Dynamic simulation of urban expansion through a CA-Markov model
Case study: Hyrcanian region, Gilan, Iran

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Abstract
Urban sprawl has become a remarkable feature in urban development, especially in developing countries, in the last decades. To face this phenomenon, it is required to first forecast auto-spreading orientation rural areas over time in order to avoid shapeless urban growth. Although GIS/RS and CA- Markov models are applied to study urban growth patterns the world over, very few studies have applied these methods to examine the urban growth of Iran. A major land use change is detected here from 1989 to 2013. In this study the future sprawl of this province is forecasted for target years of 2025 and 2037 through a simulation. The results predict an alarming increase in urban development for the target years of 2025 and 2037, with an expansion is predicted to develop of 11510 and 18320 ha, respectively. In sum, this model is an efficient tool for the support of urban planning decisions and facilitates the process of sustainable urban development providing decision-makers.

Keywords: Urban growth, Markov chain, cellular automata, Multi Criteria Evaluation, forecast, Gilan Province.

Introduction
By the 2050 according to the United Nations estimates, the urban areas would encompass more than 60% of the rural population. Urbanization phenomenon a major dilemma in most parts of the world subject to disorganized spreading where proper planning is absent [Samat et al., 2011]. Rapid urbanization, in developing countries in specific, is accompanied with
major ongoing socio-economical phenomena [Sui and Zeng, 2001]. This is accomplished, by exploiting natural resources which in turn has its direct effect on the ecosystem, its functionality and dynamism, making which has urban areas susceptible to many enforced risks.

The term urban sprawl is known as a manifold concept dealing in expansion of auto-oriented and low-density urban development with a direct negative impact on the surrounding ecosystem [Gong et al., 2015]. These features have promoted the awareness on preventing the negative effects of urban sprawl, which have has become as a topic of great debate among the researchers [Albizua et al., 2012; Nazarnia et al., 2016]. At the beginning of the second half of the 20th century urban growth modeling with a futuristic view became a major concern. According to Deng et al. [2009] and Yang et al. [2012], the models introducing urban land use change contribute to urban growth modeling(s), land transformation management, land use plans preparation and provide appropriate procedure for urban planner to achieve sustainable urban development.

The studies run on urban sprawl issue are mostly focused on big cities and metropolitan areas while the middle sized and small urban areas which might be exposed to the highest rates influx and urban growth is secondary. This concept is more prevalent in developed countries than developing countries. The knowledge-based management of urban growth has been and is the focal point of literature in urban planning literature [Dadhich and Hanaoka, 2010]. The advances made in GIS and RS, facilitate the mapping, modeling and further analysis of urban growth and land use change [Vaz and Nijkamp, 2015].

The connection between CA-based urban growth models and GIS introduce new concepts in urban modeling and expansion in a practical manner providing the possibility. According to integration of GIS spatial analysis techniques with spatial dynamic models like cellular automata (CA) provides a robust methodology for exploring urban complex systems. During the mid-1980s, CA models were proposed as alternative to traditional models due to their simplicity, capability of dynamic spatial simulation and the potential in generating high resolution modeling through the capabilities of GIS and remotely sensed data [Torrens and O’Sullivan, 2001].

It should be noted that a CA model is affected by neighborhood type, size and cell size parameters, which should be considered in obtaining optimum simulation results [Wang et al., 2012]. Wu et al. [2006] incorporated a potential model with a CA model in order to simulate the landscape dynamics of Beijing metropolitan area. Sui and Zeng [2001] approved of GIS-based CA modeling. They emphasized on the bottom-up approach of CA in modeling, where different local factors are incorporated. Barredo et al. [2004] developed a CA model for predicting land use change in Dublin and Lagos, Nigeria, respectively. In their study, the transition rules were internalized based on four general factors of accessibility, neighborhood, sustainability of a cell and zoning status. In this context, there exist many studies on integrated application of CA modeling with logistic regression [Munshi et al., 2014] optimization algorithms [Feng and Liu, 2013] and simulation methods [Arsanjani et al., 2013].

Gilan, the subject of this study, is a victim of an urban population growth in an exclusive sense. According to the first Iranian census, in 1956, there exist only 199 cities in Iran.
and the proportion of urban population to that of the national was only 31%. In 2006, the number of cities was reported to be 1012 and the proportion of urban population exceeded 70% of the national [Iranian Statistic Center, 2011; Shahraki et al., 2011] Urban population in Iran will constitute about 80% of the national population by 2020 according to the United Nations. Gilan Province is one of the medium sized provinces undergoing rapid physical change leading to its physical growth.

Every year, great number of rural influx adds to the existing population of the citizens, which in turn promotes the urbanization culture.

Unsustainable growth of the city has caused many socioeconomic and environmental problems like landscape determination, pollutant emission, heavy traffic jam, deforestation, and land use change [Sidle et al., 2006; Czamanski et al., 2008; Macedo et al., 2013]. In general, the pleasant climate, picturesque landscape of Hyrcanian forests, and the majesty of Caspian Sea have made the area as one of the most densely populated areas in Iran. This region is a favorite resort site for local tourists and holidaymakers of Iran and Middle East. The objective of this study is to simulate future land use changes based on the Markov-CA model in order to forecast auto-spreading orientation of Gilan Province and its suburb areas within two target years of 2025 and 2037. The finding here could assist the decision makers and relevant authorities with future orientations of urban growth with further restrictions on the city boundaries.

**Materials and methods**

**Experimental features**

This province covers a territory of 14042 km², extending from 36°34’ - 38°27’ N in latitude and 48°53’ - 50°34’ E in longitude in the Hyrcanian district, covering the eastern one third of the Caspian sea’s southern coastline with MSL of -27 m on the plain to 3897 m on the mountain top (Fig. 1).

This area is of moderate annual climate are distinctly. The national annual precipitation average is 341 mm. Annual precipitation amounts to 1506 mm, 38% of which is confined to the autumn season, October in specific. The region has a population of approximately 2.48 million. According to Statistical center of Iran [2011] there exist 52 cities in this province, 13 of which are in coastal line, and 2916 villages.

The landscape maps are presented five classes: 1) forest coverage, 2) built-up area, 3) agricultural land, 4) water bodies and 5) barren land: include Barren and Open land. Immigration and tourism are two important factors for the significant increase in temporary and permanent population of the province in recent decades in a sense the total population increased from 2.08 million in 1986 to 2.48 million in 2011. This growth has caused urban sprawl and extensive land degradation. The area is selected as the study area because during the last three decades, the predominant forestry forms of land coverage. The magnificent Hyrcanian forests and rangelands have been and are being converted in to new residential and commercial areas.
Data preparation
Addressing the changes inflicted on a given land cover and land use provides an essential input for environmental analysis, planning, and management of the same. Nevertheless, land use/cover detection like detections in other fields is not an easy task due to several innate uncertainties. The comparative analyses through classifications obtained independently from different data are named map-to map comparisons or post-classification comparisons. The main components used in changes in the land cover change and use regarding future. The process occurs in a raster data environment, most often with a grid of uniform cells of a specified resolution. The coupled Markov-CA model that integrates GIS software to
simulate land use changes and spatial distribution in the future is applied here. The detailed steps as a flowchart are shown in Figure 2. The land use maps of 1989 to 2013 are obtained by GIS technology and remote sensing (Tab. 1); the transition matrices were introduced by running Markov chain analysis, where the number of pixels to be expected to change each land cover class to another class over a specified time interval (1989-2001, 2001-2013) is revealed. The six assessment indicators, Table 4 are selected to compute the transition matrices by Markov chain and multi-criteria evaluation (MCE) order to simulate the spatial distribution of land use on the basis of the transition rule of CA model.

Table 1 - Description of Landsat resources used in Gilan Province.

| Year | Sensor | Satellite | Path/Row       | Spatial resolution (m) | Classification Overall accuracy (%) |
|------|--------|-----------|----------------|------------------------|------------------------------------|
| 1989 | TM     | Landsat 5 | 165/34 - 166/34 | 30                     | 89.2                               |
| 2001 | ETM+   | Landsat 7 | 165/34 - 166/34 | 30                     | 90.8                               |
| 2013 | OLI    | Landsat 8 | 165/34 - 166/34 | 30                     | 91.1                               |

Figure 2 - Paradigm of the study.
Research methods
An overview of the workflow, comprised of the following stages: 1) Landsat images of 1989, 2001 and 2013 processed to extract the land use maps of the aforementioned years (Fig. 2) by spatial classification, 2) computation of transition probability maps on the basis of auxiliary data, based on MCE and 3) these maps, in combination with the land use maps, are required for the MC-CA simulation model in predicting future urban land use change for the target dates 2025 and 2037.

Markov model
The Markov chain model is one of the spatial statistical models applied in describing dynamics of land use change and predicting future land use change. The theory of this model is based on the progression of the information of Markov stochastic process systems in projecting the conversion of status. This model provides a set of conditional probability images for each land-cover class. It is generally used in prediction of geographical features lacking after-effect events and which has become an important prediction method in geographical research. In the model proposed by this, Markov chain model is applied to predict future changes by considering land-cover classes from the satellite data and evaluating the future simulation within a span of 24 years in two periods of (1989-2001 and 2001-2013) in IDRISI Selva (Fig. 6).

Markov chains can be expressed as [Fan et al., 2008]:

\[
P\left( x_t = j \mid x_0 = I_0, X_1 = i_1, \ldots, X_{t-1} = i_{t-1} \right) = P\left( x_t = J \mid X_{t-1} = i_{t-1} \right) \tag{1}
\]

If a Markov sequence of random variant takes the discrete value \(a_1, \ldots, a_n\), then:

\[
P\left( x_n = a_m \mid x_{n-1} = a_{m-1}, \ldots, X_1 = a_{n-1} \right) = P\left( x_n = a_m \mid X_{n-1} = a_{m-1} \right) \tag{2}
\]

Chi-square (X2-test) is used to test the change matrix in meeting Markov chain, which is expressed as follows:

\[
\sum_{i=1}^{r} \sum_{j=1}^{c} \frac{(Q_{ij} - E_{ij})^2}{E_{ij}} \tag{3}
\]

Where: \(X^2=r \) = number of rows, \(c\) = number of columns \(Q_{ij}\) = Actual number in cell \(ij\) \(E_{ij}\) = Expected number in cell \(ij\), \((r-1) \ast (c-1)\) = degrees of freedom.

Urban growth model
CA-Markov modeling is a combination of modeling techniques where the strengths of a spatially explicit, deterministic modeling framework are bound through a stochastically based temporal framework; it is a combination of Markov chain and cellular automata models applied in obtaining the trend and spatial structure of different land use. The focus
of this method is on the quantity of projections for land use changes, which has a weak performance next to different types of its counterparts’ changes in the spatial context. On the contrary, CA-Markov model, which incorporates the theories of Markov and CA, is about the time series and space with the advantage of forecasting better simulation for temporal and spatial patterns of land use changes in quantity and space [Bobade et al., 2010]. CA as a, the topological grid features of CA which is a bottom-up approach makes CA an appropriate model for incorporating the spatial and temporal dimensions a given processes [Santé et al., 2010]. This model consists of a kind of discrete grid dynamic model where space is divided into regular spatial cells and time progresses in discrete steps. The state of each cell is updated according to local rules, that is, the state of a cell at a given time depends on its own state and the estates of its neighbors at the previous time step [Torrens, 2001]. The findings in the studies conducted by Liu and Phinn [2003], Helbich and Leitner [2009], Sang et al. [2011], Triantakonstatics and Mountrakis [2012], and Waseem et al. [2015] affirm that combination of the MC-CA model, the multi-criteria evaluation (MCE) and analytic hierarchy process (AHP) can improve the representation and modeling of urban dynamic growth. Combining the MC-CA model and AHP to determine indicator weight of land use transition potential maps, provides a comprehensive and rational framework for drawing decision and evaluating alternative solutions. The AHP can be used to determine the weights of the fuzzy potential maps through pair-wise comparisons of the many various factors involved. The main advantage of AHP is credited to its structural conceptualization in decision-making, where several values in a range of different scales are compared.

Result and discussion

Land use/cover structure change

According to the spatial overlay analysis in GIS environment, from 1989 to 2013, the land use classification (Fig. 3) adopted in this proposed model consist of 5 classes: forest coverage, built-up area, barren land, water bodies and agricultural land (Tab. 2). The configuration changes in this area are shown in Figure 5 and the change detection results are tabulated in Table 3.

| Class Name         | Land use 1989 (ha) | Land use 2001 (ha) | Land use 2013 (ha) |
|--------------------|-------------------|--------------------|--------------------|
| Built - up Area    | 36010             | 54850              | 59755              |
| Forest Coverage    | 782870            | 768540             | 751240             |
| Barren / Open Land | 318985            | 281880             | 266960             |
| Water Bodies       | 8630              | 12235              | 7215               |
| Agricultural Land  | 257560            | 286550             | 318885             |

Changes in the land use types are clearly visible over a 24-year period. For evaluation of the classification results, a random sample of 250 well-distributed points is extracted before being visually verified through Google Earth and official 1/25000 reference maps. Subsequently, the overall accuracy of the generated maps was estimated by error matrices.
The Kappa coefficient of 89.23%, 90.84% and 91.08% confirmed the accuracy of the classified maps in 1989, 2001, and 2013, respectively (Tab. 1). During these periods, built-up areas (urban) increased from 36010 to 59755 ha, which results in an increase in 23745 ha in urban development within the past 24 years. The built-up areas in 2013 are surrounded by fertile farmlands, mostly paddy fields covering 318885 ha and a strip of Hyrcanian forests 751240 ha in the south in an area of. During this period, agricultural lands increased by 4.4%. In addition, due to the increasing trend of urban construction, Hyrcanian forest has faced a decrease of 2.3% during 1989-2013 periods (Fig. 4 and Tab. 2).
Conversion of 12635 ha of forest lands and 6745 ha agricultural lands into barren land could a clear symptom for extensive land degradation in the study area in periods 1989-2013 (Fig. 5 and Tab. 3) is the highlight here. Thus, a correlation exists between increasing population, demand for land, and the resulting increase in built-up areas.

**MCE standardization and weighting of factors**

The criteria that are impacting the suitability and the effect of land use transition probabilities are selected from the experts conclusions found in the preliminary studies [Lawal et al., 2011; Anane et al., 2012; Arsanjani et al., 2013]. To assure the logical consistency of the selected weights, their the consistency ratio (CR) is calculated; otherwise, the values of CR ≤ 0.1 indicates the consistency of this matrix, while the CR obtained here is 0.04, lower than the critical value of 0.1, hence the suitability of the defined weighting scheme is confirmed [Boroushaki and Malczewski, 2008]. The selected 6 main criteria of this study are listed in Table 4. Factors with higher weights are statistically more important. According to Eastman [2012], fuzzy membership function can be classified in the two aspects of type and shape. Types include are of S-shaped (sigmoidal), J-shaped and linear. Shapes increase and decrease in a gradual manner and are symmetric, while in contrast, if CR does not reach the threshold value, the matrix will be inconsistent, that is, so the process should be revised. According to EC [2000], access to public areas is essential if the community sustainability and quality of life is of concern. Distance from existing settlement areas shows that future areas trend to be developed closer to existing built-up sites, indicating that the free space closer to the settlement have higher probability to change than the farther.
| Class             | 2001       | 2013       | 1989       |
|------------------|------------|------------|------------|
|                  | Built-up   | Forest     | Barren/    | Agricultural| Total     |
|                  | Area       | Coverage   | Open Land  | Land        |           |
| Built-up Area    | 36010      | 0          | 0          | 0           | 36010     |
| Forest Coverage  | 1835       | 774540     | 2405       | 9015        | 787795    |
| Barren/Open Land | 6785       | 2140       | 313620     | 30395       | 352940    |
| Agricultural Land| 10075      | 6190       | 2960       | 218145      | 237370    |
| Total            | 54705      | 782870     | 318985     | 257555      | 1414115   |
|                  | 54850      | 0          | 0          | 0           | 54850     |
| Forest Coverage  | 240        | 741270     | 10230      | 16800       | 768540    |
| Barren/Open Land | 1860       | 1180       | 247400     | 31435       | 281875    |
| Agricultural Land| 2545       | 7790       | 3785       | 272426      | 286546    |
| Total            | 59495      | 750240     | 261415     | 320661      | 1391811   |
| Built-up Area    | 36410      | 0          | 0          | 0           | 36410     |
| Forest Coverage  | 2075       | 733940     | 12635      | 25820       | 774470    |
| Barren/Open Land | 8645       | 3320       | 247580     | 61834       | 321379    |
| Agricultural Land| 12625      | 13980      | 6745       | 231235      | 264585    |
| Total            | 59755      | 751240     | 266960     | 318889      | 1396844   |

For example, distance from the built-up area (with final weight of 0.24), the distance from the major roads (with final weight of 0.21) and distance from forest area (with final weight of 0.16), are the most effective criteria in evaluating capability of land use in the study area, respectively (Tab. 4). The fuzzy membership function in IDRISI software is provided for the standardization of factor applying many fuzzy set membership functions. There exists a direct relation between fuzzy standardize values and land capability. Selection of the parameters for standardization depends on analyst’s knowledge and experiences. These potential change maps are considered in the MC-CA model.
Table 4 - Fuzzy model standardization of variable.

| Factors                        | Fuzzy Membership functions type / shapes | Control point | Weight |
|--------------------------------|-----------------------------------------|---------------|--------|
| Distance from built-up area    | Linear / increasing                      | 0-6.5 km      | 0.24   |
| Distance from forest area      | Linear / increment                       | 200-2500 m    | 0.16   |
| Distance from water bodies     | Linear / increment                       | 200-2500 m    | 0.11   |
| Distance from the major road   | J-Shaped / decreasing                    | 0-2.5 km      | 0.21   |
| Slope in percent               | Sigmoidal / decreasing                   | 0-15 °        | 0.13   |
| Land use                       | Boolean                                 | ......        | 0.15   |

CA-Markov projection model

Transitional probability matrix of CA-Markov model in Table 5 reflects the probability of land use changing accompanied with possible quantitative in prediction future changes in different land use types in the study area. According to the results, the greatest land use changes in 1989 - 2001 period could be detected in the conversion of barren lands into both urban areas (probability rate = 0.1367) and agricultural lands (probability rate = 0.1147). Well-approved by the results of change detection analysis approve this phenomenon.

Table 5 - Markov transition probability matrixes for 1989-2001, 2001-2013 and 1989-2013.

|                  | 1989-2001                  | 2001-2013                  | 1989-2013                  |
|------------------|----------------------------|----------------------------|----------------------------|
|                  | CA - Markov 2013           | CA - Markov 2025           | CA - Markov 2037           |
|                  | Built - up Area            | Forest Coverage            | Barren / Open Land         | Water Bodies | Agricultural Land |
| Built - up Area  | 0.9697                     | 0.0098                     | 0.0084                     | 0.0053      | 0.0068            |
| Forest Coverage | 0.0548                     | 0.8397                     | 0.0915                     | 0.0003      | 0.0137            |
| Barren / Open Land | 0.1367                    | 0.0069                     | 0.7349                     | 0.0068      | 0.1147            |
| Water Bodies     | 0.0000                     | 0.0014                     | 0.0089                     | 0.9858      | 0.0039            |
| Agricultural Land | 0.0557                    | 0.0239                     | 0.0489                     | 0.0000      | 0.8715            |
|                  | CA - Markov 2025           | CA - Markov 2037           | CA - Markov 2037           |
|                  | Built - up Area            | Forest Coverage            | Barren / Open Land         | Water Bodies | Agricultural Land |
| Built - up Area  | 0.9859                     | 0.0084                     | 0.0031                     | 0.0002      | 0.0024            |
| Forest Coverage | 0.0431                     | 0.8195                     | 0.1289                     | 0.0002      | 0.0083            |
| Barren / Open Land | 0.1235                    | 0.0043                     | 0.7456                     | 0.0049      | 0.1217            |
| Water Bodies     | 0.0000                     | 0.0013                     | 0.0106                     | 0.9872      | 0.0009            |
| Agricultural Land | 0.0521                    | 0.0102                     | 0.0445                     | 0.0000      | 0.8932            |
|                  | CA - Markov 2037           | CA - Markov 2037           | CA - Markov 2037           |
|                  | Built - up Area            | Forest Coverage            | Barren / Open Land         | Water Bodies | Agricultural Land |
| Built - up Area  | 0.9881                     | 0.0055                     | 0.0033                     | 0.0002      | 0.0029            |
| Forest Coverage | 0.0691                     | 0.8164                     | 0.1023                     | 0.0006      | 0.0116            |
| Barren / Open Land | 0.1449                    | 0.0074                     | 0.7095                     | 0.0059      | 0.1323            |
| Water Bodies     | 0.0000                     | 0.0007                     | 0.0085                     | 0.9892      | 0.0016            |
| Agricultural Land | 0.0579                    | 0.0312                     | 0.0504                     | 0.0000      | 0.8605            |
As mentioned earlier, the area of barren lands is changed by about 52025 ha over the years 1989 to 2013, which confirms the fact that barren lands underwent the greatest changes in the study area. By comparing the stimulated and real land use for the year 2013, it is deduced that this developed model is capable of estimating future land use changes. The Kappa coefficient here is 0.89, indicating a good fitness between the actual map and simulated maps; consequently, based on the obtained Kappa values, the CA-Markov model can be applied in simulating future land cover conditions.

The successful simulation of area change and spatial distribution in 2013, allow the authors to forecast the area change of future land use and land use maps from the target 2025 to 2037, dates are forecasted through using land use base map of 2013, transition probability matrix of 2001 - 2013 period, and transition potential map of 2013. According to this probability matrix, barren lands have the highest potential to be converted into urban areas by the year 2025 with a probability rate estimated at 0.1235. Agricultural lands and forests areas with probability rates of 0.0521 and 0.0431, respectively, are the two other land uses with a big potential to be changed into urban areas by 2025. As expected, the conversion of water bodies into the built-up areas is almost out of question with a probability rate of zero, in simple terms; water bodies are the only category to remain unchanged in the known future. The remarkable point here is the high probability in conversion of forest (probability rate is 0.1289) into barren lands.

| Year        | Actual Land use 2013 | CA-Markov 2013 | CA-Markov 2025 | CA-Markov 2037 |
|-------------|----------------------|----------------|----------------|----------------|
| Class Name  | ha                   | %              | ha             | %              | ha             | %              |
| Built-up Area | 59755               | 4.3            | 58750          | 4.2            | 71265          | 5.1            | 78075          | 5.6            |
| Forest Coverage | 751240            | 53.5           | 747153         | 53.2           | 733290         | 52.2           | 726140         | 51.7           |
| Barren/Open Land | 266960            | 19.0           | 265390         | 18.9           | 257030         | 18.3           | 245185         | 17.5           |
| Water Bodies | 7215                | 0.5            | 6302           | 0.4            | 7080           | 0.5            | 7310           | 0.5            |
| Agricultural Land | 318885           | 22.7           | 326460         | 23.3           | 335390         | 23.9           | 347345         | 24.7           |

Changes in the area of agricultural land be significant in this context and there exist the high possibility of its loss by 335390 ha (23.9 %) by 2025 and 347345 ha (24.7 %) by 2037. It is likely to loss 257030 ha (18.3 %) and 245189 ha (17.5 %) of barren land by 2025 and 2037, respectively. The future expansion of urban areas by the target years 2025 and 2037 is illustrated in Figure 6, whereas observed the urban development would occur primarily on the periphery of the current population centers and would gradually expand towards surrounding agricultural and forest areas. Majority of the advanced built-up areas will observe in the center with a concentration and in a scattered form in a network of low-density constructions. The results of this simulation could be applied as a guiding feature in to conservation planning of the study area, with a combination to the decision-makers improve land use management and to balance artificial development and ecosystem conservation.
Figure 6 - Markov Change Simulation for built-up areas.

Conclusion
Urban expansion as a complicated phenomenon has become a major issue worldwide due to the rapid trend in urbanization. Both the developed and developing countries have experienced and are experiencing urban sprawl on an unprecedented scale, which had and has negative impact on intensive land use and land cover if not managed properly in a scientific manner. Therefore, understanding the dynamics of urban expansion would significantly assist managers and urban planner to make proper decision for the control of urban sprawl and the consequences thereof in future. The subject of this study is a middle-sized province located in the North of Iran that has experienced a rapid process of urban growth since the mid-1980s. As in many provinces of the developing countries, expansion in
this area has followed an unplanned and a disordered pattern. Such rapid and unsustainable urban development has had its adverse effect the natural landscape by destroying a great area of Hycranian forests and rangelands, in addition to initiating major problems with respect to local climate change, coastal pollution, energy consumption, flooding, insecurity etc. In this study the GIS and remote sensing and Cellular Automata model are integrated to first, analyze the spatio-temporal dynamics and evolution of land use change as a result of rapid urbanization process in the past 30 years and second to predict urban planning in future for target years of 2025 and 2037. In a close approximation according the findings by CA, the extent of built-up areas will be about 71265 ha by the year 2025 and 78075 ha by the year 2037. According to the findings of this study, the trend of urbanization in this province has caused many changes in the land use in the peripheral areas, expanded by about 42060.5 ha in total over the period among 1989-2037. The results reveal that forest coverage is the major resource converted into urban development. The annual decline rate of forest coverage is increased in the last decade significantly. Extensive loss of forests and natural rangelands will exacerbate the situation of the province and make it even more unsustainable. To prevent this wrong necessary to control the increasing urban growth and protect forest coverage in a planned and scientific manner in order to promote land use and sustainable urban environment. The evidence shows that the orientation of the future urban development of the province is towards the mountains and plain areas of the Hycranian forest and agricultural lands, respectively, which have the best forest coverage and most fertile lands. The simulation land use maps of 2025 and 2037 reveal an alarming expansion on the existing natural land. Furthermore, based on the predicted results, urban areas would be expanded in a scattered pattern. These forecast maps the actual notable relevant findings must make the makers aware of proper, urban planning, and land use management. Through this and studies alike the authorities at national and province level would be guided for urban expansion in future, accordingly they would be able to introduce plan sustainable development plans with respect to urbanization.

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