Monitoring Land Use/Cover Changes Using Different Change Detection Techniques (Case Study: Falavarjan Area, Isfahan, Iran)

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Abstract

Land use/cover change mapping is one of the basic tasks for environmental monitoring and management. In recent years, a variety of change detection techniques have been developed. This research compares three change detection techniques, including image differencing, image rationing, and image regression to study land use/cover changes in Falavarjan /Iran. The data sources used in this study were Landsat Multi-Spectral Scanner (MSS) and AWiFS images taken in September 1972, and September 2008, respectively. First, images were geometrically and radiometrically corrected. The root mean square (RMSe) obtained 0.5 pixels for each images. The Three change detection methods were performed. Then, a supervised maximum likelihood classification was used as a crossclassification to detect "from-to" change which allowed to assess the accuracy of each change detection technique. Based on accuracy assessment, the image differencing method was the most accurate one with an overall accuracy of 85% in detecting land use/cover changes in Falavarjan area. This was followed by the image rationing technique with an accuracy of 84%.

Keywords: Change detection, Image differencing, Image rationing, Post-classification.

1. Introduction

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times [1]. A variety of algorithms have been developed for change detection including, image overlay, image differencing, image regression, image rationing, vegetation index differencing, principal components analysis, spectral/temporal classification, post-classification comparison, change vector analysis, and background subtraction [1,2].

Among the different change detection techniques, image differencing, image rationing, image regression and change vector analysis (CVA) are widespread [3-6]. In theses algorithms, selecting threshold is necessary to determine the changed areas. Petit et al. (2001) found the combination of image differencing and post-classification was better than the only single method in determining "from–to" change in south-eastern Zambia [7]. Berberoglu and Akin (2009) and Prakash and Gupta (1998) compared different change detection methods. They found that each algorithm have its own merits and advantages [8,9]. Angelici et al. (1977) applied the difference of band ratio data and a threshold method to separate change and no change areas [10]. Jensen and Toll

(1982) and Chavez and Mackinnon (1994) found the usefulness of visible red band data in change detection analysis in both vegetated and urban environments [11,12]. Ridd and Liu (1998) applied four change detection algorithms, including image differencing, regression method, tasselled cap transformation, and Chi-square transformation for urban land-use change detection in the Salt Lake Valley area. They indicated that the regression of TM band 3 was the most accurate for detecting changes [13].

This research compares three techniques, including image differencing, image rationing and image regression to evaluate the most accurate one for change detection in the study area.

2. Methodology

2.1. Study area and data

The study area is Falavarjan area in western part of Isfahan city, which covers approximately 17550.6 ha (Fig.1). It is located in 32°29′-32°37′N and 51°20′-51°35′E. Falavarjan city, located in the center of the study area, is on the bank of Zayandehrud River. Zayandehrud River emanates from Zardkuh Mountain and flows in eastern Falavarjan. The climate is hot and dry with an average temperature of about 16.4°C and average annual rainfall of 162 mm/year. The study area includes agricultural fields, Zayandehrud River, bare lands and urban areas.

In the present study, Landsat Multi-Spectral Scanner image (MSS) 4, 1972 and high spatial resolution (56m) Indian remote sensing satellite (IRS-P6) AWiFS sensor data acquired on September, 2008 were used to detect changes over a period of 36 years.

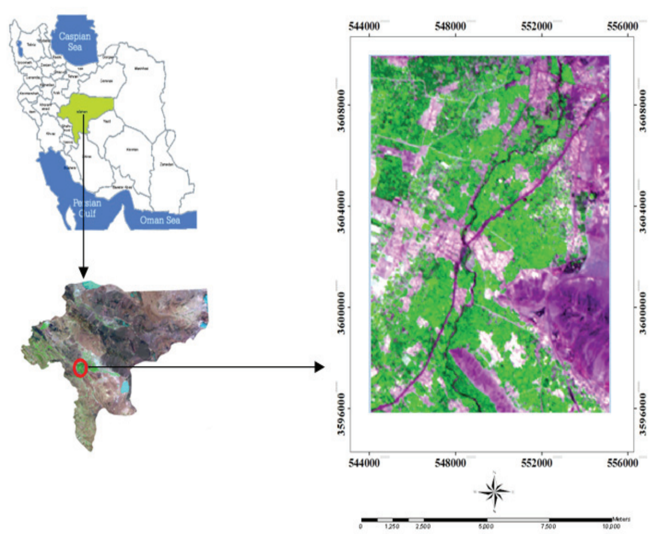

Fig 1. Study area: AWiFS image of Falavarjan area, taken inSeptember 2008 (right) in the west of Isfahan (below left) in central of Iran .

2.2. Image pre-processing

The images were geometrically corrected and geocoded to the Universal Transverse Mercator (UTM) coordinate system using 20 ground control points (GCPs). Resampling was applied using a nearest neighbor method. Root mean square (RMS) error obtained 0.5 pixels for each image.

Radiometric normalization was necessary to reduce differences because of atmospheric or a sensor variation between the two dates. In this paper, the images were radiometrically normalized based on the method developed by Markham and Barker (1986) [14].

2.3. Change detection

In order to detect land cover changes, three common methods, Image differencing, Image rationing, Image regression were applied.

2.3.1. Producing change images with three techniques

Image differencing was applied with each of different bands. The four difference images (Dif1, Dif2, Dif3, Dif4) were created by subtracting the 1972 image from the 2008 image. In this method, digital numbers in the resultant difference image are often considered to be normally distributed where pixels with small change are observed around the mean. Pixels which have been changed largely are distributed in the tails of histogram [1]. For image rationing, the bands were rationed for each image pair on a pixel-by-pixel basis and four change images (Ratio1, Ratio2, Ratio3, Rati4) were produced. The assumption in the image regression technique is that the later image is a linear function of the earlier image. The MSS band 2 was considered as the independent variable and the AWiFS band 3 was taken to be the dependent variable. It was observed a linear relationship between these two images. Then, the predicted image and the base image were subtracted from each other.

2.3.2. Optimal threshold determination

Threshold levels, ranging from 0.1 to 3.0 standard deviations from the mean, were tested on the change images in order to determine the optimal threshold values. Consequently, 1σ was identified as the most accurate one among others as determined from the aerial photographs and ground data. Then, the change images were reclassified into two classes. The value '0' was assigned for 'no change' areas and '1' for change areas.

2.3.3. Classification

Post-classification comparison is an important method in improving the quality of classifications [15-17]. A supervised maximum likelihood classification method was performed for 1972 and 2008 to classify land cover in the study area. Four land use/cover classes including river, bare land, agriculture and urban were observed. This method provides a "from-to" matrix of change information. The change category is divided into five subcategories as shown in Table 1.

Category	From (1972)	To (2008)
0	No Change	
1	Agriculture	Bare Land
2	Agriculture	Urban
3	Bare Land	Urban
4	Bare Land	Agriculture

Table 1. Categories of land use /cover change (1972-2008)

2.4. Accuracy assessment

In order to assess change detection accuracy, an error matrix and a kappa analysis were utilized. The error matrix is the most common method for accuracy assessment [18]. To properly generate the error matrix, Ground data set, air photos and field survey records and RGB composites were used.

3. Results

3.1. Change detection

For accuracy assessment, changed and unchanged pixels were cross-tabulated against the resultant images derived from the different algorithms. Overall accuracies were calculated by dividing the total number of correctly classified pixels to the total number of pixels. Accuracy of change images were estimated at change/no change level. At level change/no change detection the overall accuracies were 85.02% (image differencing), 84.13% (image rationing) and 75.46% (image regression), respectively.

The result from the image differencing and image rationing techniques were very similar (Fig.2). These methods were very effective in separating change from no-change with the visible bands. The MSS band 2 and the AWiFS band 3 had the best accuracies. Therefore, the changed images derived from these bands are more practical than the others for change detection in this study area.

Because the image differencing, image rationing and image regression methods do not provide the detail information about the kinds of land cover change, the outcome of post-classification was crossclassified with the each three techniques to identify "from-to" change and to assess the accuracy of the three change images in detecting the four kinds of change (table 2).

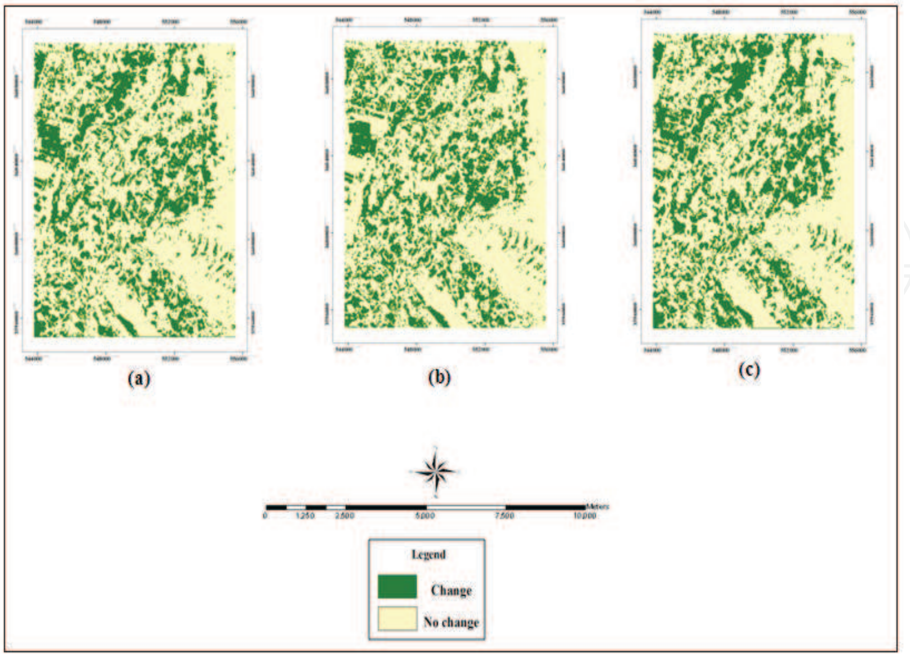

Fig 2. Change images derived from the (a) image differencing, (b) image rationing and (c) image regression.

Based on producer's accuracy, the percent correctly classified for each category, is listed in Table 2. For change type 1, agriculture to bare land, the highest accuracies are from the image differencing and image rationing. For category 2, agriculture to urban, the best result is from the image differencing and image rationing, too. For category 3, bare land to urban, image differencing is the best with an accuracy of 15.44%. For category 4, bare land to agriculture, image differencing at 55.5% is the best, followed by image rationing at 55.23% and image regression at 50.55%. It is observed that the results of image differencing and image regression techniques are very similar. Image regression technique identified all of the categories of change with the least accuracy.

Change detection techniques	Categories of land use/cover change			
	1(%)	2 (%)	3 (%)	4 (%)
Image differencing	93.1	79.81	15.44	55.5
Image rationing	91.81	77.32	8.84	55.3
Image regression	87.93	76.5	14.6	50.50

Table 2. Producer's accuracies of the change images for detecting four kinds of land cover/use change

4. Conclusion

Change detection algorithms have long attracted the attention of the researchers and scientists. In recent years, a variety of approaches have been applied for the monitoring land use/cover change. Each method has some advantages and disadvantages. Many factors such as selection of suitable change detection approach, suitable band and optimal threshold, may affect the success of a classification [19,20].

This research aimed to examine the utility of three techniques, including image differencing, image rationing and image regression in detecting land use /cover changes from 1972 to 2008. Among the different bands, the MSS band 2 and the AWiFS band 3 had the highest accuracies. The optimal threshold was 1 standard deviation from the mean. Results showed that the image differencing and image regression techniques had the highest accuracy in separating change and no change areas. However, these techniques cannot provide a complete matrix of change detection. Therefore, the post-classification method was performed in order to provide details about the nature of changes. In fact, the combination of image differencing, image rationing and image regression with post classification was used. It showed that this technique can provide better change detection results than simple method.

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6. References

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