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Guiding SLEUTH land-use/land-cover change modeling using multicriteria evaluation: towards dynamic sustainable land-use planning

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Abstract. Upgrading the SLEUTH urban-growth and land-use-change model, realizing its full capability in modeling change simultaneously in land-use and land-cover types, and using it as a self-organizing dynamic land-use planning tool have been the three main objectives of this study. In doing so, SLEUTH was applied to design a better plan for future and assess two scenarios concerning land-use and land-cover changes in Gorgan Township of the Golestan Province of Iran. Four land-use and land-cover maps were derived from Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper Plus imagery through a hybrid method including unsupervised, supervised, and on-screen classification for four years. To provide a more desirable forecast of future land-use and land-cover changes, SLEUTH's exclusion layer was combined with an urbanization-suitability layer from a multicriteria evaluation (MCE) using fifteen map layers that most influence land suitability for urban development. The layers used in the MCE process were related to landform, vegetation, soil and geology, and surrogate socioeconomic factors; hence, they portrayed the desirability of the urban growth. SLEUTH was used for forecasting with both this new and a standard exclusion layer. Using the new layer, the fragmentation of the future land-use pattern was controlled and urban development along roads was restrained, thereby safeguarding the remaining urban green space and remnant rural vegetation patches. The results were also compared with a separate site selection process for future urban development showing the desirability of MCE-guided SLEUTH modeling over original SLEUTH and the standalone urban MCE in terms of landform, surrogate socioeconomic factors, and landscape metrics such as patch size, shape, and proximity and fractal dimension. As SLEUTH derives change rules simultaneously for different land-use and land-cover types in a self-modifying self-organizing manner, we showed the approach can be regarded as a tool for dynamic land-use planning.

Keywords: SLEUTH, Gorgan, multicriteria evaluation, urbanization, land-use planning, sustainable land use

1 Introduction

With both increasing human population and shrinking natural resources, the ability to model change and to direct outcomes towards more sustainable land-use patterns has become a necessity. Many approaches have been offered for modeling and predicting land-use and land-cover change and two of these are regression-based and cellular automata-based models. Theobald and Hobbs (1998) described these approaches as regression type and spatial transition-based model type.

SLEUTH (Clarke and Gaydos, 1998) is a commonly applied model of land-use/land-cover change prediction used mainly for forecasting urban development. The model derives its name from the input map layers used for change prediction: slope, land-use/landcover, excluded zones, urban areas, transportation network, and hillshading. The first five layers are employed in the modeling process and affect the way urban areas and other land-use/cover classes change through time. The model has many capabilities that are yet to be explored fully, of which the option to model land-use and land-cover changes simultaneously and to assign weights to components of the excluded layer and road networks are noteworthy. The ease with which the forecasts can be joined to other environmental data is a strength of SLEUTH, which has been described in the related literature (see, for example, Arthur-Hartranft et al, 2003; Clarke and Gaydos, 1998; Goldstein, 2008; Salman Mahini and Gholamalifard, 2006; Toby et al, 2000) as having 'loose coupling' and 'linking' applications.

SLEUTH has two core modules: the Urban Growth Model (UGM) and the land-cover deltatron model (LCD) (Clarke et al, 2007). The UGM is used for urban change modeling and prediction while the LCD is applied to model and predict changes among land-cover types. The method uses a Markovian cellular automata approach to model and predict change and the two core modules run sequentially at each time step (Candau et al, 2000). Several parameters have been suggested and tested through time to help calibrate and assess the accuracy of SLEUTH modeling. In recent research, a subset of seven selected parameters, jointly termed the optimal SLEUTH metric (OSM) was recommended for calibrating and calculating the accuracy of the results in the modeling process (Clarke et al, 2007; Dietzel and Clarke, 2007).

SLEUTH has been applied in twenty-three locations inside the United States and nine countries around the world with promising results (Clarke et al, 2007). Recent attention has been focused on Iran, where problems of land-use change, rapid urbanization, and the need for conservation resemble those of other countries. Of the recent applications in Iran, SLEUTH was used for the cities of Gorgan and Mashad in the northeast and Nowshahr and Chalus in the north. In Gorgan, urban change was modeled and linked to landfill demand through which the best candidate areas were suggested for future waste disposal sites (Salman Mahini and Gholamalifard, 2006). For Mashad, the results of SLEUTH forecasts were coupled with information on waste transfer stations, and locations were defined for future use (Rafiee et al, 2009). For Nowshahr and Chalus, two rapidly growing towns in northern Iran, SLEUTH was used to model urban change over time and linked to a long term hydrological impact assessment (Teller and Engel, 2009) for the region to assess the effects of urbanization on surface runoff (Hosseinnia et al, 2009).

However, none of the studies conducted in Iran has made use of the capability to model both change in urban area and in other land-cover types. Also, no studies were found that specifically incorporated multicriteria evaluation (MCE) into SLEUTH modeling. MCE is generally used for combining raster map layers to arrive at a single suitability layer (Malczewski, 1999). Inclusion of the MCE results can help to arrive at a more desirable pattern for the given development as the MCE process entails considering important ecological and socioeconomic factors. Wu and Webster (1998) integrated MCE with urban cellular automata to derive urban transition rules. Li et al (2008) applied results of an MCE to urban cellular automata modeling to improve compact development in the Pearl River Delta. Also, Li and Liu (2008) used cellular automata in conjunction with agent-based modeling to provide a spatial exploratory tool for generating alternative development patterns in a rapidly expanding city in the Pearl River Delta. However, SLEUTH derives transition rules in three calibration steps and does this in a self-modifying self-organizing manner. Hence, the software requires very little user intervention to devise the growth and change rules. In doing so, the approach also takes into account change in urban areas and in nonurban areas such as forests and rangelands. These capabilities of SLEUTH make it a powerful tool to model and guide land-use/land-cover change. When applying the model, there is the possibility of game playing by changing growth coefficients derived through the calibration phase of SLEUTH and hence guiding the pattern of changes towards more sustainable outcomes.

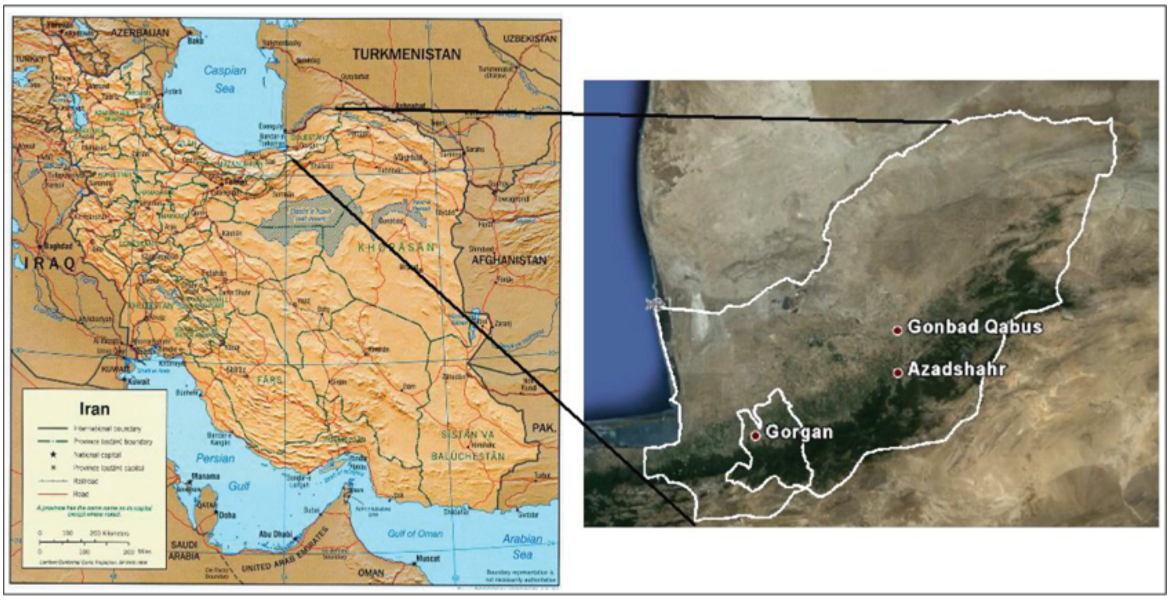
Including the MCE result in the excluded layer has the advantage of dealing with the elements on a pixel-by-pixel basis. The pixel-based approach keeps the information intact by not grouping the cells into polygons, is more compatible with the raster layers, and offers more flexibility while modeling.

In this study, simultaneous urban growth and land-use/land-cover change modeling were conducted for Gorgan Township through SLEUTH. An MCE was conducted for urban suitability assessment, its result was incorporated into the excluded layer, and the model applied a second time. We discuss the application, compare the results of both approaches, and discuss the method and approach.

2 Materials and methods

2.1 Area of study

The area of study encompasses Gorgan and Ali-Abad townships, collectively named Gorgan Township. The area of 98 000 ha is located in the northeast of Iran close to the coast of the Caspian Sea (figure 1). The study area is part of Golestan Province and in the south is covered with Hyrcanian temperate forests, while in the north plains farms and rangeland dominate the landscape. Golestan Province is one of the major agricultural centers in Iran. Following the designation of the area as a new Iranian province, rapid population growth has occurred with an accompanying sprawl of urban and industrial areas.



(a) (b)

Figure 1. [In color online.] (a) Iran; (b) Golestan Province and Gorgan Township as the study area inside the province.

As a result of growth in population and the increase in size of the urbanized areas and infrastructural facilities, environmental degradation and pollution have occurred, creating a need for environmentally friendlier development plans to be designed and implemented. Such plans should be informed by quantitative assessment modeling and prediction of changes in land-use and land-cover, so that effective preventive measures can be identified and applied through possible growth rules and coefficients. Also, ideally, such a game playing model should help the managers of the area direct changes towards more environmentally desirable goals.

2.2 Data used for SLEUTH modeling

SLEUTH needs a slope layer in percentage slope, at least two land-use maps, one excluded layer depicting areas which cannot be developed, at least four urban layers showing the expansion of human habitation over a timespan that provides enough change in urban areas for the model to work properly. There is also the need for two transport-network layers for two time periods.

The slope layer was derived from the 30 m digital elevation model (DEM) of the area interpolated from VMAP1 (http://www.mapability.com) and ancillary information from the Iranian Cartographic Center, at 1:50 000 scale. For the flat areas, a minimum 1% was allocated and a mean three-by-three filter applied using Idrisi (Eastman, 2009) to smooth the sharp artificial changes caused by integerization and interpolation. Land-use and land-cover maps of the area were the most time-consuming layers to prepare for which we used Landsat TM and ETM+ imagery collected by the satellites in 1987, 1992, 2000, and 2005. After coregistration of the imagery, a hybrid process including unsupervised, supervised, and on-screen visual classification was undertaken. In the process, a normalized-difference vegetation-index layer was also produced to guide the classification, since this better outlined vegetated areas. For unsupervised classification, an ISODATA clustering with fifteen categories was applied, based on trial and error and previous experience. The supervised classification method used maximum likelihood and the main roads layer was prepared using the original VMAP1 layer plus on-screen digitization on false color composite of the ETM+ bands 2, 3, and 4. The road layer was prepared for all four years and used in the modeling process.

Nine classes were defined: forest, rangeland, barren, urban, urban vegetation, agriculture, water bodies and rivers, road networks, and remnant vegetation in the form of tree-covered but isolated patches. The layers acquired through unsupervised, supervised, and visual classification were merged and cross-tabulated across different years for accuracy and consistency. Thus, the 1987 and 1992 maps were cross-tabulated and revised and then the revised 1992 map was used for cross-tabulation with the 2000 map. After the forward cross-tabulation and revision, a backward revision was conducted, such that in the end no apparent inconsistency was present in the maps. This was undertaken because the results of SLEUTH modeling are known to be dependent on the quality of the input layers.

The excluded layer included zones outside of the province, water bodies, and road networks. In the study area, urban sprawl is widespread even inside the Jahannama Protected Area. Hence, for modeling changes, no other completely excluded components were defined. The hillshading was also prepared from the DEM using Idrisi (Eastman, 2009), reclassified, and enhanced by stretching.

2.3 Data used for urbanization suitability assessment through MCE

MCE is generally a raster operation on multiple digital input maps that are believed to affect the suitability of the land for a particular use. During MCE, raster maps of the environmental parameters are prepared containing cells with different values. Then, using fuzzy set theory (Zadeh, 1965), the maps are fuzzified. This standardizes values in the layers and allows for recognition and inclusion of uncertainty in the data layers and provides a means of conflating different opinions on their importance. Another method used in MCE is the analytical hierarchy process (AHP) (Saaty, 1980). AHP allows pairwise comparison of the fuzzy layers called 'factors' and assigns weights to the factors based on matrix calculations. The method has gained universal application and is used in many different disciplines.

A second group of digital map layers used in MCE are those depicting absolute unsuitability for the land-use in question, called 'constraint' layers, and they contain 0 or 1 showing impossibility and possibility, respectively, of developing the land use in question. Generally, the fuzzified factor layers and the constraint layers are combined through such methods as weighted linear combination and ordered weighted averaging (Eastman, 2009).

In the MCE process for Gorgan Township, fifteen factors were included (table 1). These were deemed to be the most important for the Iranian context, cited in major textbooks (Makhdoum, 2007), and were available for our analysis. The variables reflected the suitability of any land area with regards to terrain stability, erosion and runoff control, energy use in the constructed buildings, minimal impact on river buffer areas, environmental protection and land price, seismic activity, water availability and water protection from pollution, and land position in the landscape. Topographic slope was considered to be both a factor and a constraint, and slopes >20% were restrained from development. Slopes in the range 0%–20% were linearly fuzzified using a monotonically decreasing trend in the range 0–1 with 1 showing the highest suitability.

Table 1. Data layers used in the multicriteria evaluation of urbanization suitability assessment.

1	Slope
2	Aspect
3	Pedology
4	Geology
5	Proximity to rivers and water-bodies
6	Proximity to roads
7	Proximity to town edges
8	Land use or land cover
9	Distance to geological faults
10	Forest density
11	Distance to protected areas
12	Underground water depth
13	Distance to villages and industrial sites
14	Climate classification, minimum and maximum temperature
15	Elevation

As the area has relatively warm summers, eastern and western aspects were given priority, with the north-lying areas coming next, while the south-facing slopes were given the lowest fuzzy value. This helped control the amount of solar radiation received on the developed land. Flat areas with no aspect were given the highest fuzzy value of 1, as the slope plays an even more important role in locating development areas (figure 2).

A land-suitability layer provided by the Iran Soil and Water Research Institute (http://www.SWRI.IR) was used for pedology. The map contained eight categories with a full description of soil properties, making it possible to assign fuzzy values using the standard land-use planning procedure used in Iran (Makhdoum, 2007). A geology layer was available

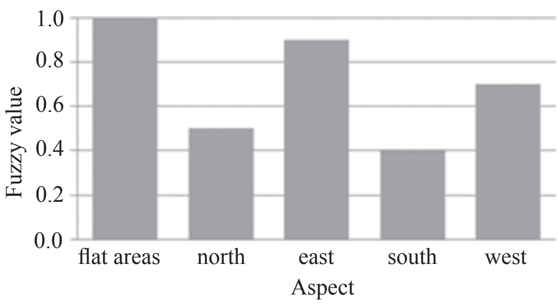


Figure 2. User-defined fuzzy values for aspect layer.

through the National Geodetic Database of Iran (http://www.ncc.org.ir). Using guidelines available in Makhdoum (2007), the suitability of different rock formations in the area were defined by twelve categories and given fuzzy values in the range 0–1.

Most of the towns and villages in the area obtain their water from rivers and underground sources. As such, the distance to rivers and water bodies was calculated and fuzzified through the linear symmetrical function. Distances of 0–200 m were assigned value 0 (normal practice in Iran) to protect water resources and their riparian vegetation and at the same time prevent damage to settlements from flooding. Then, the suitability increased linearly up to 1000 m, stayed the same up to 3000 m and then decreased. These are first-guess arbitrary values that can be changed interactively through repeating the MCE process if deemed necessary.

A distance of 200 m was used as a constraint for the main road layer and assigned value 0. The constraint zone for roads inside towns was of width 60 m. Also, to encourage clumped and centralized urban growth and to prevent sprawl, a distance map was generated from the current urban areas and fuzzified through a linear monotonically decreasing function up to 5000 m, the maximum distance.

Using the 2005 land-use map, we defined fuzzy values for the nine land-use categories through a user-defined option (table 2). To take precautionary measures for future urban development in relation to seismic activity and earthquakes, which are frequent, a distance up to 3000 m from fault lines was assigned the value 0 to act as a constraint and greater distances were given fuzzy values using a linear monotonically increasing function, on the basis that the further away an area is from fault lines, the better. The choice of 3000 m was made bytrial and error and the area of land left after application of such a constraint.

Table 2. User-defined fuzzy values assigned to land-use/land-cover types.

Land use or land cover	Fuzzy value
Forest	0.50
Rangeland	0.80
Barren areas	1.00
Urban	0.85
Urban vegetation	0.00
Agriculture	0.70
Water	0.00
Roads	0.00
Remnant vegetation	0.00

The normalized difference vegetation index (NDVI) of the area was calculated using bands 3 and 4 of the Landsat ETM+ imagery, and, through trial and error and using previous knowledge of the forested area, was fuzzified. NDVI values > 0.25 were assigned 0, protecting the most healthy vegetation. In the range 0–0.25, the higher the NDVI value the lower the fuzzy value, using a linear monotonically decreasing function.

For the Jahannama Protected area, a 1000 m buffer was given value 0, and for distances > 1000 m a linear monotonically increasing function was used to fuzzify the layer and encourage urban development away from protected areas. The protected area itself was considered a full constraint to development. A minimum distance of 210 m was considered as a no-construction zone for the villages; areas more distant were fuzzified using the linear monotonically decreasing function, encouraging aggregation around existing settlements.

The De Martonne classification system and the WorldClim dataset (Hijmans et al, 2004) were used to define climate. Also, minimum temperature for the coldest month of the year and maximum temperature for the warmest month were prepared, as we postulated that energy usage is dependent on air temperature. In the warmest part of the year energy consumption increases with rising air temperatures. Energy consumption also increases in the coldest period of the year, but with less magnitude. However, natural gas is used to heat buildings and this is abundant and relatively inexpensive. Due to the humidity of the area, keeping houses and offices cool with air conditioners during the summer uses a lot of energy.

Maximum temperatures for the warmest month ranged from 26 °C to 33.6 °C, and minimum temperatures for the coldest month from −13.6 °C to 4.2 °C. We used a user-defined classification for fuzzification of these layers (table 3).

Table 3. User-defined fuzzy values for minimum temperature.

Minimum temperature (0 °C)	Fuzzy value
−13.60–−1.99	0.1
−2.00–−0.01	0.3
0.00–2.99	0.9
3.00–4.21	0.6

In a lower hierarchy, we combined three climatic layers: De Martonne classification, the minimum temperature of the coldest month of the year, and the maximum temperature of the warmest month using 0.4, 0.35, and 0.25 as weights, respectively. The result was used in the MCE process.

Elevation was the last layer included in the MCE. To encourage urban growth in the middle altitudes—where daily and nightly winds through the valley bottom can ventilate the city, remove air pollution, and decrease the need for air conditioners—a linear symmetrical fuzzy function was used (figure 3).

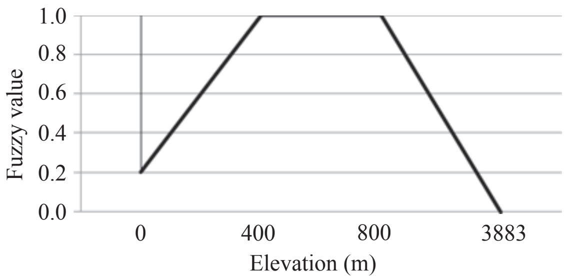


Figure 3. Fuzzy membership function for elevation in the study area.

We used the analytical hierarchy process (AHP) (Saaty, 1980) for weighting the fifteen factors (table 4) using experience and general knowledge of the area. The measured consistency ratio of the AHP weighting was 0.09, which is within the acceptable limit.

A weighted linear combination using equation (1) below was used for summing up the factors and constraints.

$$\text{Multicriteria evaluation of urban suitability} = \left(\sum_{i=1}^{n} W_i X_i\right) \prod C_i \, , \tag{1}$$

where W_i is the weight of factor i, X_i is the fuzzified factor i, $\prod$ is the multiplication operator and C_i is constraint i. The result of the MCE is a single layer with pixel values in the range 0–1 or 0–255 based on the fuzzification range. The higher the value is, the higher the suitability.

Table 4. Weights derived for the factors through the analytical hierarchy process method.

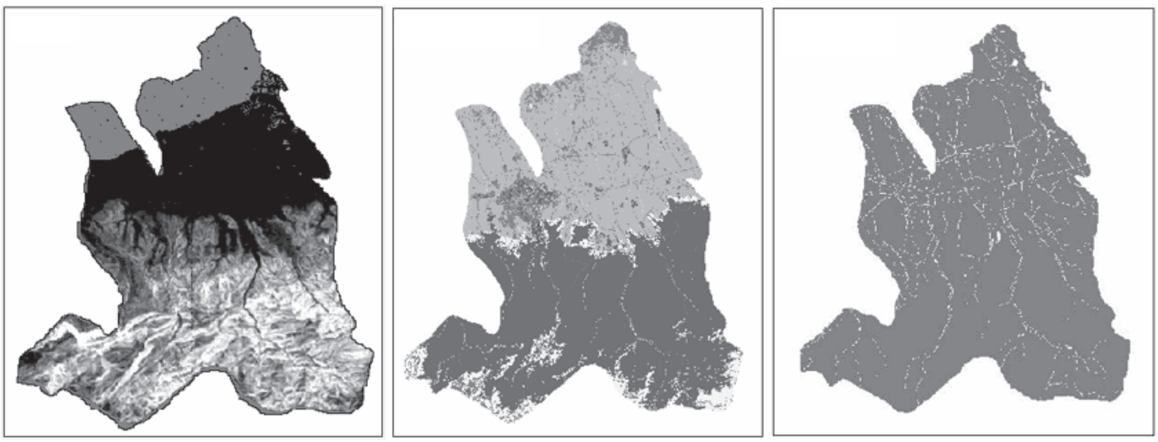
Factor	Weight
Slope	0.2329
Aspect	0.0104
Pedology	0.0614
Geology	0.0866
Proximity to rivers and water bodies	0.1605
Proximity to roads	0.0360
Proximity to town edges	0.0528
Land use or land cover	0.0143
Distance to faults	0.1202
Forest density	0.0244
Distance to protected areas	0.0213
Underground water depth	0.1177
Distance to villages and industrial sites	0.0165
Climate classification, minimum and maximum temperature	0.0357
Elevation	0.0094

2.4 SLEUTH modeling

The slope layer was converted to an 8-bit gray scale and the image color table was accessed and assigned values for slopes of 0%–100%, which is necessary for the model to function properly. SLEUTH uses GIF file format and is able to verify the formats during the testing phase.

The land-use/land-cover layers were converted to GIF format, and edited the same way. Roads and rivers were excluded from urban development by assigning them a value > 100 in the excluded layer. We assigned a value > 100 to pixels outside the study area to prevent the model from attempting to urbanize those areas, and converted the layer to GIF format (figure 4). The process was the same for the four years for urbanization and road layers (figures 5 and 6).

Figure 4 shows the slope as a percentage, amended for the flat areas such that no zero values exist in the layer. Initial tests with the model suggested areas with a zero slope value attract urbanization in an unrealistic way. Figure 5 shows the urbanized area for the four years, after being compared in a forward and backward manner so that no urban pixels exist in prior years that are not present in the later maps. We have ensured that the reverse of this trend also holds true. The same procedure was applied to the road networks (figure 6).



(a) (b) (c)

Figure 4. (a) Slope, (b) land use 1987, and (c) excluded layers used in the SLEUTH modeling.

After using SLEUTH's naming convention for the files, the layers were used in the three automated calibration phases: coarse, fine, and final. SLEUTH was compiled and executed under the Cygwin environment, a Windows-based UNIX emulator (http://www.cygwin.com).

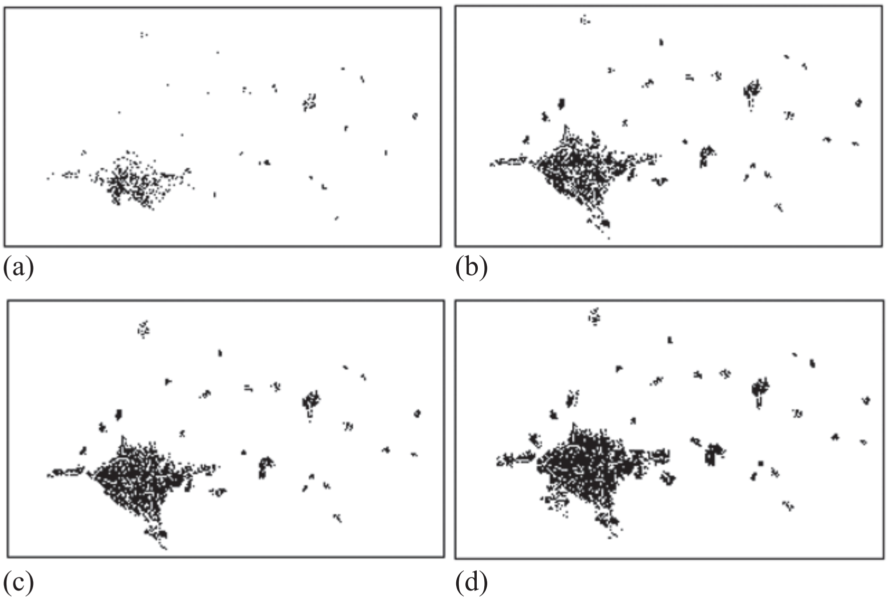


Figure 5. Urbanization maps used for SLEUTH calibration for the years (a) 1987; (b) 1992; (c) 2000; (d) 2005.

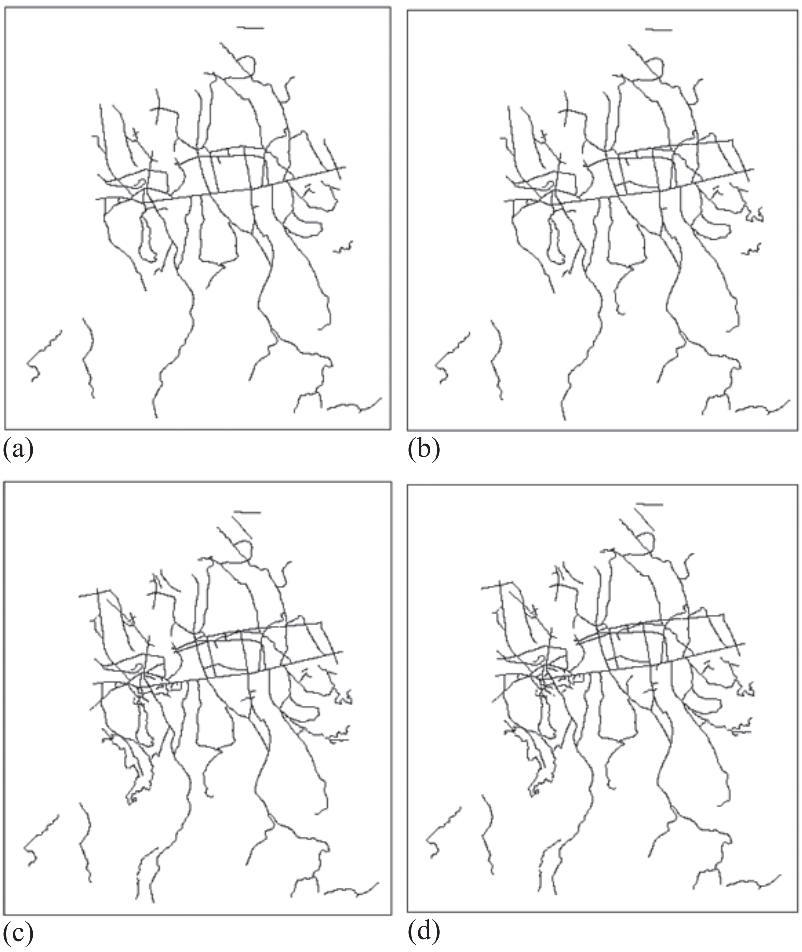


Figure 6. Road network maps used in the SLEUTH calibration for the years (a) 1987; (b) 1992; (c) 2000; (d) 2005.

For the calibration the full resolution maps were included at all three stages of the process, as recommended by Jantz et al (2003). The processing time increased proportionally, but this ensured that the full information content of the layers was used during calibration. SLEUTH uses four urban growth rules in an iterative Monte Carlo way to arrive at five coefficients that define urban growth based on the input data (Silva and Clarke, 2002).

For 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. Four Monte Carlo iterations were assigned for coarse calibration, and diffusion, breed, spread, slope, and road gravity coefficients were set at 0, 25, 100 for start, step, and stop values, respectively.

On the basis of the study by Dietzel and Clarke (2007), of the twelve metrics provided by SLEUTH for assessing the success and accuracy of modeling, a subset of seven can be used for choosing the best performing iterations. The seven metrics, in the range of 0–1, are multiplied together and called the optimized sleuth metric (OSM). The iterations are then sorted based on this metric and the best values and ranges for the five coefficients are chosen for the next calibration step using a utility program posted on the SLEUTH user bulletin board. Using the OSM metrics of the best performing iterations, the ranges for the five coefficients were narrowed down and used in the fine calibration step.

The fine calibration step used the full resolution maps in six Monte Carlo iterations. On the basis of the OSM values, the ranges for the five coefficients of urban growth in SLEUTH were further narrowed for the final calibration step, which used eight Monte Carlo iterations with 7874 runs. The five best performing iterations in the final calibration step are shown in table 5 and their corresponding coefficients and OSM values are shown in table 6. The ranges for averaging values (table 7) of the five coefficients of urban growth in SLEUTH were set using figures shown in table 6. The averaging was then run for 150 Monte Carlo iterations.

Using the averaged calibration values over the 150 Monte Carlo iterations, the final coefficients were set at 34, 24, 56, 1, and 48 for diffusion, breed, spread, slope, and road gravity, respectively. Since these values are the results of 150 iterations they are slightly different from those shown in table 7, which are normal values. The values were used to predict urban and land-cover changes up to the year 2040. Note that these are final values for the most recent time period, and differ from the start parameters due to self-modification within the model runs.

Table 5. Five best performing iterations and twelve SLEUTH accuracy metrics generated in the final calibration step.

Run	Product	Compare	Pop	Edges	Cluster	Cluster size	Leesalee
7573	0.1184	0.9976	0.9475	1.0000	1.0000	0.7116	0.4013
6036	0.1161	0.9967	0.9471	0.9997	1.0000	0.7315	0.4031
6778	0.1173	0.9895	0.9450	0.9989	0.9999	0.7204	0.4095
7565	0.1155	0.9995	0.9485	1.0000	0.9996	0.6757	0.4002
5818	0.1171	0.9706	0.9485	0.9992	0.9987	0.7413	0.4070
	Slope	%Urban	Xmean	Ymean	Rad	Fmatch	
7573	0.8307	0.9158	0.9984	0.6419	0.9315	0.9656	
6036	0.7961	0.9154	0.9994	0.6372	0.9312	0.9655	
6778	0.8091	0.9134	0.9986	0.6431	0.9290	0.9658	
7565	0.8438	0.9169	0.9981	0.6481	0.9327	0.9654	
5818	0.8045	0.9180	0.9991	0.6360	0.9323	0.9653	

Note. See Rafiee et al (2009) and Mahiny and Gholamalifard (2007) for descriptions.

Table 6. Best performing iterations for growth coefficients and their optimized SLEUTH metric in the final calibration step.

Diffusion	Breed	Spread	Slope	Road gravity	Optimised SLEUTH metric
29	24	42	2	35	0.3581
28	24	43	1	45	0.3499
29	21	45	4	20	0.3496
29	24	42	1	40	0.3495
28	23	45	2	35	0.3481

Table 7. Averaging calibration values for the five growth coefficients of SLEUTH modeling.

	Start	Stop	Step
Diffusion	29	29	1
Breed	20	20	1
Spread	47	47	1
Slope	2	2	1
Road gravity	47	47	1

2.5 Incorporation of MCE result into the excluded layer

The MCE layer for urban suitability assessment included values in the range 0–1. Higher values shown in the map indicate greater suitability for urban land-use (figure 7). The layer was stretched between 1 and 100 and the values reversed so that the highest suitability had the lowest value in the excluded layer. Areas most suitable for urbanization had the lowest resistance to urbanization in the excluded layer and vice versa. The areas unsuitable for urbanization were given the value 255 to introduce absolute resistance to urbanization (figure 8). Using the same average values arrived at in the final calibration step of SLEUTH,

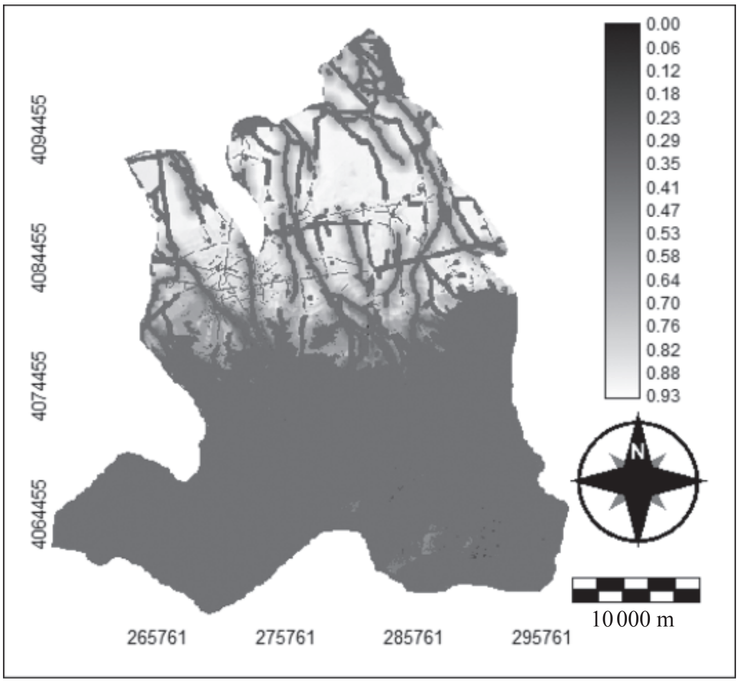


Figure 7. Urban-suitability assessment layer for the area of study from the multicriteria evaluation process.

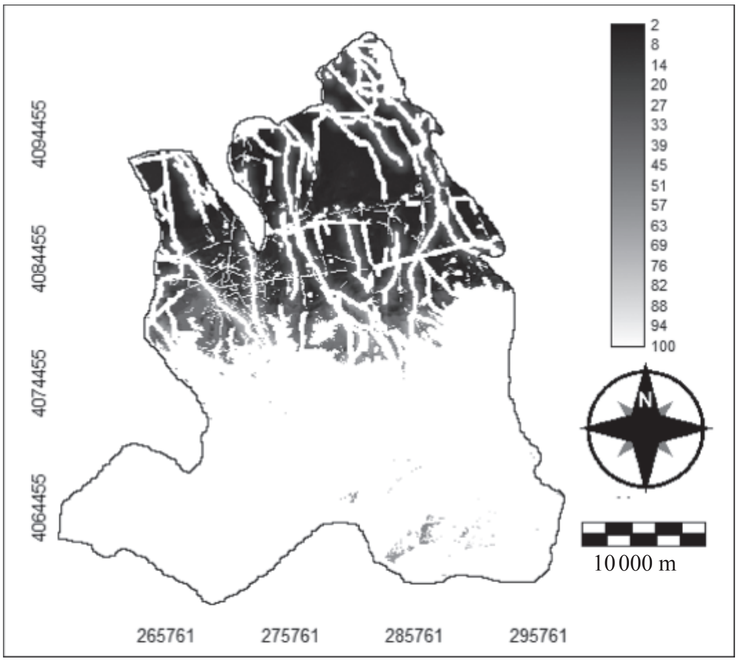


Figure 8. New excluded layer with a gradient of resistance to urbanization based on multicriteria evaluation weights.

the new excluded layer was introduced to the forecasting process. SLEUTH was run in the prediction mode to forecast urban expansion up to 2040.

To assess the effects of the MCE for urban suitability, we compared the amount of predicted urbanization under the original excluded layer with that of the excluded layer based on the MCE suitability values. To do this, urban pixels selected by the two modeling efforts for urban growth were superimposed on the MCE for urban suitability and the range of suitability values occupied by the new urban cells were studied for their minimum, maximum, and average suitability.

As we modeled both land-use and land-cover in the area using UGM and LCD simultaneously, we also investigated the pattern of land-cover changes using selected landscape metrics from Fragstats 3.3 (McGarigal and Marks, 1995) that included various aspects of patches such as size, proximity, shape, and fractal dimension. This allowed quantitative comparison of the pattern of changes predicted in the two modeling efforts.

3 Results and discussion

The high accuracy values of the twelve SLEUTH goodness-of-fit metrics (table 5) are indicative of success in mimicking the trend of land-use and land-cover change in the study area. In table 5, columns such as Compare, Pop, Slope, %Urban, Xmean, Ymean, Rad, and Fmatch are mostly above 0.9 showing the success of the modeling effort [for a description of these metrics and others refer to Rafiee et al (2009) and Mahiny and Gholamalifard (2007)]. The model was able to define correctly the pattern of land use and land cover, and the model coefficients can be reliably used for forecasting and modifying future conditions.

SLEUTH's Cumulate_Urban output layer shows the Monte Carlo-derived probability of urbanization for each pixel in the range 0%–100%. Prediction of land-use and land-cover with the original excluded layer resulted in a Cumulate_Urban layer that allowed urbanization over the entire study area with the exception of dense forests (figure 9).

Figure 9 shows that the highly probable locations for urbanization are located on the boundaries of current urban areas. Nearly all the pixels within the urban areas are prone to urbanization by the removal of urban green spaces. The same phenomenon happens to the

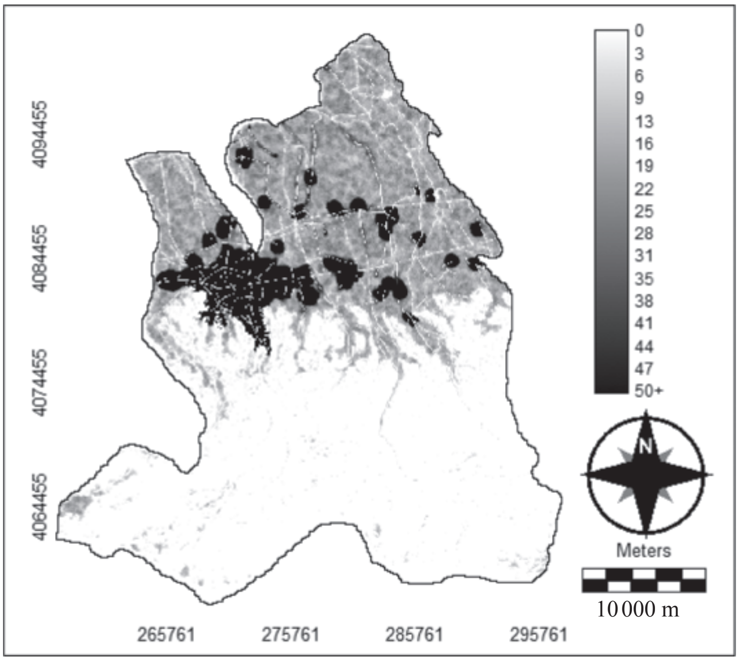


Figure 9. The probability of urbanization in the study area using the original excluded layer, where the higher the value (shown as darker), the greater the probability for urbanization.

remnant vegetation, as these land-cover types are at high risk of urbanization. Infill happens in urban areas such that with the exception of roads, which were excluded from urbanization, most other open locations within the cities and towns are developed over time. Roads had a large influence on urban development, and looking at the north east of the image shows that in the absence of a buffer new settlements are established along major road networks (figure 10).

The road network has a strong influence on the urban spread, as reflected in the road gravity coefficient value, the second highest among the five SLEUTH coefficients. The spread coefficient has the highest value, which is indicative of urban cells growing inside and in the periphery of currently urban areas.

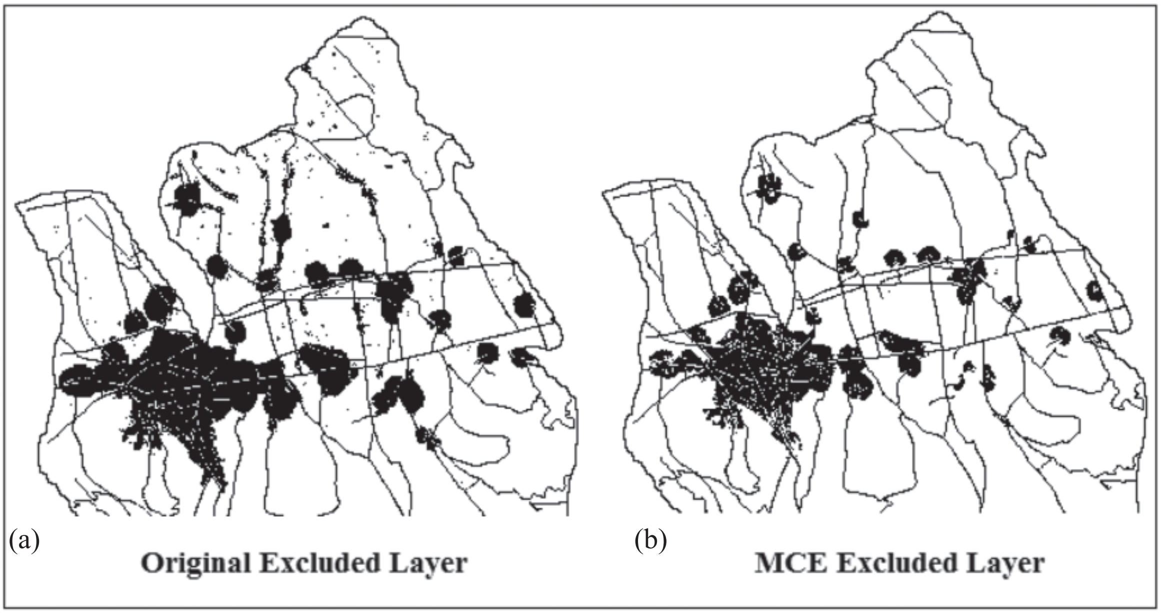


Figure 10. Urban probability of expansion and the attractive effect of roads in the north east of the area using 27% cut-off probability on the original (a) and multicriteria evaluation excluded layers (b).

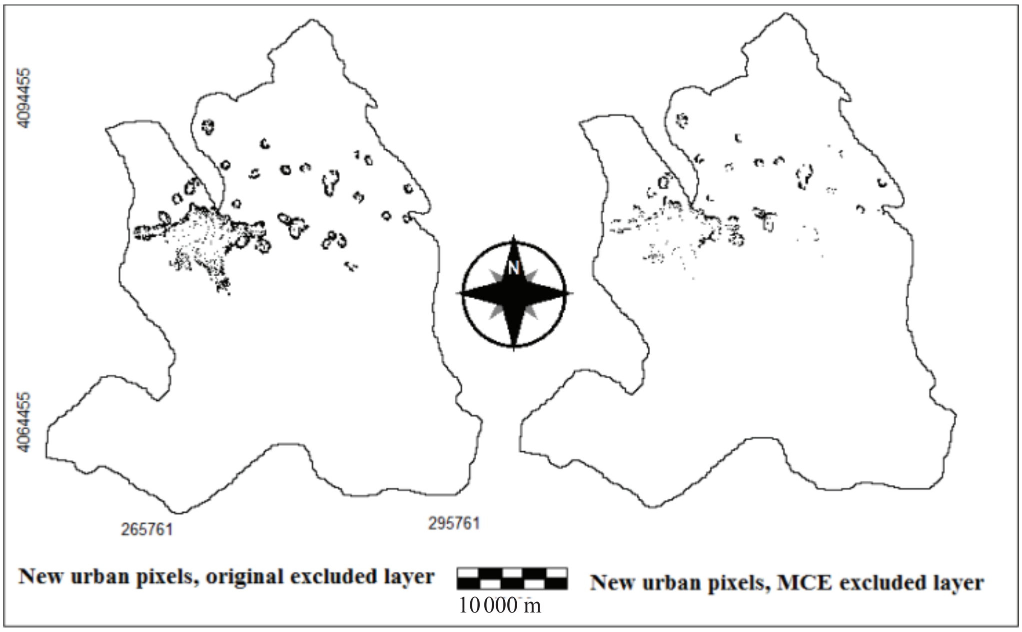
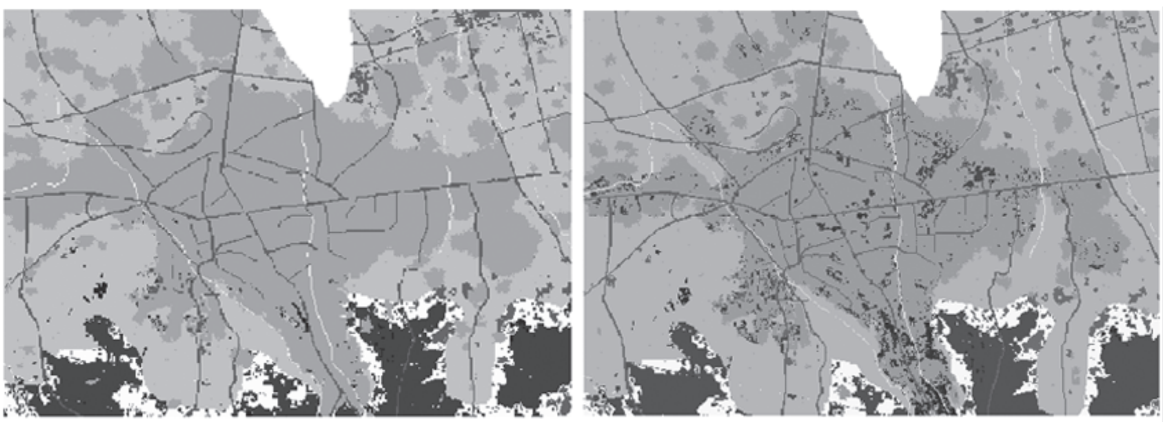


Figure 11. Predicted urban pattern for the year 2040 using the whole range of cut-off probability values on the original excluded layer and the multicriteria evaluation excluded layer, (a) and (b), respectively.

SLEUTH also provides images of the predicted urban growth and other land-use/land-cover growth through time. The final prediction year was set as 2040, by which time the probable urban expansion depicted as a very scattered and disaggregated pattern (figure 11). However, guiding land-use/land-cover change using the MCE urban suitability layer restrained the dispersed urban growth, leading to a more sustainable future land-use pattern.

Figure 11 compares the urban expansion prediction through application of the original excluded layer and the MCE excluded layer and shows how inclusion of the MCE excluded layer prevented urban growth in the south of the area, close to high-density forest, fault lines, protected areas, and on steeper slopes. Urban green spaces are better conserved through inclusion of the suitability map into the development forecast. This is desirable, as the green spaces provide the open air and scenic qualities required for a healthy life in urbanized areas.

Figure 12 also shows that forecast urban growth using the MCE suitability layer is triggered more by SLEUTH's organic growth behavior rule and resembles growth experienced in real situations, while that of the original excluded layer appears more artificial. This statement



(a) (b)

Figure 12. Predicted urban vegetation pattern for the year 2040 through the original (a) and the multicriteria evaluation (b) derived excluded layers. Light gray = agriculture; medium gray = urban; dark gray inside urban = urban green spaces; white = rangeland.

is made using previous experience of the area, which shows that even under extreme circumstances some green spaces are preserved.

Two difference maps were prepared using the predicted urban cover for the year 2040 from the two modeling efforts and the known pattern in 2005 and the differences were overlain on the urban suitability layer to assess the correspondence between suitability and predicted growth (table 8).

Table 8. Statistics of urban suitability for the two modeling efforts

	Urban suitability values				
	minimum	maximum	average	range	standard deviation
Original excluded layer	1	99	54.45	98	39.90
Multicriteria evaluation excluded layer	27	99	84.43	72	11.41

Inclusion of the MCE layer upgraded the SLEUTH predictions since it selected more-suitable pixels for urbanization. It also prevented changes in other land-use/land-cover categories based on the constraints incorporated into the MCE excluded layer. The same was true for those pixels predicted to have a 100% chance of future urbanization.

Using the 100% cutoff point for the results of SLEUTH forecast and the original excluded layer, around 2630 ha of land were found to be probably urbanized by the year 2040. For the MCE upgraded SLEUTH, this area was found to be 1164 ha. Using the average of the two figures, namely 1900 ha, we applied a single objective land-allocation operation. To do so, we selected the highest ranking suitability values such that the desired area is achieved through application of zonal land suitability (Eastman, 2009), which delineates suitable areas in compact and manageable zones. We applied zonal land suitability through the Siteselect Idrisi Macro Language file using a suitability threshold of 95/100 and a minimum size of 5 ha. The result was then ranked and the highly suitable sites were chosen such that 1900 ha of new urban pixels was achieved (figure 13).

The process of Siteselect includes ranking the suitability of pixels, by clumping and calculating the suitability of pixels within each polygon. We used the average suitability of pixels to rank the polygons for their suitability. Figure 13 shows the twenty top polygons of urbanization that demonstrate that the north and east of the area are suitable for urbanization. The clumped groups of pixels provide a summation of the situation for a single

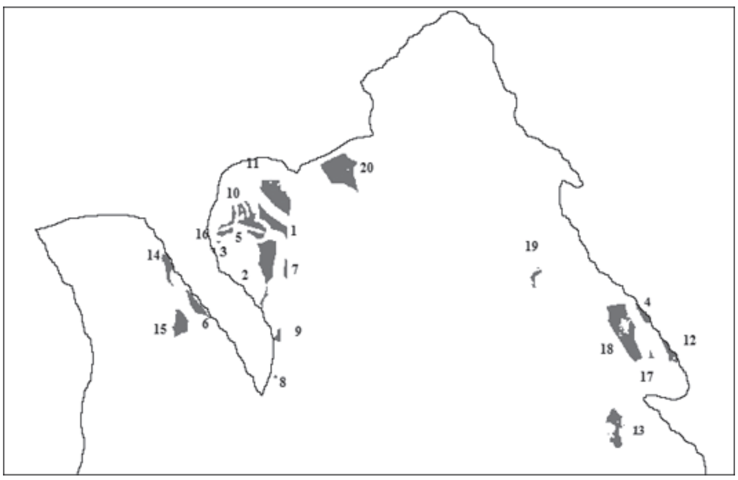


Figure 13. New urban development areas selected through single-objective site selection.

objective, which in this study is urbanization, in the absence of area dynamics and interaction of different land-use/land-cover types. It lacks the desired trends of urbanization in the area, such that urban development in the outskirts of towns and their periphery, proximity to town centers and other factors that are important in achieving organic growth are not realized.

When the urban suitability layer from the MCE processs is incorporated into the dynamics, and other guiding factors, such as the shape of urban growth, are applied to the selection of new urbanization pixels, a more suitable pattern is generated (figure 14). The desired pattern of growth is achieved through the growth behaviors in SLEUTH. When the MCE excluded layer is used in the predictions, the simulation benefits from the five growth coefficients acquired through the SLEUTH calibration and fifteen digital layers from the MCE.

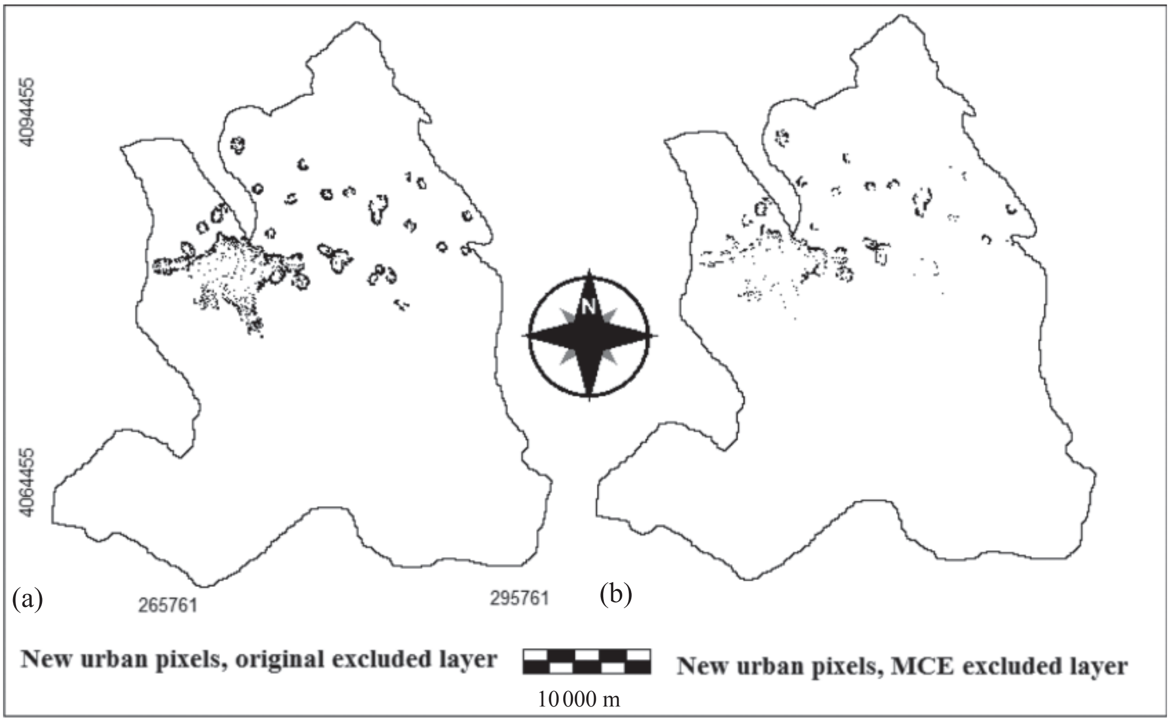


Figure 14. New urban development areas defined through SLEUTH modeling using 100% cutoff probability on (a) the original excluded layer and (b) the multicriteria evaluation excluded layer.

Most of the new urbanized pixels are located in the periphery of the existing developed areas (figure 14), similar to those of figure 13, with the exception that in the dynamic growth design change in land use and land cover and the desired pattern of change are also taken into account.

SLEUTH produces an uncertainty map, whereby the number of times a land-use is predicted at a given location during Monte Carlo simulation determines the certainty of that prediction holding true (Clarke et al, 2007). In the modeled urban areas for 2040 we found that the original modeling had a maximum uncertainty of 60%, average 10.8%, and standard deviation 11.5%, while these percentages for the MCE guided modeling were 53%, 6.2%, and 9.6%, respectively.

The most-common and least-correlated landscape metrics portraying ecological conditions of the nine land-use/land-cover classes and the whole landscape were calculated (table 9) using Fragstats 3.3 (McGarigal and Marks, 1995).

The number of patches (NP) and the patch density (PD) in the MCE-guided SLEUTH modeling is less than that of the original excluded layer, as a less dispersed and denser land-use/land-cover pattern has resulted. The largest patch index (LPI) for MCE is higher than in the original SLEUTH modeling, indicating the presence of larger patches and a more aggregated

Table 9. Landscape metrics for predicted land-use and land-cover for the year 2040 using the original and the multicriteria evaluation (MCE) excluded layers.

Landscape metrics	Original excluded layer	Multicriteria evaluation excluded layer
NP	9079	8915
PD	4.5159	4.4344
LPI	22.4531	22.6681
LSI	36.0120	34.4602
AREA_MN	10.8387	11.0381
SHAPE_MN	1.3171	1.3154
FRAC_MN	1.0462	1.0476
PARA_MN	1045.3598	1034.2236
ENN_MN	158.3829	140.2128
IJI	63.6678	65.3530
CONNECT	5.3697	7.1599
SHDI	1.4203	1.3933

patch pattern, which is usually preferred in land-use planning. The mean perimeter to area (PARA_MN) ratio is smaller for the MCE-guided modeling, showing compacter patches. The mean Euclidean nearest neighbor (ENN_MN) is smaller for the MCE-guided modeling, again showing that patches are found closer to each other.

The interspersion and juxtaposition index (IJI) of the MCE-guided modeling is larger than that for the original modeling, showing that within any window in the landscape there are slightly more land-use/land-cover types when compared with the original modeling results. The larger connectance (CONNECT) for the MCE-guided modeling results shows the patches are closer and more aggregated. The slightly smaller Shannon's diversity index (SHDI) for the MCE-guided modeling effort indicates less-equitable allocation of space among land-use/land-cover classes. The results of MCE-guided modeling are generally more favorable than those of the original modeling effort.

Metrics were also studied at the class scale, where each land-use/land-cover type is treated as a class. This is useful for investigating the landscape in more detail. Eight metrics were computed for the nine land-use/land-cover types (figure 15). Class area shows the coverage of the landscape with each of the land-use/land-cover types. Forests have a higher coverage in the MCE-guided SLEUTH modeling than in the original modeling. The same is also true for urban vegetation, agriculture, and remnant vegetation, while areal coverage for other cover types is nearly equal. Generally, the fewer the number of the patches, the more compact they are. The number of patches for the MCE-guided SLEUTH modeling is less than for the original modeling for all cover types except urban vegetation and remnant vegetation. The latter two, being larger than for the original modeling, are indicative of the protection given to these important manmade and natural areas, because the higher coverage of urban and remnant vegetation inevitably means they are found in more patches.

Patch density in the MCE-guided SLEUTH modeling is lower than in the original modeling for forest, range, urban, and agriculture cover types, showing the more aggregated nature of these cover types, while the metric is higher in the MCE guided modeling for barren, urban vegetation, and remnant vegetation cover types. The higher patch density for these cover types shows the success of the modeling in keeping a larger area of the preferred cover types in the landscape.

The largest patch index is nearly the same in the two modeling efforts for all cover types with the exception of agricultural areas, for which patches are generally larger in the

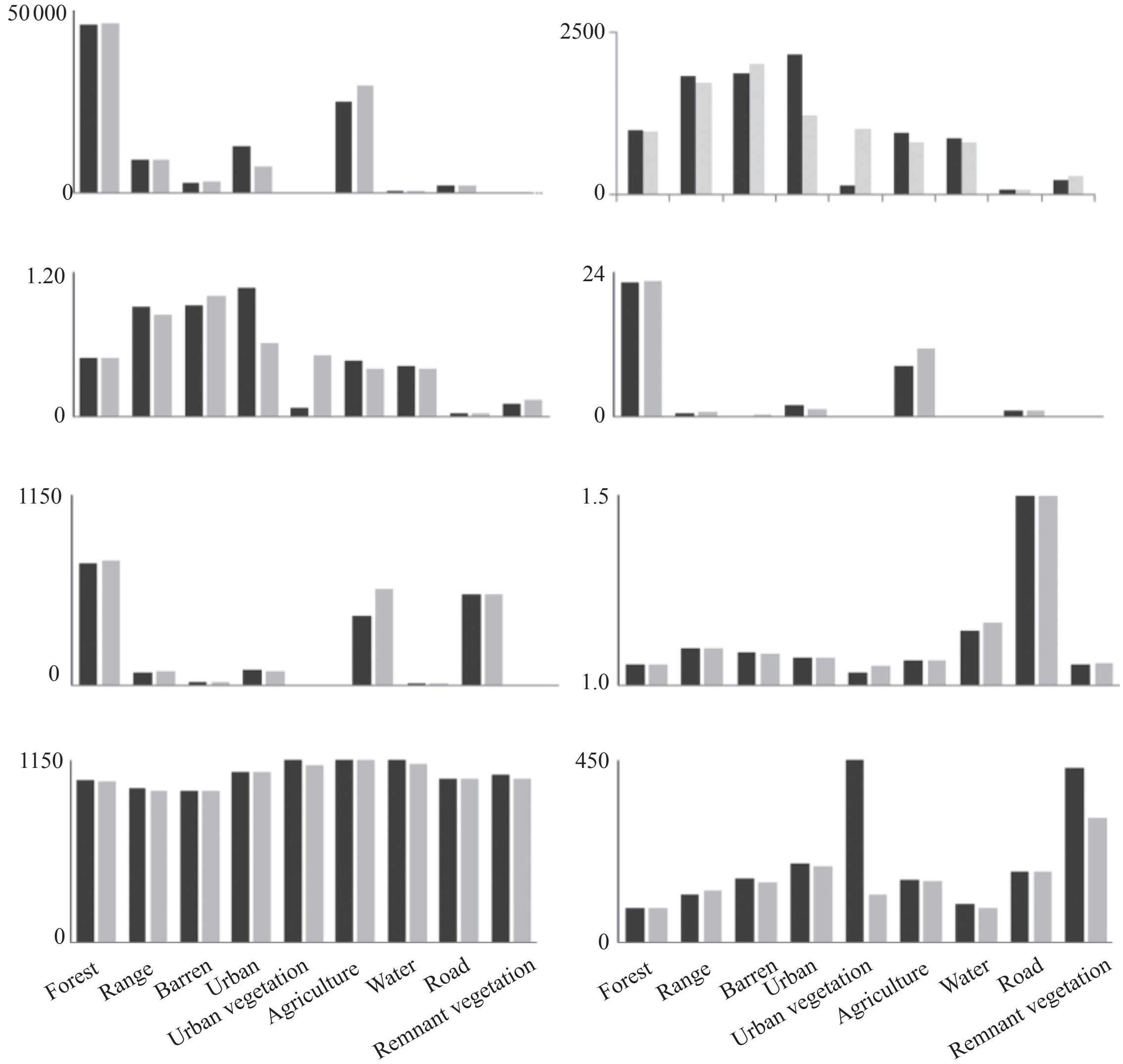


Figure 15. Comparison of patch metrics for the original SLEUTH modeling (black) and the multicriteria evaluation-guided SLEUTH modeling (gray).

MCE-guided modeling compared wuth the original modeling. Mean area of patches for the nine cover types is also larger in the MCE-guided SLEUTH modeling compared with the original modeling effort, which is a desirable outcome. The mean shapes of the patches are relatively similar for the two modeling efforts with the exception of urban vegetation which is greater in the MCE-guided modeling. This is indicative of the success in keeping these vitally important elements of towns.

The perimeter to area ratios of the cover types were lower in the MCE-guided modeling efforts compared with the original modeling, which is also a preferred outcome. Mean nearest neighbor for the patches of all cover types in the MCE-guided modeling effort is smaller than in the original modeling, with the exception of rangelands. This shows that these patches are closer to each other in the MCE-guided modeling effort, which is desirable in terms of ecological function and management practice. The managers can try to achieve such a favorable land-use/land-cover pattern through application of criteria considered in the MCE derivation and also by manipulation of growth coefficients in SLEUTH.

4 Conclusion

No earlier studies have specifically linked SLEUTH modeling to multicriteria evaluation for urban suitability assessment. This was accomplished in a study of Gorgan Township in Iran using an initial SLEUTH model and a second MCE-guided model in which the result of the MCE was incorporated into the excluded layer of SLEUTH. The MCE result affected the way SLEUTH behaved in predicting the future conditions of the land-use/land-cover types in the study area. With regard to the road-attracted urban growth, its patchiness, and the safeguarding of urban green spaces and remnant vegetation, the MCE-guided modeling results are more realistic than those of the original forecast. When uncertainties of modeled land-use and land-cover were assessed it was shown that the MCE-guided modeling also produced more certain results.

We showed that including the urban suitability layer in the excluded layer of SLEUTH alters the urban growth behavior and changes in the other land-use/land-cover types. We compared the results of a stand-alone single-objective urban site selection with those of the original and the MCE-guided SLEUTH models and demonstrated the enhancement of the results from the MCE-guided SLEUTH model.

Using landscape and class metrics for the nine land-use/land-cover types, we showed that the results of the MCE-guided model are generally more favorable than those of the original model when ecological, social, and management aspects are considered. Our goal of achieving less dispersed, more compact, closer, larger, and rounder patches through modeling with the urban suitability layer was confirmed by the results. SLEUTH provides an environment in which to make use of a self-organizing cellular automata approach towards guided modeling and prediction of land-use and land-cover change.

More-finely tuned results could be achieved if the MCE layers for other land-use/land-cover type suitability, such as for forestry and agriculture, were prepared and incorporated into the excluded layer. For each we could assign weights when incorporating them into the final excluded layer and forecasts. This approach might be called 'multiobjective dynamic land-use planning' when the inevitable changes and preferred directions for future landscapes are considered simultaneously. Such coupled modeling shows promise for developing more sustainable land-management strategies that help deal with the challenges of impacts on the landscape due to rapid population growth and land-use change.

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