

Article

Land use change detection using remote sensing and artificial neural network: Application to Birjand, Iran

Saeed Ahmadizadeh¹, Maryam Yousefi², Mehdi Saghafi³

¹Faculty of Environmental Science, University of Birjand, Iran

²Environmental Science, University of Birjand, Iran

³Payamnoor, University of Birjand, Iran

E-mail: ssahmadizadeh@yahoo.com

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Abstract

Land is becoming a scarce natural resource due to the burgeoning population growth and urbanization. Essentially, detecting changes in land surface is significant for understanding and assessing human impacts on the environment. Nowadays, land use change detection using remote sensing data provides quantitative and timely information for management and evaluation of natural resources. This study investigates the land use changes in Birjand of Iran using Landsat TM⁵ images between 1986 and 2010. Artificial neural network was used for classification of Landsat images. Five land use classes were delineated include Pasture, Irrigated farming Land, Dry farming lands, Barren land and Urban. Post-classification technique applied to monitor land use change through cross-tabulation. Visual interpretation, expert knowledge of the study area and ground truth in formation accumulated with field works to assess the accuracy of the classification results. Overall accuracy of 2010 and 1986 image classification was 89.67 (Kappa coefficient: 0.8539) and 88.78 (Kappa coefficient: 0.8424) respectively. The results showed considerable land use changes for the given study area. The greatest increase was related to Barren land class almost 378 percent. The dry farming lands reduced by almost 48 % during the study period. Urban class has increased drastically about 219 percent, 3% of dry farming lands, 61 % of pastures lands, 4% of irrigated farming land in 1986, converted to urban and industrial land in 2010 and alone 31 % of urban land in 1986 had conformity to urban in 2010. Irrigated farming land increased about 17.16 % predominantly due to population growth. The result of this study revealed a successful application of the ANN approach for land use change detection. Although this model demonstrated high sensitivity to training samples data, it required trial and error for attainment more accurate. But high accuracy of classification in last two years proved that ANN was highly efficient for classification of Landsat images in the study area.

Keywords land use; change detection; artificial neural network; post-classification; Birjand.

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1 Introduction

Land use change detection is one of the main approaches to expand our knowledge about the impact of human activities on environmental change (Dickinson, 1995; Zhang et al, 2006; Ballestores and Qiu, 2012; Prashant et al, 2012). Since most of land use changes are not reversible (Mertens and Lambin, 2000), evaluation of these changes are necessary as essential prerequisites for planners and land managers, whereas it has been inadequately authenticated in arid and semi-arid land use changes (Lambinet al., 2001). In recent years, plain of Birjand which located in dry and cold regain of Iran, has experienced a lot of land use changes, such as becoming the center of province in 2005, physical extension of the urban areas, increasing pressure from growing human population, destruction of agriculture land and shift them to urban area. So, it is important to know land use changes across time, while there is not a recent report about of land use change in this area.

Whereas, the changes in land use have occurred in a wide range, fast and accurate estimates of such changes without using new technologies would be impossible. Nowadays, integration of GIS and remote sensing has been provided accurate information about land use changes (Imam, 2011; Abdullah et al., 2013). Various classification algorithms exist for land use change detection of satellite images (Aplin and Atkinson, 2004; Lu et al., 2004; Singh and Khanduri, 2011), however, there is not guarantee to use the best algorithm in all conditions (Yang et al., 2002; Prashant, 2012). In this study, we used post classification change analysis. This method provides "from" to "to" transition rules (Yuan et al., 2005; White et al., 2013) and has been in many related studies (Abd El-Kawya et al., 2011; Singh, 1989). Post classification method also is known to be more appropriate method for change detection (Lilles et al., 2004). Whereas this method is depends on the accuracy of individual maps (Foody, 2002). In this study, artificial neural network (ANN) has been selected, which are widely used for the classification of remote sensed images for mapping land use change (Grekousis et al., 2013; Qiu and Jensen, 2004; Gomez et al., 2008). ANN has been used abundantly for supervised (Fkirin et al., 2009; Helmy and El-taweel, 2010; Zhang, 2007a, b; Watts, 2011; Zhang, 2010) and unsupervised remote sensing images classification (Sveinsson et al., 2001; Baraldi and Parmiggiani, 1995). There are three types of networks that have been used a lot, including multi-layer perceptron (MLP), Hopfield and Kohonen (Mostapha et al., 2010; Zhang, 2010). MLP has been applied in environmental science (Maier and Dandy, 2001) and imageclassification (Atkinson and Tatnall, 1997). The purpose of this study is to detect land use change from 1986 to 2010 using Landsat TM⁵ images in the plain of Birjand located in Iran. We used ANN with back propagation-training algorithm to provide the land use maps in the ENVI software.

2. Materials and Methods

2.1 Study area

The study area is located in Southern Khorasanin eastern Iran. The total area is about 995.5 km² (Fig. 1).

2.2 Data source and methods

2.2.1 Data source

The Landsat TM⁵ images used in this study were acquired from www.usgs.gov. The dataset were on 17st of July 2010 and 15th of June 1986, with nearly zero percent cloud cover over the region. We tried to select all images almost during the growing seasons for decreasing the effect of seasonal on land use change results. The received Landsat images were already geo-referenced at the Universal Transverse Mercator (UTM) projection system (zone: 40N, datum: WGS-84) with 30 m spatial resolution. Finally, the image of 1986 was geometrically corrected in comparison to the image of 2010 with 0.005 RMS pixels.

2.2.2 Training site for supervise classification

Selecting training site for supervised classification remotely sensing images is related to the effective field visit within the local area and collecting exact and useful information, accordingly, the field visit was done in two

steps in this research. At the first time, for the identification of the area, we choose the present application of the area and training data for introduction to the software due to the supervised classification process. In the second step, after classification in order to field validation and comparison the output of the software (the final map land use) with the ground-truth and conduct accuracy assessment. According to the first time field visit, five land use classes were determined in the study area as Irrigated farming land, Pasture, Dry farming land, Urban and Barren land. Then for each defined class, the illustrative number of pixels was carefully selected from the study area to identify the same pattern in the satellite imagery of 2010 and 1986. As well, the average of spectral bands of different land uses was calculated (Fig. 2).

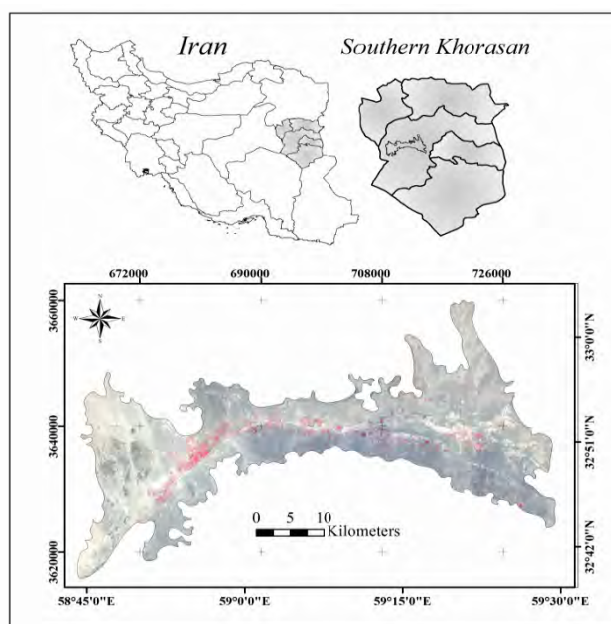


Fig. 1 Study area .The satellite image belongs to the false color composite of the satellite imagery of the study area consisting of Landsat TM⁵ 2010 extracted as plain of Birjand.

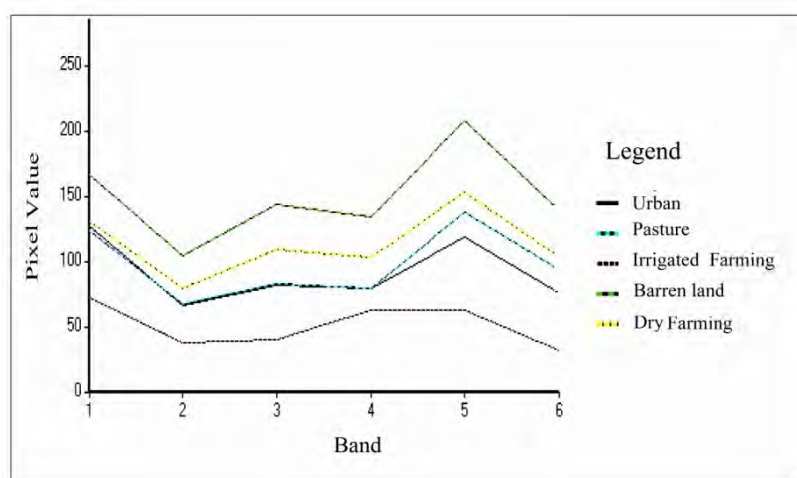


Fig. 2 Spectral signatures of different land uses.

Based on Fig. 2, in this study spectral mixing reflectance was a main problem in classification scope. Whereas impervious surface is considered an important component in the urban area that confused with soil and Pasture (Lu and Weng, 2004; Moran, 2010). Due to importance of the grow of the urban area between two time studied, and because of the resolution restriction of the Landsat TM data (Hasmadi and Jusoff, 2008), Consequently, urban area from each image was extracted and masked.

2.3 Spectral indices and spectral separability

The separability on sample pixels was checked. The Jeffries-Matusita and Transformed Divergence statistical (ENVI User's Guide, 2009) measured based on training samples. The propose of such test was selecting the best training data to require acceptable land-use classification

Table 1 Separability of the determined class training samples from the Landsat TM⁵ image at 2010. The values are calculated with the Jeffries-Matusita and Divergence transformed test.

Divergence transformed	Jeffries-Matusit	Land use class	
2.00	1.83	Irrigated farming land	Pasture
1.60	1.99	Dry farming land	
1.99	1.53	Barren land	
1.07	1.90	Barren land	Dry farming land
2.00	1.83	Irrigatedfarming land	
1.99	1.63	Irrigatedfarming land	Barren land

Table 1 provides the separability results achieved for the training classes of the 2010 Image. A good separation was represented by a value ranging from 1.9 to 2 and a very low separation was described with values less than 1. According to Table 1 Pasture and Dry farming land have Minimum value and Irrigated farming land with another class has maximum value.

2.4 ANN classification method

2.4.1 Network architecture

Multi-Layer Perceptron (MLP) has advantages to other types of ANN models from ANN can be trained using supervised and unsupervised learning algorithms (Zhang, 2010). In supervised learning, ANNs fit a model to data based on the relationship between the input and the output. Conversely, in unsupervised learning, data are classified to different classes based on the similarity between input data. MLP uses a supervised learning algorithm which can estimate a function between input-output pairs without knowledge of the form of the function (Tayyebi and Pijanowski, 2014). MLP uses data in at least two periods of time to train the networks. MLP has been applied successfully in image classification (Atkinson and Tatnall, 1997). For this purpose, three-layer structure has more application (Paola and Schowengerdt, 1995). Three layers consist of one input layer, one output layer and one hidden layer. In the structure of MLP usually one hidden layer must be

adequate for classification. On the other hand, the relationship which determines the number of hidden layer does not clearly exist and it is usually determined through trial and error (Dai and Khorram, 1999). In this study, ANN classification method was performed by ENVI software. ENVI software prepares a standard back propagation for supervised learning (Tayyebi and Pijanowski, 2014). The input layer includes 6 nodes comprising, band 1 to 5 and 7 Landsat TM⁵ image, the output layer includes four land use classes (Fig. 3). The band six is a thermal band which its resolution is half of other bands (60 m). Consequently due to the different modality, this band was not used in any of the classification methods.

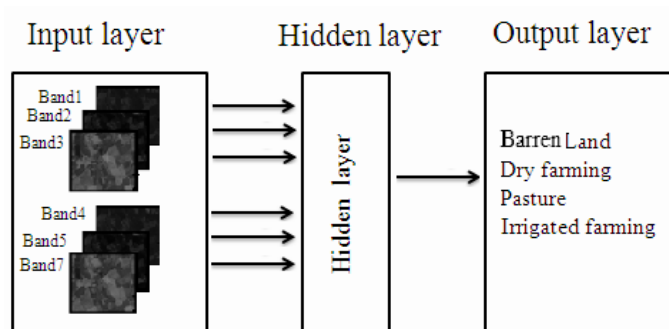


Fig. 3 ANN architecture for change detection.

The back propagation algorithm used to train the weights in network and adjusting weights of a multilayered network in the supervised training presses (Fkirinet al., 2009). This algorithm includes two steps: 1) Feed forward: the process start by putting the training data into MLP network with the random weights starts, the error vector is calculated and the level of network error is clarified. The error vector equals to the difference between target output and real response of the network (equation 1) (Helmy and El-Taweel, 2010).

$$E = \frac{1}{2} \sum_k (t_k - O_k)^2 \quad (\text{Subramaniana et al., 1997}) \quad (1)$$

where, E is the square of error between the desirable output and the real (actual) output, O_k and T_k indicate the actual and desired output from the network, respectively.

2) Backward step: The learning algorithm iteratively adjusts the weights to correct the error back propagation algorithm. The process of adjusting the weights continues to minimize error function between actual and desired outputs continue (Rumelhart et. 1986).

2.4.2 Determining the training parameters in the ANN

In this research, different quantities of training parameters was under trial and error in each time the output of the ANN system was studied, finally the amounts which provided better results was chosen, which is as the following:

- 1). Training threshold contribution: it determines the size of inner weight for improving the activation level of the neurons and is used to modulate the inner weight of the neuroses, modulation of the nodes can lead to a better classification and vice-versa, this parameter can be from zero to 1. In this research, 0.9 was chosen.
- 2). Training rate: the training rate has the value between zero to one the higher rate improve the speed of training, but it proportionately, increase the risk of disharmony with the level of 0.2.
- 3). Momentum (the rate of learning): this parameter leads to the lowering of fluctuations. The rates greater than zero indicate higher level of training without fluctuation. The network with different quantities was tested which finally a number of 0.9 was chosen.

4). The error level was considered 0.1. While less than that would be stopped in training. Different tests from the number of frequency were gained with the trial and error. Different tests from (10-100) frequency were done for doing suitable number of frequency, but not only the error has not decreased and had fluctuation of .07. But also the time of processing (to 12 hours) increase uselessly. Fig. 4 indicates the diagram of RMS training in 1000 frequencies in this research.

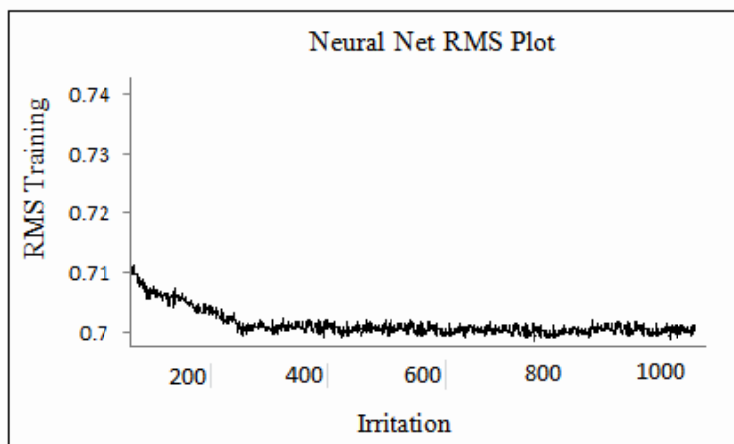


Fig. 4 RMS error of the training in 1000 repetitions.

As it is noticed in the first shape, the error fluctuates around 0.7 and as a result 10 frequencies for both of the images (Fig. 5).

Fig. 6 indicates classification image for the Plain of Birjand 1986 (a) and 2010 (b) respectively.

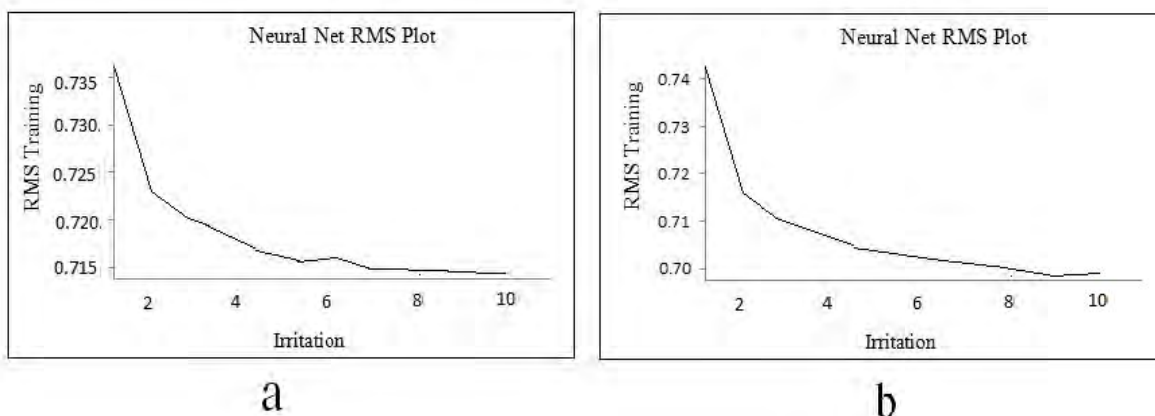


Fig. 5 RMS error of the training 10 repetitions a: 2010; b: 1965.

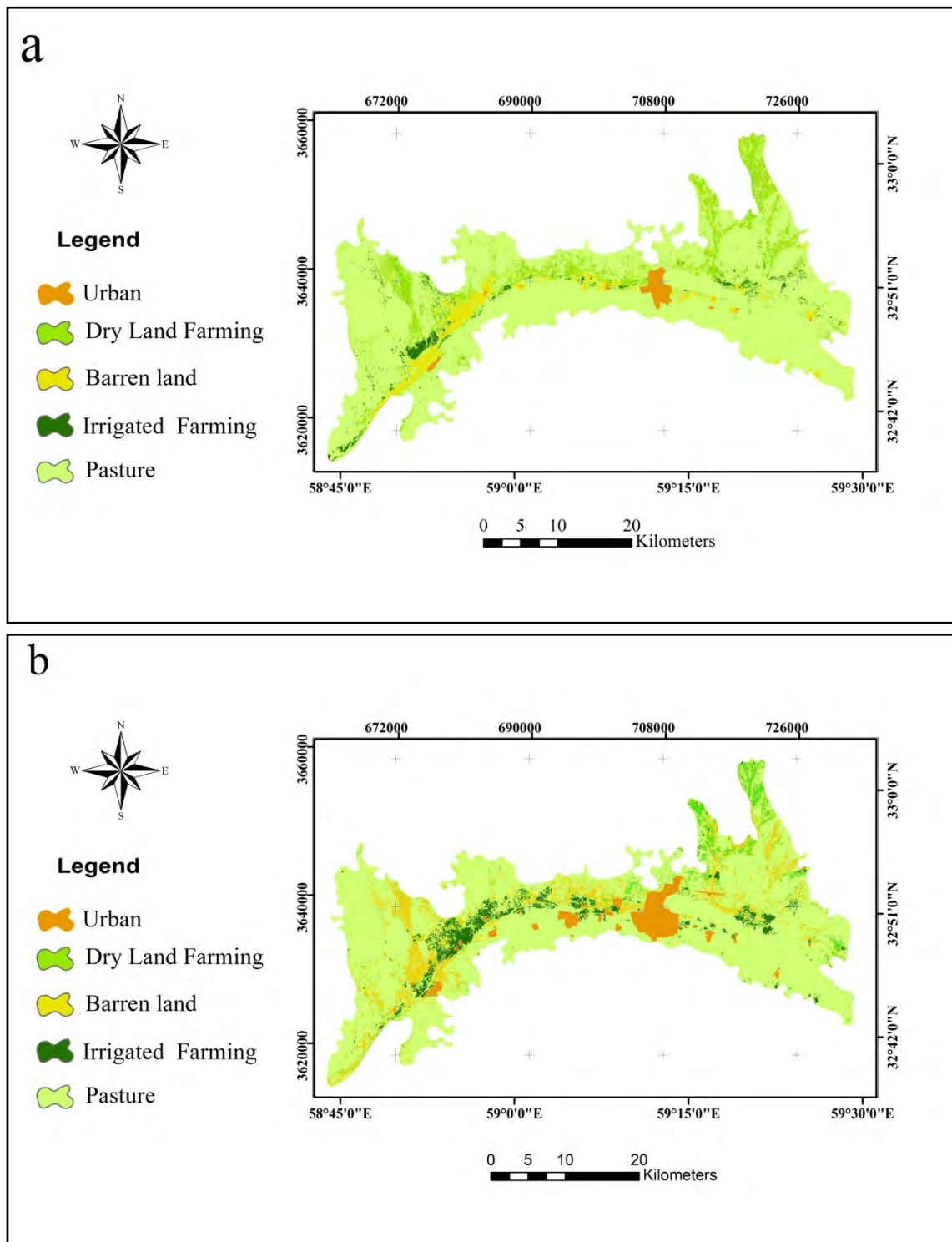


Fig. 6 Classification image for the Plain of Birjand, 1986 (a); 2010 (b) respectively.

2.5 Accuracy assessment

The most common way to present the accuracy of the classification results is using an error matrix (Foody, 2002). Error matrix has known as a standardized and very effective method to expose accuracy of classification remote sensing data results (Congalton, 1991; Foody, 2002).

In this study, the error matrix was generated by comparing the classification results against reference dataset. This reference dataset consists of 300 points randomly placed over all classified images. for the 2010 images, the reference points was controlled with more detailed images from the author's previous knowledge of the area and grand truth extracted field work we used 30 GPS points acquired randomly during a field work in the growth season (through the second time field work). For the 1986 images, reference data controlled base on visual interpretation on the false colored 1968 Landsat TM. Table 2 indicates Overall accuracy and Kappa coefficient statistics for two classification image.

Table 2 Overall accuracy and Kappa coefficient statistics achieved for the investigating Ann classification method.

Overall Accuracy (%)	Kappa Coefficient	Classified Image
88.78	0.8424	1986
89.67	0.8539	2010

2.6 Change detection

Change detection was done through the post classification by using the gained maps by the help of ANN method. For this propose the tabulate area order was used in GIS software as confusion matrix. This provides "from" to "to" transition among defined land use classes (Table 3).

Table 3 Confusion matrix for the changes obtained from the LULC change analysis between the initial state (classification image at 1986) and the final state (classification image at 2010).

classes	2010										
	Urban		Dry Farming		Irrigated Farming		Barren land		Pasture		Total
1986	(Km ²)	(%)	(Km ²)	(%)	(Km ²)	(%)	(Km ²)	(%)	(Km ²)	(%)	(Km ²)
Urban	14.70	31.3	0	0	0	0	0	0	0	0	14.70
Barren land	0.41	0.89	0.99	2.39	2.14	4.53	17.44	13.46	0.82	6.05	27.04
Irrigated Farming	1.68	3.57	2.20	5.34	19.74	41.84	4.53	3.49	1.65	12.10	40.26
Dry farming	1.37	2.92	15.72	38.02	5.18	10.99	32.99	25.48	3.42	25.02	80.3
Pasture	28.78	61.28	22.42	54.23	20.10	42.67	74.53	57.55	94.08	687.05	832.89
Total (Km ²)	46.96	100	41.34	100	47.18	100	129.50	100	100	730.23	995

3 Results

The classified maps for 1986 and 2010 images have been presented in Fig. 6. The results showed a fundamental change in the study areas. According to Table 3 and Fig. 7, the greatest increase was in Barren land about 378.8 %, as this class has been increased of 27.04 km² in initial year (1986) to 129.50 km² in final year (2010). Because 4.5 km² of irrigated farming land class, 32.99 km² of dry farming land and 74.53 km² of pasture in initial year (1986) have been converted to Barren lands in the final year (2010). 17.44 km² of "barren land" in initial year remained the same in the final year.

Urban class to last 24 years (from 1986 to 2010) has increased about 219 %, 3% of dry farming land, 61 %

of pasture lands, 4% of irrigated farming lands in 1986, converted to urban and industrial land in 2010 and alone 31 % of urban areas in 1986 had conformity to urban area in 2010. Dry farming land has been reduced (from 80.3 km² in 1986 to 41.31 km² in 2010). The largest decrease was observed in the class dry farming land nearly 48%. The area under irrigated farming land was 40.26 km² in 1986. This class has been increased about 17%, thus the irrigated farming has been increased to 47.18 km² in 2010 was due to population growth and more utilization of underground water reservoirs. There was little change in the pasture from 1986 to 2010.

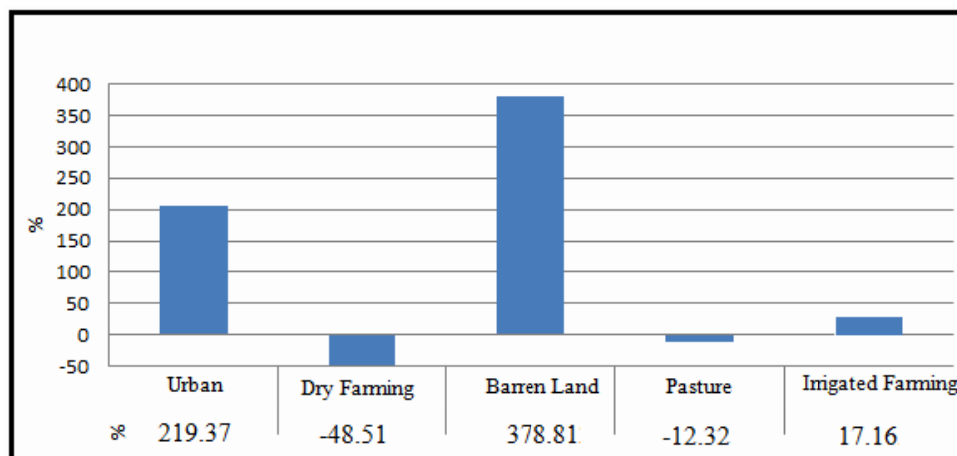


Fig. 7 Land use change among 1986 and 2010.

4 Discussion

Based on the Convention to Combat Desertification (CCD) (UNCED, 1994), land degradation leads to desertification in arid and semiarid areas. Plain of Birjand is a representative instance of arid and semi-arid areas that according to results of this study, has been faced drastic changes in the past 24 years. During the examined period, Substantial increase of the size of the Barren land class was identified. Those changes are considered mostly due to natural factors such as drought and human activities such as over cultivation, overgrazing and abandonment of the agricultural region. Abd El-Kawya et al (2011) also expressed the main reason of land degradation is human activities. From an environmental viewpoint, it was detected a significant urbanization of the study area and an increasing trend of degradation of the physical environment, including destruction of Dry farming land. A substantial increment of urban class was also revealed. The spatial change of the urban class indicated residential and road network expansion. Tayyebi and Pijanowski (2014) also demonstrated urban increased in areas of high urban density, close to roads.

From the satellite imagery, by utilizing the classification ability of ENVI software by help of ANN method, albeit there are several factors implicated in terms of the accuracy of the classification results elicited, there was the advantage to have high coefficient of accuracy of this model while being simple to use. This model demonstrated high sensitivity to training samples data and it needs to trial and error for achieving more accuracy, but high accuracy of classification in last two years, proved that this model was highly efficient for classification Landsat images in the study area. Field works was an integral part of the interpretation of satellite images. The strength of this study was synchronous with field works and acquired satellite image.

5 Conclusions

This research presented an analytical approach to describe land use changes of the environmentally sensitive of Birjand. For this purpose, remotely sensed data obtained from Landsat TM⁵ satellite that is one of the the most common data source for land use classification (Moran, 2010), from 1986 and 2010 were used. After pre-processing the two Landsat images, the separated training sample have been selected for determined land use class of the study area. ANN classification method used to classify satellite images. Post-classification technique applied to monitor from- to land use change through cross-tabulation. An integration of visual interpretation, expert knowledge of the study area and ground truth in formation accumulated with field works was applied to assess the accuracy of the classification results.

The result of accuracy assessment indicated the overall accuracy of 2010 and 1986 image classification was 89.67 and 88.78 respectively. The kappa coefficient of 2010 and 1986 image was 0.8539 and 0.8424 respectively. It is concluded that ANN method can provided acceptable classification accuracy values in this study.

Whereas arid and semi-arid region are recognized as fragile ecosystem, reliable land use detection are essential prerequisites and essential tools to planning in these areas. Plain of Birjand is a representative example of arid and semi-arid areas, hence the urbanization and the industrialization in this area are required incessant monitoring. It is recommended for future studies to achieve an accurate results with advanced precision should be used higher-resolution images and shorter time intervals.

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