Eco. Env. & Cons. 20 (4) : 2014; pp. (1441-1452)
Copyright@ EM International
ISSN 0971–765X

Using remote sensing satellites images in detection and predication of land use changein Jiroft area S.E. Iran

M.R. Mazaheri[1], M. Esfandiari[2], M. H. Masih Abadi[2] and A. Kamali[3]

[1]College of Agriculture and Natural Resources, Islamic Azad University, Science & Research Branch, Tehran
[2]College of Agriculture and Natural Resources, Islamic Azad University, Science & Research Branch, Tehran
[3]Soil Science Department, Faculty of Agriculture, Vali-e-Asr University of Rafsanjan

(Received 07 May, 2014; accepted 15 June, 2014)

ABSTRACT

Planning and resource utilization plays an important role in monitoring changes in land use. As a result, an effective and useful sources of information is to analyze the changes through remote sensing data to detect environmental changes. This can be also used in close monitoring of processes, and appropriate management practice. Change detection is a process that allows viewing and identifying differences in temporal phenomena series, patterns, and surface conditions. Various change detection methodologies and techniques, which use remotely sensed data, have been created. Landsat TM images of the years 1987, 2000 and Landsat ETM$^+$ image of the year 2010 were used to determine spatial and temporal land use changes in the period of 1987-2010 while the Markov chain was used to predict land use changes between 2010 and 2020 based on 2000-2010 trends. In this study, the current progress in change detection methods using multi-temporal remotely sensed imagery has been reviewed and the different methods of classification comparison were compared. The possible existing problems in the current development of multi-temporal change detection were analyzed, and the development trend is discussed. Finally, there is a brief discussion and projection of the land use changes for the next decade when the studied area envisages by achieving Vision 2020 in using Markov chain analysis.

Key words : *Remote sensing, Change detection, Markov chain, Jiroft area*

Introduction

Land use (LU) is defined as practices and purposes of man's use of land and resources. Identification of the causes of changes in LU provides a better understanding of human communication and interaction with land resources (Afify, 2011). Such recognition of the relationship leads to a better management of and sustainable use of these resources. Changed lands are those lands which have changed compared to their previous climate, topography, and soil characteristics conditions and their uses (Sala *et al.*, 2000). If the changes are to reduce the production potential of the land, land degradation can be interpreted. Most processes of land use change (LUC) occur in the arid and semi-arid lands and cause adverse effects on land resources. Dry lands have a higher vulnerability to change, due to the climatic

***Corresponding author's email:** Rowshanzamir_r@yahoo.com
1. PhD. Student of Pedology, 2. Associate. Professor, 3. Assistant Professor

effects and increasing population pressures (Farifteh *et al.*, 2006).

Monitoring of LUC in time intervals is achieved through remote sensing technique in a shorter time, with lower cost and with greater accuracy. Satellite data because of its particular characteristics including extensive coverage, repeatability, multi-spectral nature, and being continuously updated can play a key role in mapping LUC. Currently, due to lack of data, high cost, and quality of spatial data as well as the continuous changes in the LU, the use of satellite images are increasing in the field studies projects. (Chen *et al.*, 2012).

The output maps can be analyzed to provide information on percentage of LU and its change among or between a time-series of satellite images or aerial photography. Based on this knowledge, future land use trends can be postulated and action plans can be framed (Coppin *et al.*, 2004).The use of RS technique in LUC depends on factors like proper understanding of the area's landscape, the sensor type, and the technique to collect data (Suresh *et al.*, 2012). The most important environmental factors in such studies include the study of atmospheric condition, soil humidity, and phonologic features of plants at the time of receiving data (Lu *et al.*, 2004).

To tackle the problems of using the multi-temporal and multi sensor images, a suitable technique should be used which separates the changes related to spectral reflection from the pre-processing changes. In this technique, detecting the post classification changes of two images from different times will be coded and classified differently. Then, the scale of change will be reached from comparing the results of those images (Lunetta *et al.*, 2006).

A number of procedures or methods of RS technologies are used to spot LUC. Some research projects have used RS techniques, others have combined remotely sensed data with GIS data plus a great number of studies have reviewed a number of change detection techniques.

More ever, time and expertise are key factors which affect the performance of post-classification comparison and the quality of the classified image for each date. Training data and prior knowledge of the selected objects are required for supervised classification. Another form of supervision is unsupervised classification in which the data are partitioned without prior knowledge and then thematic labels will be applied (Lu *et al*, 2004).

Another useful technique for extracting land use information is post-classification comparison. Once classification is done, the compare method will be used on two or more images after registration. Each image of multi-temporal images is classified separately and then the resulting images are compared. If the corresponding pixels have the same category label, the pixel will not change, otherwise the pixels will change (Lu *et al.*, 2004).

Modeling and prediction of future changes are significant factors in understanding the quantity and quality of knowledge about possible future changes. Thus, detecting and predicting changes are required to preserve an ecosystem especially in areas of rapid changes in developing countries (Huang *et al.*, 2008). Spatial and temporal predictions of land uses can be done by empirical models based on past patterns of change that have been observed with an array of limiting factors such as changes in such models (Rimal, 2011). Markov Chain Model, which is capable of making such prediction, is a method for modeling LU. The method can be used when the changes in the landscape are not easily explicable. Markov Chain is a sequence of random values whose probability in given intervals is dependent on the quality and quantity of past changes. There are some limitations to the method. 1) It does not take the cause of LUC into consideration, 2) it leaves out the forces and processes that produce the observed patterns and 3) it assumes that the forces that produced the changes will continue to do so in future (Clark Labs, 2012).

Hence, from remote sensing perspectives, this study evaluates the effect of time-interval on predicting LUC with the Markov chain model so that the time interval of satellite imagery with the highest accuracy of prediction will be recommended for predicting future land use.

The following specific objectives will be pursued in order to achieve the aim above.

1. To create a LU classification scheme.
2. To determine the trend, nature, rate, location and magnitude of LUC.
3. To forecast the future pattern of LU in the studied area.

Materials and Methods

Study area

The present study is carried out in Jiroft, an area in the south of Kerman Province, Southeast of Iran, which is spread from the North of the city of Jiroft to the region of Bahadorabad, and covers most of the wideJiroft plain (Fig. 1). The northeastern part of this area is mountainous and cold whereas Jiroft and its surrounding plains have a tropical climate. The soil of the detected area is that of arid moisture regime and hyper-thermic thermal regime. In addition, Jiroft area has experienced a variety of droughts for a 30-year period from 1971 to 2001.

Geomorphologically, the area has five geomorphological levels of alluvial fan, relatively stable covered pediment, an intermediate level between pediment and alluvial plain, alluvial plain ground level, and the low lands. The area of the region being studied was approximately 103,245 hectares.

Data collection

To study LUC, using spatial and descriptive data, the geographical database of study area was formed. Two data series from Lands at TM and ETM$^+$ sensors were used which are shown in Table 1. In addition, 4 different types of LU were selected to investigate the changes in this period, which are shown in Table 2. In this study, in order to achieve for the minimum time interval between the imaging times; ETM$^+$ satellite data were used.

It was tried to select the data from the most available images in such a way that the images' dates (mid-summer) and the control point shappen to be closest to each other. Some topographic and geologi-

Table 1. Characteristics of satellite images used to extract LUC maps

Satellite	Senor	Resolution (m)	Bands	Date
Landsat	TM	28.5	7	1987-2000
Landsat	ETM$^+$	28.5	8	2010

Table 2. Mapped cover type descriptions

Cover type	LU Description
Urban areas	Type includes urban residential, semi-urban residential or rural residential housesreadily identified on satellite imagery
Gardens	A plot of land used for the cultivation of fruit (Such as apple) andnatural tree cover (Such as willow, poplar and maple)
Irrigated farming	Agricultural productsusing irrigation water (Such as wheat, barleyand vegetables)
residential land use	Other LU

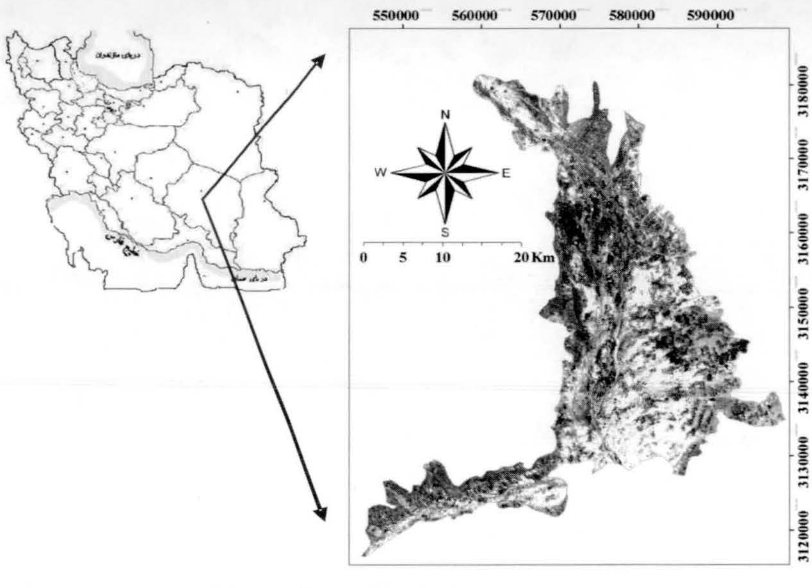

Fig. 1. Location of the study area in the Jiroft region, southeast of Iran

cal maps with the scales of 1:25000 and 1:50000, drawn by Iranian Armed Forces Geographical Organization, as well as some 1:4000-scaled aerial photographs were used to detect of the area preliminarily condition. It should also be mentioned that since the aim of this study was to investigate the changes in land use and land cover, the inhabitants' information were used in some certain sensitive and suspicious points.

The methodology for LUC applied in this work follows a well-known proposed approach state by Jähne (2005), that include preprocessing of the data, processing and post–processing. The pre-processing stage was done to prepare the data and it included image resampling, sub setting, atmospheric and geometric corrections based on standard methods (McCoy, 2005).

As a second step (processing of the data), some techniques such as enhancement, classification and change detection of images have been applied according to standard methods (Xie *et al.*, 2008). As for post-processing step, different LULC maps are produced for each year, and statistics analysis are carried out according to methods proposed by Villalon-Turrubiates and Shkvarko (2007). ENVI and IDRISI 15 software has been used to perform some of the stages.

Image Processing

Radiometric Correction

Normally one of the two types of radiometric corrections of satellite images, i.e. absolute or relative radiometric correction, is used in the preliminary processing of satellite images. These two methods are usually applied in order to decrease the atmospheric dispersion effects on the images. The first method requires a data entry related to atmospheric properties and sensor calibration, which is often a difficult task to do due to the oldness of the images. However, in the second method which is extensively applied in this study, dark object subtraction method is used (Coppin *et al.*, 2004). In addition, ENVI software is often used in the second method, which is also the case for the present study.

Geometric correction

Geo-referencing of the images was carried out using the image-to-image method. To convert the corrected images coordinates into those of the uncorrected ones, first degree function was used; And to resample the pixel value of the uncorrected images, Nearest Neighborhood Method was used. They were geo-referenced again in order for them to be more precise. To do this correction, some control points were selected, and image geometric corrections were attempted via ILWIS software (Verbesselt *et al.*, 2010). There were 14 control points for TM and ETM$^+$ images. The acquired RMSE were 0.53 and 0.49 pixels, correspondingly, which were considered to be within a desirable range (Akingbogun *et al.*, 2012).

Band Selection for Classification and making false color images

By having 7 and 8 different bands respectively, TM and ETM$^+$ sensors provide us with a lot of false color images which have a very important usage in identifying many of the earth objects and phenomena. For the best combination of bands in these sensors, Optimum Index Factor (OIF) method was used. This index, based on the correlation and variance between the bands, selects the best triple combination of bands. In fact, those band combinations with the higher OIF indicate lower data (standard deviation) and repetition (low correlation between the bands) (Lunetta and Elvidge, 1999). In this section, to determine the best training sites, the best OIF combinations were used; however, for a more accurate classification and comparison between classification methods, all the existing bands were used.

Classification

In image classification, spectral values of image pixels were compared with the training sites. The possibility that the pixels are placed in distinguishable classes was, investigated. The digital classification relies on the spectral differences between the various phenomena on different spectral bands; this does not mean, however, that every phenomenon is distinguishable on any particular band. To do so, supervised classification is considered to be an appropriate method. Neural Net Algorithms, Parallelepiped, Support Vector Machine, Minimum likelihood, and the Maximum likelihood were the classification methods of this study (Longley *et al.*, 2001). Finally, the comparison between LU classifications was conducted among the different applied methods, and the best method was determined based on visual and statistical criteria.

In achieving that, first, sampled point coordinates for all the LU classes were pointed on the images.

Some sampling polygons were drawn on the images as training sites (the specified classes of land use in this study), using these points, and the field notes of the area land use which were taken at the time of image-taking in the desert, as well as some maps based on unsupervised classifications which indicated the spectral properties of ground level with some known uses. These were carried out by using ENVI 4.7 software (Akingbogun *et al.*, 2012).

Detection threshold

Many of the algorithms used in classification, distinction, differentiation, and rationing require selection of a threshold for detection and estimation of the modified areas from the unchanged ones. This process is usually carried out through either trial and error or other statistical methods. In this study, the statistical equation Z was used to standardize all the values based on a standard deviation (Equation 1).

Equation 1: $Z=\frac{X_i-\bar{X}}{S}$

In the above equation, X_i numerical value of each pixel, $\bar{X}$ pixels' average, S standard deviation from pixels, Z normalized value of each variable.

Classification accuracy assessment

To assess the classification accuracy, some places which are appropriate for testing and different from those of training sites or those LU places should be used. Then, the classified images should be compared with the geo-referenced data in an Error Matrix. Using this matrix, the accuracy of the classified satellite images was determined.

There are a variety of methods which can be used to assess the accuracy of classification such as total accuracy, producer's accuracy, user's accuracy, and Kappa coefficient. In terms of probability theory, total accuracy is supposed to be affected by chance while Kappa coefficient is considered to be a more appropriate method given its capacity to account for incorrectly classified pixels. In this research, total accuracy, user's accuracy, and Kappa coefficient were used by following equation.

Equation 2: $Kappa = \frac{P_0-P_c}{1-P_c} * 100$

In the above equation, P_0 stands for the accuracy observed; P_C stands for the expected agreement.

It should also be mentioned that to assess the accuracy of the maps corresponding to each year, after calculating the above-mentioned indices, their commission and Omission classification errors were also calculated. Commission errors indicate the land area of a class which does not really belong to that class, while Omission errors indicate the land area of a class which belongs to another class.

Markov chain analysis

Markov chain model provides us with ratio of LUC and the ability to predict the future changes. Using LUC predictions, Its possible to determine the extent of resource degradation, and direct these changes to the right path (Hathout, 2002). In this method, the produced image retains some classes indicating the changes in each class contrasted with other classes during the study period. Thus, the area of each class, which have not changed to other classes through time, or has not turned into a green class or a class without coverage, should be evaluated.

Markov chain model includes chain sequence of random variables $X_1, X_2, X_3, \ldots$. In other words, if we have a set of states as $S = \{S_1, S_2, S_3,\ldots,S_r\}$, we can compute the correlation P_{ij} as:

Equation 3: $P_{ij}^{n} = \sum_{K=1}^{r} P_{ik} P_{kj}$

In the above equation, P_{ij}^{n} indicates the probability of going from state i to state j after n steps. In order to predict the LUC of the studied area, Markov model was used in IDRISI 15.0 software environment.

Hence, classified images of the years 2000 and 2010 were used as coverage maps for preparation of the LUC matrix. Time interval between the two images was 10 years which is used for LUC prediction. Using land cover maps obtained for each period, the land coverage class matrix between the two periods of time was calculated. The first transformation matrix was made from the 2000 cover maps, and the second transformation matrix was made from those of the year 2010. Finally, a general state transformation matrix is calculated for the years of 2020. These matrixes contain the information of change percentage of each class compared to other classes.

Results

Determine the best combination band

This result indicated that the best band combination for TM andETM+ images was 5-4-2. Several different combinations were used for a better detection of the land use. Table 3 shows the OIF values for ETM+ 6- and 7-band combinations.

Land use map

Before the separation of training sites in the supervised classification, land use maps of all the images were prepared using the unsupervised method. Number of classes varied according to the different visual interpretations along with the diversity at the area andeventually, the best class was selected. Figure 2 shows the results of the unsupervised classification. As can be seen in this figure, approximately five classes separated the different types of land used. In order for a better investigation, and in order to reduce the complexity of the map and to be able to examine the vegetation changes of the area more desirably, the three classes showing the barren areas were merged into one class (colors of blue, yellow, and turquoise). On the other hand, it should also be taken into account that the ISO Data method used in this section helped us determine the best number of classes.

Having all the LU maps drawn using unsupervised classification method, the aforementioned maps were also drawn using the supervised method. Therefore, all the information layers, including Gardens, cultivated, urban, irrigated farming and residential land uses, were specified and separated. Then, we had access to the area land use maps for the years 1987, 2000, and 2010. Figure 3 shows the land use map of the study area during these years. In this figure, the land classification map output was based on application of the neural net approach for all of the previous-mentioned years. The area of the different land use types are also presented in Table 4.

Accuracy assessment of land use map

Many studies conducted in land-use mapping have utilized the MaximumLikelihood method, Due to its precise accuracy. In this study, all the different methods of LUmapping were used. At the end, by considering Kappa coefficient, topographic maps of the region, interpretation of aerial photographs, the local population information, and visual interpretation of images that were collectively used to assess the accuracy of the classifications made by different methods. The result shows the acceptable precision of LUclassifications using satellite images with 85 percent accuracy.

Table 5 shows the comparison between the overall accuracy of all the classification methods as well as the Kappa index for this study. As can be seen, the highest level of acceptable accuracy is obtainedfor the neural net method in year of 1987 and 2010 respectively. Table 5 also shows Maximum Likelihood method has a higher overall accuracy along with Kappa coefficient in year 2000compared to other methods; whereas, neural net method shows a better separation according to the visual

Table 3. OIF values for some common compounds using bands of Landsat TM and ETM+, respectively.

Combination band	$\sum_{j=1}^{3}\lvert CC_i\rvert$	$\sum_{i=3}^{3} SD_i$	OIF	Combination band	$\sum_{j=1}^{3}\lvert CC_i\rvert$	$\sum_{i=3}^{3} SD_i$	OIF
5-4-2	2.812245	67.65	48.47	5-4-2	2.045325	71.35	49.42
5-3-2	2.642335	68.35	45.01	7-4-3	2.567455	68.76	47.29
4-5-7	2.615595	67.98	44.43	5-4-3	2.133789	69.38	47.13
2-3-4	2.847845	74.55	43.28	7-5-4	1.912555	71.05	39.43
3-5-7	2.600544	60.54	42.26	7-5-3	2.500245	60.54	38.36
1-5-7	2.753323	70.21	42.11	7-4-1	2.312125	61.11	36.32

Table 4. Summary of Landsat classification area statistical summand from 1987 to 2010

Land use	1987		2000		2010	
	ha	%	ha	%	ha	%
Urban areas	2833.92	2.7	5215.32	5.0	6552.54	6.3
Irrigated farming	9210.96	8.9	21453.48	20.8	29020.95	28.1
Gardens	26451.81	25.7	25837.56	25.0	18016.65	17.4
Residential land use	64779.03	62.7	50769.72	49.2	49685.76	48.2

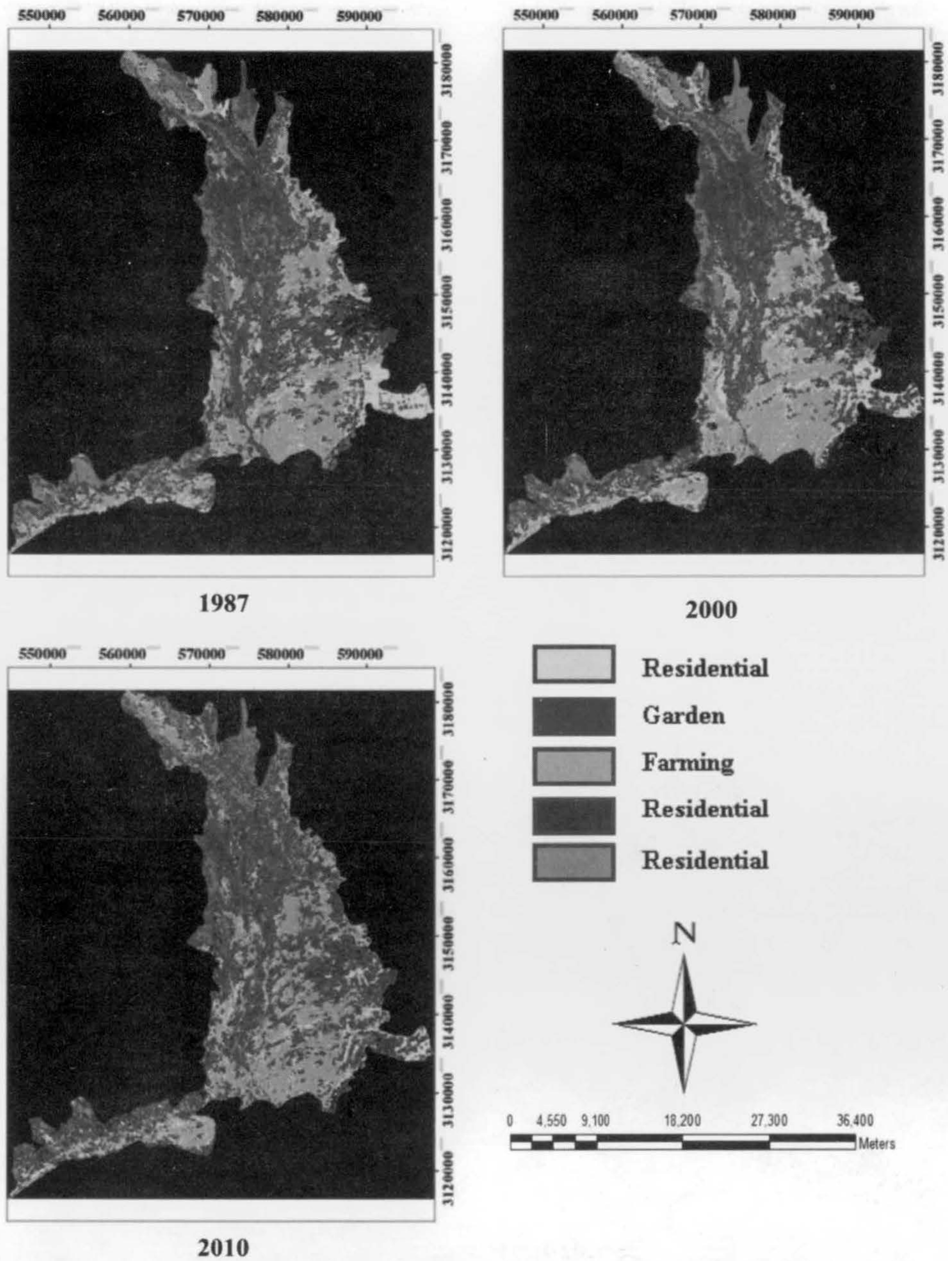

Fig 2. Map of LU in 1987, 2000 and 2010by unsupervised classification method

interpretation. In the year 2010,the results indicated that in comparing to the other methods, land-use map outputs through neural net method retains a better overall accuracy along with Kappa coefficient, and visual interpretation (Fig. 3).

Tables 6, 7, and 8 shows the commission and Omission error results. As seen, for the year 1987, the maximum and minimum commission errors are obtained forurban and residential land uses; while, the maximum and minimum Omission errors are calculated forIrrigated farming and residential land uses respectively. On the other hand, for the year 2000, the maximum and minimum commission errors are obtained forIrrigate farming and residential land uses; while, the maximum and minimum Omission errors are achieved for residential and Gardens land uses. For the year 2010, however, the maximum and minimum commission errors indi-

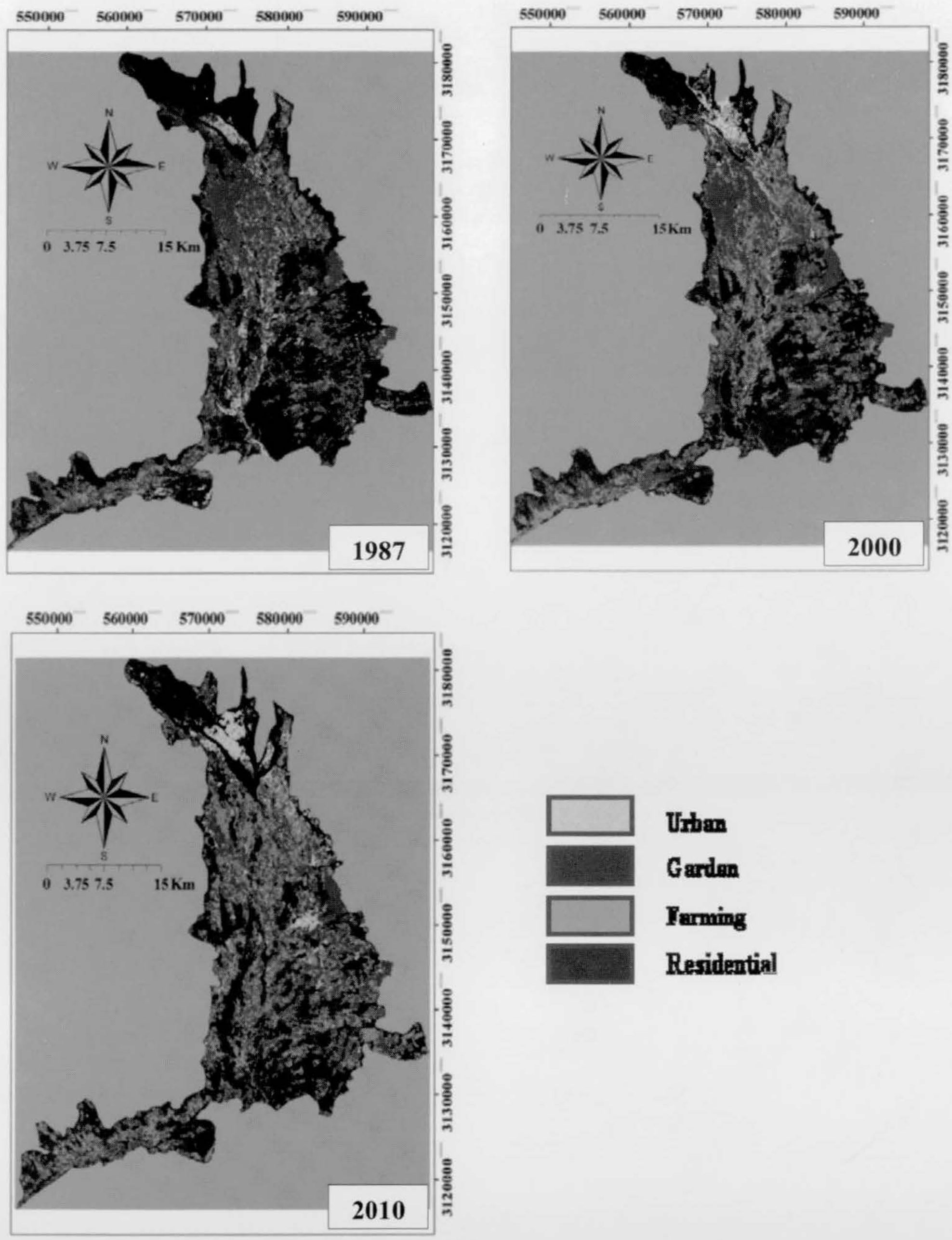

Fig 3. Map of LU in 1987, 2000 and 2010 by supervised classification method

cated forgardens and irrigated farming land uses; while, the maximum and minimum Omission errors were calculated for residential and barren land uses respectively.

These resultssummarized that the errors in this section are mainly related to the separation of irrigated farming and residential land uses. There are also some scattered farming in residential areas which reduced the degree of accuracy separation in those two sites. This conclusion is in line with the similar outcomes achieved by some other researchers. In 2004, Khalighi, for example, trying to separate the pastures (non-agriculturalland) from agricultural lands through supervised classification method in Baranduzchai area in Western Azerbaijan Province of Iran could not achieved his desirable

Table 5. Summary of Landsat classification accuracies for 1987, 2000 and 2010

Methods	1987		2000		2010	
	Overall accuracy	Kappa coefficient	Overall accuracy	Kappa coefficient	Overall accuracy	Kappa coefficient
			%			
Maximum likelihood	82.46	0.55	90.44	0.87	96.42	0.92
Minimum likelihood	29.89	0.08	73.56	0.65	61.77	0.42
Support Vector Machine	84.69	0.49	84.82	0.79	84.69	0.91
Parallelepiped	60.47	0.25	58.63	0.42	80.77	0.56
Mahalonobis	61.97	0.25	80.79	0.73	91.29	0.82
Neural Net	85.96	0.53	86.56	0.81	97.70	0.95

Table 6. Error matrices of land use map for 1987

Land use	Urban areas	Irrigated farming	Gardens	Residential land use	Sum	Commission error
Urban areas	66.67	9.15	3.36	0.89	0.95	48.27
Irrigated farming	0.05	52.82	0.55	0.31	3.10	25.77
Gardens	9.11	10.46	95.34	0.13	6.85	2.62
residential land use	24.17	27.57	0.75	98.67	89.10	1.66
Sum	100	100	100	100	100	-
Omission error	33.33	47.19	4.65	1.33	-	-

*Sum of pixels: 14841 Overall accuracy: 85.96% Total kappa coefficient: 0.53%

Table 7. Error matrices of land use map for 2000

Land use	Urban areas	Irrigated farming	Gardens	Residential land use	Sum	Commission error
Urban areas	68.80	0	0	0.69	21.58	0.9
Irrigated farming	8.27	73.16	0	0	12.22	21.03
Gardens	10.92	26.84	0	0	34.53	20.08
residential land use	12.01	0	100	99.31	31.67	11.79
Sum	100	100	100	100	100	-
Omission error	31.20	26.84	0	0.69	-	-

* Sum of pixels: 2062 Overall accuracy: 86.56 % Total kappa coefficient: 0.81%

results and thereby he used visual interpretation method to classify and separate the two sites from each other. On the other hand, Luna andCesar(2003) in the study of drawing the land use maps indicated that it is impossible to separate the residential areas from agricultural areas and natural coverage using supervised and unsupervised image classification methods. This in fact has made the separation between the rural residential land use from the agricultural and gardenarea a difficult task to obtain.

1987 – 2010 Land Use Change

As shown in the Table 9, between the years 1987 to 2000, the maximum LUC is for residential land use with 47.9 percent, and the minimum LUC is for gardens land uses with approximately 2.1 percent. Nevertheless, it appears that in this 13 y ears, due to good precipitation, sufficient underground water storage, and water channel projects had led people to cultivate a traditionally barren land. In addition, a two-percent decrease in gardens land uses along with a 42-percent increase in irrigated farmingland uses indicates a change in tillage behavior moving toward irrigated farming land use. On the other hand, the increase in residential land uses shows a population growth in the area which is indicated by studied investigation.

In the table 9, it is also indicated that most of LUC between the years 2000 to 2010 is related to garden (decreased) and irrigated farming (increased) land uses. It appears that in this decade, the lack of precipitation, insufficient underground water storage, and increased agricultural water conservation in the region have led people to change the land uses from garden to irrigated farming (Bagheri and Mohammadi, 2012). As a result, it causesthe changes of the green space and agricultural land uses into urban land uses.The main reason of this degradation is the urban development that causes the changes of these lands to barren lands, because of lack of vegetation cover protection.

The overall review of this 23-year period (1987-2010) indicates that the total uncultivated land uses were reduced, and has changed to agricultural or residential usage. However, according to the area obtained for each land used type in this study (Table 3), it can be seen that garden land use of this prepared and productive area was decreased.This is something unpleasant and joyless for this area and for the country as whole. It seems that in this period, the hydrology of the area and other un-seen factors had affected such changes.

It is also noteworthy to mention that other possible reasons such as Halil-Rud Dam construction (reducing the amount of available water and underground water storage), land reforms (land reductions, and lack of supply of agricultural inputs by farmers), government economic programs in social sectors (quick impact jobs with less risks), and less attention to the agricultural sector are among the factors influencing land use change in this area, which is subject to future study by the same authors.

Markov chain analysis

We derived the first-order Markov chain models, which can serve as an indicator of the direction and magnitude of LUC in the future as well as a quantitative description of changes in the past. An important aspect of change detection is to determine which land-use classes is changing and how it is changing. This information reveals both the desirable and undesirable changes and classes that are relatively stable overtime that can be used for manage mental decisions.

Table 9. Changes (in percent) of area from 1987 to 2010

Date	Land use	Area change (%)
(1987 to 2000)	Urban areas	+8.14
	Irrigated farming	+41.86
	Gardens	-2.10
	residential land use	-47.90
(2000 to 2010)	Urban areas	+7.51
	Irrigated farming	+42.49
	Gardens	-43.91
	residential land use	-6.09
(1987 to 2010)	Urban areas	+7.90
	Irrigated farming	+42.10
	Gardens	-17.93
	residential land use	-32.07

As shown in Table 10, the conversion of agricultural land use to urban and residential land use in the next 10 years is more likely to occurcompared to other changes. On the other hand, other land uses are more likely to be converted to irrigate farming than to horticultural use. The results are a warning sign for the loss of agricultural resources in the current and future generations. The findings of this research revealed that there are an urgent needed to investigate the possible cause of such changes. The reduction of ground water resources, reduce rainfall precipitation, mismanagement of the LU are the factors that should not be over looked in our future investigation.

Discussion

Appropriate results were obtained from the inter-

Table 8. Error matrices of land use map for 2010

Land use	Urban areas	Irrigated farming	Gardens	Residential land use	Sum	Commission error
Urban areas	90.34	0.63	0.29	0.08	10.05	1.54
Irrigated farming	0.03	92.24	2.24	0.06	11.76	1.52
Gardens	0	5.21	97.47	0.02	6.36	10.39
residential land use	9.63	1.92	0	99.84	71.83	1.80
Sum	100	100	100	100	100	-
Omission error	9.66	7.76	2.53	0.16	-	-

* Sum of pixels: 29034 Overall accuracy: 97.70 % Total kappa coefficient: 0.95%

Table 10. Markov chainmatrix for 2020

Land use	Gardens	Irrigated farming	Urban areas	Residential land use
Gardens	0.3882	0.3894	0.0482	0.1742
Irrigated farming	0.2484	0.4679	0.0606	0.2230
Urban areas	0.0748	0.1281	0.3521	0.4450
Residential land use	0.0447	0.1626	0.0427	0.7500

pretation of satellite images using supervised classification method for separation of irrigated farmingand garden land uses. These two types of land uses were easily separated in these images. For separation of irrigated farmingand residential land uses, however, it was found that irrigated farmingareas had not been completely separated in satellite images, that is, many of the sites which have been classified as irrigated farmingland uses in the field inspection in the desert, were miss interpreted and incorrectly classified as residential land uses by satellite images.

It seems the lack of uniformity in vegetation cover and similarity of agesin vegetation cover of irrigated farmingand residential land uses could be the reason for difference in classifications in this area. Therefore, to separate irrigated farmingland uses from the uncultivated ones, along with image enhancement analysis, the visual interpretation can be considered as a useful tool. Meanwhile, it is quite possible to make use of good reflection of poor vegetation cover in band 3 of these areas to separate those two land use classification types from each other.

The results of this study showed that the main factors influencing the land use change in this area was the changes in precipitation fall off and insufficient underground water storage. The environmental factors were the factors that have always brought about some changes in the tillage behavior of the inhabitants of the area. In addition, based on the results of Markov Chain Model, it seems necessary to conduct some further planning as well as some further investigated studies on land evaluation and land use change. These suggest that it is important to pay more attentions in issues such as land preparation, hydrology, and patterns of urban and industrial development.

References

Afify, H.A. 2011. Evaluation of change detection techniques for monitoring land-cover changes: A case study in new Burg El-Arab area. *Alexandria Engineering J.* 50 (2): 187-195.

Akingbogun, A,A., Kosoko, S.O.A.,Aborisade, D.K. 2012. Remote Sensing and GIS application for forest reserve degradation prediction and monitoring. Fig Young Surveyors Conference - Workshop 1.2, 6208.

Bagheri, R., Mohammadi, S. 2012. Investigation on spatial variations of drought using geostatistics in Kerman province over a thirty-year period (1970- 2000). *Iranian Journal of Range and Desert Reseach.* 19 (2): 284-296.

Chen, G., Hay, G.J., Carvalho, L.M.T., Wulder, M.A. 2012. Object-based change detection. *International Journal of Remote Sensing.* 33 : 4434–4457.

Clark Labs web site. 2012. The research and development of geospatial technologies for effective and responsible decision making for environmental management, sustainable resource development and equitable resource allocation. Clark University 950 Main Street, Worcester MA 01610-1477 USA. clarklabs@clarku.edu.

Coppin, P., Jonckheere, I., Nackaerts, K., Muys, B., Lambin, E. 2004. Digital change detection methods in ecosystem monitoring: A review. *International Journal of Remote Sensing.* 25(9) : 1565-1596.

Farifteh, J., Farshad, A., George, R.J. 2006. Assessing salt-affected soils using remote sensing. Solute modeling and geoghysics. *Geoderma.* 130 : 191-206.

Hathout, S. 2002. The use of GIS for monitoring and predicting urban growth in East and West St Paul, Winnipeg, Manitoba, Canada. *Journal of Environmental Management* 66 : 229-238.

Huang, W., Liu, H., Luan, Q., Jiang, Q., Liu, J., Liu, H. 2008. Detection and prediction of land use change in beijing based on remote sensing and gis. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences. Vol. XXXVII. Part B6b. Beijing. Pp.75-82.

Jähne, B. 2005. Digital Image Processing. 6nd ed. Springer, Berlin Heidelberg.

Khaliqi, SH. 2004. Effect of Land use changeon the hydrologic characteristics of watersurface (A case study in the Barandoezchay area of West Azarbaijan province). PhD thesis, Department of Natural Resources. Tehran University. 250 pages.

Longley, P.A. and Mesev, V. 2001. Measuring urban morphology using remotely-sensed imagery. In: Donnay, J.P., Barnsley, M.J., Longley, P.A., editors. Remote Sensing and Urban Analysis. London: Taylor and Francis. Pp. 163–183.

Lu, D., Mausel, P., Brondízio, E., Moran, E. 2004. Change detection techniques. *International Journal of Remote Sensing.* 25 : 2365–2401.

Luna, A.R. and Cesar, A.R. 2003. Land use, land cover change and costal lagoon surface reduction associated with urban growth in North West Mexico. *Landscape Ecol.* 18 : 159-171.

Lunetta, R.S. and Elvidge, D.C. 1999. Remote sensing change detection (Environmental Monitoring Methods and Applications), Taylor & Fromcis Ltd.

Lunetta, R.S. ; Knight, J.F., Ediriwickrema, J., Lyon, J.G. Worthy, L.D. 2006. Land-cover change detection using multi-temporal MODIS NDVI data. *Remote Sensing of Environment.* 105 : 142-154.

McCoy, R.M. 2005. Field Methods in Remote Sensing. The Guildford press, New York.

Rimal, B. 2011. Application of remote sensing and GIS, land use/land cover change in Kathmandu metropolitan city. *Nepal. Journal of Theoretical and Applied Information Technology.* pp. 80-86.

Sala, O.E., Chapin, F.S. and Armesto, J.J. 2000. Biodiversity: global biodiversity scenarios for the year 2100. *Science.* 287(5459): 1770-1774.

Suresh, Y., Balachandar, D., Rutharvel, K., Murthy, R., Kumar Aswamy, K. 2012. Land use/land cover change detection through using remote sensing and GIS technology: a case study of st.thomas mount block, kancheepuram district, Tamilnadu. *International Journal of Current Research.* 3(11): 501-504.

Verbesselt, J., Hyndman, R., Newnham, G. and Culvenor, D. 2010. Detecting trend and seasonal changes in satellite image time series. *Remote Sensing of Environment.* 114(1) : 106-115.

Villalon-Turrubiates, I.E. and Shkvarko, Y. 2007. Dynamical post-processing of environmental electronic maps extracted from large-scale remote sensing imagery. *Geoscience and Remote Sensing Symposium.* Barcelona (Spain), pp. 1485-1488.

Xie, Y., Sha, Z., Yu and M. 2008. Remote sensing imagery in vegetation mapping: a review. *Journal of Plant Ecology.* 1(1) : 9-23.