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Full Length Research Paper

The landuse change detection in Taleghan catchment

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The effects of global warming, climate change and landuse changes on catchment water balance and quality have become the main concerns in the watershed water resources management in recent years. One such area is the Taleghan watershed in the Northwest of Tehran, the Iran's capital with an area of 930.62 km^2. This watershed has undergone excessive landuse changes during the last two decades due to the dam construction. Both dam construction and its reservoir have highly increased the land prices in this area, causing drastic landuse changes. Digital Image Processing (DIP) technique was introduced to recognize landuse change detection for different periods. To evaluate landuse change, the whole upper part of the watershed was considered over two decades of 1987 to 2007. The results of image processing indicated that after the approval of dam building, the watershed rangeland areas declined from 82.7 to 35.4%. Land ownership caused drastic degradation in landuse during that period. As the consequence, dry farming activities lost their stability and severely declined. The good rangeland (G1) area which was initially 32287 ha in 1987, decreased to 5693 ha by late 2007 due to overgrazing, weak landuse management and climate change. This is a significant change during the last 20 years from 34.5 to 5.90%. On the other hand, concurrently, the poor rangeland increased from 19.0 to 23.4%. Immigration and rush for land purchase and suburb house construction increased the percentages of rural area to urban textures which translates to 3.1 km^2 in 2007 compared with its original density of 1.74 km^2 in 1987.

Key words: Taleghan, landuse, image processing.

INTRODUCTION

Landuse change is one of the most important challenges in many regions of the world. Land use as the classification of land according to the actions undertaken on the area by people has undergone many changes in many parts of Iran, including Taleghan watershed in northwest of Tehran, the capital. In recent years, due to rapid population growth, the Taleghan watershed has undergone rapid landuse change, urbanization, and water resource development for agriculture, industry and domestic supply. In order of water supply to Tehran, the Taleghan dam was constructed during 2001 and 2006.

Hence, the government is concerned over the significant landuse changes resulting from acceleration in land development and village and urban expansion. These changes could have devastating effects on both water balance and water quality in the catchment in near future. Image processing is a suitable technique for landuse classification which uses spectral bands. One of the main steps of image analysis involved in this research was identifying groups of pixels that have similar spectral characteristics and determining the various features or landuse classes represented by those groups. This form of analysis is known as image classification where the objective is to match ground information classes to relevant spectral classes recorded by satellite.

Classification can be visual or digital; where visual

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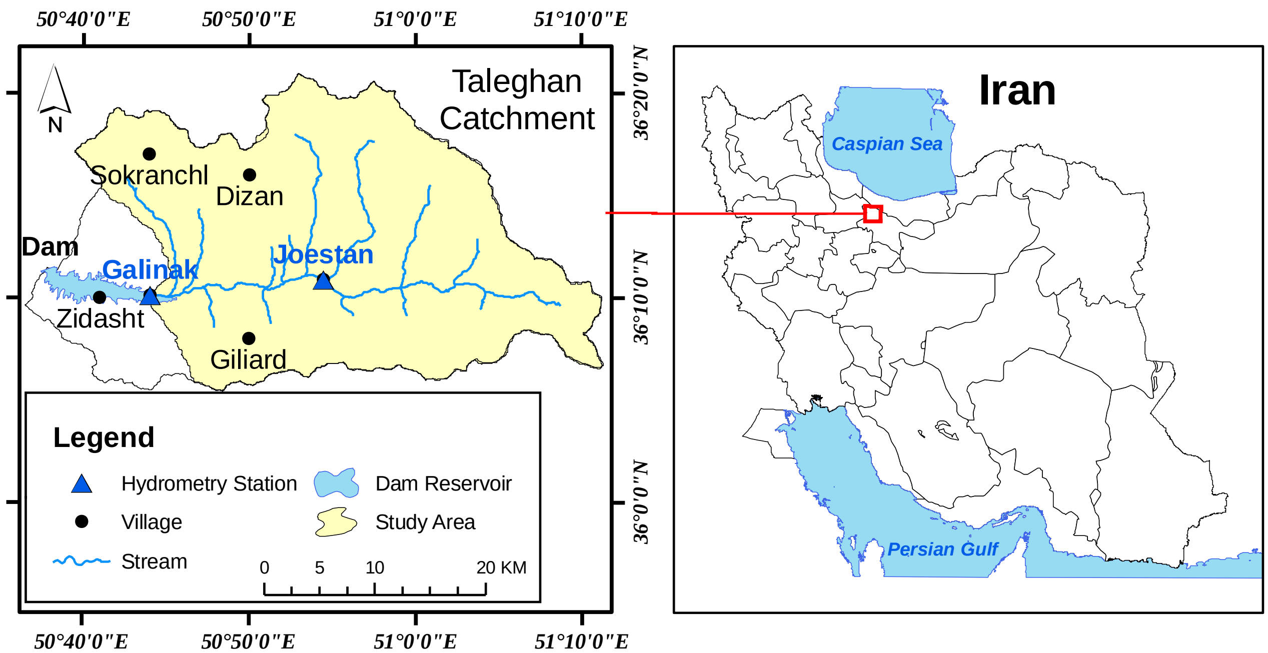

Figure 1. Location of Taleghan watershed.

classification is based on the analyst's ability to use visual elements such as tone, contrast, shape and so on to classify image elements. On the other hand, digital classification relies on the spectral information used to create the image and classifies each individual pixel based on either its band wavelengths or spectral characteristics. Eventually, all pixels in an image are assigned to classes or themes such as water, forest, rangeland and so on. Spectral and information classes are different from one another and it is the role of image analyst to distinguish between the two for an accurate classification. Spectral classes are groups of pixels that have nearly similar spectra whereas the information classes are the different themes or groups that the analyst is attempting to recognize in an image (Canty, 2006). Information classes may include such categories as rangelands, forests, agricultural types or water bodies. Any image can be classified, but multi-spectral imageries are more useful in the natural resource classification. Some land surface types may display the same digital numbers; therefore, one band classification is usually very difficult for the task. Hence, any spectral classes in a single band classification will contain several information classes where distinguishing between them would be difficult.

Usually, two or more bands are used for classification, and their united digital numbers are used to identify the spectral signatures of the spectral classes present in the image. The more the bands used to create a classification are, the more likely is the analyst to get a set of unique landuse classes (Jensen, 2005). In this study, supervised classification was applied for landuse detection. A supervised classification is performed when some previous or acquired knowledge of the classes in a field is used to identify representative samples of different surface cover types. These samples, known as training pixel groups are set up to identify the union spectral characteristics of each class. The determination of training pixel groups or sites is based on the analyst's knowledge of the surface cover types and geographical region in the image. Once the training sites have been established, the numerical information in all of the image's spectral bands or wavelengths is used to define the spectral "signature" of each class. The computer determines the signatures for each class mathematically. Thus, in a supervised classification, the researcher or analyst starts with information classes and uses them to define the corresponding spectral classes. Then, each pixel in the image is attached to the class it most closely resembles (Narumalani et al., 2006).

METHODOLOGY

Location of the study area

Figure 1 shows the location of the study area named as Taleghan watershed which has 930.62 km^2. The study area is located in the upper part of Taleghan dam watershed in the northwest of Tehran. It lies within 50˚ 38´ to 51˚ 12´ E longitude and 36° 04' to 36° 21' N latitude. In this study, Landsat and IRS images (1st August 1987, TM; 7 August 2001, ETM$^+$; 9 August 2007 and IRS) were used to identify the physical properties of the study area. Table 1 shows the spectral intensities, and their respective wavelengths associated with the band numbers that are offered by Landsat and IRS. The range of spectral sensitivity of Landsat bands varies from 0.45 to

Table 1. The spectral sensitivities of landsat and IRS bands.

Satellite	Band number	Band wavelength (µm)	Spectral response	Pixel size (m)
ETM	1	0.45-0.52	Blue-green	30
	2	0.52-0.60	Green	30
	3	0.63-0.69	Red	30
	4	0.76-0.90	Near IR	30
	5	1.55-1.75	Mid IR	30
	6	10.40-12.50	Thermal IR	150
	7	2.08-2.35	Mid IR	30
	PAN (4)	0.5-0.9	-	15
IRS	2	0.52-0.59	Green	23.5
	3	0.62-0.68	Red	23.5
	4	0.77-0.86	NIR	23.5
	5	1.55-1.70	MID	70.5

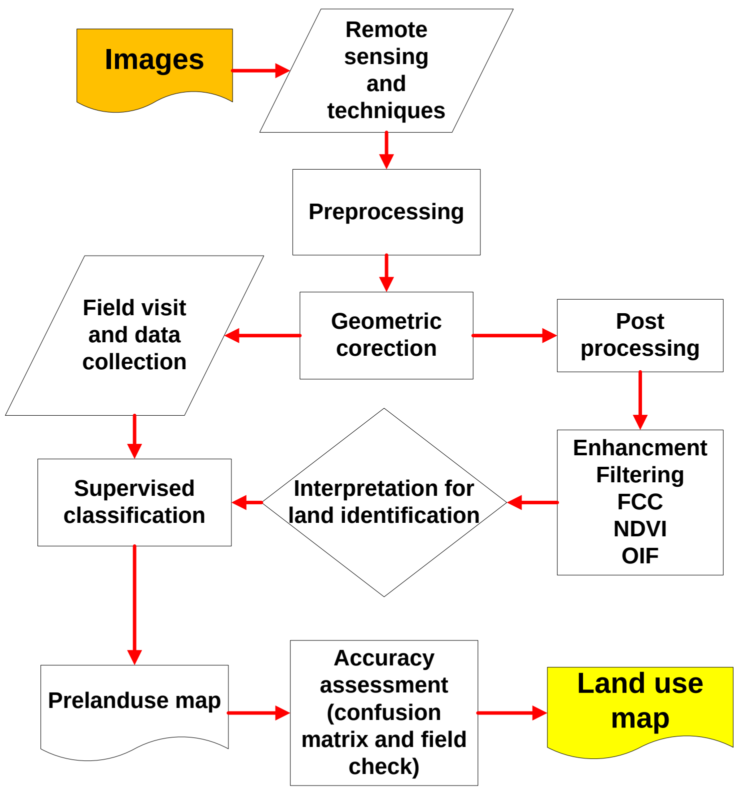

Figure 2. The general framework for image pre-processing, processing and post-processing.

12.50 µm. Red, near infrared (NIR), and mid infrared (MIR) bands are useful in detecting chlorophyll, vegetation, soil moisture, water and leaf structure. Vegetation more likely appears on the satellite image within the band ranges of 0.7 to 0.9 µm (Jensen, 2005). The satellite data used in this research was provided by the Forest, Range and Watershed Management Organization (FRWMO) in Iran. Preprocessing techniques including radiometric and geometric correction have already been carried out by analysts in FRWMO. The post-processing techniques, including filtering and enhancement have also been done by the provider. Figure 2 shows the general framework for image pre-processing, processing and post-processing for the purpose of landuse change detection.

Processing and post-processing have been carried out by the authors for images 1987, 2001 and 2007, separately. In this research, we used post-processing using the normalized difference vegetative index (NDVI), optimum index factor (OIF) and classification. According to Gates (1980), the NDVI was calculated in this study as follows:

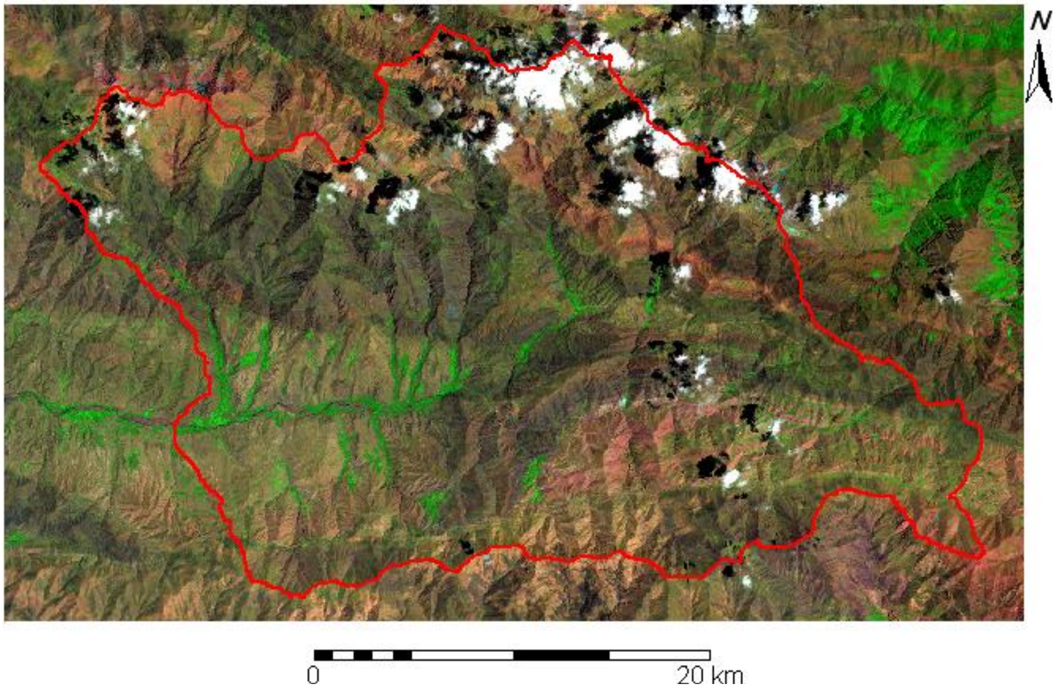

Figure 3. False color composite bands 742 for the study area (August 1987).

$$NDVI = (NIR - RED)/(NIR + RED) \quad (1)$$

The aforementioned equation is equivalent to subtracting the intensity of band 3 from that of band 4 and proportioning to the sum of the intensities of these bands. The domain of generated NDVI values is between -1 and 1 where -1 indicates bare soils, rocky outcrops and water bodies. Increases in values of NDVI from 0.05 to 1 correspond to associated increases in the intensity of vegetation. The optimum index factor (OIF) is a statistic value that can be used to select the optimum combination of three bands in a satellite image which are used to create a color composite (Koolhoven et al., 2005). The optimum combination of bands from all possible three-band combinations is the one with the highest amount of 'information' and least amount of duplication which is checked by high sum of standard deviation (lowest correlation among band pairs). The variance-covariance matrix was calculated by using ILWIS V 3.4 for the input map list, the ranked OIF values and corresponding band combinations can be displayed. By this method, 21 color composite bands with different OIF values were tested.

The maximum and minimum OIF were 26.42 and 23.51, respectively. The highest OIF value was selected for classification landuse in Taleghan area. False color composite bands 7, 4 and 2 (FCC742) with highest OIF values was used for landuse classification of 1987(Figure 3). This methodology was applied to images of three years. The images for 2007 were in different scene and date. In order of application of supervised classification, ground truth information of the study area was collected via a set of field works and a reasonably accurate handheld GPS (Magellan GPS with 5 to 10 m accuracy). Totally, 262 ground truth points were collected for accuracy assessment by field work for 1987, 2001 and 2007 land uses. For two periods of 1987 and 2001, a questionnaire and elderly resident interview were used. In this research, classification was carried out using the supervised method. False color composite and OIF led this research to apply the false color composite bands of 7, 4 and 2 (FCC742) for visual interpretation of all collected images. Finally, different landuses, that is, dry land farming, flood plains, garden and irrigation farming, inactive dry farming, range lands, water bodies and dam reservoir, and urban areas and village were extracted using an initial sample set and the maximum likelihood (MLC) method (Koolhoven et al., 2005).

In this method for each feature vector, the distances towards the class means are calculated. At the last step, the field work and aerial photographs were used for construction of the landuse themes and distinguishing the boundaries. This method was used for three years to extract the landuse frame. The landuse map of the study area has been created using TM, ETM$^+$ and IRS images of the years 1987, 2001 and 2007 by ILWIS software. The landuses of concern in the study area, as well as their codes are as follows: DF, dry land farming; FP, flood plains; G-IF, garden and irrigation farming; IDF, inactive dry farming and rangeland. The range land areas have been classified as good (R1), moderate (R2) and poor (R3) quality range lands, RESERV, water and dam reservoir, URBAN, urban and village.

Accuracy of image classification

As stated by Lillesand and Kiefer (1994), classification is not completed unless its accuracy is assessed. It is necessary to know that the quality of any results is only as good as the quality of the information which is used to establish "true" land cover types of the field. It is quite common to have the accuracy of the reference data influenced by factors such as changes in land cover between data of the classified image and the reference data (Gibson and Power, 2000). To assess the accuracy of image classification, it is a common practice to create a confusion matrix. In a confusion matrix, classification results are compared to ground truth information. The strength of a confusion matrix lies in the identification of the nature of the classification errors, as well as their magnitudes. Table 2 summarizes the results of the confusion matrix that was achieved in this research. The average accuracy is

Table 2. Results of the confusion matrix for accuracy assessment of study image classification.

Image (%)	TM_1987	ETM_2001	IRS_2007
Average accuracy	95.98	94.65	94.42
Average reliability	96.23	95.88	95.53
Overall accuracy	95.44	95.11	95.18

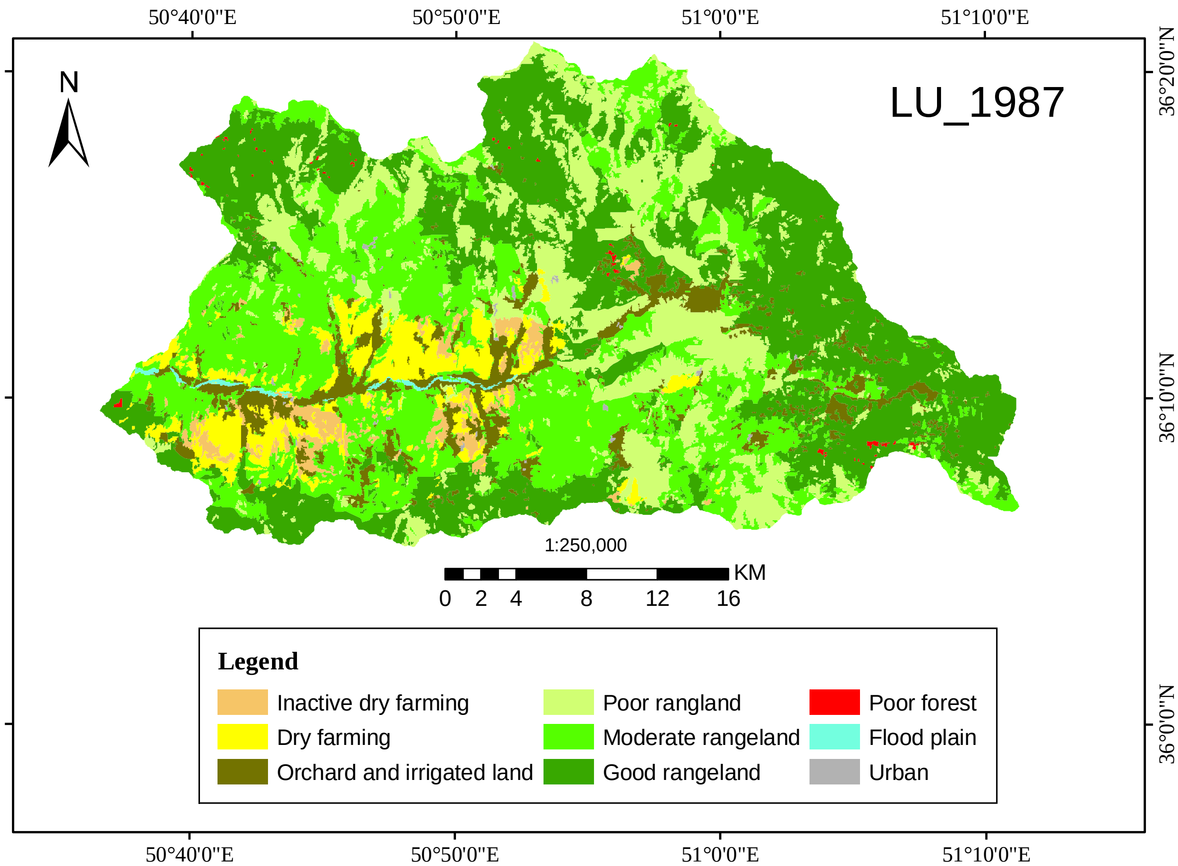

Figure 4. Maps of the detected landuses for 1987 (before dam construction).

calculated as the sum of the accuracies divided by the number of classes. The average reliability is calculated as the sum of the reliabilities divided by the number of classes.

The overall accuracy is calculated as the sum of all correctly-classified pixels (diagonal elements) divided by the total number of test pixels (Koolhoven et al., 2005).

RESULTS AND DISCUSSION

Landuse evaluation

The landuse analysis indicated unstable landuse conditions during the study period (1987 to 2007) in Taleghan watershed. Dam construction and its scenic reservoir have highly affected land prices in the area. Therefore, dry farming activities lost their stability and severely declined and changed into fallow land. Figures 4, 5 and 6 shows the landuses detected by image processing for 1987, 2001 and 2007. Figure 7 portrays the landuse changes in a clustered column chart type from 1987 to 2007 in Taleghan area. In our effort to evaluate landuse changes during the study period, we considered two continuous periods over the whole upper part of the watershed as 1987 to 2001 and 2001 to 2007. Since the time of the approval of dam erecting in the watershed, the whole rangeland area decreased gradually from 82.3% during the early stages of dam construction to 35.4% by the end of the study period. In addition, inactive dry farming (IDF) by plowing along land slopes increased from 6.5% in 1987 to 41.6% in 2007. These unusual activities increased sediment yield and soil erosion drastically. Pressure on the rangeland due to unsound land management had severe impacts on creation of landslides too. Ownership of the land by

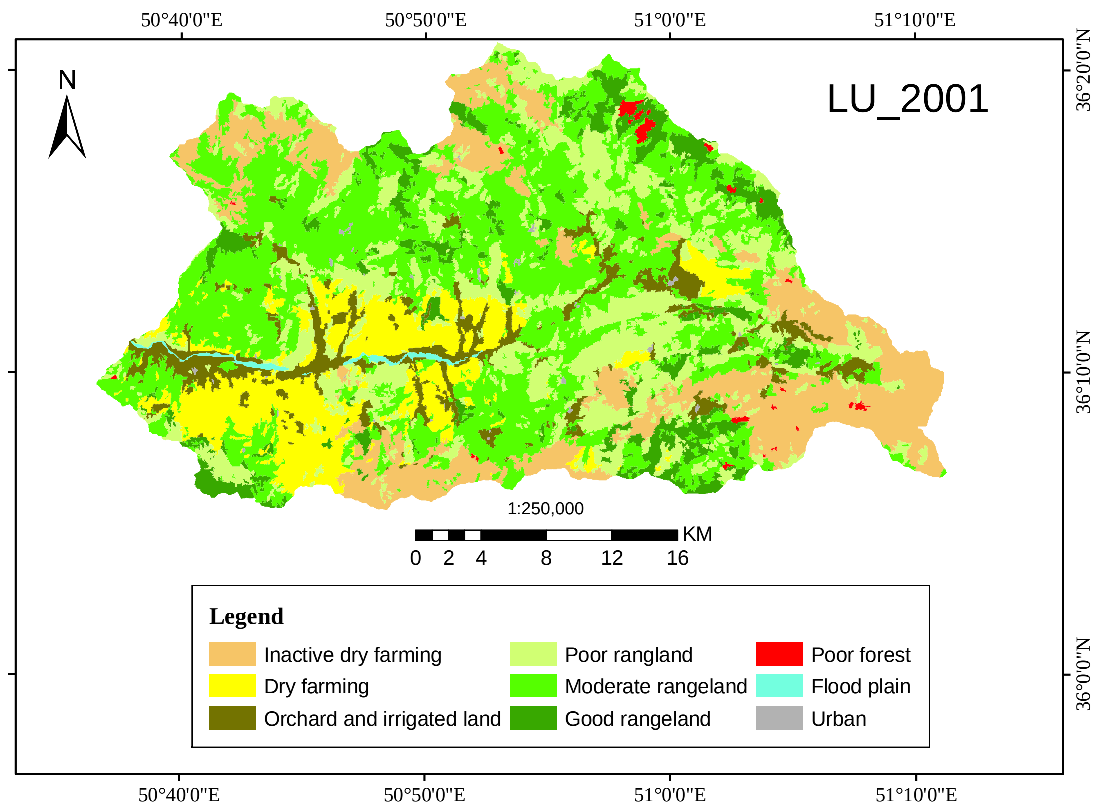

Figure 5. Maps of the detected landuses for 2001 (before dam construction).

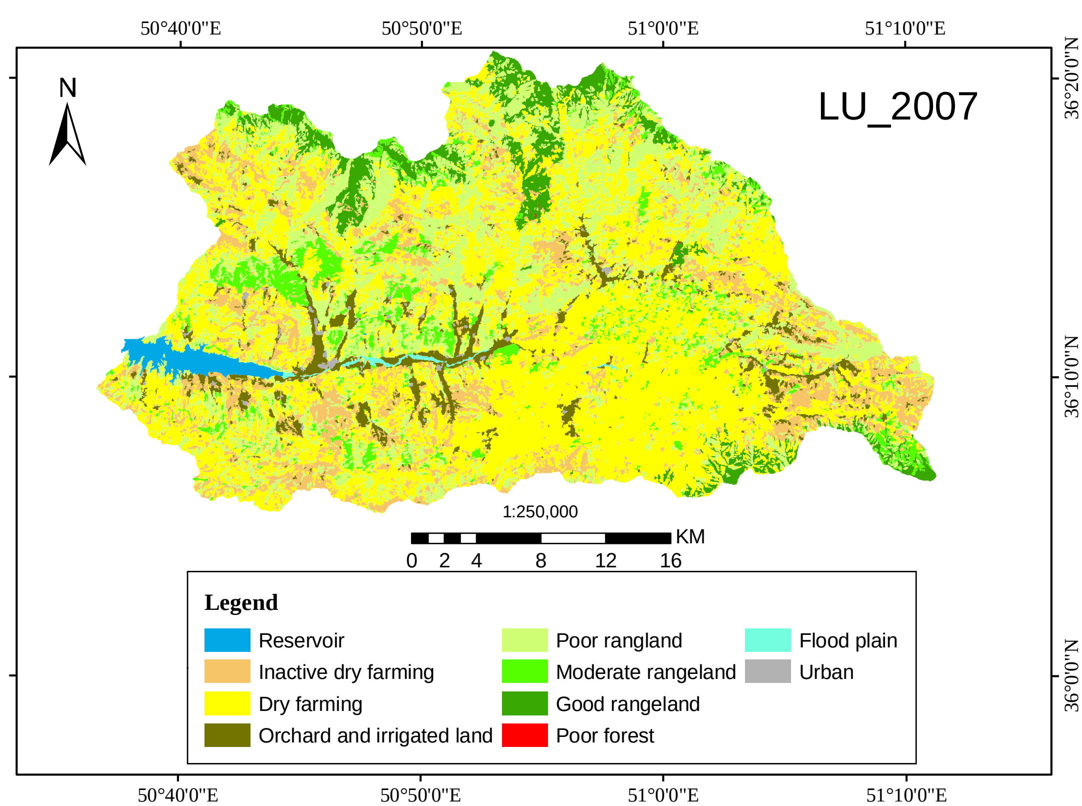

Figure 6. Maps of the detected landuses for 2001 (after dam construction).

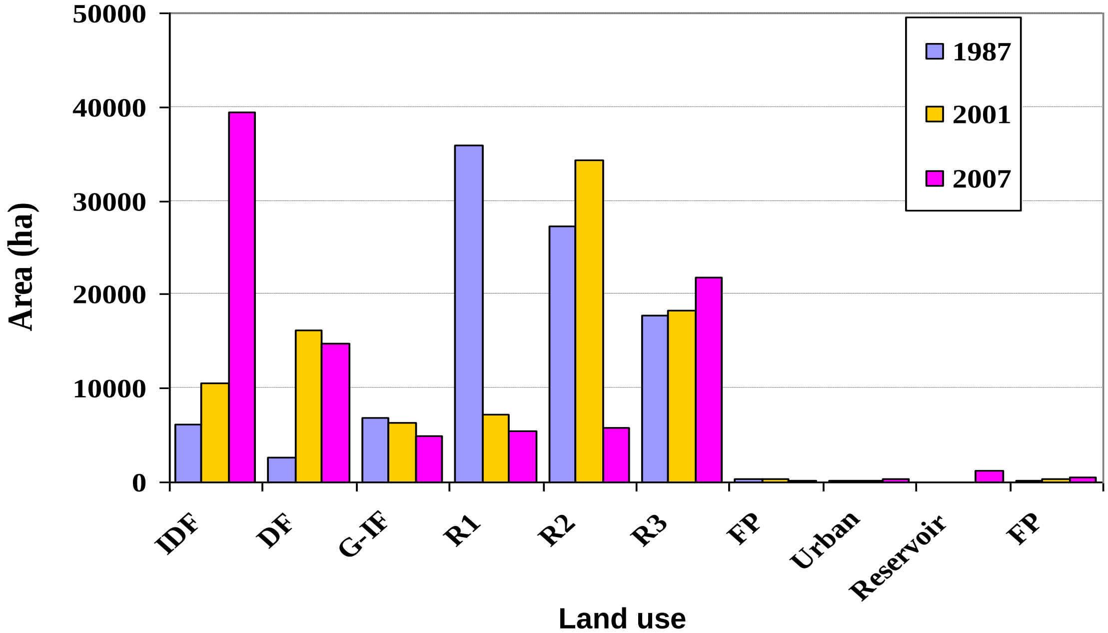

Figure 7. Comparison of landuse changes in terms of area from 1987 to 2007 in Taleghan watershed.

Table 3. The landuses areas and codes in year 1987, 2001 and 2007.

Landuse	Description	Code	1987		2007		LU area change	
			ha	%	ha	%	ha	%
IDF	Inactive dry farming	AGRL	6085	6.5	39507	41.6	+33422	+540
DF	Dry farming	AGRL	2657	2.8	14709	15.8	+12052	+457
G-IF	Garden and irrigation farming	ORCD	6862	7.3	5265	5.4	-1597	-27
R1	Good rangelands	RNGE	32287	34.5	5693	5.9	-26594	-83
R2	Moderate rangelands	RNGE	27287	29.2	5800	6.1	-21487	-79
R3	Poor rangelands	RNGE	17824	19.0	22091	23.4	+4267	+23
FP	Flood plain	NCRP	273	0.29	241	0.2	-32	-16
Urban	Urban areas	URBN	174	0.19	317	0.3	+143	+78
F3	Poor forest	RNGB	174	0.19	-	-	-174	-
Total			93623	100	93623	100	93623	100

immigrants increased the areas of dry farming (DF) lands during the first part of the study period from the 2657 to 14709 ha; that is, more than a five-fold increase.

However, due to the large increase in the area of IDF land, the area of DF land showed less decrease in the second period of this study than that in the first period (Table 3).

Growing settlements had great effects on the orchard-planted areas in the study area which decreased severely as another consequence of the dam building. Hence, the areas of this highly important landuse underwent 7.3 and 5.4% decreases during the first and second periods of this study, respectively. The good rangland R1 area was 32287 ha (34.5%) in 1987 but decreased to 5693 ha (5.9%) by late 2007, this could be due to overgrazing, weak land use management and climate change". The moderate rangeland area decreased from 29.2 to 6.1%. The difference is accounted for by switching uses of these areas to poor quality rangelands (R3) or to inactive dry farming (IDF) (Table 4). On the other hand, poor rangeland increased from 19.0% in 1987 to 23.4% in 2007. Human immigration increased the percentages of rural and urban areas from 1.74 to 3.1 Km^2 during1987 to 2007.

Conclusions

The primary results obtained by overlaying landuse maps from image processing by ILWIS software indicated

Table 4. Landuse change matrix for Taleghan catchment between 1987 and 2007.

Year		Area (ha) in 2007									
	Landuse	**IDF**	**DF**	G-IF	**R1**	**R2**	**R3**	**FP**	**Urban**	**F3**	**Total for 1987**
Area (ha) in 1987	Inactive dry farming (IDF)	2113	639	406	0	749	2104	43	31	-	6085
	Dry farming (DF)	1081	720	230	1	113	503		9	-	2657
	Garden and irrigation farming (G & IF)	1863	1399	2344	15	272	692	111	166	-	6862
	Good rangelands (R1)	12964	7193	1008	1755	1333	8023		11	-	32287
	Moderate rangelands (R2)	13145	3675	859	1989	2282	5210	35	92	-	27287
	Poor rangelands (R3)	8207	939	293	1898	996	5478	12	1	-	17824
	Flood plain (FP)	8	60	79	27	35	22	40	2	-	273
	Urban areas (URBAN)	76	9	22	2	14	46		5	-	174
	Poor forest (F3)	50	75	24	6	6	13		-	-	174
	Total for 2007	39507	14709	5265	5693	5800	22091	241	317	-	93623

severe landuse degradation during the period of 1987 to 2007. The main landuse change corresponded to transformation of different landuses to inactive dry farming by fencing and plowing along land slopes in order to claim land ownership. This area increased from 6085 to 39507 ha during 1987 to 2007. In another word, inactive dry farming (IDF) increased from 6.5 to 41.6% during the last two decades. The increasing soil erosion and subsequent sediment yield is a result of unusual activity aggravated by landuse change. In addition, dry farming (DF) increased from 2.8 (2657) to 15.82% (14709 ha) during 1987 to 2007. More degradation of good rangeland towards moderate and poor rangeland occurred during this period. As a consequence, rangeland area substantially decreases from 77398 (82.7) to 33584 ha (35.4%) during the early stages of dam construction to the end of the study period. Good range land and moderate range land decreased by 83 and 79%, respectively and poor rangeland area increased up to 23% in the same period.

Moreover, the urban and rural area increases from 174 to 317 ha during the mentioned period due to the people's rush for suburban houses and hobby farms.

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