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Full Length Article

Forecasting of land use changes based on land change modeler (LCM) using remote sensing: A Case Study of Talar Watershed, Mazandaran Province, Northern Iran

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ABSTRACT

Land use dynamics play vital role in the ecological sustainability of any region. One of the important features in any watershed is land use changes and it is important for social, economic and regional development and environmental changes. Today, techniques such as remote sensing and geographic information system (GIS) are useful for the early identification and evaluation of land use changes and it can be useful tool for planning and management environment. The main objective of this paper is to predict and analyze the present and future land use change of Talar Watershed, Mazandaran Province, using Landsat satellite images of 1985, 2000 and 2015. These data are used for change prediction and for preparation of prediction map of year 2025, 2040 and 2055. IDRISI, Land Change Modeler (LCM) was used to analyze the land use change between various classes. The result shows that during the 1985–2015, the percentage of forest land and rangeland has decreased, due to increase of population and increase of livestock in village which grazing more than rangeland capacity. In contrast, percentage of the garden land, Rain-fed agriculture, irrigated and residential land increased during the 1985 and 2015. Results of LCM show that between 2015 and 2055 it was observed the area of forest land has been decreased and degraded. The Rangeland, gardens, Rain-fed agriculture, irrigated and residential area have been increased according to the process of increase of population and industrialization, during this period. As a result, we indicated that distance from the forest lands and Slope showed the highest and lowest Cramer's coefficients in different land use with different scenarios, for all the conversion types.

Key words: Land use, Land change modeler, Talar Watershed, Remote Sensing

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INTRODUCTION

Land use changes have many faces, and these changes are often not carried out in a sustainable way. Land use change is important for social, economic and regional development, environmental changes and rooted in the spatiotemporal interaction between biophysical and human aspects [4, 5]. Changes in land use encompass the greatest environmental concerns of human populations today, including species extinction [8] biodiversity loss [16], declines in water quality and air quality [17], increases in carbon dioxide emissions [7], and climate change at regional and global scales [11]. These changes will finally influence significant aspects such as human health, ecosystem quality and natural resources [1]. In this context, it is much needed to estimate the land use changes over the time and predict the future scenario. Today, there are several ways and methods for monitoring environmental changes for evolution of land use change, traditional methods and large-scale precision land surveying on the ground is expensive and time-consuming and, in some cases, impossible [2]. Application of remotely sensed data made possible to study the changes in land cover in less time, at low cost and with better accuracy. Satellite remote sensing, in conjunction with geographic information systems (GIS), has been widely applied and has been recognized as a powerful and effective tool in detecting land use change. (Peled and Gilichinsky, 2013; Ye and Fang, 2011). Remote sensing technology offers high spatial resolution and is a valuable mechanism for the monitoring, diagnosis, identification and zoning of natural resources, especially in land-use mapping [120]. For this study, analysis is performed by a remote sensing based Land Change Modeler (LCM) method. Based on past trend (from 1985-2015) of land use changes, the future land use prediction map of Talar watershed for the year 2025, 2040 and 2055 have been generated.

Some extensive research efforts have been made by international scholars for land use change detection using remotely sensed images and land change modeler. Roy et al [18] investigated prediction of land cover change in a Mediterranean catchment at different time scales including short (2003-2008), intermediate (1982-2003), and long (1950-1982) using Land Change Modeler (LCM) of IDRISI. Good to perfect level of spatial and perfect level of quantitative agreement were observed in long to short time f scale simulations. Kappa indices (K quantity = 0.99 and K location = 0.90) and confusion matrices were good for intermediate and best for short time scale. The results indicate that shorter time scales produce better predictions. Aithal et al [3] investigated Land use Dynamics in the Rapidly Urbanizing Landscape using Land Change Modeler. The results suggest an urban expansion of 108% (from 59103.9 in 2012 to 123061.6 hectares in 2020), with the decline of green space to 7% from 33.68% (2012). Kurt [10] investigated Land Use Changes in Istanbul's Marmara Sea Coastal Regions. Landsat 30 m satellite images from 1987 and 2007 are used in the study. The results indicate that residential areas increased by 45% in the two decades while agricultural areas decreased by 64%, forest areas by 97%, free land by 15% and bush and grass land by 54%. Rawat and Kumar [15] presented the spatio-temporal dynamics of land use/cover of Hawalbagh block of district Almora, Uttarakhand, India by using remote sensing and GIS techniques. The results indicate that during the last two decades, vegetation and built-up land have been increased by 3.51% (9.39 km2) and 3.55% (9.48 km2) while agriculture, barren land and water body have decreased by 1.52% (4.06 km2), 5.46% (14.59 km2) and 0.08% (0.22 km2), respectively. The aim of this study is to evaluate land use changes in Talar watershed. For this purpose, Landsat-TM's images of 1985, 2000 and 2015 were used and land use changing was studied.

MATERIALS AND METHODS

-The study area

Talar watershed the area of which is 1762 km^2 is located in the northern part of Iran, within the limits of 35° 44' 41" to 36° 19' 13" Eastern longitudes and 52° 35' 38" to 53° 23' 56" Northern latitudes which drains by a main river named Talar that stretches from south to north [9]. Figure 1 shows the location of the study area in Iran. The climate of the zone is semi-humid and cold, and its average annual precipitation is 791 mm and average temperature is 11°C. The maximum and minimum height of the watershed is 3910 and 215, respectively. The average slope of the watershed, the average slope of the main channel, and the length of the main channel are 15.8%, 13%, and 100 km, respectively. There is a hydrometer station in the outlet of the watershed and a rainfall recorder station in the upstream of it.

METHODOLOGY

- The method of case study

At the firs the study area with 1:2500000 topography maps was determined. The satellite images of 1985, 2000 and 2015 have been used for investigating the land use changes during the recent three decades (Table 1).

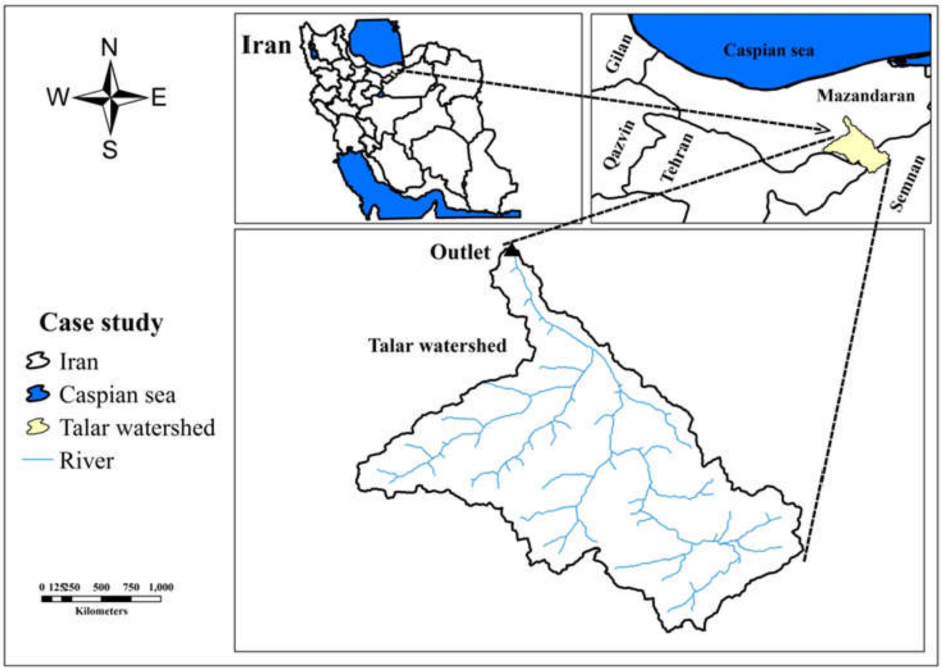

Fig. 1. Study Area

Table 1. Landsat data sources

satellite	Sensor	Spatial resolution (m)	Scene (Path/ row No.)	Date
Landsat 5	TM	30	163-035	14-06-1985
Landsat 5	TM	30	163-035	19-07-2000
Landsat 8	OLI	30	163-035	24-06-2015

After preparing Satellite Images from USGS website, Pre-processing, processing and post-processing was done on these images in order to extract the land use map. To fix atmospheric error in the images of TM and OLI Land sat, QUICK Atmospheric Correction Module in ENVI 5.1 software was used [13]. To classify the images, training samples were taken using simple random sampling from the studied area [12]. These samples were taken from areas that show a homogeneous type of vegetation within 30 meters so that the area of each of the training samples is equal to at least 6 pixels of the image for every use. The next step is to choose appropriate algorithms for classification, which is the most important step in the classification. In this study, the algorithm of maximum likelihood was used [13]. Satellite images classification using the algorithm of maximum likelihood in most cases is more accurate than the classification with minimum distance and Parallelepiped algorithms [14]. The Number of training samples for each of the satellite images of the years of 1985, 2000 and 2015 was 182 samples which 70% of the data was used for calibration and 30 % of it was used for model validation. After classification of satellite images, six classes including irrigated agriculture, Rain-fed agriculture, forest lands, rangelands, gardens and residential lands were selected considering appropriate composition using maximum likelihood algorithm. Schulz et al [19] stressed the importance of these variables in modeling land use changes. Then the land use map for the years of 1985, 2000 and 2015 was prepared and these maps were evaluated with ground truth maps, topographic maps and field operations and local query. After the formation of error matrix, the assessment of validity of classification results based on overall accuracy, Kappa coefficient, Producers Accuracy and User Accuracy was done.

- Application of LCM for Land use Modeling

Land Change Modeler (LCM) is an integrated software environment for analyzing and predicting land use change, and for validating the results [6]. It is embedded in the IDRISI software, where only thematic raster images with the same land cover categories listed in the same sequential order can be input for land use change analysis [18]. LCM evaluates land use changes between two different times, calculates the changes, and displays the results with various graphs and maps.

- Change detection analysis and prediction using LCM method

This category is a process that determines the condition changes of phenomena from the images obtained at different times. This technique is often used for the study of environmental change [22]. After preparing the land use maps for the years of 1985, 2000 and 2015, it was started to detect changes and to investigate changes happened during the time period studied. In this study, land use maps of years of 1985- 2000, 2000-2015 and 1985-2015 were entered LCM model to analyze and detect changes of the area. In this study, each of the periods was considered as a scenario. The periods of 1985- 2000, 2000-2015 and 1985-2015 were named scenario A, B and C respectively.

- Potential transfer modeling

In this part of the modeling, transmission power of a user (such as forests) to other users (such as agriculture) is done according to the explanatory variables of the model. At this stage, three scenarios with 6 variables (Digital elevation model (DEM), slope, distance from residential areas, distance from the forest, distance from the road and distance from the river) were considered. When variables were selected for each scenario, any transfer was modeled using logistic regression. Finally the output of this section is a map of changes and tables with coefficients of all the variables and Relative Operating Characteristic (ROC) value. Table 2 shows that provided transfer maps in different scenarios. The variable of digital elevation model, slope and distance from the river were considered as static variables and the distance of the forest, distance from residential areas and distance from road were entered to the model as dynamic variables (dynamic with time) .Outputs of the potential transfer stage are applied as the inputs of the stage of changes prediction. The value of changes of each transfer is predicted by Markov chain [13].

RESULTS

To assess the accuracy of the produced maps, the kappa coefficient and overall accuracy coefficient were used. The results of validation of maps are presented in table 3. The area of different uses related to this year is presented in Table 4. The land use map in 1985, 2000 and 2015 showed in figure 2.

Table 2. Provided transfer maps in different scenarios

Row	Transfer types	Scenarios		
		A	B	C
1	Forest lands to Pasture lands	✓	✓	✓
2	Forest lands to Rain-fed agriculture	✓	✓	✓
3	Forest lands to Garden lands	✓	✓	✓
4	Forest lands to Residential lands	✓	✓	✓
5	Pasture lands to Rain-fed agriculture	✓	✓	✓
6	Pasture lands to Irrigated agriculture	✓	✓	✓
7	Pasture lands to Residential lands	✓	✓	✓
8	Rain-fed agriculture to Garden lands	✓	✓	✓
9	Rain-fed agriculture to Residential lands	✓	✓	✓
10	Garden lands to Residential lands	✓	✓	✓

Table 3. The Kappa coefficient and the overall accuracy of the produced maps

Landsat name	Used bands	Classifier algorithm	Kappa coefficient	Overall validity (%)
TM	1-7	Maximum likelihood	0.74	78.78
TM	1-7	Maximum likelihood	0.78	82.42
OLI	1-7	Maximum likelihood	0.85	88.18

Table 4. Area of different uses in the case study area

Year	1986		2000		2015	
Land use name	Square kilometer	Percent	Square kilometer	Percent	Square kilometer	Percent
Residential lands	11.697	0.664	15.592	0.885	29.196	1.657
Forest lands	594.490	33.731	552.023	31.332	539.262	30.598
Pasture lands	1085.380	61.584	1074.127	60.946	1052.584	59.724
Rain-fed agriculture	13.977	0.793	15.535	0.881	20.971	1.190
Irrigated agriculture	47.258	2.681	93.416	5.300	101.198	5.742
Garden lands	9.630	0.546	11.722	0.665	19.206	1.090
Total	1762.41	100	1762.41	100	1762.41	100

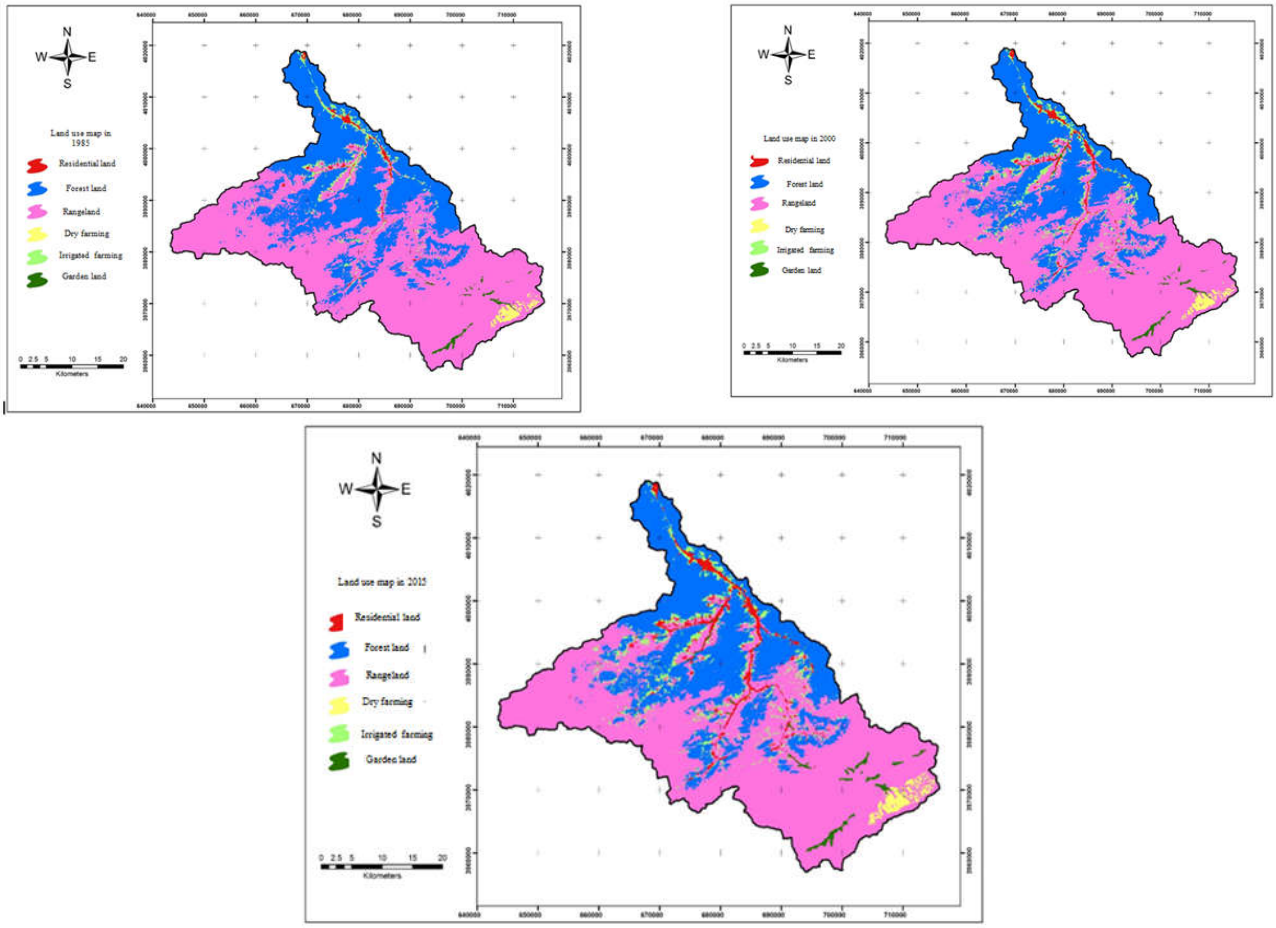

Fig. 2. Land use map in 1985, 2000 and 2015.

Single parameters such as kappa coefficient and overall accuracy only deal with the entire classification and do not provide information about individual classes or spatial distribution of error. So in order to assess the accuracy of the produced land use map, user accuracy and manufacturer accuracy were calculated and appointed and removed errors related to land use classes were studied. At the end, the results of verification are provided in Table 5.

Tables 6 shows the results of the validation of maps produced for the years 1985, 2000 and 2015 according to the number of training points in the validation stage. Table 7 shows Cramer's coefficients for different land use in different scenarios. This coefficient shows the relationship between variables and land cover classes [21].

Distance from the forest lands and Slope showed the highest and lowest Cramer's coefficients in different land use with different scenarios, in the whole land (table 7). The results of modeling of the potential for transfer of different uses to each other using logistic regression during the years 1365 to 1394 are shown in Table 8. The coefficients that affect each explicative variable in the logistic regression equation, and the correlation degree between variables and transitions (ROC) are included. According to this table, the correlation between transfers and variables was in the range of 0.5909 to 0.9884 for the first scenario, in the 0.6788 to 0.8900 for the second scenario and it was in the range of 0.7092 and 0.9123 for the third scenario that shows a high correlation between transfers and the variables. The sign of the coefficients of the logistic regression equation allows us to know if the relation between the variables is direct or inverse [21].

Table 5. Evaluation results of the validity of Classification maps

Year	Land use type	User accuracy	Producer accuracy	Appointed error	Removed error
1986	Rain-fed agriculture	90.91	83.33	16.67	9.09
	Forest lands	90.91	94.34	5.66	9.09
	Garden lands	60	60	40	40
	Residential lands	83.64	66.67	33.33	16.36
	Irrigated agriculture	81.82	83.33	16.67	18.18
	Pasture lands	65.45	92.31	7.69	34.55
2000	Rain-fed agriculture	96.36	84.13	15.87	3.64
	Garden lands	78.18	89.58	10.42	21.82
	Residential lands	54.55	71.43	28.57	45.45
	Irrigated agriculture	83.64	76.67	23.33	16.36
	Forest lands	92.73	94.44	5.56	7.27
	Pasture lands	89.09	77.78	22.22	10.91
2015	Rain-fed agriculture	96.36	88.33	11.67	3.64
	Garden lands	92.73	91.07	8.93	7.27
	Forest lands	65.45	81.82	18.18	34.55
	Residential lands	94.55	85.25	14.75	5.45
	Irrigated agriculture	92.73	92.73	7.27	7.27
	Pasture lands	87.27	88.89	11.11	12.73

Table 6. Validation of lands different classes using validation data (according to the number of training points)

Year	Land use	Rain-fed agriculture	Forest lands	Garden lands	Residential lands	Irrigated agriculture	Pasture lands
1986	Rain-fed agriculture	50	0	10	0	0	0
	Forest lands	0	50	1	0	2	0
	Garden lands	5	5	33	3	5	4
	Residential lands	0	0	6	46	2	15
	Irrigated agriculture	0	0	5	4	45	0
	Pasture lands	0	0	0	2	1	36
	Total	55	55	55	55	55	55
2000	Land use	Rain-fed agriculture	Garden lands	Residential lands	Irrigated agriculture	Forest lands	Pasture lands
	Rain-fed agriculture	53	0	10	0	0	0
	Garden lands	0	43	5	0	0	0
	Residential lands	2	4	30	4	2	0
	Irrigated agriculture	0	4	2	46	2	6
	Forest lands	0	0	3	0	51	0
	Pasture lands	0	4	5	5	0	49
	Total	55	55	55	55	55	55
2015	Land use	Rain-fed agriculture	Garden lands	Forest lands	Residential lands	Irrigated agriculture	Pasture lands
	Rain-fed agriculture	53	0	7	0	0	0
	Garden lands	0	51	3	0	0	2
	Forest lands	2	2	36	0	3	1
	Residential lands	0	1	3	52	1	4
	Irrigated agriculture	0	1	3	0	51	0

Pasture lands	0	0	3	3	0	48
Total	55	55	55	55	55	55

Table 7. Cramer's coefficients for different land use in different scenarios

	Scenario A by 1986-2000 period						
Variable	Pasture lands	Garden lands	Irrigated agriculture	Residential lands	Forest lands	Rain-fed agriculture	Total
DEM	0.4567	0.2780	0.3876	0.1456	0.1111	0.00001	0.2567
Slope	0.1279	0.3467	0.1234	0.1897	0.1450	0.0002	0.1134
distance from the river	0.1499	0.1388	0.3249	0.3675	0.0987	0.0001	0.1780
distance from the road	0.4688	0.2587	0.3128	0.1239	0.1234	0.00012	0.2789
distance from the forest lands	0.6098	0.2238	0.2012	0.2345	0.4010	0.0009	0.4457
distance from the residential lands	0.5510	0.3498	0.5127	0.1987	0.3909	0.0008	0.3309
	Scenario B by 2000-2015 period						
Variable	Pasture lands	Garden lands	Irrigated agriculture	Residential lands	Forest lands	Rain-fed agriculture	Total
DEM	0.4433	0.2213	0.3212	0.1798	0.0876	0.0021	0.2789
Slope	0.0932	0.3050	0.1456	0.1676	0.1455	0.0008	0.1343
distance from the river	0.1232	0.1787	0.2555	0.3245	0.0843	0.0001	0.1544
distance from the road	0.4447	0.2465	0.2987	0.0897	0.0567	0.0009	0.2289
distance from the forest lands	0.6578	0.2298	0.1616	0.2232	0.4488	0.0002	0.4121
distance from the residential lands	0.5987	0.3321	0.5544	0.1717	0.4921	0.0001	0.3287
	Scenario C by 1986-2015						
Variable	Pasture lands	Garden lands	Irrigated agriculture	Residential lands	Forest lands	Rain-fed agriculture	Total
DEM	0.5359	0.2369	0.2345	0.1620	0.0700	0.0003	0.2890
Slope	0.0800	0.305	0.1352	0.1785	0.1381	0.0000	0.1129
distance from the river	0.1363	0.1515	0.2259	0.2335	0.0508	0.0001	0.1586
distance from the road	0.3418	0.2013	0.2759	0.0733	0.0630	0.0002	0.2126
distance from the forest lands	0.6934	0.1988	0.1519	0.2183	0.4325	0.0022	0.3708
distance from the residential lands	0.5658	0.2873	0.4697	0.1765	0.3333	0.0012	0.3621

Table 8. Logistic regression results for Predicting of transfer potential in different periods

Scenario	Transfer	ROC value
1986-2000	Forest lands to Pasture lands	0.7692
	Forest lands to Rain-fed agriculture	0.725
	Forest lands to Garden lands	0.7455
	Forest lands to Residential lands	0.8765
	Pasture lands to Rain-fed agriculture	0.5909
	Pasture lands to Irrigated agriculture	0.9884
	Pasture lands to Residential lands	0.9494
	Rain-fed agriculture to Garden lands	0.8992
	Rain-fed agriculture to Residential lands	0.7661
	Garden lands to Residential lands	0.7191
2000-2015	Forest lands to Pasture lands	0.7832
	Forest lands to Rain-fed agriculture	0.6788
	Forest lands to Garden lands	0.8344
	Forest lands to Residential lands	0.7899
	Pasture lands to Rain-fed agriculture	0.8900
	Pasture lands to Irrigated agriculture	0.7800
	Pasture lands to Residential lands	0.8790
	Rain-fed agriculture to Garden lands	0.7832
	Rain-fed agriculture to Residential lands	0.7612
	Garden lands to Residential lands	0.7942
1986-2015	Forest lands to Pasture lands	0.8999
	Forest lands to Rain-fed agriculture	0.7655
	Forest lands to Garden lands	0.7566
	Forest lands to Residential lands	0.8891
	Pasture lands to Rain-fed agriculture	0.9123
	Pasture lands to Irrigated agriculture	0.8674
	Pasture lands to Residential lands	0.7654
	Rain-fed agriculture to Garden lands	0.7567
	Rain-fed agriculture to Residential lands	0.8921
	Garden lands to Residential lands	0.7091

To assess the accuracy of model, the maps of land use predicted by the model and ground truth map of the year have been used. Then three important factors (overall kappa, accordance caused by the location and the value) were calculated (Table 9). The results showed that the highest kappa coefficients are related to the calibration period (1985-2015) and the lowest coefficients of kappa are related to the calibration period of (1985-2000). So the third period was considered as the best time to predict changes in land use related to 2015. At this stage the likelihood of transfer to each user using Markov chain in different calibration periods (1985- 2000, 2000-2015 and 1985- 2015) was assessed that its results are presented in table 10. The area of predicted different uses related to this year is presented in Table 11.

Table 9. Evaluation of Logistics regression accuracy in different calibration periods

Scenario	period	Matching caused by the location (K-location)	Matching caused by the value(k-no)	Overall Kappa (K-standard)
A	1986-2000	0.82	0.76	0.79
B	2000-2015	0.89	0.84	0.86
C	1986-2015	0.93	0.90	0.91

Table 10. Calculated transfer likelihood using Markov chain in different calibration periods

	Period 1986-2015					
	Rain-fed agriculture	Garden lands	Residential lands	Irrigated agriculture	Forest lands	Pasture lands
Rain-fed agriculture	0.989	0.003	0.008	0.000	0.000	0.000
Garden lands	0.000	1.000	0.000	0.000	0.000	0.000
Residential lands	0.000	0.000	1.000	0.000	0.000	0.000
Irrigated agriculture	0.000	0.000	0.000	0.997	0.000	0.003
Forest lands	0.002	0.000	0.000	0.000	0.996	0.002
Pasture lands	0.002	0.000	0.000	0.000	0.000	0.998
	Period 2015-2025					

	Rain-fed agriculture	Garden lands	Residential lands	Irrigated agriculture	Forest lands	Pasture lands
Rain-fed agriculture	0.948	0.013	0.040	0.000	0.000	0.000
Garden lands	0.000	0.999	0.001	0.000	0.000	0.000
Residential lands	0.000	0.000	1.000	0.000	0.000	0.000
Irrigated agriculture	0.000	0.000	0.000	0.978	0.000	0.022
Forest lands	0.011	0.000	0.000	0.000	0.974	0.015
Pasture lands	0.012	0.002	0.002	0.002	0.000	0.983

Period 2015-2040

	Rain-fed agriculture	Garden lands	Residential lands	Irrigated agriculture	Forest lands	Pasture lands
Rain-fed agriculture	0.864	0.034	0.103	0.000	0.000	0.000
Garden lands	0.000	0.997	0.003	0.000	0.000	0.000
Residential lands	0.000	0.000	1.000	0.000	0.000	0.000
Irrigated agriculture	0.000	0.000	0.000	0.940	0.000	0.060
Forest lands	0.030	0.000	0.000	0.000	0.928	0.042
Pasture lands	0.029	0.005	0.007	0.006	0.000	0.953

Period 2015-2055

	Rain-fed agriculture	Garden lands	Residential lands	Irrigated agriculture	Forest lands	Pasture lands
Rain-fed agriculture	0.783	0.054	0.163	0.000	0.000	0.000
Garden lands	0.000	0.995	0.005	0.000	0.000	0.000
Residential lands	0.000	0.000	1.000	0.000	0.000	0.000
Irrigated agriculture	0.000	0.000	0.000	0.903	0.000	0.097
Forest lands	0.047	0.001	0.002	0.000	0.883	0.067
Pasture lands	0.046	0.009	0.013	0.009	0.000	0.924

Table 11. Area of different land uses in the future different periods

Year	2015*		2025		2040		2055	
Land use	Square kilometer	Percent	Square kilometer	Percent	Square kilometer	Percent	Square kilometer	Percent
Residential lands	29.018	1.647	31.827	1.806	37.910	2.151	43.952	2.494
Forest lands	539.632	30.620	532.872	30.237	520.555	29.538	509.226	28.895
Pasture lands	1053.308	59.768	1055.230	59.887	1057.735	60.019	1059.609	60.125
Irrigated agriculture	20.955	1.189	22.120	1.255	24.028	1.363	25.877	1.468
Rain-fed agriculture	100.224	5.687	100.451	5.700	101.262	5.746	101.845	5.779
Garden lands	19.199	1.089	19.840	1.126	20.848	1.183	21.830	1.239
Total	1762.41	100	1762.41	100	1762.41	100	1762.41	100

* The land use of this year is related to the predicted land use using LCM model.

DISCUSSION

Accuracy assessment of the land use classification results obtained showed an overall accuracy of 78.78% for landsat 5 Tm 1985, landsat 5 tm 2000 and Landsat 8 OLI 2015 is 78.78%, 82.42% and 88.18%, respectively (Table 3). The result shows that percentage of forest land and rangeland has decreased, due to increase of population and increase of livestock in village which grazing more than rangeland capacity [2]. In contrast, percentage of the garden land, rain-fed, irrigated and residential land increased during the 1985 and 2015. During the last three decades, the residential in the study area has increased from 11.697 km2 in 1985 to 29.196 km2 in 2015 which accounts for 1.657% of the total study area (Table 4). The garden land has increased from 47.258 km2 in 1985 to 19.206 km2 in 2015 which accounts for 1.090%. The rain-fed agriculture and irrigated area has increased from 13.977 km2 and 47.258 km2 in 1985 to 20.971 km2 and 101.198 km2 in 2015, respectively (Table 4). The forest and rangeland has been decreased from 594.490 km2 and 1085.380 km2 in 1985 to 539.262 km2 and 1052.584 km2 in 2015, respectively. As a result, we obtain that distance from the forest lands and Slope showed the highest and lowest Cramer's coefficients in different land use with different scenarios, for all the conversion types. Results of LCM shows that the highest kappa coefficients are related to the calibration period (1985-2015) and the lowest coefficients of kappa are related to the calibration period of (1985-2000). In studies of Mishra et al [13] accuracy of more than 80% was obtained for all the conversion types. The results showed that between 2015 and 2055 it was observed that there is an increase in residential area by 0.847 % (Table 11). This is mainly due to housing and infrastructure development during the last three decades. Rangeland was found to increase by 0.357%. From the change detection analysis it is observed that there is an increases in garden land, dray farming, irrigated area by 0.15 %, 0.279% and 0.092 %, respectively and forest land was found to decrease by 1.725%. This reduction of the area forest land leads to the exclusion of unsuitable and erosive lands and result in higher bulk density, lower hydraulic conductivity, thereby exacerbating soil degradation and decline in SOC concentration.

CONCLUSION

Land use change is a process by which human activities transform the landscape. Today, destruction of lands and land use change are occurs in all the big cities, daily. There are many evidences that show a lot of transformation in various fields of land has created due to the demands and needs of civil society. However, conversion of different land and villages reduces the amount of lands available for food. In this work prediction of future land use in Talar watershed has been studied over a period of 30 years in the past (from 1985 to 2015) to predict the future land use in the year 2025, 2040 and 2055. Landsat satellite images of 1985, 2000 and 2015 are used for this study. Land use developed in ERDAS Imagine and the future land use was predicted using Land Change Modeler (LCM). The overall model efficiency in predicting the future land use was found more than 80%. The result shows that during the 1985–2015, the percentage of forest land and rangeland has decreased, due to increase of population and increase of livestock in village which grazing more than rangeland capacity. In contrast, percentage of the garden land, Rain-fed agriculture, irrigated and residential land increased during the 1985 and 2015. Results of LCM show that between 2015 and 2055 it was observed the area of forest land has been decreased and degraded. The Rangeland, gardens, Rain-fed agriculture, irrigated and residential area have been increased according to the process of increase of population and industrialization, during this period. This conversion of natural vegetative may have serious environmental impacts unless proper environmental management plans were implemented for this area. This kind of prediction of future land use can be helpful for planning proper environmental management.

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