Linking SLEUTH Urban Growth Modeling to Multi Criteria Evaluation for a Dynamic Allocation of Sites to Landfill

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Abstract. Taking timely measures for management of the natural resources requires knowledge of the dynamic environment and land use practices in the rapidly changing post- industrial world. We used the SLUETH urban growth modeling and a multi-criteria evaluation (MCE) technique to predict and allocate land available to landfill as affected by the dynamics of the urban growth. The city is Gorgan, the capital of the Golestan Province of Iran. Landsat TM and ETM+ data were used to derive past changes that had occurred in the city extent. Then we employed slope, exclusion zones, urban areas, transportation network and hillshade layer of the study area in the SLEUTH modeling method to predict town sprawl up to the year 2050. We applied weighted linear combination technique of the MCE to define areas suitable for landfill. Linking the results from the two modeling methods yielded necessary information on the available land and the corresponding location for landfill given two different scenarios of town expansion up to the year 2050. These included two scenarios for city expansion and three scenarios for waste disposal. The study proved the applicability of the modeling methods and the feasibility of linking their results. Also, we showed the usefulness of the approach to decision makers in proactively taking measures in managing the likely environment change and possibly directing it towards more sustainable outcomes. This also provided a basis for dynamic land use allocation with regards to the past, present and likely future changes.

Keywords: SLEUTH, MCE, Landfill, Land Use Planning, Gorgan.

1 Introduction

Urbanization is one of the most evident global changes. Small and isolated population centers of the past have become large and complex features, interconnected, economically, physically and environmentally [1]. One hundred years ago, approximately 15% of the world's population was living in urban areas. Today, the

B. Murgante et al. (Eds.): ICCSA 2011, Part I, LNCS 6782, pp. 32–43, 2011.

percentage is nearly 50%. In the last 200 years, while the world population has increased six times, the urban population has multiplied 100 times [1]. Urban settlements and their connectivity will be the dominant driver of global change during the twenty-first century.

Understanding land use change in urban areas is a key aspect of planning for sustainable development. It also helps in designing plans to counter the negative effects of such changes. According to Clarke et al., [2], simulation of future spatial urban patterns can provide insight into how our cities can develop under varying social, economic, and environmental conditions. Since the late 1980s, applications of computers in urban planning have changed dramatically and concepts such as cellular automata have been included in the computer programs. Cellular automata (CA) are discrete dynamic systems whose behavior is completely specified in terms of a local relation. They are composed of four elements: cells, states, neighborhood and transition rules. Cells are objects in any dimensional space that manifest some adjacency or proximity to one another. Each cell can take on only one state at any one time from a set of states that define the attributes of the system. The state of any cell depends on the states of other cells in the neighborhood of that cell, the neighborhood being the immediately adjacent set of cells that are 'next' to the cell in question. Finally, there are transition rules that drive changes of state in each cell as some function of what exists or is happening in the neighborhood of the cell [3].

According to Dietzel and Clarke [4], of all the CA models available, SLEUTH may be the most appropriate because it is a hybrid of the two schools in CA modeling—it has the ability to model urban growth and incorporate detailed land use data. The name SLEUTH has been derived from the simple image input requirements of the model: Slope, Land cover, Exclusion, Urbanization, Transportation, and Hillshade. Reasons attributed to choosing this model are: (1) the shareware availability means that any researcher could perform a similar application or experiment at no cost given they have the data; (2) the model is portable so that it can be applied to any geographic system at any extent or spatial resolution; (3) the presence of a well-established internet discussion board to support any problems and provide insight into the model's application; (4) a well documented history in geographic modeling literature that documents both theory and application of the model; and (5) the ability of the model to project urban growth based on historical trends with urban/non-urban data.

The SLEUTH incorporates two models: The urban growth model (UGM) and the land cover deltatron model (DLM). In order to run the model, one usually prepares the data required, verifies the model functions, calibrates the model, predicts the change and builds the products. The user can implement SLEUTH modeling in different modes. In running the model, five coefficients including diffusion, breed, spread, slope-resistance and road gravity are calculated that are governed by estimation of four growth rules consisting of spontaneous growth, new spreading centre growth, edge growth and road-influenced growth. These are achieved in growth cycles each equal to one year or other appropriate time unit. The coefficients thus acquired are then refined in a self-modification mode. The results are then passed through coarse, fine and final modes during which the growth coefficients are refined and final growth rules are set and a growth rate is calculated. Figure 1 below depicts a growth cycle in the SLEUTH.

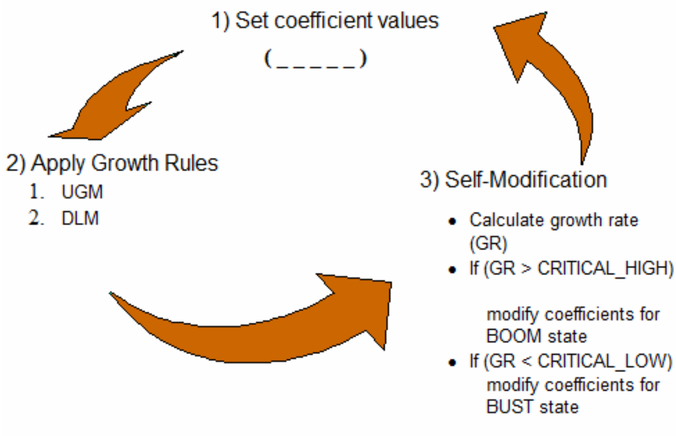

Fig. 1. A growth cycle in the SLEUTH

When the best growth rate is achieved and the growth coefficients are calculated, these parameters are then applied to the data layers in the model and those pixels most likely to become urban in the next time periods are determined. This is also applied to other land use/cover types through the land cover deltatron model and in the end model balances change in urban areas and other land use/cover types.

Predicting urban growth can help environmental managers in taking timely measures to counteract or offset possible negative effects. It also helps in locating the affected areas and dynamically planning land use based on the capability and availability of the land under investigation. Besides, it is possible to graphically explore the results of different growth and land use planning scenarios. One of the pressing land use items nowadays is landfill which itself is directly related to the built-up areas and their expansion over time.

Landfill is an essential part of any waste management system which is composed of waste minimisation, reuse of products, recovery of materials and energy from the waste and placing the remaining material in landfills [5]. Even if a combination of the above or other management techniques is utilized and policies of waste reduction and reuse are applied, the existence of a sanitary landfill is necessary to a municipal solid waste management system [6]. In spite of the fact that landfill has been taken to the bottom of the hierarchy of options for waste disposal it has been the most used method for urban solid waste disposal. Landfill has become more difficult to implement because of its increasing cost, community opposition to landfill siting, and more restrictive regulations regarding the siting and operation of landfills. Land is a finite and scarce resource that needs to be used wisely. According to Lane and McDonald [7] a successful landfill site allocation process involves evaluating the basic suitability of all available land for sanitary landfills as an aid in the selection of a limited number of sites for more detailed evaluation. Appropriate allocation of landfills involves the selection of areas that are suitable for waste disposal. With regards to waste management, site selection studies reported in the literature cover the allocation of urban solid waste landfills ([8], [9], [10],[11], [12], [13]), hazardous solid waste centers ([14],[15]), and recycling operation facilities ([16]).

In the present study, we first detected the change in the extent of the Gorgan city using classification of the Landsat TM and ETM+ data. We then modeled the change in the city extent using two different scenarios through the application of the SLEUTH method. SLEUTH with its self-modification rule extracting approach to land use/cover change is deemed an intelligent method of exploring possible future scenarios. Then, we applied the weighted linear combination technique as a multi-criteria evaluation (MCE) method to define areas suitable for landfill. Linking the results of the SLEUTH modeling and the MCE showed the areas available to landfill under scenarios of urban sprawl and waste production and management. We also determined the suitability of land available under each scenario. Our literature review showed no other studies for Iran that contained any attempt to link the results of the two methods for dynamic site selection of the landfill areas.

2 Materials and Methods

Gorgan is the capital city of the Golestan Province in the north east of Iran. The economic growth in the area in the recent past has led to a large increase in population, causing dramatic urban expansion and land use change. We used the SLEUTH modeling method to simulate and project the change in the area of the city. SLEUTH requires an input of five types of digital raster files (six if land use is being analyzed). For all layers, zero is a nonexistent or null value, while values greater than zero and less than 255 represent a live cell. We used a digital elevation (DEM) layer of the area with a 20 meter resolution to derive slope layer. Landsat TM and ETM+ scenes of the Gorgan City covering around 1316 Km^2 were selected for this study. The scenes which dated July 1987, September1988, July 2000 and 2001 were imported into Idrisi 32 software [17], co-registered with other layers and re-sampled to 20 meters resolution. Then, the scenes were classified using knowledge from the area and Maximum Likelihood classifier in supervised classification method with purified training samples [18]. We identified seven classes: water, agriculture, fallow lands, built-up areas, dense broad-leaved forest, thin forest, pastures and needle-leaved woodlands. Total accuracy was 96% and the user's and producer's accuracy for urban class was 98.84% and 99.33% respectively. The urban extent was derived through reclassification of these detailed land cover classifications into a binary urban/non-urban map (Fig. 2).

For deriving the excluded layers and transportation, we used visual image interpretation and on-screen digitizing to generate individual vector layers that were transformed into raster layers with 20 meters resolution. We ensured that all data layers followed the naming protocol for SLEUTH, were in grayscale GIF format and had the same projection, map extent, and resolution. The hillshade map was also generated using the same DEM layer.

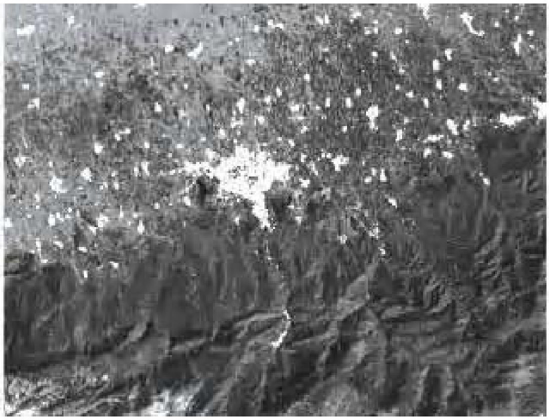

Fig. 2. Grey scale color composite image of the study area, bands 2, 3, and 4 of ETM+ sensor of Landsat satellite, 30th July 2001, with lighter spots showing residential areas

Model calibration was conducted in three phases: coarse, fine and final calibration. The algorithm for narrowing the many runs for calibration is an area of continuous discussion among users, and so far no definitive “right” way has been agreed upon. At the end of each calibration step, several fit metrics are produced which can be used as indicators of modeling success. Examples of the general approaches is use include: sorting on all metrics equally, weighting some metrics more heavily than others, and sorting only on one metric. More recently, the OSM (optimized SLEUTH metric) as the product of 7 metrics including “Compare”, “Population”, “Edge”, “Clusters”, “Slope”, “Xmean”, and “Ymean” [19] has been introduced. In this investigation, the last method, namely sorting on one metric, was applied. Simulations were scored on their performance for the spatial match, using Lee-Sallee metric which was around 0.4 showing the success of the modeling.

Adopting the procedure used by Leao et al., ([12], [13]) and Mahiny [20], we devised two different urban growth scenarios for model prediction. One scenario described the city as growing following historical trends, according to the parameters calibrated based on historical data. The second scenario described a more compact growth as a response to hypothetical policies and the shortage of land to harness urban spreading. Inspection of developing areas in Gorgan showed that at the moment both historical and compact scenarios of urban growth are underway. To apply these, we manipulated the value of some of the calibrated growth parameters. In the historical growth scenario, when the final calibration process was completed, the best selected parameters were run through the historical data many times and their finishing values were averaged considering the self-modification approach towards the included parameters. In the simulation for a compact city, the spread and road-gravity coefficients were reduced to half of the calibrated and the averaged best values were derived in the process.

The resulting forecast of future urban growth was produced as a probabilistic map. In the map, each grid cell will be urbanized at some future date, assuming the same unique ‘‘urban growth signature’’ is still in effect as it was in the past, while allowing some system feedbacks termed self-modification. For both the back-cast and projected urban layers, a probability over 70% (given 100 Monte Carlo simulations) was used to consider a grid cell as likely to become urbanized. This was derived through several trial and error attempts and comparison with real maps of the area. The final results of the model application were annual layers of urban extent for the historical time frame (1987–2001) and projected future urban growth (2002–2050).

Multi criteria evaluation (MCE) is most commonly achieved by one of three procedures [17]. The first involves Boolean overlay whereby all criteria are reduced to logical statements of suitability and then combined by means of one or more logical operators such as intersection and union. The second is known as weighted linear combination wherein continuous criteria (factors) are standardized to a common numeric range, and then combined by means of a weighted average. The third option for multi-criteria evaluation is known as the ordered weighted average (OWA) [21]. According to Hopkins [22] the most prevalent procedure for integrating multi- criteria evaluation and multi-objective evaluation (MOE) in GIS for land suitability analysis is using a weighted linear combination approach. The WLC procedure allows full tradeoff among all factors and offers much more flexibility than the Boolean approach.

We applied the weighted linear combination technique to locate areas suitable for landfill. We also employed the zonal land suitability to prioritize land based on the suitability of the pixels comprising zones of suitable land. This was the first application of the MCE for landfill in the area of study. As such, the MCE was faced with shortage of data layers explaining suitability for landfill site selection. Three different scenarios were considered for waste management and disposal. The Maximum Scenario meant that all the waste produced would go to landfill for disposal. In Optimum Scenario, 3% of the waste would be recycled, 11% would be composted and the rest would go to landfill. In the Minimum Scenario, waste production would decrease by 5%, the same amount would be recycled, 27% percent would be composted and the remaining amount would go to landfill. These scenarios were constructed by investigation of the trend in the population size, waste production habits and other social and technical factors involved in waste management currently seen in the area of study.

We used six factors including slope, water permeability, depth of the underground water table, distance from residential areas, distance from roads and wind orientation for the MCE. The factors were all standardized to a range of 0-255 using fuzzy membership functions. Then, weights were derived for the factors using the analytical hierarchy process (AHP) [23] and asking from a range of specialists [24]. We put all the factors on the same level and computed the relative weights through the pairwise comparison technique. Using the standardized factors, their weights and the constraints in the form of Boolean layers, we demonstrated areas suitable for landfill for the three scenarios. We then used the predicted urban sprawl for the Gorgan city as a constraint that limited our choice for the suitable landfill and as a factor affecting some of the other parameters that had been used in the MCE procedure. The result was a dynamic land allocation to landfill based on two scenarios of urban sprawl and three scenarios of waste production and management. In each case, the suitable land for waste disposal was determined and ranked relative to other available areas.

3 Results and Discussion

The three calibration steps and the predictive growth coefficients in the SLEUTH modeling were developed based on the rules that are depicted in the Table 1 below. Most of the statistics for best fit parameters of the simulation results of Gorgan through SLEUTH present high values of fit, indicating the ability of the model to reliably replicate past growth. This suggests that future growth predictions can also be used with confidence.

Table 1. Figures used for calibration and derivation of predictive coefficients in SLEUTH modeling

	Coarse Calibration		Fine Calibration		Final Calibration		Predictive Coefficients	
	Range	Increase	Range	Increase	Range	Increase	Range	Increase
Diffusion Coefficient	0-100	25	0-20	5	1- ,5	1	1-,1	1
Breed Coefficient	0-100	25	0-25	5	10-25	5	15-15	1
Spread Coefficient	0-100	25	25-50	5	22-27	1	22-22	1
Slope Coefficient	0-100	25	0-25	5	0-20	5	1 ,1	1
Road Coefficient	0-100	25	50-100	10	60-80	5	75-75	1
Monte Carlo Simulations	5		8		10		100	
Total Runs	3124		6479		2999		---	

For the simulation of Gorgan city expansion, the final averaged parameters that were used in the prediction phase are presented in Figure 3.

Each parameter in Figure 3 reflects a type of spatial growth. For Gorgan City, the diffusion coefficient is very low, which reflects a low likelihood of dispersive growth. The value for the breed coefficient shows that it is somehow possible to witness growth of new detached urban settlements. The spread coefficient being larger than breed demonstrates the growth outwards of existing and consolidated urban areas is more likely. 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. Slope resistance shows the slight influence of slope to urbanization. In Gorgan area, topography was shown to have a very small effect in controlling the urban development, where even the hilly areas are likely to urbanize (Fig. 3). Inspection of the newly developed areas in the Gorgan City proved this to be true.

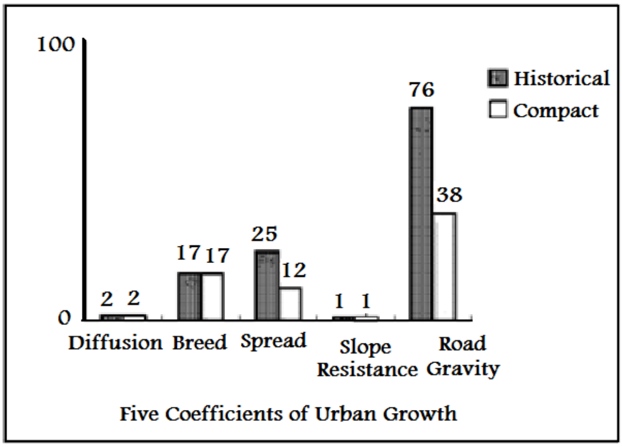

Fig. 3. Best fit parameters for modeling Gorgan city using SLEUTH

Figure 4 illustrates the future urban form and extent of Gorgan City area according to the model simulation using the historical scenario.

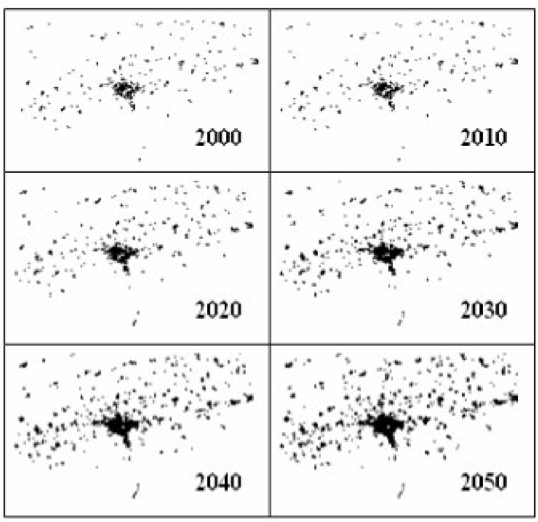

Fig. 4. Simulated Urban Growth in Historical Scenario

Looking at Figure 4, managers and decision makers can easily find the locations and the corresponding intensity of the areas where the city may increase. This information is of great importance, as it gives the managers an upper hand in controlling the unwanted expansion of the built-up areas from happening. It also helps land use planners in optimizing land allocation exercises given the dynamic nature of

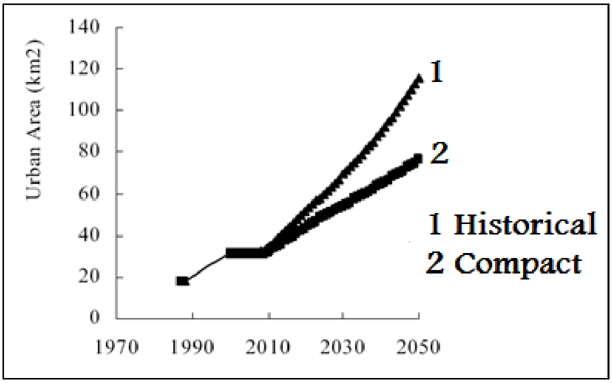

Fig. 5. Gorgan city expansion for the two scenarios

possible changes. Figure 5 shows the extent of urban development over time for the two growth scenarios.

Table 2. Zonal land suitability for 18 suitable land fill sites

Number of zones	Minimum suitability	Maximum suitability	Total suitability	Area (ha.)	Average (zonal) land suitability
1	142	162	90458	23.28	155.42
2	136	169	123346	31.96	154.37
3	127	165	105105	28.28	148.66
4	128	155	140077	38.49	144.26
5	92	169	361351	102.18	141.48
6	89	168	190362	54.65	139.35
7	114	161	255207	73.65	138.62
8	111	162	338971	101.02	134.24
9	116	154	75293	22.52	133.73
10	93	168	675239	207.68	130.07
11	95	161	396163	121.90	130.01
12	104	157	80403	24.80	129.68
13	87	145	80095	27.64	115.91
14	74	147	57110	20.24	112.86
15	65	155	271272	108.34	100.17
16	24	152	477351	204.40	93.43
17	42	129	79193	45.73	69.28
18	29	92	154535	96.38	64.14

Quite expectedly, the compact city scenario predicts a smaller increase for the future as compared to the historical scenario. However, the choices are open to the users to construct different scenarios and immediately assess their effects on the fate of the city. Modification of the driving parameters of city change, as defined in this study, can help in defining the best method for preventive measures in terms of feasibility and economy. Urban change control, cumulative effects assessment of land use/cover changes and land use planning and land allocation optimization are among other applications of the basic research conducted here.

The application of the MCE in the Gorgan city followed by zonal land suitability assessment indicated that initially there are 18 zones for landfill sites. The zonal land suitability of these sites varied from 155.42 to 64.14 (Table 2) and (Fig. 6). The analysis of the level of suitability of the zones selected and the allocation process shows the little available land suitable for landfill. This situation indicates that the areas to be used for landfill are going to become progressively less accessible. This has consequences on the costs of the waste disposal system, as well as on the risks for the environment and the community.

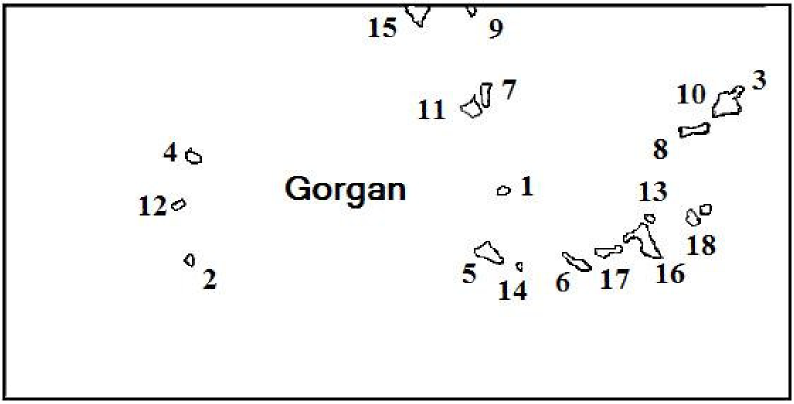

Fig. 6. Suitable zones for landfill and their rank in terms of zonal suitability

4 Conclusions

Planning and management are based on generic problem solving. They begin with problem definition and description, and then turn to various forms of analysis, which might include simulation and modeling, and finally move to prediction and thence to prescription or design, which often involves the evaluation of alternative solutions to the problem [25]. According to Rubenstein-Montano and Zandi [26], modeling tools form the majority of approaches developed to assist decision-makers with planning activities. The method described in this paper combines the power of SLEUTH urban expansion prediction with that of the MCE for landfill site selection. The evaluation abilities of MCE method and the analytical tools of GIS show the use of GIS as a decision support system (DSS). The first step of the process reveals possible areas of urban expansion under two different scenarios. The second step, assesses the availability of land for waste disposal by combining the relevant criteria (constraints and factors) for landfill plus the minimum area requirement constraint (20 ha) under three waste management scenarios. The relative importance weights of factors are estimated using the analytical hierarchy process (AHP). Initially, the land evaluation is performed on a cell by cell basis. The suitability of each cell for landfill is calculated by means of weighted linear combination (WLC) of multiple criteria in raster GIS.

The WLC approach results in a continuous suitability map that requires the user to decide what locations should be chosen from the set of all locations, each of which has some degree of suitability. This was addressed by adding the post-aggregation constraint that suitable sites must be at least 20 hectares in size. The model then calculated the suitability for landfill for each zone. This zonal suitability is obtained by calculating the average of the suitability of all cells belonging to each zone. In the final step, zones were ranked in descending order by the value of their zonal land suitability. Maps of suitable zones under each scenario were produced that provided the decision makers with several options for waste management. From among the zones, managers of the city can choose the best in terms of availability, price and social considerations and so forth such that a sustainable environmental management is achieved.

Results can be useful for policy and decision makers in Gorgan city. It must be noted that the presented method is only a tool to aid decision makers; it is not the decision itself. We successfully modeled the change in the extent of the Gorgan City using the SLEUTH method for the first time in Iran. The process was shown to be feasible, considering the time, facilities and the background knowledge it requires. The results, although not tested thoroughly, were found very useful in terms of providing insight into the process of city change for the managers and decision makers. Using this information, the authorities can take preventive measures for controlling negative effects of the predicted change. They can also use the information for preparing the infrastructure required for waste management in near future and mitigate the unwanted changes through possible means. One such measure can be control of the development of transportation network, as this was shown to have high effect on causing urban sprawl in the area. Also, focusing on consolidated urban areas and minimizing their expansion can be regarded as a measure towards harnessing the unwanted urban growth in Gorgan. This is also the case with the development of new detached urban areas, as shown by the breed coefficient. Using a combination of the past, present and future city sizes and their impact on the surrounding land use and land cover which ultimately affect land suitability, information can be also compiled for a proper, dynamic and timely land allocation for landfill sites in the area.

Acknowledgements. Authors are grateful to authorities of the Gorgan University for supporting development and presentation of this paper at GEOG-AN-MOD 2011.

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