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Forest Change Detection in the North of Iran using TM/ETM+Imagery

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Abstract: Spatial and temporal dynamics of land use/land cover changes were quantified using TM/ETM+images. Time series were selected for forest cover change evaluate in the North of Iran in 1989-2000. In this study, we used a supervise classification algorithm and five techniques based on thresholding involved radiance/reflectance band differencing, NDVI differencing, tasseled cap, change vector differencing and NDVI ratio. Between five change detection approaches, NDVI differencing approach was the best method for changes detecting occurred in the study area. According to measurements from satellite images, 4843.42 ha were detected in this area in 1989-2000. Man-made expansion in the forest North of Iran has been largely derived by population growth and economic development. Land use maps produced will contribute to both the development of sustainable management land use planning decisions and also for forecasting possible future changes in growth patterns. There is a merit to each of the several land use change detection methods studied and appears to be no single best method in which to perform change analysis. The resulting different spectral response of types of disturbances can be used to classify and forecast natural and man made disturbances and artificial neural network or knowledge-based expert offer further opportunities.

Key words: Change detection techniques, land cover change, monitoring, accuracy assessment

INTRODUCTION

Subsequent changes in forest cover area will be applied to determine the impacts of anthropogenic activities on wildlife habitat, recreational opportunities and ecosystem services such as mechanisms to clean air and water and sequester carbon. Iran is a developing country where deforestation and forest degradation could play a major role in promoting forest fragmentation. The importance of mapping, quantifying and monitoring changes in the physical characteristics of forest cover has been widely recognized as a key element in the study of global change (Nemani and Running, 1996). In practice, several change detection techniques are often used to implement change detection, whose results are then compared to identify the best product through visual assessment or quantitative accurate assessment. Automatic change detection methods share similar sequential steps: preprocessing to create a multi-temporary dataset; image differencing and thresholding to derive change/no change information. Geometric correction and relative radiometric correction are widely accepted as necessary preprocessing steps.

A review of change detection in forest revealed that, in addition to the standard problems encountered in change studies (i.e., registration error, variation in atmospheric illumination and sensor

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variability), the effects of topography, heterogeneous vegetation types and interannual phonological variability (caused by variable precipitation patterns) can produce errors in identifying inter date change (Shoshany, 2000). Most studies in the forest of Iran have employed the most widely used change detection approaches post classification comparison.

There are many options for creating differencing image, among which image radiance/reflectance differencing, NDVI differencing and Change Vector Differencing (CVD) are widely used (Schowengerdt, 1997). Regardless of the technique used, the success of change detection from imagery will depend on both the nature of the change involved and the success of the image pre-processing and classification procedures; image differencing, PCA and post-classification are the most commonly used.

In recent years, Artificial Neural Networks (ANN) and GIS have become important techniques to improve change detection accuracy. Different change detection algorithms have their own merits and no single approach is optimal and applicable to all cases. In practice, different techniques are often compared to find the most useful change detection results for a specific application (Lu *et al*., 2004).

The selection of an appropriate change detection technique is important. Five change detection techniques, radiance/reflectance band differencing, NDVI differencing, tasselled cap (KT), change vector differencing and NDVI Ratioing are used widely in the remote sensing context. These algorithms have a common characteristic in that they all involve selecting a threshold to determine the changed areas. Image differencing is a common change detection approach for forested and agricultural areas (Cohen *et al*., 1998). Image rationing mitigates the effects of topology like shadowing and illumination.

Sepehry and Liu (2006) used radiance/reflectance differencing, NDVI differencing, change vector analysis and post-classification comparison to detect flash flood triggered by torrential rain in August 2001 damaged many agricultural fields and forest areas of Golestan National Park located in North of Iran. Results show that among different techniques, change vector analysis produces more correct change/no change map of the flooded area.

In this study, some change detection techniques, radiance/reflectance band differencing, NDVI differencing, tasseled cap (KT), change vector differencing and NDVI Ratioing were assessed to evaluate the most accurate technique for the for the north of Iran environment.

MATERIALS AND METHODS

Satellite Data

The two closest and available cloud free Landsat images (spatial resolution 30×30 m) were acquired and Imagery collection data, satellite platform and sensor type scene identifier for data acquisitions corresponding to (path 165 and row 34) (Table 1).

Study Area Description

The study area is situated in Eastern Guilan Province North of Iran (Fig. 1). Approximately 43218.111 ha on the Northern slopes of the Guilan Province, altitudinal range 50-1800 m. The region is characterized by a Mediterranean-type climate and flora (dominated by Fagus and Quercus species). This research project was conducted from 2008-2009 dates. The study area is located in the 394000 to 420000 m (UTM) and 4092000 to 4112000 m (UTM).

This region has a temperate climate and rainfall is distributed throughout the year. The study area is flat at the North and rugged mountains cover Southern parts. The land use of the areas is intensive and is dominated spatially by deciduous forest and the most important species are *Fagus orientalis*,

Table 1: Satellite data used in study

Imagery data	Organization	Satellite and sensor	Scene identifier
May 8,1989	NASA, USA	Landsat 5 (TM)	elp165r034_5t19890508
July 25,2000	NASA, USA	Landsat 7 (ETM+)	elp165r034_7t20000725

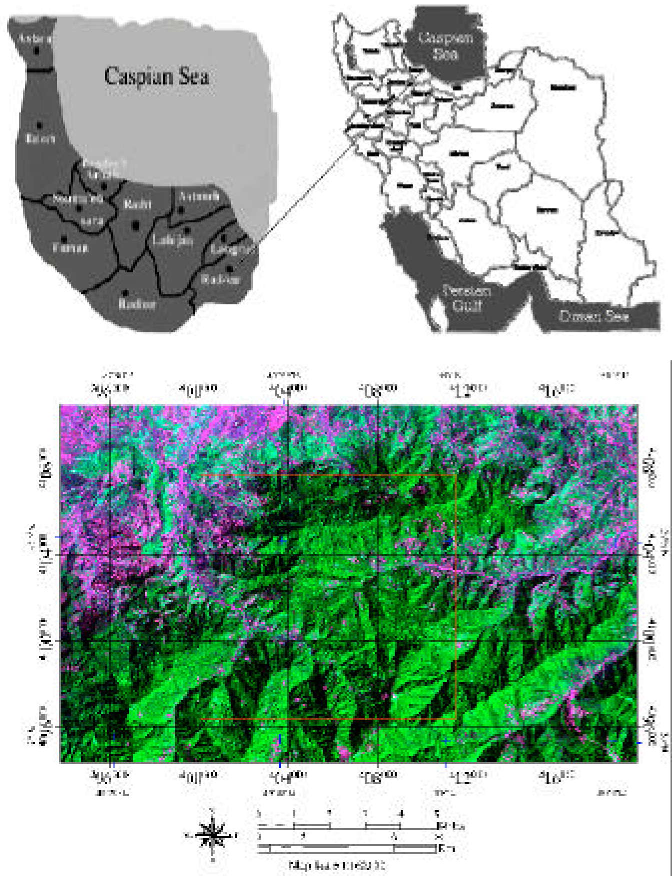


Fig. 1: Location of the study site, Guilan Province, Iran

Carpinus betulus, *Quercus castaneifolia*, *Zelkova carpinifolia*, *Acer velutinum*, *Gleditschia caspica*, *Alnus subcordata*, *Alnus glutinosa*, *Diospyros lotus*, *Parrotia persica*, *Ulmus glabra*, *Taxus baccata*, *Populus caspica*.

Image Pre-Processing

Pre-processing techniques are used to attenuate geometric and radiometric variations in orbital images. In order to get a cartographic uniformity of the different scenes used, a geometric correction technique was applied based on control points from a pre-registered image. Accordingly, the 2000 image was used as the bases image to more precisely geo-reference the other scenes. The correction were made using first order polynomial transformation model and nearest neighbor method for resampling. Root Mean Square (RMS) errors were obtained to 0.5 pixels. The geo-referenced images were then clipped to the final study area.

The DN values of both scenes were converted into radiance and reflectance. Landsat-7 ane TM images converted to at-satellite radiance using Eq. 1.

$$L\lambda = \frac{LMAX\lambda - LMIN\lambda}{QCALMAX - QCALMIN} \times QCAL - QCALMIN + LMIN\lambda \quad (1)$$

where, LMAXλ is band-specific spectral radiance scaled to DNMAX (Wm^{-2} sr^{-1} μm^{-1}), LMINλ is band-specific spectral radiance scaled to DNMIN (Wm^{-2} sr^{-1} μm^{-1}), DNMAX is maximum quantized calibrated digital number (255) and DNMIN is minimum-quantized calibrated digital number (0 for LPGS data, 1 for NLAPS data). Equation 1 accounts for gain state (i.e., high/low setting) by using the respective published LMIN/LMAX values.

After conversion to at-satellite radiance, each image was converted to at-satellite reflectance (assuming a uniform Lambertian surface under cloudless conditions) using Eq. 2:

$$\text{Reflectance} = \frac{L_{Sat} \times 3.14}{E_0 \times \text{Cos } \alpha} \quad (2)$$

where, E_0 is exoatmospheric solar constant (Wm^{-2} μm^{-1}) (corrected for solar distance) and a is solar zenith angle (Landsat-7 Science Data User's Handbook).

Finally, Dark Object Subtraction (DOS) method was applied. With assumes that within a satellite image there exist features that have near-zero percent reflectance (i.e., water), such that the signal recorded by the sensor from those features is solely a result of atmospheric scattering (path radiance), which must be removed (Chavez, 1988).

Change Detection

To enable satellite imagery from multi-date periods to be used for change detection, the imagery must be co-registered and radiometrically corrected. This ensures that changes due to misregistration are minimized and that pixels from the same features on each site correspond on the coregistered image. The summary of the change detection approaches used in the study has been shown in Table 2.

Radiance/Reflectance Band Differencing

Radiance/reflectance band differencing has a common characteristic, i.e., selecting thresholds to determine the changed areas. This method is relatively simple, straightforward and easy to implement and interpret. Bands 4 of the Landsat images were used to band differencing.

NDVI Differencing

It involves subtracting one date of original or transformed (e.g., vegetation indices, etc.) imagery from a second date that has been precisely registered to the first. With perfect data, this would result in a dataset in which positive and negative values represent areas of change and zero values represent no change. Pixels of small radiance change are distributed around the mean, while pixels of large radiance change are distributed in the tails of the distribution. For an index that is sensitive to vegetation, the left side of the change image's histogram represents a decrease in vegetation while the right side shows the opposite.

Table 2: The summary of the change detection technique used in the study

Techniques	Measurements
Radiance/reflectance band differencing	(1989_Band4)-(2000_Band4)
NDVI differencing	(NDVI_1989)- (NDVI_2000)
Greenness differencing	Greenness_1989- Greenness2000
Brightness differencing	Brightness_1989- Brightness_2000
Change vector differencing	$\{(Band4\_1989-Band4\_2000)^2+ (Band3\_1989)- Band3\_2000)^2\}^{0.5}$
NDVI ratioing	(NDVI_1989)/ (NDVI_2000)

NDVI Ratioing

Image ratioing is one of the conceptually easier to understand change detection methods. Data are ratioed on a pixel-by-pixel basis. A pixel that has not changed will yield a ratio value of one. Areas of change will have values either higher or lower than one.

Tasseled Cap (KT)

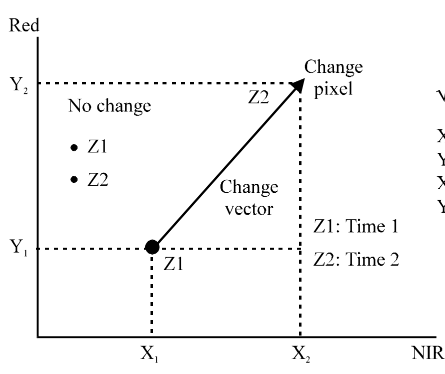
The principle of this method is similar to Principle Component Analysis (PCA). The only difference from PCA is that PCA depends on the image scene and KT transformation is independent of the scene. The change detection is implemented based on the three components: brightness, greenness and wetness. Only the first two bands (brightness and greenness) from the output transformations were used for further analysis. Image subtraction was performed between the brightness layers and then between the greenness layers for each of the successive time steps. This created four time sequential image sets containing both brightness and greenness difference images. Positive changes in greenness suggested an increase in vegetation over time, while positive changes in brightness suggested an increase in bare soil or urbanization.

Change Vector Analysis

The final detection method examined herein is Change Vector Analysis (CVA). Change Vector Analysis is a multivariate technique, which accepts suitable number of bands or vegetation indices as input or spectral features from each scene pair. For each scene pair, these bands comprise the axes of an n-dimensional space. The algorithm is robust to both the nature and number of input bands employed. The most critical pre-processing requirements for CVA are the accurate geometric registration and radiometric normalization of the input data. Among the more straightforward measures to quantify multidimensional change magnitude in CVA is the Euclidean distance between vector end-points in change space (Johnson and Kasischke, 1998). Bands 3 and 4 of the Landsat images were used to calculate the euclidean distance to estimate the magnitude of change (Fig. 2).

Supervised Classification

As a parametric classifier, maximum likelihood classification method calculates the probability that a given pixel belongs to a specific class and assigns the pixel to the class having the highest probability (Richards, 1999). Maximum likelihood supervised classification was performed for 1989 to 2000 landsat images using training data separately. It was assigned to three land use/cover classes including forest, agriculture and man made (Table 3).



$\sqrt{D} = (X_2-X_1)^2+(Y_2-Y_1)^2$

X_2: Near infrared band of time 2 (band 4)
Y_2: Red band of time 2 (band 3)
X_1: Near infrared band of time 1 (band 4)
Y_1: Red band of time 1 (band 3)

Fig. 2: Change vector differencing in two band radiometric space and euclidean distance

Table 3: Land use/cover classification scheme

Class name	Description
Forest	Deciduous forest, mixed forest lands, plantations
Agricultural	Cultivated land
Man made	Villages, residential, commercial and services, industrial, transportation, roads, mixed urban

Accuracy Assessment

Reference data were developed using a random sampling from false color composite, high spatial resolution images, the analyst's local knowledge of the region and forest road construction that detected changes due the road are drastic enough to be representative of changes that can be based for comparison with other resulted change/no change maps. It should be noted that, the boundary of road and other constructions of area was drawn visually. It is therefore wise that the relative accuracy of methods been taken into consideration not their absolute value. Finally, an error matrix and a kappa analysis were used to assess change detection accuracy. A threshold is necessary to separate the changed and non-changed pixels. The best threshold is the one that achieves the highest accuracy. The threshold with the highest accuracy in the second step is considered as the potential best threshold.

RESULTS

Mean and standard deviation values were calculated to determine the most suitable threshold values. This threshold value as a limiting factor was applied to the resulting images. Standard Deviation (SD) of the 3, 2.5, 2, 1.8, 1.7, 1.6, 1.5, 1.4, 1.2 and 1 SD was tested on the ground data to define the most suitable threshold. Threshold application was performed for each change detection technique. The value 0 was assigned for no change areas and 1 for changed areas, therefore a new coded image was constituted for each date. The total set of changed and unchanged pixels was used in accuracy assessment. The change detection results derived for the different techniques were cross-tabulated against the reference data for the image pairs of 1989-2000. Overall accuracies were estimated by dividing the total correct (sum of the major diagonal) to the total number of pixels in the error matrix (Table 4).

This study compared the utility of different sampling for assessment and monitoring: False color composite, high spatial resolution images, the analyst's local knowledge of the region and forest road construction. The criteria used include: precision and accuracy, cost. Foliar cover by species was measured for each method in the study area. There were no differences in the precision of the number of method detected. Time requirements for the supervised method were very much. Results suggest that D NDVI method provide useful data with higher precision than ocular methods. Moreover, these methods can be used to generate a much greater number of indicators that are more directly applicable to a variety of monitoring objectives, including soil degradation and wildlife habitat in the forest.

NDVI differencing is effective at identifying and detecting radiometric changes, as it is a radiometric technique. Conversion to afforestation was detected efficiently with NDVI differencing technique.

Figure 3 and 4 show the result of NDVI differencing map and its histogram. The selection of an appropriate change detection technique is important. Between five change detection approaches, NDVI differencing approach was the best method for changes detecting occurred in the study area. Image differencing was successfully implemented in identifying the areas with respect to radiance values. The change map derived from a threshold determined from the histogram can be identified with change classes as change and no change.

Maximum likelihood supervised classification was applied to landsat images acquired in 1989-2000 for the assessment of land cover classes and their cover percentage. The area was classified

Table 4: Accuracy assessment of applying different change detection methods

Method used	Thresholding value (SD)	Accuracy (%)
Radiance/reflectance band differencing	2.5	54.7075
NDVI differencing	2.0	61.7013
Greenness differencing	0.1	23.3089
Brightness differencing	3.0	53.9032
Change vector differencing	2.5	52.0768
NDVI ratioing	1.4	61.3594

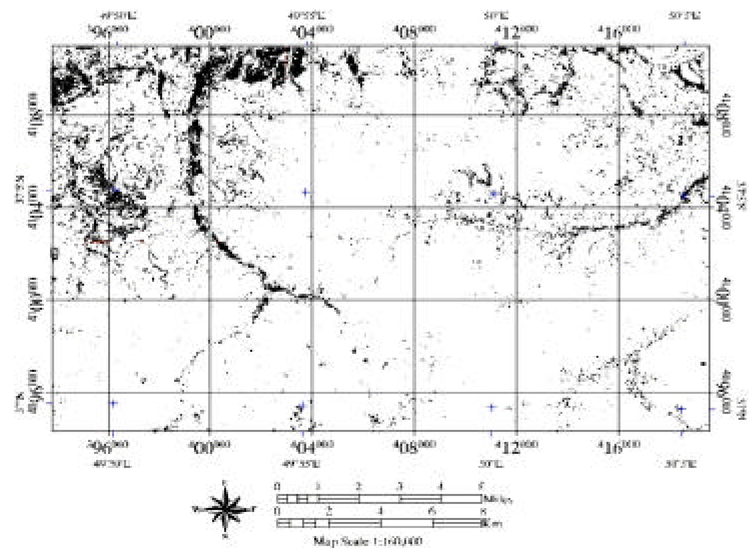


Fig. 3: The result of NDVI differencing map

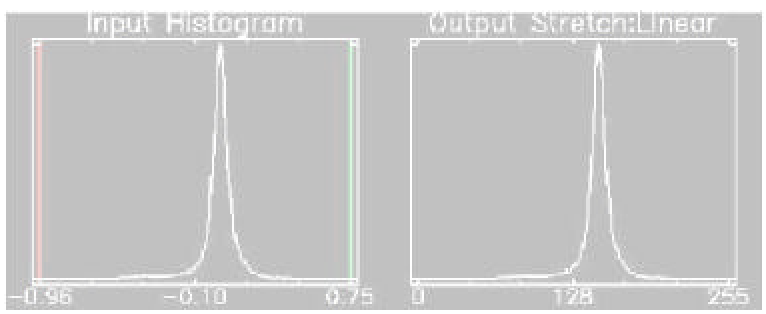


Fig. 4: The histogram of NDVI differencing methods

into tree well-defined spectral classes including forest, man made and agriculture areas. Figure 5a and b show the result of classification 1989 and 2000 images. According to measurements from satellite images, 4843.42 ha were detected in this area in 1989-2000. Man made expansion in the forest North of Iran has been largely derived by population growth and economic development. There is a merit to each of the several land use change detection methods studied and appears to be no single best method in which to perform change analysis.

Analysis of the LU/LC changes in the North of Iran over time revealed a considerable decrease in the Forest areas over the study period; forest areas increased by 24513.97 ha between 1989 and

Table 5: The result of supervised classifications for 1989 and 2000 images

Year	Forest (ha)	Forest (%)	Man-made (ha)	Man-made (%)	Agri (ha)	Agri (%)	Total (ha)
1989	29357.39	67.93	6613.186	15.30	7247.53	16.77	43218.111
2000	24513.97	56.72	12451.460	28.81	6252.68	14.47	43218.111
Differencing of area	-4843.42	-11.21	5838.274	13.51	-994.85	-2.30	0.000

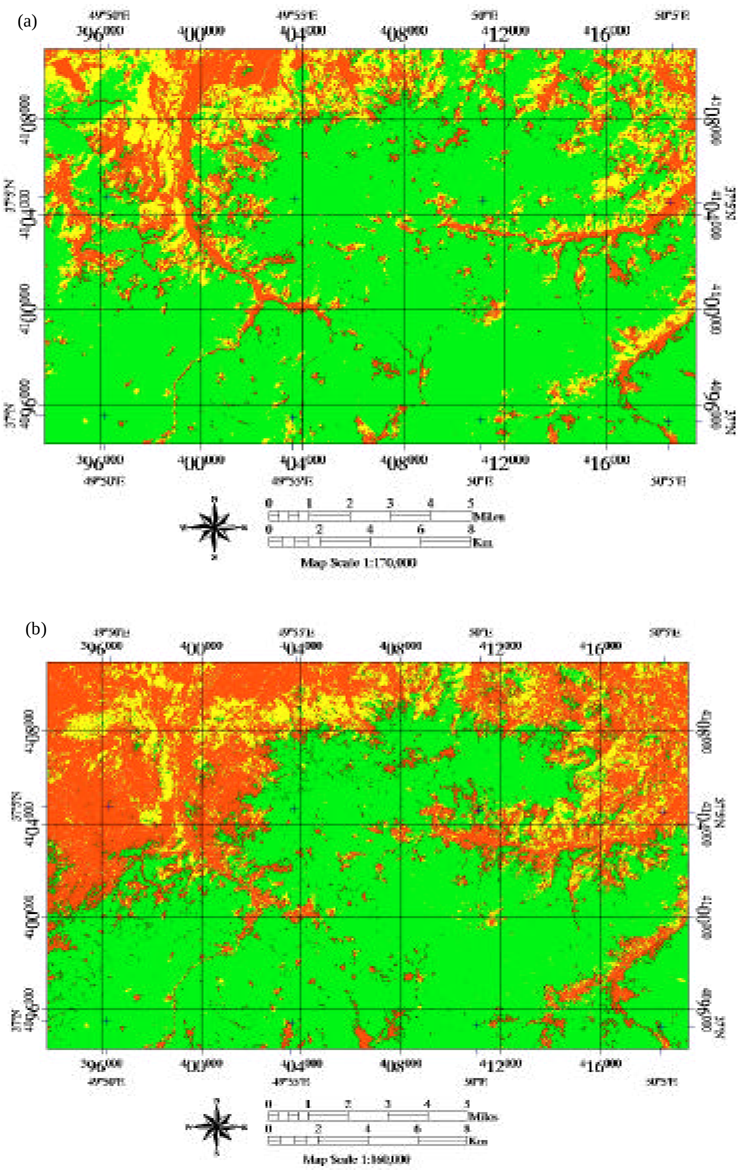


Fig. 5: The result of supervised classification (a) 1989 and (b) 2000 images

2000, which is an average of more than 2228.543 ha year^{-1}. Similarly, agriculture areas decreased in size by 994.854 ha from 1989 to 2000, more than 90.44 ha year^{-1}. Man made areas increased by 5838.274 ha between 1989 and 2000, which is an average of more than 530/75 ha year^{-1} (Table 5).

Table 6: Estimated proportion of changes for three main land cover method

Class	Forest	Agriculture	Man-made	Total
Area of change (ha)	929.19	758.04	1428.36	3115.60
Percentage (%)	3.16	10.46	21.59	35.22

Table 7: The area of forest and non forest between 1989 to 2000

Class name	Area 1989(ha)	Area 2000 (ha)	Differencing of area between 1989 to 2000 years (ha)
Forest	29357.39	24513.97	-4843.42
Non forest	13860.72	18704.14	4843.42

Combining the result of changes detected by different methods and of visual inspection of changes observed, the area induced changes for 3 main land cover classes and their estimated accuracy were estimated (using NDVI Differencing) and it has been presented in (Table 6). Also, Table 7 show that 4843.42 ha of total forest area degraded in the 11 years.

DISCUSSION

Differences in vegetation composition, phonology and coverage together with soil structure, moisture and atmospheric conditions increase the spectral variation. Different techniques provide products that vary in levels of adequacy according to the specific application, for example (1) CVA excelled in an arid environments (Sohl, 1999), (2) image differencing provide powerful interpretation of change in tropical region (Lu *et al*., 2005) and (3) post-classification presented the advantage of indicating the nature of the changes (Mas, 2005).

Among different change detection approaches, NDVI Differencing was the best in detecting the changes occurred in the study area. Regardless of the technique used, the success of change detection from imagery will depend on both the nature of the change involved and the success of the image pre-processing procedures. However, if the nature of change within a particular scene is abrupt, changes should be relatively easy to detect. In the case of forest road construction induced change detection, due to the pronounced loss of vegetation and soil in post image, delimiting changed area was easy. Greenness differencing methods indicates the lowest accuracy. Current remote sensing techniques enable the application of land use/cover change detection in temperate regions of the world.

However, the North of Iran environment limits the capability of current remote sensing techniques because (1) the high temporal variability of the spectral properties of major land covers causes large within-class spectral variability, (2) the varied spatial frequency of the landscape results in complex scenes and (3) the similar reflectance properties of major land covers makes spectral separation difficult (e.g., bare soil can have similar reflectance properties to man made areas and similar near-infrared reflectance to a crop canopy) (Berberoglu *et al*., 2000). To minimize the impacts of these problems, this paper aimed to assess application of the different change detection techniques, focusing on the techniques that were likely to help alleviate existing problems associated with change detection in the North of Iran.

In this study area, forest lands have been damaged by converting them to agricultural areas, hazelnut areas and road constructions and illegal forest utilizations etc.

In the forested areas, it can be seen that there are open and intensive clearing made to obtain agricultural and settlement areas. According to measurements from satellite images, the total amount of deforestation in the area in 1989-2000 was 4843.42 ha (Table 5). Also, man made expansion in the forest North of Iran has been largely driven by population growth and economic development. The forests which have lost their density and canopy can not fulfill their hydrologic and soil conservation functions. The land use maps produced in this study will contribute to both the development of sustainable management land use planning decisions and also for forecasting possible future changes in growth patterns.

It was demonstrated that, for change detection of land use/cover from Landsat imagery, the NDVI differencing method may be beneficial for certain land covers.

The study has demonstrated the utility of a threshold image processing to monitor changes in the forest cover and utilize the data effectively to identify changes in the study area. Because the capability to integrate the GIS data from the various commercially available packages without having to go through a process of translation, this is particularly pertinent in our country, where data are scarce and exist as islands of information.

The findings of this study can be summarized as follows: image differencing was simple and straightforward and interpreting and the results were easy. Greenness differencing was unable to define changes effectively. It provided limited change information and yielded the lowest accuracy compared to other techniques. Although, CVA identified changes using bands 3 and 4 of landsat TM imagery. It is also capable of utilizing any number of bands in change detection. NDVI differencing was the most accurate of all the techniques.

According to the aim of the study, radiance/reflectance band differencing, NDVI differencing, tasseled cap (KT), change vector differencing and NDVI ratioing were assessed. NDVI differencing approach was the most accurate technique for the North of Iran environment and the results of this research reveal that there is merit to each of the several land use change detection methods studied and that there appears to be no single best way in which to perform change analysis.

The results of this research reveal that there is merit to each of the several land use change detection methods studied and that appears to be no single best way in which to perform change analysis. It is apparent that, for any method, the accuracy of those methods can be no better than that of each of the input maps and is often quite lower. Methods such as band differencing obviate the need for a high degree of a priori knowledge, but require substantial a posteriori interpretation. The methods addressed in this research each explicitly identify a priori the types and natures of land use change to be expected to occur within multitemporal remote sensing data.

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