**Analysis and prediction of land cover changes by applying cellular automata-Markov model and geo-information: An arid and semi-arid river basin, Iran**

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**Abstract**

The prediction of future land cover changes is an important step in proper planning and management of watersheds. Various methods exist for this purpose. In this study, land cover changes were investigated in the Hable-Rud River basin in Iran, an arid and semi-arid region, using remote sensing and Geographic Information Systems (GIS). First, a supervised classification technique was applied to Landsat images acquired for 1986, 2000 and 2017 using the maximum likelihood method. Then, using pixel-by-pixel change detection, the land cover changes were predicted for 2017 and 2040 using a Cellular Automata (CA)-Markov model. The descriptive variables used included slope, aspect, elevation, and calculated distances from various land features such as rivers, roads, industrial areas, residential areas, saline land, and land in agricultural production. The predictions for 2017 were validated using the derived map from a Landsat image of 2017 with a resulting standard Kappa index of 0.74. According to the prediction results for 2040, the areas of rangeland and saline land will increase by approximately 6.5% and 2%, respectively, whereas the areas of bare land and agricultural land will decrease by approximately 6% and 2%, respectively. Moreover, the analysis of historical records since 1986 showed that the annual streamflow and precipitation have reduced by almost 44% and 29%, respectively. The reductions, particularly to streamflow, can be attributed largely to agriculture expansion, rapid population growth, and industrial developments. The analysis of the results indicates a need for more effective design, planning, and development of land cover policies for ecosystem protection.

**Keywords:**  CA-Markov model; Land cover; GIS; Satellite images; The Hable-Rud River Basin

**Abbreviations:** CA – cellular automata; GIS – geographical information system; LULC – land use, land cover; MLP – multi-layer perceptron; OLI – operational land imager; TM – thematic mapper; LCM – land change modeler.

# Introduction

The dynamic and sometimes substantial transformation in Land Use/Land Cover (LULC) occurs due to socio-economic changes and changes to the natural environment. Such changes may lead to unfavorable effects on fragile environments (Magesh & Chandrasekar, 2017) but are important indicators in understanding the interactions between human activities and the environment (Dewan, Yamaguchi, & Rahman, 2012). According to Turner et al. (1993), land-cover refers to the biophysical attributes of the earth's surface and immediate subsurface. It includes four variables, namely land, water, air, and human activity. Land-use is a description of how people utilize the land for their needs by various management practices (Fisher et al., 2005; IPCC, 2000). The LULC pattern of a region is an outcome of natural and socio-economic factors and their utilization by humans in time and space (Moss, 1987). LULC modifications occur for many reasons such as deforestation, reduced biodiversity and global warming (Dwivedi et al., 2005; Zhao et al., 2006). Land use change generally results in the modification of a piece of land. This change is based on the purposes of need and changes not only how the land is used but also how it is managed (Verburg et al., 2011).

Analyses and projections of LULC changes can provide a tool to assess ecosystem changes and their environmental implications at various temporal and spatial scales (Di Gregorio, 2005; Lambin, 1997). It is possible to build a model to predict the trends in land cover in a certain period of time through the study of past LULC changes. Such changes could provide some basis for scientific and effective land-cover planning, management and ecological restoration in a study area and guidance for regional socio-economic development. Accordingly, in order to understand and assess LULC changes, well-timed and detailed land cover change information is necessary. LULC change modeling means time interpolation or extrapolation when the modeling exceeds the known period (Paegelow & Camacho Olmedo, 2005). Commonly used models for estimating LULC changes are analytical equation-based models (Usharani & Lakshmanaperumalsamy, 2011), statistical models (Paegelow & Camacho Olmedo, 2005), evolutionary models (Aitkenhead & Aalders, 2009), Cellular Automata models (Farjad, Gupta, Razavi, Faramarzi, & Marceau, 2017; Singh, Mustak, Srivastava, Szabó, & Islam, 2015), and Markov models (Yang et al., 2012), hybrid models (Subedi et al., 2013), expert system models (Stefanov et al., 2002) and multi-gene models (Ralha et al., 2013). Various techniques of LULC change detection analysis were discussed by Lu et al. (2004). Traditionally, the method of monitoring LULC changes is based on field study (surveying) combined with large-scale aerial photography, which is often time intense, meticulous and costly (Groom et al., 2006). Recently, remote sensing technology has gained application in regional as well as in global scales (Atzberger, 2013). Satellite imagery is used for recognition of synoptic data of the earth’s surface (Ulbricht & Heckendorff, 1998). Landsat Multispectral Scanner, Thematic Mapper (TM) and Enhanced Thematic Mapper Plus (EMT+) data have been widely used in studies for the determination of land use and land cover since 1972, the starting year of Landsat program, mainly in forest and agricultural areas (Zheng et al, 2015). Today, one can process the dynamics of landscapes by using technologies such as geographical information systems (GIS) and remote sensing (Bhat et al., 2017). Significant research on computing LULC change, including the estimation of its accuracy, has been carried out (Coppin et al., 2004; Kaliraj et al., 2017; Lu et al., 2004; Magesh & Chandrasekar, 2017; Sun et al., 2016; Zhang et al., 2019).

Land change models can be used to predict and simulate future changes of one land class to another (for example, agricultural land could become saline land or rangeland could become a residential area. Accordingly, Markov models can be used to determine the extent of change of one land class to another. A Markov matrix defines the change in each class that undergoes transition to another class during a given period. The empirical Markov matrix at the calibration period can then be used to extrapolate the extent of each transition beyond the calibration period by utilizing a Markov chain (Baker, 1989). Cellular Automata (CA) models include a regular grid of cells and controls that manage how each cell’s neighbors affect the future class of each cell (Aviv & Sipper, 1994). CA-Markov models link a Markov algorithm to predict the extent of the changes and a CA algorithm to assume the allocation of change (Singh et al., 2015). The main objective of this research was to extract decadal changes of land cover in the Hable-Rud River basin in Iran and predict their transformations of land cover under a Classification System using Landsat Enhanced Thematic Mapper (ETM) and Landsat Thematic Mapper (TM) images by applying the Maximum Likelihood Classifier algorithm for the period 1986– 2040.

# Materials and Methods

## Study Area

The Hable-Rud River basin, with an area of ​​about 1.27 million hectares, is located between 34° 26' 54" to 35° 57' 31" N latitude 51° 39' 52" to 53° 8' 46" E longitude and 51° 39' 52" to 53° 8' 46" E longitude. This basin straddles the border between the provinces of Tehran and Semnan in Iran. Situated within the basin is the city of Firouzkouh and part of the city of Damavand in the province of Tehran, and parts of the cities of Garmsar, Sorkh, Aradan and Eyvanekey in the province of Semnan. The geographic location of the Hable-Rud River basin is shown in Fig. 1. Due to differences in environmental and natural characteristics, the basin area is divided into north and south regions. The majority of the northern region of the basin is mountainous, while a large part of the southern region of the basin is covered by plains.

**Fig. 1: Map of Iran showing the location of the Hable-Rud River basin, and schematic diagrams of the basin.**

## Data collection and research methods

The generation of a predicted land cover map for 2040 involved the following main steps: (1) satellite image preparation, (2) georeferencing and classification of images, (3) generate the transition area matrix and the predicted land cover maps for 2000 and 2017, (4) generate the predicted land cover map for 2040 using the CA-Markov model, and (5) interpretation long term precipitation and hydrometric data. The flowchart of the prediction process is illustrated in Fig. 2.

**Fig. 2: Flowchart of the research methodology**

## Image preparation

For this study, Landsat satellite images for the years 1986, 2000 and 2017 were applied to extract land cover and show changes in land cover, with a resolution of 900 m2 and Path/Row codes of 163/35, 163/36, 164/35 and 164/36 (Fig. 3). The images were radially and atmospherically corrected because the TM and Operational Land Imager (OLI) sensors are different; the geometric correction for the year 2000 was based on the digital elevation model data of the study area. The detailed data are shown in Table 1. There are many difficulties in simulating and predicting land cover using remote sensing images when simultaneously including the conditions of upper mountainous areas and downstream desert areas, and combining these conditions using different sensor technologies (TM and OLI sensors) on Landsat imagery.

**Table 1: Specifications of Landsat images used in this study**

**Fig. 3: Path-row codes covered in the Hable-Rud River basin**

## Land cover classification

The Maximum Likelihood classification method was applied for extracting land cover maps. The maximum likelihood classification is a supervised statistical classification approach in which class signatures are assumed to have normal distributions. This step was performed using ENVI 5.1 and ArcGIS 10.3 based on the UTM WGS 1984 zone 39N projection system.

The study area was divided into six main classes: Rangeland, Bare land, Saline land, Agricultural land, Township industrial land and Residential areas (Table 2). Training samples were collected for these defined classes from Landsat images with the support of information available in Google Earth. A stratified random sampling technique was used for sampling.

**Table 2: Class delineation based on supervised classification**

## Land cover transition and prediction

We adopted the approach of Transition analysis in investigating variation in the extent of land cover change. The approach provides a method for detailed analysis of land cover change in an area. Transited analysis depends on post-classification categorical image maps at two or more time points. Consequently, successive image pairs (1986–2000 and 2000–2017) were used to generate the transition matrix of each interval in Idrisi TerrSet software. To do this in the land changing model, the probability matrix and the area of land cover changes were obtained by using the Markov Chain model. This matrix indicates the probability of changing from one land cover class to another over the course of the study period. Then, based on major changes in the study area, six sub-models of land cover inter-conversion were defined. These sub-models included: 1. bare land conversion to rangeland; 2. rangeland conversion to agricultural land; 3. bare land conversion to saline land; 4. rangeland conversion to saline land; 5. rangeland conversion to bare land; and 6. saline land conversion to bare land. Remarkable descriptive variables as input were used to train Artificial Neural Network-Multilayer Perceptron (ANN-ANN-MLP) to make transition potential maps. Artificial neural network (ANN) is created based on the statistical training theories which are proper for resolving nonlinear problems and applications to make a relation between input variables (Wang, Shen, Tang, & Skitmore, 2013). The MLP-ANN is known as the most practical type of ANN. MLP consisted of three types of layers: an input layer, a hidden layer, and output layer. Each of these layers consisted of units called neurons. The descriptive variables to build each sub-model included digital elevation models, slope and aspect (derived from digital elevation models), distance to roads and rivers, and distances to all land cover layers including agricultural land, saline land, bare land, range land, residential areas and township industrial land as. Finally, by using the Multi-Layer Perceptron (MLP) neural networks (Razavi & Karamouz, 2007; Razavi & Tolson, 2011), Change Transition Probability maps for each land cover class were generated. The final results of these sub-models are the Transition Probability maps for all existing land cover classes in the area under study.

## Model validation

The validation method tries to adjust the quality of the predicted map for 2017 concerning to the extracted map for 2017. The validation of a model can be achieved mainly through two different approaches: the visual and the statistical approaches [8]. In the visual validation, there is a three-way cross-tabulation among the extracted maps for 2000 and 2017, and also the predicted map for 2017 to run and illustrate the accuracy of the model results. The output is a map which has four following sections [8]:

(1) Hits: Model predicted changes and they happened in reality.

(2) False alarms: Model predicted changes for each class while they persisted in reality.

(3) Misses: Model predicted persistence while they happened in reality.

(4) Null success: model did not predict changes and they did not happen in reality.

A second approach is a statistical approach that considers the agreement between two maps that show any certain variable, which can have any number of categories [8]. To validate the model, the predicted map for 2017 was examined against the extracted map for 2017 (in reality), applying statistical approaches, via Kappa index which is calculated based on Eq.1 (Cohen, 1960). The map of reality worked as the reference map, while the predicted map is the comparison map.

|  |  |
| --- | --- |
|  | (1) |

Where,(The relative observed agreement between two maps), and (The probability of chance agreement). It means k=1 has a complete agreement and k=0 has a lack of agreement.

# Results

### Land cover extraction for the past

Land cover classification results with the maximum likelihood method for years 1986, 2000 and 2017 are shown in Fig. 4. In this study, 142 polygons for Landsat TM, 139 polygons for Landsat ETM+ and 154 polygons for Landsat OLI were selected to evaluate the accuracy of classification. The assessment results for the three periods of images are shown in Table 3. Overall classification accuracy in 1986, 2000 and 2017 was 84.13%, 87.14% and 93.78%, respectively, with Kappa indices of 0.756, 0.788 and 0.811, respectively.

**Fig. 4: The classification land cover maps extracted from ENVI 5.1 for 1986, 2000 and 2017 for the Hable-Rud River basin**

**Table 3: Classification accuracy verification values**

The area and area percent of land cover differences for 1986, 2000 and 2017 are shown in Fig. 5. From Fig. 5, it can be concluded that rangeland comprised the greatest area within the study area. The rangeland areas were 7904, 6715 and 5581 km2 in 1986, 2000 and 2017, respectively. Corresponding areas for bare land were 3249, 3808 and 4344 km2 and those for saline land were 954, 1319 and 1823 km2. From these land area values, it is evident that from 1986 to 2017 rangeland area was decreasing, while areas of bare land and saline land area were increasing. Simultaneously, areas of agricultural land, residential areas and township industrial land were also increasing. Thus, according to these trends, there was a gradual conversion of rangeland to other classes of land cover during this 32-year period. There are many reasons for the conversion of rangeland to other classes of land cover. One of the main reasons is that the study area is situated in an arid region which faced several years of drought from 1986 to 2017. Secondly, during this period, rangeland was widely available for conversion to other land cover classes.

**Fig. 5: Changes in land cover area and percent of land cover changes for 1986, 2000 and 2017 for the Hable-Rud River basin**

### Land cover conversion

For the 1986 to 2000 period, the area of rangeland that was converted to other land cover classes was 1904 km2, or a decrease of approximately 24%. During the same period, the area that was converted into rangeland was 711 km2, so the net decrease in rangeland was 1193 km2 or approximately 15% (Table 4, Fig. 6). Conversion of other land classes to bare land was 1521 km2, an increase of approximately 48%. However, the conversion of bare land into other land classes was 960 km2, so the net increase in bare land was approximately 17%. The area of saline land increased by 842 km2 (approximately 88%), but with conversion into other land classes of 476 km2, the net gain was 38%. The area converted into agriculture land was 423 km2 whereas loss of agricultural land was 171 km2 for a net gain of 46%. For township industrial land and in residential areas, area increases exceeded decreases because of rapid population growth. The greatest land cover class area changes between years 1986 to 2000 were related to rangeland, the area of which decreased by 1193 km2 (15 %). In contrast, increases were observed for agricultural land [252 km2 (46%)], saline land [367 km2 (38%)], bare land [561 km2 (17%)], township industrial land [5.74 km2 (3%)] and residential areas [7.57 km2 (3%)]. The total area of land conversion for all land classes from 1986 to 2000 was 3513 km2 with most of the change related to rangeland (1903 km2). In other words, the reduction in the rangeland area was essentially equal to the increase in all other land class areas.

**Table 4: Area changes in land cover maps from 1986 to 2000, 2000 to 2017 and 1986 to 2017.**

From 2000 to 2017, rangeland was the land cover class with the greatest gains (25%) and losses (27%), with a net 2% loss of 136 km2 (Table 4, Fig. 6). The land cover class with the greatest difference between gains (15%) and losses (42%) was saline land which experienced a 347 km2 decrease (26%). Fifteen percent of bare land was converted into other land cover classes whereas the conversion into bare land was 29%, resulting in an increase in bare land area of 483 km2 (13%). This increase in area of bare land most likely resulted from a shortage of rainfall during the 2000 to 2017 period with consequent losses from range land and saline land. There was little conversion of agricultural land, township industrial land and residential areas during this period. Total conversion of one land cover class to another from 2000 to 2017 was 2983 km2 and most of the changes were related to rangeland (1844 km2). Total land conversion in 2000-2017 was 15 % less than that in 1986 to 2000.

**Fig. 6: Comparison of land cover Gains and Losses from (a) 1986 to 2000, (b) 2000 to 2017 and (c) 1986 to 2017 for the Hable-Rud River basin**

During 1986 to 2017, the area of rangeland experienced the greatest percent inter-conversion with other land classes that resulted in 40% gains and 53% losses (Fig. 7e) for a net loss of 13% (Table 4). Corresponding values for bare land were 29% and 15% (Fig.7a), respectively, for a net gain of 14%, and those for saline land were 26% and 18% (Fig. 7b), respectively, with a net gain of 8%. The area of agricultural land experienced very little inter-conversion with other land classes (Fig. 7f) and showed a net loss of 4%. No significant area inter-conversion occurred with either residential area (Fig. 7d) or township industrial (Fig. 7c). There was no significant change in residential area (Table 4) during the 1986 to 2017 period, but township industrial land showed a 2% increase most likely due to rapid population growth, advances in industry and economic development. Generally, the area of rangeland from 1986 to 2017 decreased by 2323 km2 while bare land, saline land, agricultural land, township industrial land, and residential areas increased by 1095, 869, 345, 150, and 130 km2, respectively. The maximum and minimum area inter-conversions occurred during the 1986 to 2017 and 2000 to 2017 periods, respectively.

**Fig. 7: Map of the gains and losses in different land classes from 1986 to 2017: a) bare land; b) saline land; c) township industrial land; d) residential areas; e) range land; and f) agricultural land for the Hable-Rud River basin**

### Transition area matrices

The descriptive variables used to construct each of the sub-models of land cover change are presented in Table 5. Besides descriptive variables, Table 5 shows other features of the Multi-layer Perceptron (MLP) model for the construction of sub-models. Accuracy is a parameter that is used to express the validity of the MLP model. Greatest (86.20%) and least (49.86%) accuracy were related to the sub-models of saline land to bare land and rangeland to agricultural land, respectively. The maximum number of variables used was 9, including slope, aspect, digital elevation model and the maps of distances to rivers, roads, township industrial land, residential areas, saline land, and agricultural land.

After creating each of the sub-models (Table 5), the MOLA model was used to predict the land cover map in 2040. Based on these sub-models, the model identifies the pixels that have the most probability of converting to specific land cover classes in the target year and allocates them to the classes. As a result, the spatial distribution pattern of land cover for 2040, based on the probability of future changes, can be modeled and predicted. The transition probability maps for all six sub-models are shown in Fig. 8. The Kappa Index of Agreement indicates the overall accuracy between the two reference maps and comparisons. One of the disadvantages of the standard Kappa index is that it ignores the position and quantity of pixels that have been categorized. In fact, it examines the chance agreement between two reference maps and comparisons. For this reason, in order to obtain a more accurate estimation by the model, the use of the quantity Kappa index and location Kappa index has been suggested (Pontius & Malanson, 2005). In the current study, the values for the standard Kappa index, quantity Kappa index and location Kappa index were 74%, 83%, and 79%, respectively.

**Table 5: Specifications for different land cover conversion sub-models from 1986-2000 for the Hable-Rud River basin**

**Fig. 8: The transition probability maps of land cover during 1986 to 2000: a) Sub-model of bare land conversion to rangeland, b) Sub-model of rangeland conversion to agricultural land, c) Sub-model of bare land conversion to saline land, d) Sub-model of rangeland conversion to saline land, e) Sub-model of rangeland conversion to bare land and f) Sub-model of saline land conversion to bare land for the Hable-Rud River basin**

The state transition area matrix and state transition probability matrix were created from the land cover maps for 1986 and 2000. Then, the land cover map was predicted for 2017 and this prediction was compared to the extracted map from ENVI in 2017. Finally, because the overall Kappa index was close to (74%), the land cover could be predicted for 2040 (Fig. 9). As seen in Fig. 10, the area of rangeland increased by 181 km2 whereas the areas of bare land, saline land, and agricultural land decreased by 416, 386 and 300 km2, respectively, compared to values extracted for 2017. On the other hand, the area of rangeland and bare land in 2040 decreased and the area of saline land, agricultural land, township industrial land, and residential areas has increased compared to the predicted map for 2017. Saline land in the land cover map of 2040 has increased, especially in the south-east of the basin, whereas the area of rangeland decreased more in the south-west of the basin. Increases in residential areas, township industrial land and agricultural land can be the result of rapid population growth; in contrast, both the decrease in rangeland and increase in saline land can result from drought and rapid population growth.

**Fig. 9: The extracted and predicted land cover classification: a) extracted map from ENVI for 2017, b) predicted map for 2017 and c) predicted map for 2040 in the Hable-Rud River basin**

**Fig.10: Area changes for extracted and predicted land cover classification for the Hable-Rud River basin**

### Consequences of land changes

Most land cover changes samples for each class in the past and the future are shown in Fig.11. The Figure shows some remarkable anthropogenic changes in agriculture, rangeland degradation, residential and industrial areas expansion. These changes are more visible for 2017 based on Landsat 8 and showing a big growth in agriculture, residential and industrial areas. The last column well shows the change in area for each class, the area was calculated based on square kilometers. This should be noted that the increase in some classes such as agriculture, residential and industrial areas will increase water consumption. Obviously, these expansions in the first stage affect output stream flow. Water flow fluctuations are largely attributed to anthropogenic activities such as changes in the land use patterns, develop in the agriculture area, decrease in forest cover, urbanization, and streamflow regulations (Sharma, Patel, & Jothiprakash, 2019).

**Fig.11: Illustration of transitional changes for main land cove classes and the predicted area for 2040 in the Hable-Rud River basin**

The present study is indicative of the large influences that land cover change has on water resources. Based on the data those were collected from the Garmsar Synoptic station and Bonkouh hydrometric station, as shown in Fig.12, streamflow and precipitation trends revealed that rainfall decreased slightly in the studied period, while the trends of the observed streamflow showed a remarkable reduction. Before 1995, the streamflow and precipitation followed similar trends (Fig.12). Approaching to 2017, the precipitation and streamflow represent different trends and behavior. The annual of precipitation during 1986-1996, 1997-2007, and 2008-2014 was measured approximately 125.5 mm, 127mm, and 88mm, respectively. Besides, the annual of streamflow in these years was calculated approximately 9m3/s, 5.8m3/s, and 5.1m3/s, respectively. Moreover, precipitation declined by approximately 29%, while the streamflow declined by 44% over the same period (Fig.12).

**Fig. 12: link between precipitation and streamflow trends in the area under study**

The results signified that streamflow declined almost 1.5 times more than the reduction in precipitation, which can be attributed to increased water withdrawal because of land cover change, especially agricultural activities.

# Discussion

The research combined Remote Sensing (RS) and Geographic Information Systems (GIS) techniques as well as applied the LCM and the Markov chain prediction model to enable investigating land cover change. For this purpose, a supervised classification technique is applied to Landsat images acquired for 1986, 2000 and 2017. Then, Appling a pixel-by-pixel change detection, the land cover changes are predicted for 2017 and 2040 using the CA-Markov model. The environmental variables used include slope, aspect, elevation, and calculated distances from various land features such as rivers, roads, industrial areas, residential areas, saline lands, and agriculture. The outcomes showed that the model can predict land cover changes in the study area with an accuracy of 74% based on the Kappa index. The patterns of land cover change over the past 32 years showed that the bare land, saline land, agriculture, industrial areas, and residential areas have increased at an average rate by approximately ~8, ~6.2, ~2.7, ~0.63 and ~0.48%, respectively, while rangeland has decreased by approximately ~18 %. Based on the predicted outcomes for 2040, the areas of rangeland and saline land will increase by approximately ~6.5 and 2%, while the areas of bare land and agricultural land will decrease by approximately ~6 and 2%, respectively. Land cover change occurs at the local scale, but its ecological impacts spread across regional and global scales (Foley et al., 2005). Most of the lands that are currently under agricultural practicing, were occupied by forests, rangeland, and wetlands in the past; this conversion has resulted in the loss of biodiversity associated with these natural habitats (Castelletta, Sodhi, & Subaraj, 2000; Fang, Rao, & Zhao, 2005).

According to the captured satellite images for years 1986, 2000 and 2017, rangeland has some significant changes in this period. Most changes took place in 2000 and with a decreased area of 790416 to 671467 hectares during 1986-2000 period, and also this reduction continued from 2000 to 2017. Although the rangeland class has decreased over the past 32 years, the agriculture class has increased and it seems to be the main reason for the reduction in rangeland. Based on Fig.11 there are some remarkable anthropogenic changes in agriculture, rangeland degradation, residential and industrial areas. Development of agriculture (both rainfed and irrigated) started at least two decades ago when the Iranian government implemented a new strategy for agricultural products (Madani, 2014). The government raised economic growth with increased agricultural production. More production not only needs more land but also, in this case, more water withdrawal. Meantime, ensuring food security led to the expansion of the agricultural area mostly at the cost of rangeland (Shirmohammadi et al., 2020). The Fig.11 showed that most changes happened between agriculture and rangeland classes. Implementation of development projects without considering the principles of sustainable development, as well as socioeconomic matters, let stakeholders be unrestricted in changing rangeland to agriculture, particularly within 1993–2004 (Alipour & Olya, 2015) Nevertheless, land cover plays a significant role in the sustainability of water resources in a basin and can have both direct and indirect influences that are beyond the borders of basins (Alipour & Olya, 2015; Faramarzi, 2012). The water resources of a river basin primarily depend on input variables such as precipitation (Shirmohammadi et al., 2020). This should be noted that the rise in some classes such as agriculture, residential and industrial areas will raise water consumption. As shown in Fig.12, streamflow and precipitation trends exposed that precipitation declined slightly in the studied period, while the trends of the observed streamflow presented a striking reduction. Although before 1995 the streamflow and precipitation followed similar trends, approaching to 2017, the precipitation and streamflow represent different trends and behavior. This should be noted that precipitation declined almost 29%, while the streamflow declined almost 44% over the same period (Fig.12). This means that streamflow declined approximately 1.5 times more than the reduction in precipitation, which can be attributed to increased water withdrawal because of land cover change, especially agricultural activates.

Rangeland degradation has led to the siltation of rivers, and wetland restoration has decreased the capacity of river basins to regulate stream flow and, as a result, extensive flooding has resulted. Both of these activities alter freshwater habitats, making the decline or disappearance of species therein (Dudgeon, n.d.; Kumar & Kanaujia, 2018). Deforestation and rangeland degradation created also significant threats to the flora and fauna that live inside (Zhao et al., 2006). This investigation gives an entry point for land cover as part of the discussion on more sustainable and adaptive water management in the basin. Consequently, the outcomes presented in the study should be interpreted as an approach to discuss and create awareness of the consequences of land cover change.

# Conclusion

The results of this investigation indicate that the supervised classification of remote sensing images is a reliable method for extracting appropriate land cover maps. This paper explores the simulation of future land cover changes in the Hable-Rud River basin using a CA–Markov model in combination with GIS technology. Based on this model the prediction for the year 2017 was validated (standard Kappa index = 0.74 %). Therefore, it can be concluded that the CA-Markov model is an important tool for land cover prediction and defining goals for sustainable land cover development. The patterns of land cover change during the 32-year 1986-2017 period showed that the bare land, saline land, agricultural land, township industrial land, and residential areas have increased by approximately 8, 6.2, 2.7, 0.63 and 0.48%,respectively, while rangeland has decreased by approximately 18%. According to the predicted results for 2040, the areas of rangeland and saline land will increase by approximately 6.5 and 2%, respectively, while the areas of bare land and agricultural land will decrease by approximately 6 and 2%, respectively. As results showed, the long term annual average streamflow has reduction by 44%, while the long term annual average precipitation has reduction only by 29%, it means large proportion of these changes can result from drought conditions, rapid population growth and industrial development, but further investigations are needed to discover if these factors are the main cause for these changes. The output of the prediction in this research could serve as spatial guidelines for monitoring future trends of land cover dynamics as well as to address threats that bring from changing in residential areas and agriculture. Hence, the rapid growth of residential areas and agriculture in some parts of the basin have significantly affected rangeland cover and bare land as well as causing environmental damage. Several negative consequences of losing rangeland cover and bare land can be distinguished, such as poor quality of the environment, increasing water consumption, rangeland degradation, as well as higher chronic morbidity.

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