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Research Paper

Prediction of future urban growth scenarios using SLEUTH model (Case study: Urmia city, Iran)

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Abstract

Rapidly increasing urbanization in the world, especially in developing countries, let to increasing urban extents. Rapid urban growth causes to appearance many problems such as wasting environmental resources, inability of providing necessary services for citizens and unplanned growth. Urban mangers and planners need tools for understanding amount and size of future urban growths to prevent these problems. Urmia as capital city of west Azerbaijan province, in the last decades has considerable growth in both extent and population. This rapid growth caused to lose most high value agricultural resources in its surrounding. It has also caused many problems for urban management. Therefore, how city managers and urban planners can be aware of magnitude and location of Urmia city's future growth and what is the best growth scenario for Urmia city? This paper uses a quantitative analysis research methodology to prediction and evaluation of growth scenarios for Urmia city. In this paper, SLEUTH model was applied to predict future urban growth of Urmia until 2050. Two different scenarios were employed include: Historical Growth Scenario (HGS) and Environment Protection Scenario (EPS). The result highlight that if the city continues its growth based on HGS scenario, in compare with growth based on EPS scenario, it would occupy more area. In this paper, we concluded that the EPS scenario can be more sufficient than HGS scenario. In addition, SLEUTH urban growth model can be used as a planning support model for urban planners and managers decisions for Urmia city based on scenarios.

Keywords: *Urban growth modeling, SLEUTH model, Cellular automata, Urmia city*.

1. INTRODUCTION

The world is undergoing the largest wave of urban growth in history. World population is about 7 billion and more than 50% of them already live in urban areas. By 2030 this number will swell to about 5 billion [1]. In developing countries in particular, cities are sprawling rapidly, as the number of metropolitan areas has increased considerably [2]. As a developing country, Iran is now witnessing an almost continual large-scale urbanization [3]. During the last three decades, the population of Iran has grown from 33.7 million in 1976 to 69.5 million in 2005 with this growth occurring mainly in cities [4]. The population in 2011 was 75 million.

The proportion of urban population to total population of Iran in 1976 was 47% and this ratio 61% in 1996 [5] and reached 71% at 2011 [6]. Due to increasing urbanization in Iranian cities [7], the city of Urmia, as the tenth large city in Iran, in the past two decades has seen tremendous growth in both population and extent. population of Urmia has increased from 67600 in 1956 to 667500 in 2011 [6].

Urban expansion in one of the results of rapidly urban population growth, [8]. Urbanization, has radically transformed societies in recent years. More people tend to live in cities because they are major centers of urban development, innovation, culture, and economic activity [9]. Urbanization and demand for development and housing growth causes urban spatial expansion. Urban growth has been speeding up; as a result, an extreme stress to the environment has occurred [10], [11]. Urbanization and the rapid growth of urban areas causes many issues such as climate change, carbon emissions, the urban heat island, urban sprawl, the loss of prime agricultural land, increasing water and air pollution, overcrowding, crime, traffic congestion, and the deterioration of old and unplanned or poorly planned land development [12], [9], [13].

Decision makers and urban planners require precise and detailed information about potential urban growth and land conversion in order to assess new development needs, their location, characteristics, as well as consequences of prior and subsequent urban development [14]. To foster

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improved decision-making, these dynamic processes require permanent monitoring with respect to past developments and to forecast future growth [15]. The quantity and the location of land use changes are main issues to be addressed by urban planners and decision makers, especially in rapidly changing environments. Thus, the main objective of the modeling process is to understand and to predict future urban growth [16]. Understanding the dynamics of complex urban systems and evaluating the impact of urban growth on the environment involve procedures of modeling and simulation, which require innovative methodology and robust techniques. A number of analytical and static urban models have been developed that are based on diverse theories such as urban geometry, size relationship between cities, economic functions and social and ethnic patterns with respect to city structures. But these models were developed to explain urban expansion and evolving patterns rather than to predict future urban development. For understanding the spatial consequences of urban growth, a dynamic modeling approach is preferred [17]. Dynamic spatial urban models provide an improved ability to assess future growth and to create planning scenarios, allowing us to explore the impacts of decisions that follow different urban planning and management policies [18].

A CA model is a dynamic model with local interactions to reflect evolution of the system, where space and time are considered as discrete units and space is often represented as a regular lattice of two dimensions. Because of the strong ability to represent non-linear, spatial and stochastic processes of CA models, it does not take long for geographers to apply CA to simulate land use change, urban development and other changes of geographical phenomena [19]. Among all the documented dynamic models, those based on cellular automata (CA) are probably the most impressive in terms of their technological evolution in connection to urban applications [17]. Cities are now increasingly recognized as complex systems and display many of the characteristic traits of complexity, i.e. non-linearity, self-organization and emergence. Cellular Automata (CA) offer a modeling framework and a set of techniques for modeling the dynamic processes and outcomes of self-organizing systems [20]. The ability of CA to simulate urban growth is based on the assumption that past urban development affects future patterns through local interactions among land uses. The interest of CA-based models for urban simulation can be explained in terms of the simplicity, flexibility, intuitiveness and transparency of CA. Additionally, CA can be easily integrated with Geographical Information Systems (GIS) and Remote Sensing (RS) [21].

SLEUTH is a Bottom-up approach it is not dependent on intensive preliminary studies regarding the general causes of urban growth in a study area or the location-specific driving forces [22]. SLEUTH provides a simulation environment for exploring the consequences of policies taken by decision makers. This method can define a set of scenarios for urban area expansion based on historical data to assess the likely areal coverage in the final year [23]. In this study we used SLEUTH model because of following reasons: i) SLEUTH has been successfully applied worldwide to simulate land use change and urban growth modeling. SLEUTH has been known to be applied to over 66 different cities and regions [24], ii) 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, iii) Capability of dynamic spatial simulation, iv) Natural compatibility to GIS and remotely sensed data. 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 [25].

There are many studies that used SLEUTH model to urban growth modeling; Rafiee etal, 2009 [3]. They simulated urban growth in Mashhad City through the SLEUTH model. In their work, three scenarios were designed to simulate the spatial pattern of urban growth under different conditions. The results showed the utility of the modeling method in explaining the spatial pattern of urban growth. Sakieh etal, 2014 [3]. They adopted SLEUTH model to simulating urban expansion. 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, 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. Hui-Hui etal, 2012 [10]. They studied Scenario Prediction and Analysis of Urban Growth Using SLEUTH Model in Dongguan City, china. In their study, three urban development scenarios, historical trend (HT) scenario, forest protection (FP) scenario, and growth restriction (GR) scenario, were designed and transplanted into the SLEUTH model through the parameter self-modification method the result showed that under all the scenarios, the urban patches would become bigger and the form would become more compact, and the urban form under the GR scenario would be the smallest and most heterogeneous. Leao etal, 2004 [26]. In their work, the urban growth model was applied to Porto Alegre City, Brazil. An expected contiguous expansion from existing urban areas has been obtained as following the historical trends of growth of the region. Moreover, the model was sensitive and able to portray different pattern of growth in the study area by changing the value of its parameters.

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 and predicted scenarios. This study offers a comparative basis, which facilitates evaluation of spatial decisions made by land use planners and policy makers. However other works, in this study first we adopted more important locale characteristic of Urmia city that effect future urban growth and then prepared best scenarios. Finally, this paper survey two main purposes:

1. Calibration the SLEUTH model for accountability to Urmia city’s local specifications and for quantifying regnant growth modes of the targeted area.

2. Predication the urban dynamic growth under two policy scenarios including uncontrolled growth (historical growth) and controlled growth alternatives from the year 2015 to 2050.

2. MATERIALS AND METHODS

The study workflow can be summarized in three stages (Fig. 1): (i) Preparing SLEUTH input data using the remote sensing (RS) and GIS (ii) SLEUTH test, calibration and predication through the two different management scenarios from year 2015 to 2050 (iii) comparing and analyze the result of two scenarios.

2.1. Study Area

Urmia is the capital city of Urmia province, located in northwest of Iran (Fig 2). It has an area of 10500 hectare and its current population is 667000. It has witnessed rapid growth in the last three decades, mostly because of economic, social and immigration attractions. After the since 1985, population has grown from 306700 to 667500 in 2011. While its extent at the same time period has tripled. Increasing of urbanization and urban extent growth caused major problems for city managers and planners and In addition led to loss of agriculture lands around the city. The SLEUTH model has been used as one of the most widely used model in the world and Iran to projected urban growth. Modeling of future growth of Urmia city is necessary because of the importance of preserving agricultural land around the city, and to prevent uncontrolled and unplanned growth to urban management. The model was used to predict future growth of the city under scenarios such as environmental protection.

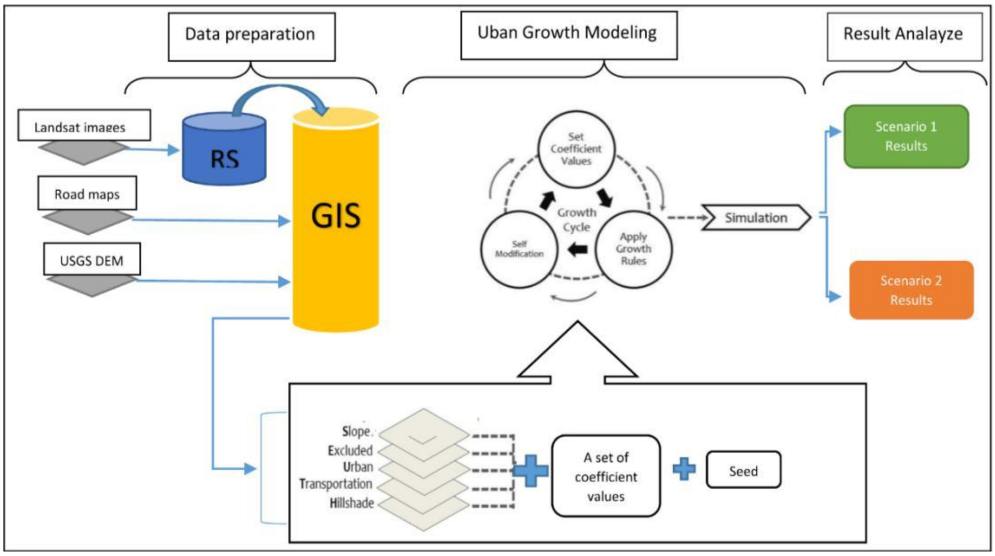

Fig. 1 Study main workflow

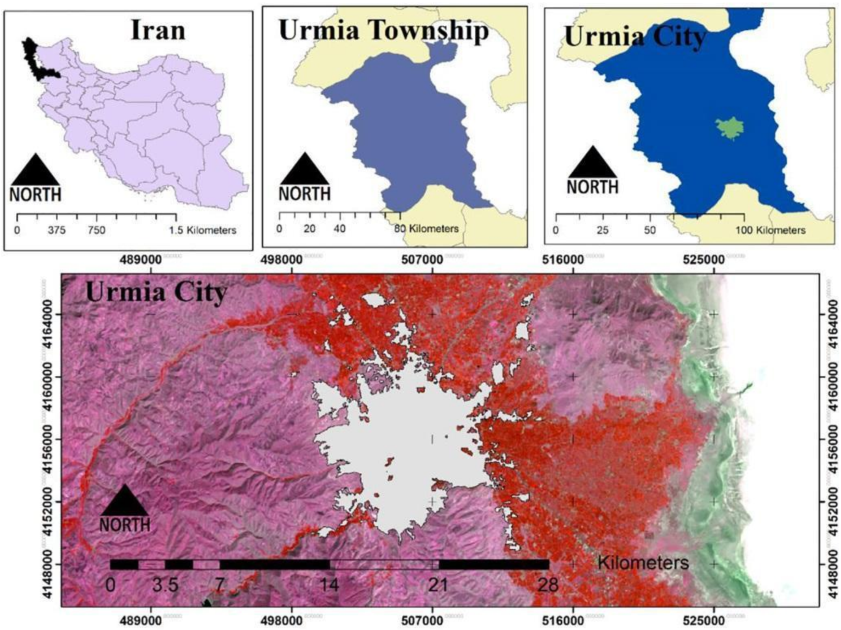

Fig. 2 Location of study area

2.2. The SLEUTH Urban Growth Model (UGM)

The SLEUTH urban growth model is a cellular automaton-based model that originally developed by Keith Clarke at the University of California at Santa Barbara. The cellular automaton is a rule-based algorithm that has been long employed in computer science to explore social and physical phenomena. The model uses cellular automata to model the urban expansion based on growth rules in a gridded representation of geographic space on a cell-by-cell basis. The SLEUTH model can easily integrate remote sensing (RS), geographic information system (GIS), and spatial pattern analysis technologies [23].

The model is able to control behavior of system by several parameters and by modification of the growth rules [18].

SLEUTH employs four growth rules (Table 1) and five parameters to control the influence of the rules on urban spread. Each coefficient has a value that ranges from 0 to 100. (Table 2) [26].

The Land Cover Deltaron Model (LCD) is tightly coupled (i.e. integrated at the code level) with the earlier Urban Growth Model (UGM) and together they are called SLEUTH. SLEUTH has been derived from the simple data input requirements of the model: Slope, Land cover, Exclusion, Urbanization, Transportation, and Hillshade [27]. Landcover input data required when Deltaron Model (LCD) desired. This study use UGM Model for urban growth modeling.

Table 1 Growth types in SLEUTH model [26]

Growth type	Description
Spontaneous growth	models the development of urban settlements in undeveloped areas
Diffusive growth	permits isolated cells to be locations for new urban spreading centers
Organic growth	promotes the expansion of established urban cells to their surroundings
Road influenced growth	Promotes urbanization along the transportation network because of increased accessibility

Table 2 Growth control parameters in SLEUTH model [26]

Growth control parameters	Description
Diffusion	controls the overall dispersiveness of growth
Breed	Determines how likely a newly generated, detached or road influenced settlement is to begin its own growth cycle
Spread	controls the amount of outward 'organic' expansion
Slope resistance	influences the likelihood of settlement extending up steeper slopes
Road gravity	encourages new settlements to develop near the transportation network

The procedures of model implementation in this project were through four-steps as follow: preparation of required input data and model test, model calibration, model prediction and evaluation of output results. Clarke UGM is implemented as a computer program written in the C programming language that runs under UNIX. The model simulates nonurban cells being converted into urban use over time [28]. We runned the model using Cygwin linux compiler in windows environment.

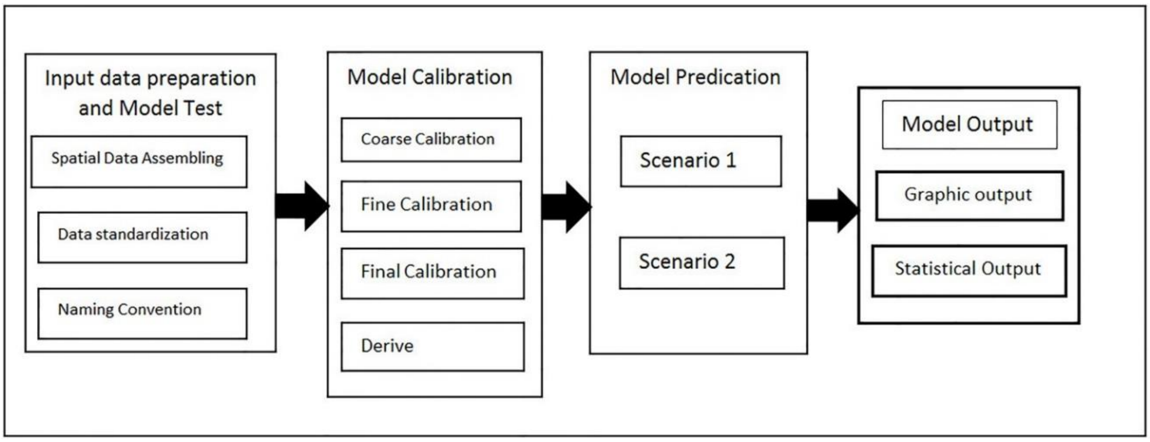

Fig. 1 General procedures for the model implementation [17]

2.3. Input Data Prepration

Similar to other predictive models, this model requires some input data in order to initiate the simulation. For this study input data were prepared and analysed using ArcGIS 10.3, ENVI 4.8 and SLEUTH3.0. SLEUTH UGM of requires an input of at least five types of eight-bit GIF format data. If land use/cover is being analysed, the input data should have six types of layers. Du to the using UGM model in this study, five types of data prepared (Fig. 4):

I. Four historical urban extent layers to showing initial or seed configuration of urban areas. At first landsat sattelite historical images for year 1985, 1995, 2006 and 2014 obtained from USGS (United States

Geological Survey) site and classiffied in ENVI software using the supervised maximum likelihood classification method. Then, this layers imported to ARCGIS 10.3 and reclassiffied to binary rasters (0 = non urban, 255 = urban).

II. Four historical transportation layers which the model reads and uses sequentially as their year of construction is reached. This 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.

III. Slope layer was extracted from 28 m DEM which was obtained from United States Geological Survey (USGS). This layer was changed to percent slope.

IV. the Hillshade layer was created for the study area from 28 m DEM, was obtained from (USGS) which was used as the background for model image output.

V. Two Excluded layer consist of forest parks (for scenario 1) and forest parks and agricultural- garden areas protection (for scenario 2) were rasterized on the 2014 Landsat satellite image.

The input layers were resampled to 30 m * 30 m resolution using nearest neighborhood algorithm and same row and columns.then converted to 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 8-bit 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 3.

The resultant GIF files are named according to the convention stipulated by the model. Before performing model calibration, we conduct a test run to determine if everything works. The test run is successful, indicating that everything is in the right place.

Table 1 Input data set for SLEUTH model

Input layer	Source	Format and year
Urban	Classified from satellite image	Raster, 1985, 1995, 2006,2015
Transport	Digitized on satellite image	Rasterized from vector, 1985, 1995, 2006, 2015
Slope	DEM generated by USGS	Raster
Hillshade	DEM generated by USGS	Raster
Excluded	On screen digitization	Rasterized from vector

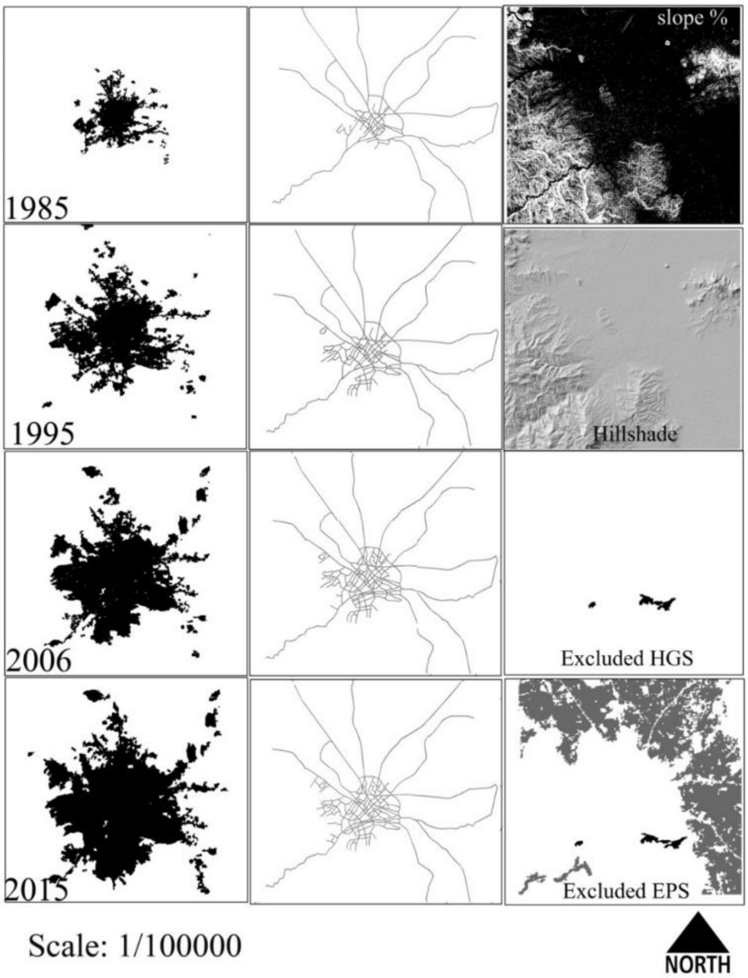

Fig. 4 Input data for calibration and simulation of urban growth of Urmia City using urban growth model

2.4. Model Calibration

Both growth rules and self-modification rules are the core of the model, they reflect the universal understanding of the process of urbanization, but, to be successfully used they need to be refined to the locale. Without calibration it will be impossible to correctly describe the behavior of the system and predict its possible futures; this is done through the process of calibration [27]. The purpose of model calibration is to determine 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 and land use/cover as the reference. This process has been automated, so that the model code tries many of the combinations and permutations of the control parameters and performs multiple runs from the seed year to the present (last) data set, each time computing 13 different measures of the goodness of fit between the modeled and the real distributions The calibration primarily relies upon statistical measures of historical fit although graphic calibration is also attempted.

The calibration process, known as ‘‘brute force calibration’’, relies on the availability of significant This procedure in the SLEUTH was completed through a number of Monte Carlo iterations. By running the model, a set of control parameters is refined in the sequential calibration phase (coarse, fine and final calibrations). Between phases in the calibration, the user tries to extract the values that best match the five factors that control the behavior of the system. Coefficient combinations result in combinations of the 13 metrics (Showed in Table 4): each either the coefficient of determination of fit between actual and predicted values for the pattern (such as number of pixels, number of edges, number of clusters), for spatial metrics such as shape measures, or for specific targets, such as the correspondence of land use and closeness to the final urban pixel count.

Table 2 Indicators for evaluating accuracy of simulated output of SLEUTH model in the calibration phases [27]

Index	Description
Composite score	all other scores multiplied together
Compare	comparison of modeled final population1 to real data final population
r^2 Population	least squares regression score for modeled urbanization compared with actual urbanization for the control years
Edge_r^2	least squares regression score for modeled urban edge count compared with actual urban edge count for the control years
r^2 Clusters	least squares regression score for modeled urban clustering compared with known urban clustering for the control years
Mean_cluster_size_r^2	least squares regression score for modeled average urban cluster size compared with known mean urban cluster size for the control years
Leesalee	a shape index, a measurement of spatial fit between the model’s growth and the known urban extent for the control years
Average_slope_r^2	least squares regression of average slope for modeled urbanized cells compared with average slope of known urban cells for the control years
pct_Urban_r^2	least squares regression of percent of available pixels urbanized compared with the urbanized pixels for the control years
xmu_r^2	(center of gravity [x]) least squares regression of average x_values for modeled urbanized cells compared with average x_values of known urban cells for the control years
ymu_r^2	(center of gravity [y]) least squares regression of average y_values for modeled urbanized cells compared with average y_values of known urban cells for the control years
sdist_r^2	standard deviation averaged over (XY)
lu_Value	a proportion of goodness of fit across landuse classes

The SLEUTH utilizes Monte Carlo iterations stochastically to generate the multiple simulation of growth and each parameter may take values between 0 to100 independently, the model calibration is carried out in three phases, Coarse, Fine and Final [3] and we used leesalle index for chosing best range for growth roule parameters beetwen each phase.

In the Coars step, input data were resampled to four times of their original resolution (30 m resolution data was resampled to120 m) and considered the widest range of parameters (0–100), a large value (25) for incrementing the parameters. The result of the coarse calibration phase was evaluated using the fit statistics generated during the model run leading to a narrower range of the best fit set. for the fine calibration step, the input data were resampled to twice of their original resolution (30m resolution data was resampled to 60 m) and the number of Monte Carlo iterations were increased and the range of parameters was narrowed down. in the final calibration step, the input data were used in ten Monte Carlo iterations with full resolution for inputs and by using the statiscal results of fine calibration, we narrowed down the range of parametes. according to the self-modification of the SLEUTH model, parameter values are constantly altered through a run from the first date to the last date and the best calibrated parameters of the stop date are selected. 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. However, due to the random variability of the model, averaged parameter results of more Monte Carlo iterations will produce a more robust forecasting parameter set [3, 29]. finally, in derive step, the best parameter values in 100 Monte Carlo iterations used with one step increment to derive an average for each parameter.

2.5. Model Predication

Predication have been attempted to model the urban growth from the present to project future changes for different scenarios. There are several methods to create a scenario in the SLEUTH model to futhure prediction [25]:

1. different values of protection are assigned to excluded areas to indicate different levels of cells potential for urbanization, e.g. [30].
2. selforganization constraints are manipulated, e.g. [17].
3. and the third method concerns changing parameter values, which dictates the form of urban growth and affect urban growth rules, e.g. [28], [3], [29].

we used the first method of model prediction. Based on the calibration data, future urban growth trends were predicted to 2050 assuming two development scenarios, each of which is linked with different conditions for future urban development:

historical growth scenario (HGS): This scenario assumed that growth and development would continue along historical trends; urban growth was simulated without unchanging current conditions. For this scenario, forest parks were fully excluded from future development.

One of the most important characterisctics of the Urmia city is agriculture and garden lands over it. and must be save and protect from uncontrolled developments. we desgined bellow scenario according to importance of agricultural lands in urban economy and enviromental protection.

Environment Protect Scenario (EPS): in this scenario, forest parks were completely excludede from futher development. In addition high-value garden and agricultural land was protected in highly degree, but not excluded fully from futher urban growth.

3. RESULTS AND DISCUSSION

3.1. SLEUTH Calibration Results

The model was calibrated in three phases using three different spatial resolutions. In coarse calibration phase we used input data size at ¼ original resolutions (120 m) with narrowing the range of parameters that described the growth of the system more accurately. In coarse phase this range was equal for each five parameter (start =0, step =25, stop =100). In the second phase named fine phase, to using the results of coarse phase, the ranges of the five urban growth coefficients in SLEUTH were further narrowed to the final calibration step with LeeSalle metric, which sorted best values. The goal of the fine calibration is to further narrow down the ranges. We used ½ original resolution size (60 m) of input data for this stage. Because using fewer steps, the resultant combinations of different coefficient values should decrease substantially compared coarse calibration. This means that entire computation time should decrease proportionally. Thus, more times of Monte Carlo computations could be allowed to reduce the level of errors. The number of Montcarlo is therefore increased to 8. After successfully calibration of fine phase, output result were sorted again according to the best results LeeSalle metric and the range of Five controlling parameters values even more narrowed. 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 [25]. In next step (the final phase) with goal to determine best combination, model was calibrated using original resolution size (30 m) of input data and growth control parameter which resulted from fine phase. More time for Monte Carlo computations is possible. Thus, the number of Mont Carlo was increased to 10. The results of calibration phases are presented in table 5, 6, 7, 8.

Table 5 The result of calibration phase

	Coars Calibration		Fine Calibration		Final Calibration		
	Montcarlo = 5 3125 Runs		Montcarlo = 8 5400 Runs		Montcarlo = 10 8640 Runs		Best fit
Parameter	Range	Increment	Range	Increment	Range	Increment	
Diffusion	0-100	25	0-25	5	0-20	4	1
Breed	0-100	25	0-25	5	0-20	4	1
Spreed	0-100	25	50-75	5	70-75	1	73
Slope resistance	0-100	25	0-100	25	25-100	10	67
Road gravity	0-100	25	0-100	25	50-85	5	77

Finally, best values which derived from the final calibration, were used as the starting values for the five control coefficients in order to simulate the urban growth in derive step. Because only one combination is available for the computation, the number of times for Monte Carlo computations can be increased in order to minimize the level of errors. Thus, a large number, namely, 100, is used. Finally, these values further averaged using the MEAN utility provided by the model. The final values of the control coefficients are determined (fig.5): diffusion coefficient (1), breed coefficient (1), spread coefficient (73), slope resistance (67), and road gravity (77). According to the model structure, each parameter reflects a type of spatial growth. For Urmia city, the diffusion coefficient is very low, which reflects low likelihood of dispersive growth. The low value for the breed coefficient reinforces it, given low probability of growth of new detached urban settlements. On the other hand, the spread coefficient is very high. It stimulates growth outwards of existing and consolidated urban areas. The high value of the road gravity coefficient denotes that the growth is also highly influenced by the transportation network, occurring along the main roads. Finally, the high value for the slope resistance coefficient shows that topography is a barrier to urban development in the region, and most of the hilly areas are likely not to urbanize.

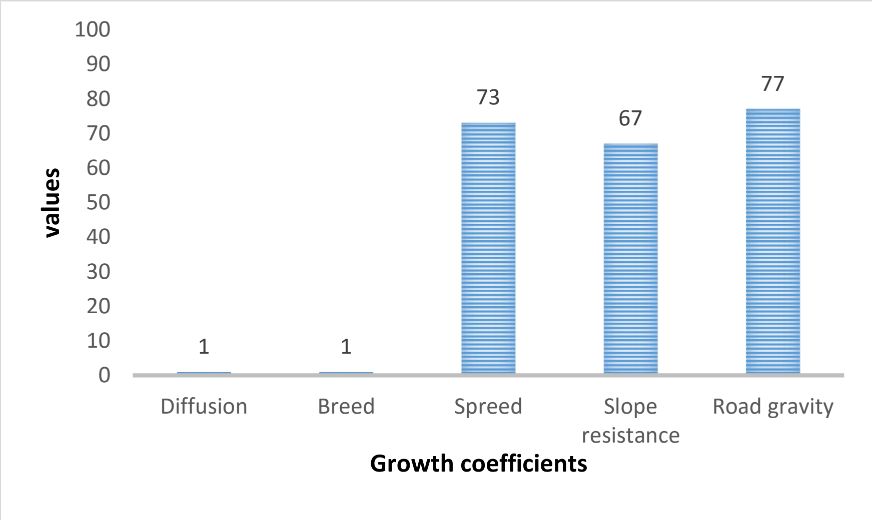

Fig. 2 Best fit Growth prameters for predication

To assess simulation accuracy, comparison between the provided indices and real data set are presented for each calibration stage [25].

Due to the model final results,‘‘r2 population’’ (number of urban pixels) indicates a high correlation of 0.997 and for ‘‘compare’’ it is 0.685, 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 0.56 spatial fit between the modeled growth and the known urban extent for the control years.

Table 3 Results of coars calibration

Compare	r^2 Population	Edges	Clusters Size	Leesalee	Average slope r2	%Urban	xmu r2	r2 ymu r2	Rad
0.871	0.991	0.657	0.979	0.589	0.898	0.991	0.924	0.337	0.990
0.871	0.991	0.657	0.979	0.589	0.898	0.991	0.924	0.337	0.990
0.918	0.992	0.900	0.930	0.589	0.865	0.992	0.988	0.566	0.992
0.918	0.992	0.969	0.916	0.588	0.864	0.992	0.985	0.562	0.991
0.859	0.991	0.808	0.998	0.588	0.842	0.991	0.530	0.374	0.990
0.859	0.991	0.808	0.998	0.588	0.842	0.991	0.530	0.374	0.990
0.871	0.989	0.253	0.995	0.588	0.924	0.989	0.994	0.345	0.988
0.871	0.989	0.253	0.995	0.588	0.924	0.989	0.994	0.345	0.988
0.871	0.989	0.253	0.995	0.588	0.924	0.989	0.994	0.345	0.988
0.858	0.988	0.437	0.916	0.588	0.836	0.989	1.000	0.359	0.987

Table 7 Results of fine calibration

Compare	r^2 Population	Edges	Clusters Size	Leesalee	Average slope r2	%Urban	xmu r2	r2 ymu r2	Rad
0.820	1.000	1.000	0.980	0.580	0.490	1.000	0.950	0.990	1.000
0.820	1.000	1.000	0.980	0.580	0.500	1.000	0.950	0.990	1.000
0.820	1.000	1.000	0.980	0.580	0.500	1.000	0.950	0.990	1.000
0.820	1.000	1.000	0.990	0.580	0.370	1.000	0.910	0.990	1.000
0.820	1.000	1.000	0.980	0.570	0.190	1.000	0.940	0.990	1.000
0.820	1.000	1.000	0.980	0.570	0.260	1.000	0.950	0.990	1.000
0.820	1.000	1.000	0.980	0.570	0.500	1.000	0.950	0.990	1.000
0.850	1.000	1.000	0.980	0.570	0.220	1.000	0.910	1.000	1.000
0.850	1.000	1.000	0.990	0.570	0.360	1.000	0.940	0.990	1.000
0.820	1.000	1.000	0.980	0.570	0.070	1.000	0.940	0.990	1.000

Table 4 Results of final calibration

Compare	r^2 Population	Edges	Clusters	Size	Leesalee	Average slope r2	%Urban	xmu r2	r2 ymu r2	Rad
0.685	0.997	0.964	0.868		0.569	0.691	0.997	0.945	0.006	0.996
0.684	0.997	0.962	0.884		0.568	0.693	0.997	0.942	0.008	0.995
0.687	0.996	0.966	0.832		0.568	0.626	0.997	0.931	0.000	0.995
0.687	0.996	0.966	0.832		0.568	0.626	0.997	0.931	0.000	0.995
0.687	0.996	0.966	0.832		0.568	0.626	0.997	0.931	0.000	0.995
0.687	0.996	0.966	0.832		0.568	0.626	0.997	0.931	0.000	0.995
0.687	0.996	0.966	0.832		0.568	0.626	0.997	0.931	0.000	0.995
0.687	0.996	0.966	0.832		0.568	0.626	0.997	0.931	0.000	0.995
0.686	0.997	0.973	0.767		0.568	0.678	0.997	0.937	0.001	0.995
0.686	0.997	0.973	0.767		0.568	0.691	0.997	0.945	0.006	0.996

3.2. SLEUTH Simulation Accuracy

Accuracy of the results is an essential part of predictive modeling and is more important when the models are used for decision making purposes. To accurate simulation resuslt, a past to present predication was simulated based on historical trend (from year 1985 to year 2105).

The final growth coefficient values that determined in figure 5 was used as the starting values for the control coefficients. The simulated cumulative probability output image for the year 2015 was compared with binary 2015 urban image that resulted from satellite mapping (as the reference).

The Kappa statistic has been the most popular measure of accuracy used in the field of remote sensing and map comparison. Validation was performed using the Kappa coefficient. The result of measuring the Kappa coefficient for the years 2015 was 70%, which indicates acceptance of prediction accuracy.

Some possible reasons for this considerable. In addition to considers a range of various factors that controlling new developments, some factors are not considered, as, urban or regional development policies, human behaviour, tax, income, zoning, and other socio-economic factors.

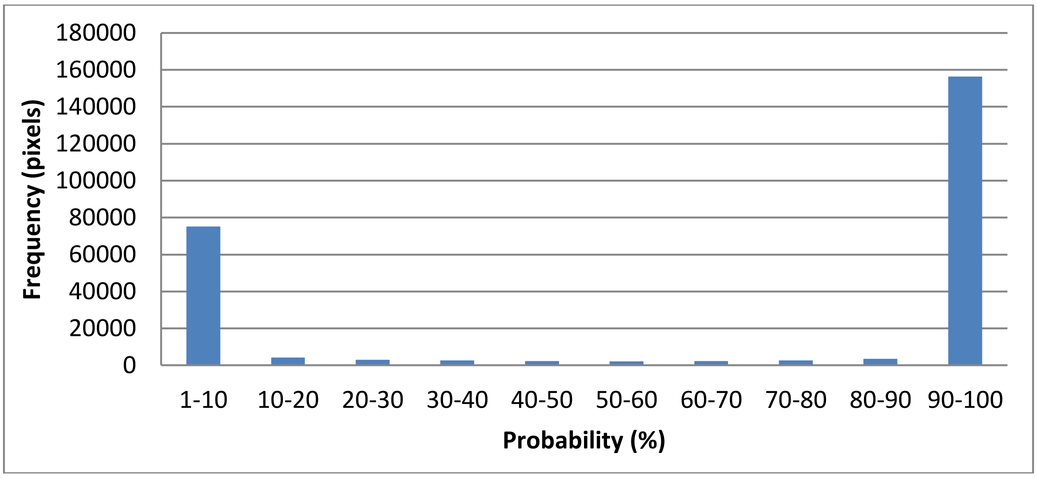

Fig. 3 Frequency histogram of probability urbanized map for the year 2040

3.3. Model Scenarios and Predication Results

Prediction was completed using the full resolution data and 100 or higher Monte Carlo iterations. predication have been attempted to model the urban growth from the 2015 to 2050 using growth cofficient average values, which resulted from calibration stage and two deffirent scenarios. We defined the two scenarios according to the local characteristic to show the usefulness of the SLEUTH modeling method and also to provide a context comprehensible for the city managers and urban planners. Urban growht was predicted based on two historical growth scenario (HGS) and Environment Protect Scenario (EPS), which described in part 2.5. Final result of the SLEUTH model is a probability Map for every year frome the first years to the last year (2050). This map showe each cell probability value to become an urbanized we used frequency histogram of the final year and the cutoff point method to evaluate and creat crisp map. there are diffirent methods for selecting the urbanization threshold on the probability map. Frequency histogram is just one tool. According to the results of Fig. 6, around the 90 % - 100% probability value, there is a sharp increase in the number of cells converting to urbanized cells. So we selected 80% probability value as cutoff and considered every cell with a probability above 80% would convert to urbanized cell.

HSG and EPG scenarios and final result are presented in Fig 7. The result of HSG scenario illustrate that if urban grows without any controlling condition, only besade on historical growth trends, untill year 2050 about 15576 hectars will be added to current area in 2015. In the other hand, city extent will be 1.7 times more. This is While Urmia city has high-value agricultural resourceses in its surronding area especially in northen. If the urban growth continues historical trends, most of these resources will be wasted. So in this paper we considerd enviromental protection scenario to preventing fertile lands in surronding areas. The result of prediction based on EPS scenario shows that 13943 hectares will be added to existing city extent till 2050. In the other hand 1.5 times more. With Utilizing this scenario increasing urban extent in northen of the city will be controlled and led to protection from agricultraul and garden resources. Considering the result of two current scenario, local characteristics and urban manager policies, we founded that urban growth according to the EPS scenario is prefered scenario for the urmia city future growth. This scenario will be resulted in the least damage to environment.

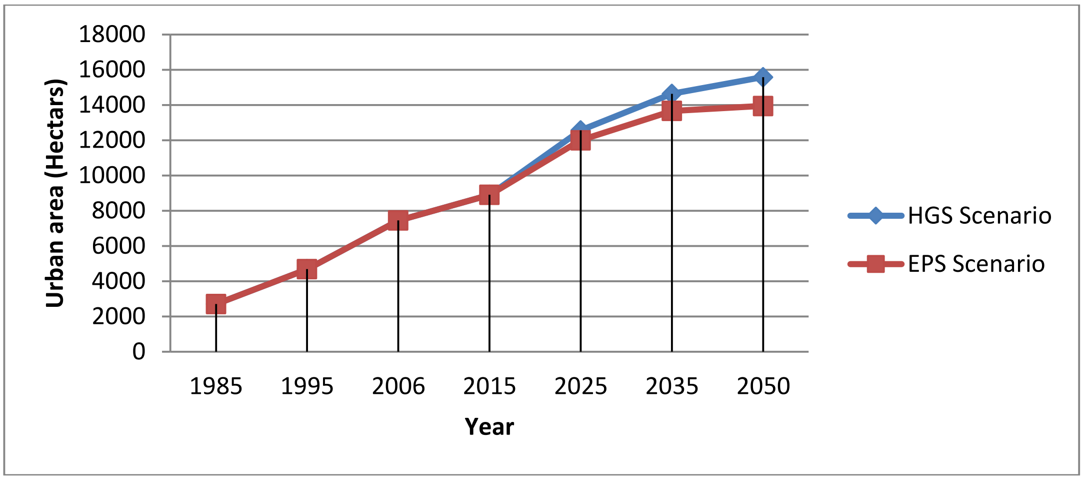

Fig. 4 Future Growth of the Urmia City based on two scenarios till year 2050

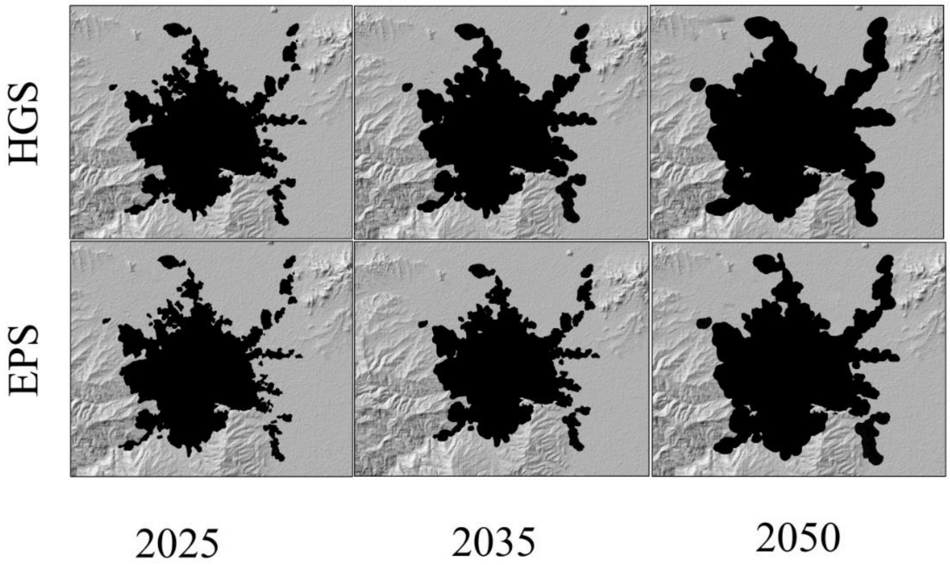

Fig. 5 Future extent of Urmia city from 2025 till 2050

4. CUNCLUSION

Increasing in urban population and urbanization led to the development and growth of cities. urbanization especially in developing countries, cause urban physical growth and expansion. If urban expand uncontrolled and unplanned, serious managing and environmental problems will engender. So to prevent these problems and to control them, decision takers and urban managers need to some tools to simulate and predict location, size and pattern of future urban growth. urban growth models and especially CA-basic models were highly paid attention in the recent years. Although models would not predict the reality exactly, but can help to make the future state more clear. SLEUTH as one of the most successful CA-based urban growth prediction models, is being used all over the world. In this paper, we applied the SLEUTH model for prediction urmia urban growth. Prediction occurred based on two different scenarios and compre the results showed that considering more local characterisctics of the model can reach to the appropriate growth scenario. The accuracyof simulation outputs showed that SLEUTH can be as an appropriate tool for urmia urban managers for future urban planning. They can identify the effective local characteristics that affect future growth of the city, and consider their polices for future of city, by creating multiple scenarios. However, there are some limitiation to employ this model. Primary limitiation from urban planning discipline can be that urban or regional development policies, human behaviour, tax, income, zoning, and other socio-economic factors not participated by the SLEUTH model. Comparing the result of scenarios show when a policy or factor are considered, how the city growth and can help urban planners and decision makers to take proper policy and planning for future development needs.

CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest regarding the publication of this manuscript.

NOTES

1. Masjid= Mosque
2. Madreseh= School
3. Likert Scale is a psychometric scale commonly involved in research that employs questionnaires.
4. In statistics, Cronbach's α(alpha) is a coefficient of internal consistency. It is commonly used as an estimate of the reliability of a psychometric test for a sample of examinees

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