MONITORING LAND USE CHANGE PROCESSES IN KERMAN BASED ON MARKOV MODEL AND SATELLITE DATA

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Understanding the reasons for land use change over time is necessary for optimal planning and management of urban areas. Identification of alterations and the patterns they reflect allows prediction of future changes, and appropriate planning can then be undertaken. In the last two decades, the city of Kerman, Iran, has gone through several identifiable changes, including significant increases in its urban population and growth of its urban residential areas. As a result of population increase, provision for Kerman's human needs, which requires extensive use of natural resources, will undoubtedly increase the demand for land resources, both in agricultural and non-agricultural sections. Due to the fact that development without planning leads to inappropriate use of lands and resources, the present study was set to contribute in planning through an analysis of land use changes in various areas of Kerman city between 1989 and 2017, and to predict probable changes during the next ten years through performing visible and near infrared data of Landsat TM/ETM+/OLI. Classification of land use classes, and analysis of methods and their changes, was carried out by ENVI 5.1 and IDRISI 17 software. Maximum likelihood method was selected for Image classification. Classified images were applied as input for Land Change Modeler (LCM). Results indicated that by 2017, LCM had approximately doubled, bare surface had decreased, and vegetation had significantly increased. Furthermore, the results of Cellular Automata (CA) Markov method in 2017 showed that according to the predictions the area of bare surface and vegetation have respectively decreased by 118 and 219 hectares and the area of built-up land had not changed significantly when compared with the base year 2017. This research is anticipated to help local managers better view on the addressed land use system for improved land use management strategies upon urban expansion balance.

KEYWORDS:

Land use; land change modeler; Markov model; GIS; Geography; Iran.

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1. Introduction

Nowadays in this competitive world, people emigrate from rural areas to urban areas to find more job opportunities and infrastructure facilities, and this population shift has caused significant changes in both regions. Because of the rapid process of urbanization, the haphazard growth of major cities is one of the most challenging situations confronting any country. Connected to rapid urbanization, land-cover change presents a complicated, dynamic, and spatially explicit problematic phenomenon. Research indicates that such a change is affected by many factors related to location; for example, proximity, physical conditions, and socio-economic factors and that consequently, land-cover change is a complicated, dynamic, location-related phenomenon (1-4). Current studies indicate that timely and accurate detection of changes in earth's surface features provides a better understanding of interactions between human and natural phenomena, which in turn allows for better management and use of resources (5). In the last two decades rapid growth of some technologies such as Geographical Information Systems (GIS) and Remote Sensing (RS) was useful for mapping the composition of urban settings, hazard-prone areas, and analyzing changes over time (6-9); their use in urban and environmental planning has resulted in the formation and presentation of spatial modeling methods such as cellular automata (10), neural networks (11), and statistical models (3) as decision-support tools. These models make available a quantitative tool to assist in decision-making for urban and environmental planning, capability management, and the assessment of the suitability of land for development (12). Numerous studies have revealed that the CA–Markov model, which efficiently matches with GIS and RS, is able to devise an appropriate approach in dynamic temporal and spatial modeling of land-cover/land use changes (3, 13). In the light of these considerations, this study simulates land use changes in Kerman in the time period 1989-2017 and predicts its spatial pattern by assessing the performance of integrated CA–Markov model.

2. Study area

Kerman, located at 30.2839° N, 57.0834° E, is the capital of Kerman province, the largest province of Iran. Kerman's altitude is 1755 meters above sea level, covers about 7644 hectares with population more than 738,724. Kerman has historical, industrial, economic, touristic, and university attractions, and in recent years has developed into one of the major population-attracting poles in the urban hierarchy of Kerman province. The presence of active faults in Kerman province, along with the occurrence of large earthquakes in nearby cities of Kerman, is one of the other factors that caused the population to migrate to this city (14-18). Situation of large mines and their related industries such as copper, iron, coal, chromite, etc. in Kerman province are among other factors in the development of Kerman city (19-23). This trend has resulted primarily from population migration and increase, which has led to unplanned urban construction, noteworthy changes in the spatial-bodily structure of the city, and the expansion of that structure into surrounding areas. Understanding current acceptable models of urban development and predicting the trend of urban expansion can play a major role in future planning and management of the city, and

it can help prevent further unplanned construction, expansion, and undesirable land uses.

3. Materials and method

This study utilized images reflecting conditions between 1989 and 2017 derived from the Landsat-series satellite. After the necessary editing and processing of the satellite data, the emergent images were inserted into the LCM and the CA-Markov software. The amount of decrease and the amount of increase of land use change was determined, and the trend and direction of such change was calculated. These data allowed predictions of probable changes during the next 10 years. In this study, images obtained by implementing the distant-measurement technology on the Landsat satellite series, for the four time periods of 1989 (Landsat 5 - TM measurer), 2000, 2008 (Landsat 7- ETM+ measurer), and 2017 (Landsat 8 - OLI measurer), were used to provide land cover map of the study area. In the pre-process stage, through application of atmospheric and geometric editing that utilized visible-limit bands of each measurer on the images, a monitored classification method was generated to perform the desired maps.

In order to determine the changes that had occurred over time, then to model and predict future changes, LCM and CA-Marko were applied with IDRISI software. LCM delivered a complete analysis of land changes through creation of charts and use-change maps, the transfer of use class and trend, and the direction of changes. LCM provided a tool which allowed us to empirically analyze and model the land-cover changes, as well as their effects on the habitat and biological variety of resident species. After the changes had been modeled, future changes could also be predicted by means of the Markov cycle. This cycle is a dynamic method based on the Markov causal process. The Markov cycle, which has been defined as a probability transition matrix (3), calculates probability of changes but cannot express those changes in terms of a spatial concept (24, 25). Because of that limitation and in an effort to minimize its weakness, the Markov cycle was combined with cellular automata (25). The cellular automata showed the spatial term and position of changes, while the Markov cycle predicted the changes quantitatively. Consequently, the combination of both methods led to more accurate results (26).

Accurate evaluation and assessment of the outcome of this process is very important because a superficial interpretation can provide misleading results. There are two ways to evaluate the modeler: one kind of assessment is visual, and the other involves application of two statistical methods. Although the visual method provides a modeling evaluation that is fast, that approach is subjective and can suggest misleading results. Statistical analysis is required in order to obtain precise information about modeling results. Validation by means of IDRISI software is one of these reliable statistical methods because it produces information about the match or mismatch of the two key maps. Accurate modeling evaluation involves a comparison of the map IDRISI produces for a certain time to the real map of the same time. It requires comparison of the real map and the predicted map in terms of the number of cells for

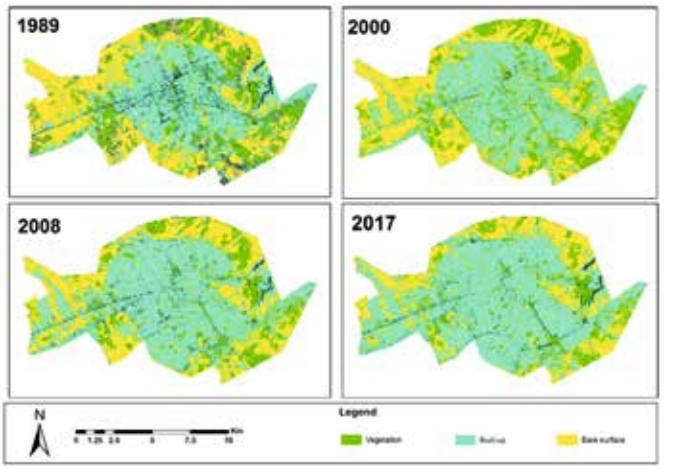

Fig. 1. *Land-cover changes that occurred in Kerman city between 1989 and 2000, 2000 and 2008, and 2008 and 2017. According to this Figure, construction has doubled, and vegetation and bare surface has decreased significantly*

each class and the location of cells in the two images. The Kappa coefficient is applied to interpret the results.

The Kappa coefficient is established as a result of the statistical concordance and relation between the two images. It determines what type of concordance exists between the numbers of cells in each class in the two images, or to what extent cells of each class in the two images accord with each other in terms of location. In a study in the eastern part of Massachusetts, Pontius and Chen (27) confirmed the calculation of the Kappa coefficient in order to establish accurate modeling. Additionally, Wang et al. (28) introduced the application of the Kappa coefficient as the most suitable way to evaluate modeling by means of the CA-Markov method. This study involved a thorough analysis of the validity of the predicted map of 2017 and the real map of 2017, based on a comparison of the numbers of cells for each class with the location of each cell in the two images. The Kappa coefficient was then applied in order to produce an accurate interpretation of the results.

4. Results and Discussion

To clarify and predict land use changes of Kerman, this study has analyzed the existing data during a period of 28 years. The analysis involved a careful evaluation of the maps of land-cover within the boundaries of Kerman city for the years of 1989, 2000, 2008, and 2017 (Fig. 1). This was followed by classification of the data into three classes: 1) built up lands, 2) vegetation, and 3) bare surface through use of the maximum-probability method, which was utilized to ensure the greatest accuracy compared with other methods. The resulting numbers indicated that in general there was excellent correspondence between that classification and the different use-classes which existed naturally in the imaged land (29).

4.1. Modeling land use changes with the LCM Method

In order to reveal land use changes, the LCM model was applied. Results indicated that significant changes in the land-cover of Kerman city, particularly that of built-up lands, had occurred during the past 28 years. Analysis of the results of land-cover changes between 1989 and 2000 indicated that during this period, approximately 5600 hectares of built-up lands had decreased, and that the same amount had been

added to the other classes, particularly vegetation and bare surface. Between 2000 and 2008, the changes between the classes differed significantly from the previous period, to the extent that almost 2600 thousand hectares of vegetation had decreased, and that amount had been added to the built-up lands. It should also be noted that gains and losses of land change were not significantly different in the other two classes. Bare-surface land had decreased by approximately 3000 hectares between 2008 and 2017, and the other two classes, particularly vegetation, increased by almost the same amount. However, the area of the three classes during the periods under study was not identical, to the extent that between 2000 and 2008 the built-up area had significantly increased. The total land use change map for 1989-2000, 2000-2008, and 2008-2017 presented in Figure 2. Figure 3 shows the trend and direction of the changes between 1989-2000, 2000-2008, and 2008-2017, as obtained by the LCM method. Areas with larger numbers were susceptible to more changes, and the data clearly indicate which area had maximum change during the period covered by this study.

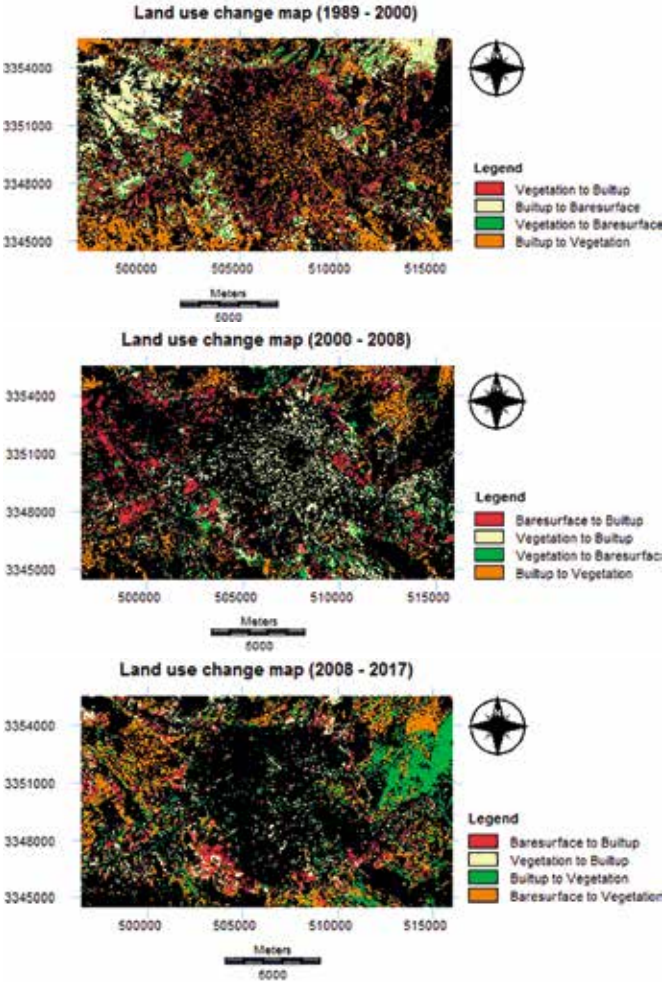

Fig. 2. *Total land use change, map conversion: 1989-2017*

After the changes had been determined, the Markov-cycle model was applied to predict land use changes. This model predicts the probability of the future change of one cell into another cell according to the image changes within the designated period. In fact, it can be validly asserted that the art of the Markov cycle lies precisely in its dependable calculation of the probability of one class's changing to another class. Figure 3g,h shows two maps for the selected study area: one indicates the real-map classifications for a specific year, and the second provides predictions for three land use classes, including built-up lands, bare surface, and vegetation for the same year. The areas of the classified real-map classes of 2017 and the predicted map produced by CA-Markov of 2017, both in hectares, are provided in Table 1. Comparison of the areas of the real map and the predicted map indicated that the area of built-up lands in the predicted map produced by CA-Markov was 656 hectares more than similar areas in the real map. Furthermore, the area predicted as bare surface by the model was more extensive than it was in the real area. Additionally, the calculated vegetation in the predicted map was less than the amount of real vegetation.

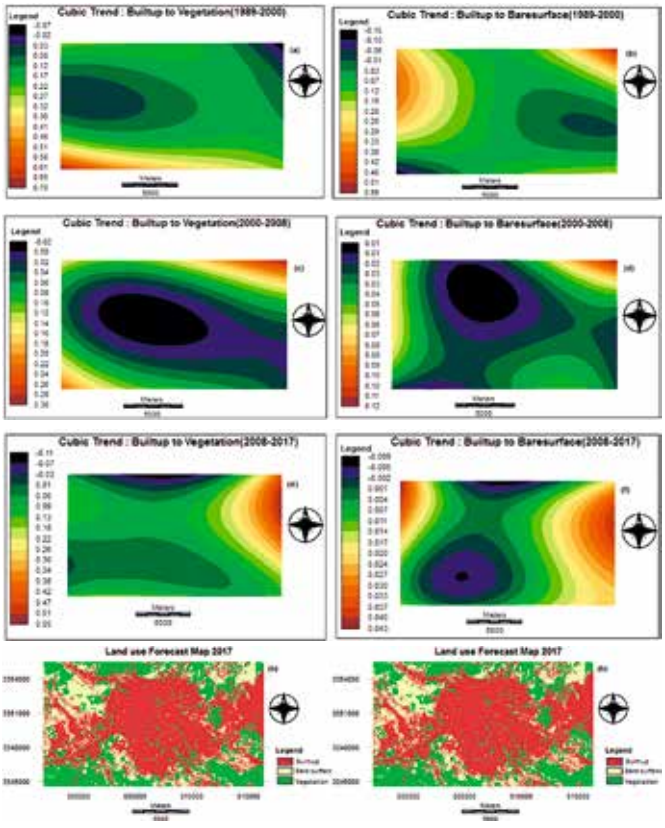

Fig. 3. *Map of trend and direction, a) built-up lands to vegetation, susceptible to changes in the southern area with a high southwest orientation, b) built-up lands to bare surface, susceptible to changes in the northeast and west. c) built-up lands to vegetation, susceptible to changes with only a slight orientation in southwest and northeast areas, d) built-up lands to bare surface, susceptible to changes in the northeast areas. e) built-up lands to vegetation, with a high potential of extension into the eastern area, f) built-up lands to bare surface, susceptible to changes in the eastern areas and extending into the northwest. g) Classified map: 2017, h) Predicted map, CA-Markov: 2017*

Table 1. Real-map areas, generated classes: 2017 (A) and Predicted areas, CA-Markov-derived classes: 2017 (B)

(B) Hectares	(A) Hectares	Legend	Categories
10829	10173	Built-up	1
3885	1111	Bare surface	2
6650	10202	Vegetation	3

Comparison of the areas of the real map and the predicted map indicated that the area of built-up lands in the predicted map produced by CA-Markov was 656 hectares more than similar areas in the real map. Furthermore, the area predicted as bare surface by the model was more extensive than it was in the real area. Additionally, the calculated vegetation in the predicted map was less than the amount of real vegetation.

4-2- Evaluation of Modeling

In order to calculate the accuracy of the classification proposed in this study, the earth data should be compared to the classification images within an error matrix. Different methods to ensure the accuracy of classification are available; some of these are *general* accuracy, *user* accuracy, *Kappa coefficient*, and others. Among these, the Kappa coefficient represents a better choice because of its capacity for excluding incorrectly classified pixels.

Agreement between the actual map and the predicted map [M(m)] was 0.82, disagreement between the two maps with regard to the relation 1-[M(m)] was 0.18, and agreement by chance [N(n)], which is obtained without any information about location and quantity, was 0.33. Agreement due to quantity, which derives from the number of cells comprising each class in the two maps and is obtained from the relation [N(m)]-[N(n)], is 0.12. Lack of agreement due to quantity, which is obtained from the formula [P(p)]-[P(m)], is 0.02. Furthermore, agreement and lack of agreement of location–location of classes in the real and predicted map–is 0.37 and 0.16 respectively. The Kappa coefficient, which shows the ability of the model to predict the location of pixels, is 0.69. The $K_{quantity}$, which quantifies the ability of the model to predict number of pixels, is obtained from the following formula:

$$Kquanteity = \frac{M(m) - NQML}{PQML - NQML} = \frac{0.8230 - 0.6069}{0.8183 - 0.6069} = \frac{0.2161}{0.2114} \cong 1$$

The obvious conclusion regarding general agreement between the maps for both years–0.82–is that there was noteworthy accord between them, and that the model displayed an outstanding capability of predicting classes. Furthermore, regarding the amounts of $K_{quantity}$ and $K_{location}$, 0.69 and 1, it can be accurately asserted that the model has effectively predicted the number of pixels and their location. The over-riding objective of this study was the prediction of the land area that would devolve from the three classes of built-up lands, bare surface, and vegetation in the study area for 2027. In accord with this objective, land use maps were derived from classifications generated in 2008 and continued through 2017. In the first step of application of the Markov model, the land use map of 2008 was introduced as the old map, and the land use map of 2017 was utilized as the new map. The change-probability matrix and the transfer-area matrix were calculated for the next ten years, based on the assumption of a 0.15 error. Use of land-cover maps for each period provided a situation-conversion matrix of land-cover classes between both time periods. The change-probability matrix presented in Table 2 was obtained from the land-cover maps of 2008 and 2017.

Table 2. Predicted probable area-change matrix, in hectares: 2027

Vegetation	Bare surface	Built-up	Probability of Change
0.5188	0.0582	0.4230	**Built-up**
0.4738	0.0432	0.4830	**Bare surface**
0.4096	0.0578	0.5326	**Vegetation**

After completion of this key step—consideration of the land use map of 2017 as the base map and introduction of the transfer-area file by means of the CA-Markov operator in the software—the land use map of 2027 was predicted according to the model. Prediction of the three classes of land use, built-up lands, bare surface, and vegetation in the study area for 2027 is shown in Figure 4 and Table 3. Land use changes according to class in 2027 is probable as indicated above. According to predictions, the bare-surface class and the vegetation class will have decreased 118 and 219 hectares, respectively. However, the built-up lands class had not changed significantly when compared with the base year 2017.

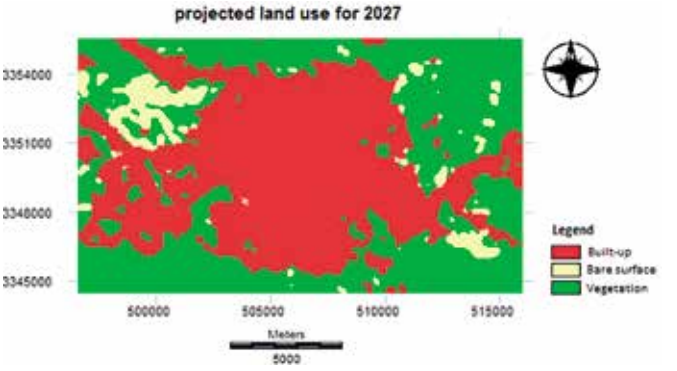

Fig. 4. *Prediction map, CA-Markov: 2027*

Table 3. Hectare areas, land use classes: 2027

Hectares	Legend	Categories
10273	Built-up	1
1229	Bare surface	2
9983	Vegetation	3

Land use changes according to class in 2027 is probable as indicated above. According to predictions, the bare-surface class and the vegetation class will have decreased 118 and 219 hectares, respectively. However, the built-up lands class had not changed significantly when compared with the base year 2017.

5. Conclusion

In this study, land use changes of Kerman city, Iran, were investigated for the period 1989-2017 by means of Landsat images. Classification of land use classes and their changes, and an analysis of effective and applicable

methods were carried out in ENVI5.1 and IDRISI 17 software. The results indicated that the maximum-probability method was the most accurate one compared to other methods. The land-change modeler was also adopted and applied to model land use changes of the study area. The results of this study revealed that significant changes had taken place in the target land use classes, especially in built-up lands, during the preceding 28 years. Investigation of those changes indicated that the amount of built-up land had increased significantly, to the extent that the area of this class had doubled during this period. A comparison of the 2017 map to the predicted map of 2027 indicates that there has been little tangible change in the area of built-up lands, inasmuch as only 100 hectares have been added to the area assigned to this class. Further, the bare-surface area has not changed significantly, with a mere 118 hectares having been added to it. Finally, the area occupied by the vegetation class in the map of 2027 has decreased by 219 hectares. These results clearly indicate that an in-depth analysis of land use changes and the prediction of future changes, as well as the expansion trend of those changes, can assist the development process. These results can be used as an effective executive strategy in future planning for Kerman city.

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