for Cities and Regions in: R.K. Brail, (Ed) Lincoln Institute of Land Policy (pp. 47–60), Cambridge

Clarke, K. C., & Gaydos, J. (1998). Loose-Coupling a Cellular Automaton Model and GIS: Long-Term Urban Growth Prediction for San Francisco and Washington/Baltimore. *International Journal of Geographical Information Science, 12*, 699–714.

Clarke, K.C., Hoppen, S. & Gaydos L. (1996). Methods and Techniques for Rigorous Calibration of a Cellular Automaton Model of Urban Growth, University of Santa Barbara

Clarke, K. C., Hoppen, S., & Gaydos, L. (1997). A Self-Modifying Cellular Automaton Model of Historical Urbanization in the San Francisco Bay Area. *Environment and Planning B: Planning and Design, 24*, 247–261.

Dietzel, C., & Clarke, K. C. (2004). Spatial Differences in Multi-Resolution Urban Automata Modeling. *Transactions in GIS, 8*, 497–492.

Ding, Y., & Zhang, Y. (2007). The simulation of urban growth aapplying SLEUTH CA model to the Yilan Delta in Taiwan. *Jurnal Alam Bina, 9*, 95–107.

Fanni, Z. (2006). Cities and urbanization in iran after the islamic revolution. *Cities, 23*, 407–411.

Gigalopolis, Project Gigalopolis: Urban and land cover modeling. (2007). Cities, Santa Barbara,CA: University of Santa Barbara at http://www.ncgia.ucsb.edu/projects/gig/

Goldstein, C. (2004). Brains vs. Brawn - Comparative Strategies for the Calibration of a Cellular Automata - Based Urban Growth Model, Department of Geography, University of California at Santa Barbara (www.geocomptation.org/2003/Papers/Goldstein_Paper.pdf, Accesed 20 June 2006)

KantaKumar, L., Sawant, N., & Kumar, S. (2011). Forecasting urban growth based on GIS, RS and SLEUTH model in Pune metropolitan area. *International journal of geomatics and geosciences, 2*(2), 568–579.

Landis, J. (2001). CUF, CUF II, and CURBA: a family of spatially explicit urban growth and land-use policy simulation models. In R. K. Brail & R. E. Klosterman (Eds.), *Planning support systems: integrating geographic information systems, models and visualization tools* (pp. 157–200). Redlands: ESRI Press.

Liu, Y. (2009). Modelling urban development with geographical information system and celluar atutomata Boca Raton, FL: Taylor and Francis Group

Mahiny, A.S. (2003). A Modeling Approach to Cumulative Effects Assessment for Rehabilitation of RemnantVegetation. PhD Thesis. SRES, ANU, Australia

Mahiny, A. S., & Gholamalifard, M. (2007). Dynamic Spatial Modeling of Urban Growth through Cellular Automata in a GIS Environment. *Int J Environ Res, 1*, 272–279.

NCGIA. (2011).Project Gigalopolis, University Of California

Oguz, H., Klein, A. G., & Srinivasan, R. (2007). Using the Sleuth Urban Growth Model to Simulate the Impacts of Future Policy Scenarios on Urban Land Use in the Houston-Galveston-Brazoria CMSA. *Research Journal of Social Sciences, 2*, 72–82.

Rafiee, R., Mahiny, A.S., Khorasani, N., Darvishsefat, A.A. & Danekar, A. (2009a). Simulating urban growth in Mashad City, Iran through the SLEUTH model (UGM). Cities, 26, 19–26, doi:10.1016/j.cities.2008.11.005

Rafiee, R., Mahiny, A. S., & Khorasani, N. (2009b). Assessment of changes in urban green spaces of Mashad city using satellite data. *International Journal of Applied Earth Observation and Geoinformation, 11*, 431–438.

Randolph, J. (2004). *Environmental land use planning and management*. D.C.: Washington.

ŞEVİK, Ö. (2006). Application of SLEUTH model in Antalya. Master thesis, The Graduate School of natural and applied science of Middle East technical University.

Silva, E. A., & Clarke, K. C. (2002). Calibration of the SLEUTH Urban Growth Model for Lisbon and Porto, Portugal. *Computers, Environment and Urban Systems, 26*, 525–552.

Soares-Filho, B. S., Alencar, A., Nespad, D., Cerqueira, G. C., Diaz, M. D. V., Rivero, S., Solórzano, L., Voll, E. (2004). Simulation the response of land-cover changes to road paving and governance along a major Amazon Highway: the Santarem-Cuiaba corridor. *Global Change Biology, 10*, 745–764.

Tang, J., Wang, L., Yao, Z. (2007). Spatio- temporal urban landcape change analysis using the Markov chain model and a modified genetic algorithm. international Journal of Remote Sensing, 28, 3255–3271

Turner, B.L. & Meyer,W.B. (1994). Global land use and land cover change: an overview, in: B.L. Turne, W.B. Meyer, (Eds) Changes in land use and land cover: a global perspectiv (pp. 1–11) New York

Verburg, P. H., Veldkamp, A., & Bouma, J. (1999). Land use change under conditions of high population pressure: the case of Java. *Global Environ Chang, 9*, 303–312.

Webster, C. & Wu, F. (2001). Coase, spatial pricing and self-organizing cities. U rban Studies, 38, 2037–2054

White, R., & Engelen, V. (2000). High resolution integrated modeling of the spatial dynamics of urban and regional systems Computers. *Environment and Urban Systems , 24*, 383–400.

Xi, F., Hu, Y., He, H., Wu, X., & Yu, J. (2009). Simulate urban growth based on RS, GIS, and SLEUTH model in Shenyang-Fushun metropolitan area north-eastern China, Urban Remote Sensing Joint Event 1–10, doi:10.1109/urs.2009.5137630

Yang, X., & Lo, C. P. (2003). Modelling Urban Growth and Landscape Changes in the Atlanta Metropolitan Area. *Int J Geographical Information Science, 17*, 463–488.