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Modeling Urban Growth Effects on Landscape Structure in Gorgan City Area

Hamid Reza Kamyab[1] and Abdolrassoul Salman Mahiny[2]*

[1] *Former MSc. Student, Faculty of Natural Resources, Tarbiat Modares University, Noor, Iran*
[2] *Associate Professor, Faculty of Fisheries and Environment, Gorgan University of Agricultural Sciences and Natural Resources, Gorgan, Iran*

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ABSTRACT Logistic regression (LR) was used to model urban growth between the years 1987 and 2001 in Gorgan city, north east of Iran. Three groups of variables including economic-social, land use and biophysical variables were used in the modeling practice. Using covariance of the independent variables, distance to administrative and sporting centers plus distance to cities were removed. ROC (Relative Operating Characteristic) value for LR was 0.87 that confirmed success of the modeling method. Using maps of urban growth probability predicted by the LR model, urban distribution patterns for the years 2010, 2020, 2030, 2040 and 2050 were created. Land use maps for the years 2001-2050 were created using urban probability pattern maps and the base land use map of the year 1987. We used landscape metrics at class and landscape levels to compare the urban growth effects on other land use types present in the area. The comparison showed that urban development influences agriculture and pasture land use types more than other land uses. Also, we found that the landscape in the study area has undergone fragmentation and will become more fragmented and heterogeneous over time. Urban growth creates higher urban patchiness and increases the number of pasture and agricultural patches. The information thus obtained is helpful in more effective management of the area.

Key words: *Fragmentation, Gorgan, Landscape Metrics, Logistic Regression, Urban Growth*

1 INTRODUCTION

Development of cities is normally associated with an increase in the environmental pollutions and deterioration that affects land use and land cover of the area under urban growth. Land cover change is regarded as the single most important variable of global change affecting ecological systems (Vitousek, 1994).

Changes in land use results from the complex interaction of many factors including policy, management, economics, culture, human behavior, and the environment in which these changes occur (Medley *et al*., 1995; Vesterby and Heimlich, 1991). Models are one of the tools that are used by decision-makers for studying the behavior and controlling land use changes and their trends. Models are also important tools for exploring the interactions between land use dynamics and the driving factors of change (Braimoh and Onishi, 2007b).

Theobald and Hobbs (1998) described two basic types of spatially explicit land use change

* *Corresponding author: Associate Professor, Faculty of Fisheries and Environment, Gorgan University, Gorgan, Iran, Tel: +98 911 921 2681, +98 171 224 5884, E-mail: a_mahini@yahoo.com*

models: regression-type models and spatial transition-based models. As an empirical estimation method, logistic regression has been used in deforestation analysis (Brown *et al*., 2001; Geoghegan *et al*., 2001), agriculture (Serneels and Lambin, 2001) and urban growth modeling (Allen and Lu, 2003; Wu and Yeh, 1997).

With the accelerating pace of urbanization in the 20th and early 21nd century, urban development that resulted from urbanization has had an increasingly powerful impact on various urban environments. Human-induced land use/cover change has produced profound impacts on landscape. As a result, the urban landscape is becoming a focus of ecological research (Andre and Jack, 2002). Landscape ecology uses pattern indices to quantitatively study landscapes in terms of structure, processes and functions (Wu, 2000; Pauleit, 2000).

Landscape structure refers to the spatial relationship among the distribution of energy, materials, and species in relation to size, shape, number, type and configuration of the landscape elements; this structure is critical to landscape/ecosystem function and habitat quality (Turner, 1989; Li *et al*., 2001). Investigating landscape structure and its change is a prerequisite to the study of ecosystem functions and processes, sustainable resource management, and effective land use planning. Numerous landscape indices have been developed to quantify landscape structure and spatial heterogeneity based on landscape composition and configuration (McGarigal and Marks, 1995; Riitters *et al*., 1995). Obtaining accurate time-series of land use/cover maps is a key to characterizing a landscape and its dynamics in structure and function. Landscape structure and composition evolves continuously in space and time. These evolutions are attributable to the complex interaction between natural environment, various organisms and human activities, resulting in the change of the stability of individual elements in the landscape system and the spatial structure of the landscape (Xiao *et al*., 1990; Li, 1997).

Landscape pattern is a focal point of landscape ecology as it plays an important role in driving ecological processes (Forman and Godron, 1986; Turner *et al*., 1989). As a consequence, landscape pattern has been increasingly measured by employing landscape metrics (Turner *et al*., 2001). Drawing on the aforesaid studies, we formulated our study in the Gorgan city area. Our objectives for the present study were:

1- Urban growth prediction using logistic regression and knowledge-based approach. 2- Investigating landscape pattern changes created by urban growth (previous and future likely changes).

The study area has witnessed a major change during past few decades which has brought about changes in landscape structure. Hence, results of this study will be of high importance to manage and direct changes in the area in a more sustainable fashion.

2 MATERIALS AND METHODS

2.1 Study area and the data used

Gorgan is located in the north eastern part of Iran close to the Caspian Sea (Figure 1).

The city is the capital of the Golestan Province which is limited to 54° 10'-54° 45' E and 36° 44'- 36° 58' N, with a surface area of around 1316 KM^2. We used Idrisi Kilimanjaro software (Eastman, 2003) for generation and collation of data layers required for the LR analysis. As an empirical estimation method, LR makes it possible to use various variables. Three groups of variables including economic-social and biophysical plus land use were used which are listed in Table 1.

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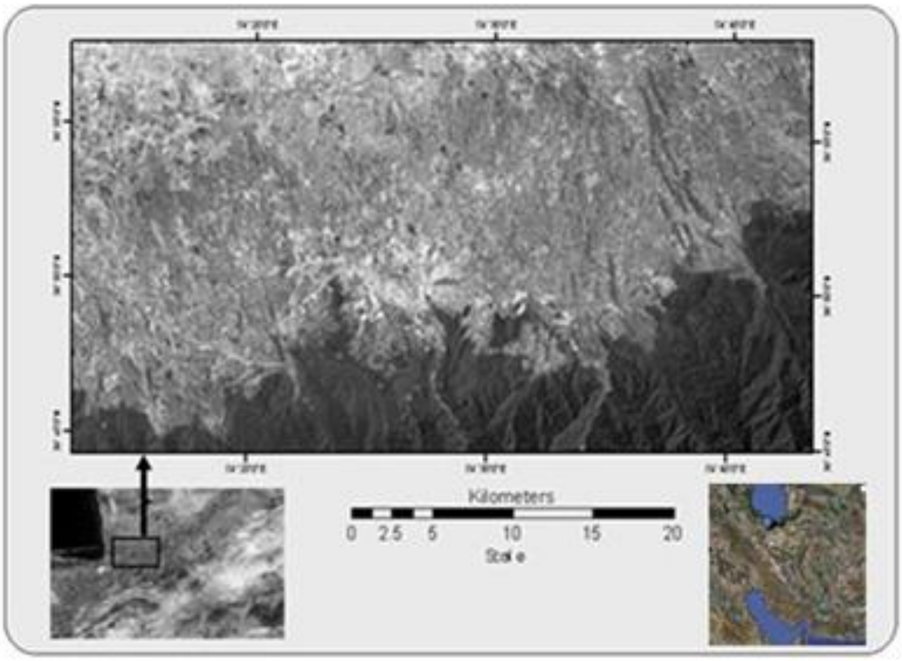

Figure 1 Image of the study area using TM sensor of the Landsat dated 19 July 1987.

Table 1 Variables included in the LR model.

Variable	Meaning	Nature of variable
Dependent	0 – no urban growth	Dichotomous
	1 – urban growth	
	Slope	Continuous
	Distance to major roads	Continuous
Independent	Distance to urban clusters in1987	Continuous
	Distance to economic centers	Continuous
	Distance to administrative centers	Continuous
	Distance to sport-pastime centers	Continuous
	Distance to medical centers	Continuous
	Distance to education centers	Continuous
	Number of urban cells within a 3×3window	Continuous
	1 – Bare land; 0 – non bare	Design
	1 – Cropland/grassland; 0 – non cropland/grassland	Design
	1 – Forest; 0 – non forest	Design
	1- Cultivated land; 0- non-cultivated	Design
Exclusion	1- able to growth; 0- non-able to growth	Design

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Similar to the manner applied in SLEUTH urban growth modeling (Clarke, 1997), we generated data layers that affect the city sprawl process and are used in SLEUTH. SLEUTH uses slope, land use, excluded areas to growth, urban areas, transportation layer and hillshading to model urban growth, hence the name. To provide excluded layer, past urban areas, road network and land use for the study area, we used Landsat TM and ETM+ images. The images dated 16 July 1987 and 30 July 2001. We applied a supervised classification approach for discerning different land use and land cover types in the area. The change in the urban area was detected using a post-classification comparison. We also identified changes in the forested areas, agricultural lands, bare lands and pastures and then converted these layers into a Boolean map containing 1 and 0 (Hu and Lo, 2007). Using the information-based approach, we also prepared surrogate layers of economic-social variables as independent layers. Biophysical variables were provided based on inputs of SLEUTH modeling method. These were slope; land use, transportation network and hillshade maps. The slope layer was derived from a digital elevation map interpolated from 1:25000 contour map of the area.

Correlation among independent variables is probable. If linear relationship between variables is observed, thus multi-collinearity exists. Principal Component Analysis with the compute covariance between variables option was used in Idrisi to survey the likely relationships. Covariance of two variables was shown to be higher than 0.9.

After assembly of the data layers acting as the independent variables, the data were fed into the logistic regression in Idrisi software. To assess the results, the predicted urban change layer was compared to that of the real one in 2001. Apart from the location of the changes that are predicted by the models and assessed by the ROC statistic, we also compared the maps in terms of the pattern of changes as well. This was achieved through class and landscape metrics. This also helped quantify changes in terms of landscape structure and assess their trends over time.

2.2 Logistic Regression

Logistic regression is a special case of multiple regression in which the dependent variable is discrete (Hosmer and Lemeshow, 1989), such as land cover types. Difference between multiple linear and logistic regression is that logistic regression is applicable when the dependent variable is discrete and its relationship with the independent variables follows a logistic curve. If dependent variable is dichotomous, Y takes on only two values: 1 and 0, where Y=1 represents the event presence and Y=0 represents its absence (Hosmer and Lemeshow, 1989). The logistic regression equation can be expressed as follows:

$$\mathrm{logit}(p)=\ln(p/(1-p))=a+\{b_1\times X_1\}+\{b_2\times X_2\}+\{b_3\times X_3\}+\ldots\{b_n\times X_n\} \quad (1)$$

where p is the dependent variable expressing the probability that Y=1, X_1, X_2, and X_3 are the independent variables; a is the intercept; and b_1, b_2, and b_3 are the coefficients of the independent variables X_1, X_2, and X_3, respectively (Cabrera, 1994).

The nature of the land use/cover change of a cell is dichotomous that presents land use change and land use non-change.

If binary values 1 and 0 are used to represent urban growth and no urban growth respectively, then the probability of a cell being urbanized can be estimated with the following logistic regression model:

$$P(Y=1/X_1,X_2,..,X_K)=\frac{1}{1+e^{-(\alpha+\sum_{i=1}^{k}\beta_i X_i)}} \quad (2)$$

2.3 Landscape pattern metrics:

To compare the maps in terms of pattern of changes and to investigate urban growth effects on other land use types, we subtracted urban growth between the years 2001-2050 from that of the base land use in 1987 and created land use maps for 2001, 2010, 2020, 2030, 2040 2050. For the year 2001, the process was done so to place it on a standard similar to other years. In doing so, we used the calculated areal coverage of urban growth and ignored conversions between land uses, because other changes were not of relevance to our study aim. The real land use image of the year 1987 and the created land use maps of the years 2001, 2010, 2020, 2030, 2040, 2050 (created through subtracting urban growth from base land use map) were fed into the software Fragstats. The program has been developed by McGarigal and Marks (1995) at the Forest Science Department, Oregon State University, U.S.A., and has been widely used for quantifying landscape structure. We measured landscape metrics of the images for comparison.

Forman and Godron (1986) defined landscape as a heterogeneous land area composed of a cluster of interacting ecosystems that is repeated in similar form throughout. Land uses spots were defined as patches in the current analysis and subjected to patch metric calculation in the Fragstats. Fragstats produces a number of metrics, some of the most common ones are: area, patch density, size and variability, edge, shape, core area, diversity, nearest-neighbor, contagion and interspersion.

In this study, we selected 6 metrics for the class level and 12 metrics for the landscape level analyses out of a large array of available metrics. The selection was based on a review of the previous studies (Liu *et al*., 2003; Matsushita *et al*., 2006; Leitao and Ahern, 2002; Griffith *et al*., 2000), ease of calculation and interpretation. Definitions for the selected metrics are listed in Table 2.

Table 2 Metrics used in this study and their definitions*.

Metrics (unit)	Description
Number of Patches	Number of patches. NP equals the number of patches in the land cover type or landscape under investigation.
Class Area (ha)	Class areas. CA equals the sum of the areas of all patches of the corresponding patch type.
Area-mean (ha)	Mean patch area. AREA-MN equals the sum of the areas of all patches of the corresponding patch type (or all patches in the landscape), divided by the number of patches of the same type (or total number of patches).
Landscape Shape Index	LSI equals the total length of edge (or perimeter) involving the corresponding class, given in number of cell surfaces, divided by the minimum length of class edge (or perimeter) possible for a maximally aggregated class.
Proximity Index-mean	PROX equals the sum of patch area (m^2) divided by the nearest edge-to-edge distance squared (m^2) between the patch and the focal patch of all patches of the corresponding patch type whose edges are within a specified distance (m) of the focal patch.
ENN-MEAN (m)	Mean Euclidean nearest-neighbor distance. ENN-MN equals the sum of the distance to the nearest-neighboring patch of the same type, based on shortest edge-to-edge distance, for each patch of the corresponding patch type, divided by the number of patches of the same type
Total Core Area (ha)	TCA equals the sum of the core areas of each patch (m2), divided by 10,000 (to convert to hectares).
FRAC-AM	Area-weighted mean fractal dimension index. FRAC-AM equals the average patch fractal dimension of patches of the corresponding patch type, weighted by patch area so that larger patches weigh more than smaller patches.

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Table 2 (Continue)

CORE-MEAN	CORE-MN equals sum of the area (m^2) all patches in the landscape, of the corresponding patch metric values within the patch that is further than the specified depth-of-edge distance from the patch perimeter, divided by 10,000 (to convert to hectares) divided by the total number of patches.
IJI (%)	Interspersion and juxtaposition index. IJI equals minus the sum of the length of each unique edge type divided by the total landscape edge, multiplied by the logarithm of the same quantity, summed over each unique edge type; divided by the logarithm of the number of patch types times the number of patch types minus 1divided by 2
CONTAG (%)	Contagion index. CONTAG equals 1 plus the sum of proportional abundance of each patch type multiplied by number of adjacencies between cells of that patch type and all other patch types, multiplied by the logarithm of the same quantity, summed over each patch type; divided by 2 times the logarithm of the number of patch types
SHEI	Shannon's evenness index. SHEI equals minus the sum, across all patch types, of the proportional abundance of each patch type multiplied by that proportion, divided by the logarithm of the number of patch types.
SHDI	Shannon's diversity index. SHDI equals minus the sum, across all patch types, of the proportional abundance of each patch type multiplied by the proportion.
Proportion of Like Adjacencies (%)	PLADJ equals the number of like adjacencies involving the focal class, divided by the total number of cell adjacencies involving the focal class; multiplied by 100 (to convert to a percentage).

*For detailed description and calculation, refer to McGarigal and Marks (1995).

3 RESULTS

3.1 Multicollinearity

In the module Principal Component Analysis in Idrisi, there's the capability of computing covariance between variables. Hence, we used this module and the correlation between variables was surveyed. The result of this analysis (Figure 2) show that significant correlation exists between four variables.

Based on the information content of the layers, degree of correlation and the easiness of preparation, distance to economic centers was selected and other three variables were removed from the analyses.

3.2 Logistic regression

The relative operating characteristics (ROC) curve (Peterson and Birdsall, 1953; Green and Swets, 1966; Mason and Graham, 1999) is a useful method of representing the quality of deterministic and probabilistic detection of forecast systems. ROC predicts the occurrence of an event by comparing a probability image depicting the probability of that event occurring and a binary image showing where that class actually exists (Lin *et al*., 2008; Hu and Lo, 2007). When there is a perfect match between reality map and the modeled one, the ROC takes a value of 1. In case where there is no spatial agreement between the maps, ROC value becomes 0.5. ROC value for our LR model was 0.87; hence the success of modeling with LR was confirmed. Since one of outputs of urban growth model is an image map of urban predicted future growth probability, we used this image (Figure 3) to create new urbanized locations and to generate land use maps based on the future urban growth.

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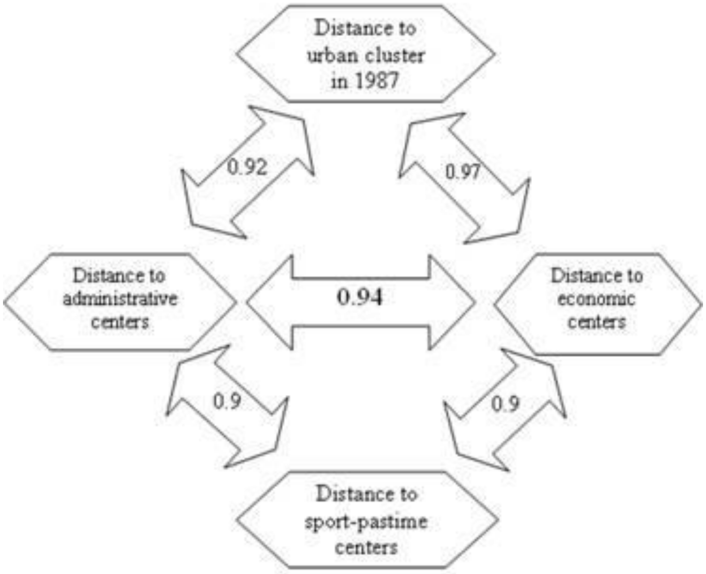

Figure 2 Correlation between variables.

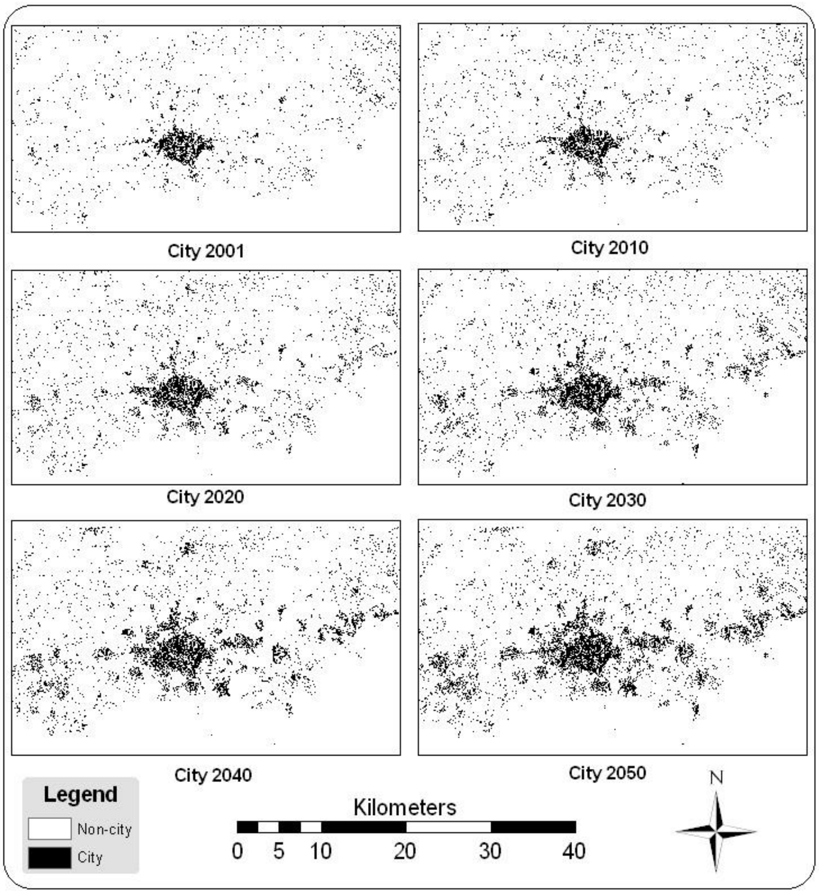

Figure 3 Maps of predicted urban by LR.

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3.3 Analysis of change in landscape structure

The real land use map of the year 1987 and land use maps of the years 2001, 2010, 2020, 2030, 2040 and 2050 that were created through subtracting urban growth from the base land use map were surveyed for landscape metrics including number, shape and size of land use patches, proximity and nearest neighbor distance and spatial pattern of all patches in the landscape. The results were compared for previous and future urban growth effects on other land use types. Note that conversion between various land uses between the years 1987-2010 was ignored.

3.3.1 Changes of landscape metrics at class level

Our results showed that the landscape in the study area has become more fragmented and heterogeneous over the years we studied and modeled here (Table 3). Urban growth caused more urban patchiness and increased number of pasture and agricultural patches. We found that the number of urban, agriculture and pasture patches is likely to decrease between the years 2030-2040. Number of forested patches was stationary in the years 1987-2050. Forest class area was almost stable and this is one of the causes of forest patches stability. Number of bare land patches showed an oscillating pattern, such that they increased during 1987-2001, and then showed decrease between the years 2001-2050. In fact, small patches of bare land are predicted to convert to urban patches after the year 2010.

Comparison of various land uses in terms of proximity and Euclidean nearest neighbor during the years 1987-2050 shows increasing trend of similarity and proximity in urban patches. However, a decrease was detected for proximity and similarity in pasture and agricultural areas. Also, in terms of area, urban patches show an ascending trend after the year 2001 while that of the pasture and agricultural land is descending. There is an irregular trend between the years 2030-2040. Mean-area of the forested land was calculated as stable after the year 2001. Bare land area decreased between the years 1987-2001 and then showed possible increase after 2001 up to 2050. Likely cause of this increase is the conversion of small bare land patches to urbanized areas after the year 2001.

Meanwhile, shape of the urban, pasture, bare and agriculture classes shows a general increase between the years 1987-2050. LSI increases without limit in these classes as the patch type becomes more disaggregated. This means that the landscape has and will continue to become more heterogeneous. Shape index of forested areas is almost stable like other metrics of this class.

3.3.2 Changes of landscape metrics at the landscape level

The total number of patches was large in the study area and it continues to increase according to our prediction, with the exception of the period 2030-2040 (Figure 4).

Additionally, we find that both Shannon's diversity and Shannon's evenness indices will increase in the years 1987-2050, suggesting the landscapes in the study area has and will become more fragmented and heterogeneous. Also, decrease in like adjacencies supports this result.

The mean Euclidean nearest-neighbor distance shows a decrease. However, as the number of the patches has significantly increased, this does not necessarily mean increasing trend in the area of these patches. Decrease of the mean Euclidean nearest-neighbor distance is, in fact, attributed to the fragmentation of previously larger patches. Meanwhile, the interspersion and juxtaposition indices become larger and the contagion index

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become smaller during the years 1987-2050, indicating that spatially different patches become more separated and the patch types become more disaggregated.

However, size of the patches in the study area gets smaller during the years 1987-2050 (Area-Mean, Core-Mean and TCA in Figure 4). Shape of the patches changes and approaches 1 (fractal dimension index), suggesting shapes with very simple perimeters such as squares will be likely to dominate the landscape in future.

Table 3 Class level landscape metrics in Gorgan city area.

Metrics	Land use	1987	2001	2010	2020	2030	2040	2050
NP	City	6017	12056	15023	17524	19401	17451	22082
	Forest	2123	2123	2123	2123	2123	2123	2123
	Pasture	9962	10571	10651	10722	10810	10773	11124
	Agriculture	22958	24259	25291	26550	26803	24657	26994
	Bare	6522	6618	6587	6577	6572	6568	6562
CA(ha)	City	2153.88	4055.13	5130.54	6404.67	7717.05	9033.12	10352.79
	Forest	32776.2	32765.67	32765.67	32765.67	32765.67	32765.67	32765.67
	Pasture	38630.34	37930.5	37801.53	37700.28	37614.51	37523.61	37332.27
	Agriculture	38303.55	37259.64	36379.08	35228.79	34019.46	32810.85	31696.74
	Bare	12974.49	12862.44	12841.47	12829.14	12822.3	12814.74	12809.43
LSI	City	75.8548	107.9765	122.6506	134.5655	141.6195	135.0032	151.4551
	Forest	18.3521	18.3405	18.3405	18.3405	18.3405	18.3405	18.3405
	Pasture	125.849	130.3865	130.3539	130.3977	130.6566	130.3034	131.2739
	Agriculture	171.3724	176.1639	176.3892	176.8738	176.2634	169.0902	174.4002
	Bare	72.7579	73.4888	73.3452	73.1971	73.2358	73.1656	73.1219
Area-Mn(ha)	City	0.358	0.3364	0.3415	0.3655	0.3978	0.5176	0.4688
	Forest	15.4386	15.4337	15.4337	15.4337	15.4337	15.4337	15.4337
	Pasture	3.8778	3.5882	3.5491	3.5162	3.4796	3.4831	3.356
	Agriculture	1.6684	1.5359	1.4384	1.3269	1.2692	1.3307	1.1742
	Bare	1.9893	1.9436	1.9495	1.9506	1.951	1.9511	1.9521
Prox-Mn	City	32.229	49.7809	107.356	117.9776	135.6553	162.0069	160.5822
	Forest	6243.2935	6242.4836	6242.4836	6242.4836	6242.4836	6242.4836	6242.4836
	Pasture	5015.367	4809.5919	4773.8982	4737.7126	4688.0218	4666.8165	4197.0845
	Agriculture	1400.4742	705.8623	447.5671	397.8393	347.2164	328.3074	261.1014
	Bare	337.4908	347.7449	341.8235	342.3516	340.9704	338.2277	335.7377
ENN-Mn(m)	City	112.4623	92.364	81.5867	75.5812	72.5758	74.107	68.2169
	Forest	113.5012	113.3998	113.3998	113.3998	113.3998	113.3998	113.3998
	Pasture	63.9192	62.914	62.8714	62.8647	62.7638	62.8992	62.5144
	Agriculture	51.7678	51.885	52.1847	52.5448	53.0724	54.4432	54.0532
	Bare	84.0909	83.5583	83.6366	83.7921	83.8129	83.6985	83.7883

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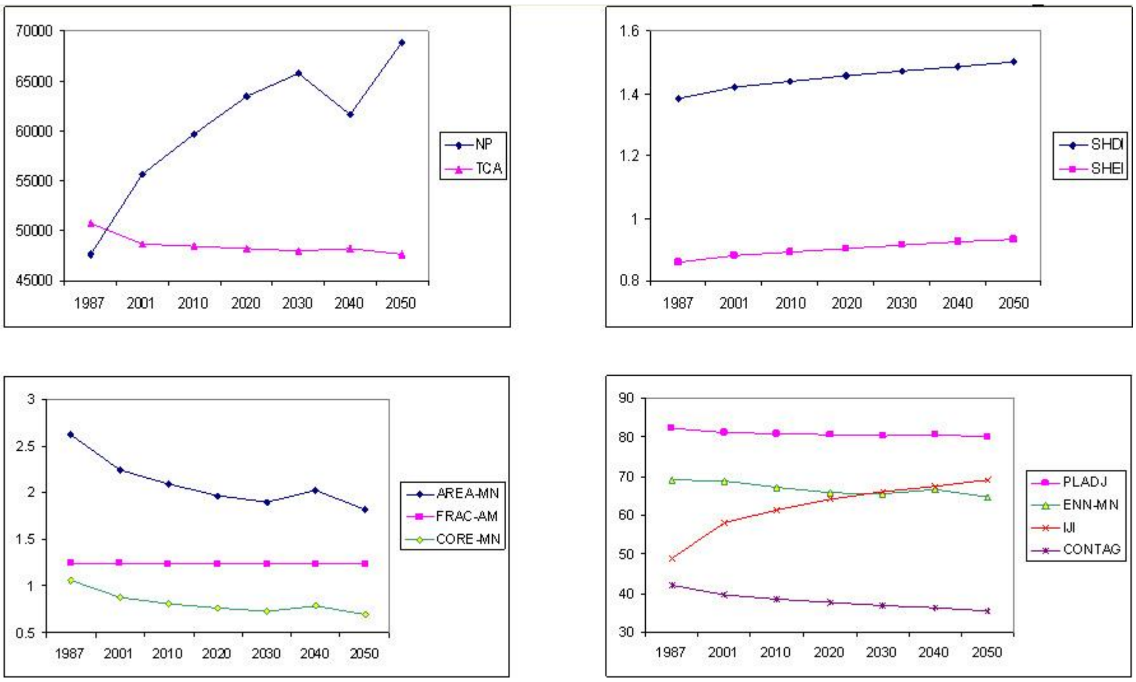

Figure 4 Comparison of landscape metrics among 1987-2050 in the Gorgan city at class level.

4 DISCUSSION AND CONCLUSIONS

Logistic regression modeling was used to identify and improve our understanding of the demographic, surrogate economic and biophysical forces that have driven the urban growth in Gorgan city area and to find the most probable sites undergoing change. One of the most important uses of the models is their capability of predicting future based on the past. We removed the highly correlated variables from our LR analysis and in doing so, distance to administrative, urban clusters and recreational centers were removed in favor of ten other independent variables.

To survey urban growth in terms of spatial patterns of new urban locations, landscape patterns and urban growth effects on other land use types were measured using Fragstats software. Real land use map of the year 1987 and other synthetic land use maps of the years 2001, 2010, 2020, 2030, 2040 and 2050 that were created through subtraction of urban growth from the base land use of the year 1987 were fed into Fragstats software. In this research, effects of urban growth on other land use types were surveyed and conversion among other land use types was ignored.

We found that the landscape in Gorgan city area has experienced rapid changes and will continue to do so between the years 1987-2050. The change in landscape structure creates a heterogeneous environment due to fragmentation. Pasture and agricultural land have similar changes to that of the urban areas. Urban growth in Gorgan has a similar trend between the years 1987-2030 and after 2040. During the years 2030-2040, urban growth pattern is likely to change and this change is traceable in other land use types. We found negligible change in landscape metrics of the forested areas.

The class area of the studied land use types has decreased in the past and is likely to decrease in future with the exception of urban areas. The decreased mean patch area is associated with decreased class area and increased patch number. These results suggest that the landscape in Gorgan city area will become more fragmented in future while the likely location of the changes has also been highlighted. However, it is not clear how the ecosystem functions have changed in response to changes in the landscape structure in our study area. We postulate that with the continuation of the current trend of landscape fragmentation in the Gorgan city area, ecosystem functions such as surface water runoff and habitats of some wildlife species, especially pasture and agriculture species, will be highly degraded.

In this study, we focused on the effect of urbanization of landscape structure and overlooked the dynamic interplay between other land use types. To achieve a more plausible and comprehensive result and to provide practical solution, it is necessary to look into these aspects in future studies. Environmental modeler of Idrisi Taiga (Eastman, 2009) is a good point to start with this concept.

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مدل‌سازی اثرات رشد شهری بر ساختار سیمای سرزمین در شهر گرگان

حمیدرضا کامیاب[۱] و عبدالرسول سلمان ماهینی[۲*]

۱- دانش آموخته کارشناسی ارشد، دانشکده منابع طبیعی، دانشگاه تربیت مدرس، نور، ایران

۲- دانشیار، دانشکده شیلات و محیط زیست، دانشگاه علوم کشاورزی و منابع طبیعی گرگان، گرگان، ایران

چکیده برای مدل‌سازی رشد شهری در شهر گرگان واقع در بخش شمال شرق ایران طی سال‌های ۲۰۰۱-۱۹۸۷ از روش رگرسیون لجستیک استفاده گردید. سه گروه از متغیرها شامل متغیرهای اقتصادی-اجتماعی، کاربری زمین و متغیرهای زیست-فیزیکی در فرآیند مدل‌سازی استفاده شد. با استفاده از آماره کوواریانس بین متغیرهای مستقل، متغیرهای فاصله از اماکن اداری، ورزشی و شهرها حذف گردیدند. میزان ROC برای مدل رگرسیون لجستیک ۰/۸۷ به دست آمد که نشان‌دهنده تایید رویکرد مدل‌سازی است. با استفاده از نقشه احتمال رشد شهری پیش‌بینی شده توسط مدل رگرسیونی، الگوی توزیع شهری برای سال‌های ۲۰۱، ۲۰۲۰، ۲۰۳۰، ۲۰۴۰ و ۲۰۵۰ استخراج گردید و نقشه کاربری زمین برای سال‌های ۲۰۵۰-۲۰۱۰ با استفاده از نقشه احتمال تغییرات شهری و بر اساس نقشه کاربری سال ۱۹۸۷ به دست آمد. معیارهای سیمای سرزمین در سطوح کلاس و سیمای سرزمین برای مقایسه اثرات رشد شهری بر انواع دیگر کاربری‌ها استفاده شد. این مقایسه نشان داد که رشد شهری بر زمین‌های کشاورزی و مراتع از سایر مناطق اثرگذار بوده است. ضمن آن‌که منطقه دچار لکه‌لکه شدگی شده و نامتناجس‌تر شده است. رشد شهری لکه‌های شهری را ایجاد نموده و تعداد لکه‌های کشاورزی و مراتع را نیز کرده است. این اطلاعات برای مدیریت بهتر منطقه می‌تواند مؤثر باشد.

کلمات کلیدی: رشد شهری، رگرسیون لجستیک، گرگان، لکه‌لکه شدگی، معیارهای سیمای سرزمین