Monitoring Protected Areas Using Remote Sensing Technology

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Abstract: Due to irrational use of natural resources, human society is facing unprecedented threats. Remote sensing is one of the essential tools to determine changes in various forms of biological diversity over time. There are many methods to determine changes in protected areas, using satellite images. In this paper after introducing different change detection methods and their advantages and disadvantages, a hybrid method is used to analyse changes in forests and protected areas in a national park. Two Landsat images of Golestan National Park in Iran (taken in 1998 and 2010) were used. This hybrid approach combines Change Vector Analysis (CVA) for flagging the occurrence of changes, followed by signature extension to assign labels to changed pixels. The main objective of this paper is to propose a method for discovering and assessing environmental threats to natural treasures.

1 INTRODUCTION

Selecting the most appropriate change detection method for a given application is difficult, and requires consideration of the change type of interest (Fraser, Olthof, and Pouliot, 2009). Wide range of change detection algorithms are now available which may be broadly grouped as classification methods (Chen and Chen, 2012), (Hermitte, Verbesselt, Verstraeten, and Coppin, 2011) and spectral approaches (Fraser et al., 2009). If sources of image noise are adequately controlled, spectral approaches quantify the magnitude of reflectance changes between different dates, which relate to a land surface change.

One advantage is the potential to fine-tune change detection sensitivity, while a limitation is the inability to provide information on the nature of change e.g. class label (Xiaolu and Bo, 2011). Examples of spectral-based methods include: image differencing, regression and change vector analysis (Fraser, Li, and Cihlar, 2000), (Johnson and Kasischke, 1998), (Prakash and Gupta, 1998), (Fraser, Olthof, and Pouliot, 2009).

Classification approaches such as post-classification comparison and two-date image clustering, in contrast identify both the occurrence of changed pixels and the type of change by directly labelling land cover at two time periods. However, they are susceptible to generating high levels of commission error due to the multiplication of individual errors (Yuan, Sawaya, Loeffelholz, and Bauer, 2005), (Fraser, Olthof, and Pouliot, 2009). There are also hybrid change detection procedures that exploit the advantages of each approach, while attempting to minimize their limitations (Luque, 2000), (Petit, Scudder, and Lambin, 2001), (Silapaswan, Verbyla, and McGuire, 2001).

This paper presents a hybrid change detection algorithm. In this approach, a mask of potential changed pixels is first created by thresholding a two-date change vector analysis (CVA) product. Land cover class is then updated for changed areas only by spectral signature extension, whereby changed pixels are matched to the most similar labelled cluster from a baseline land cover map.

This method exploits the benefits of both spectral and classification type methods, and reduces their weaknesses (Fraser et al., 2009). Thus, the accuracy of this hybrid method is expected to be higher than each method individually. It is also focused on decreasing the role of human operators in the process. This method extracts image data better than the others and also enables labelling to be done automatically using post classification comparison and pre-existing knowledge of the land cover data.

This paper is organized as follows: Section 2 describes the case study area and the required data for

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analysis. Section 3 represents the proposed change detection algorithm. Section 4 describes the environmental analysis. Finally, in section 5, our conclusions are drawn.

2 CASE STUDY AND REQUIRED DATA

Golestan National Park with 92,000 hectares area is the biggest and oldest registered national park in Iran. This forest was registered with the UNESCO World Heritage List in 1976 as one of the 50 vital protected areas on earth. The geographical area of Golestan National Park is between 55° 43' 16" to 56° 15' 31" longitudes and 37° 16' 51" to 37° 32' 27" latitudes. The average elevation of this park is 1378 meters.

Different data types used in this study are introduced below.

2.1 Topographic Map

The only map available for the study area is a 1:250,000 topographic map produced in the spring of 1998 by a group of forestry research organizations using Landsat ETM+ images (Figure 1).

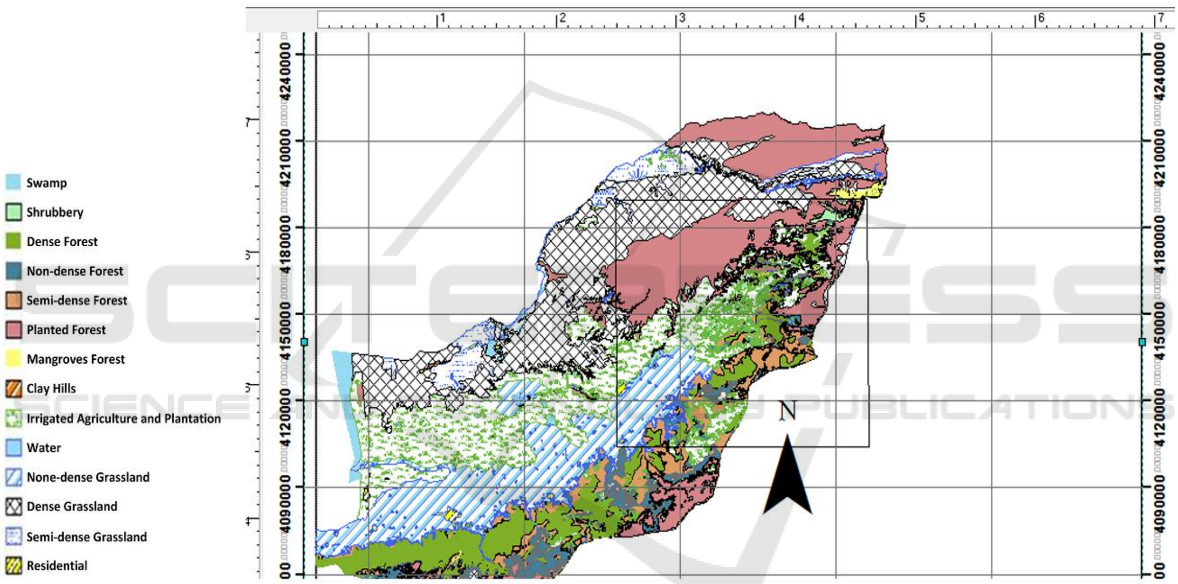


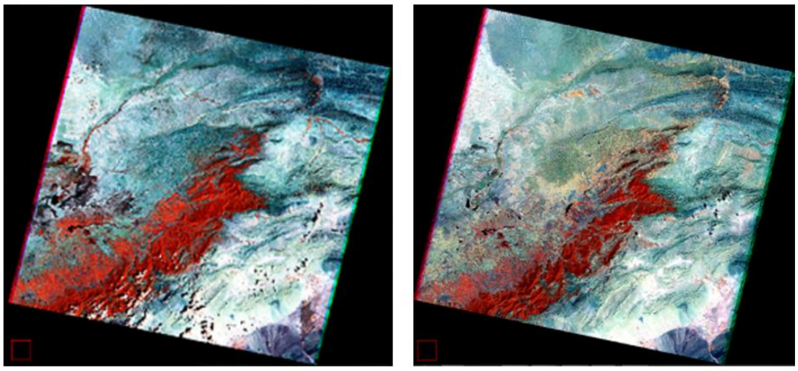
Figure 1: The topographic map of the study area in 1998

2.2 Landsat Images

For this research, two Landsat images taken in August 1998 and 2010 (a period of 12 years, which is an appropriate period for assessing environmental changes) were used. The radiometric and geometric calibration parameters of these images are available and cloud cover over the area in the images is negligible. Image dimensions are 8091 × 7231 pixels and the field of view is about 185 × 175 km (Figure 2). For Landsat TM images, the UTM system and WGS84 ellipsoid were used for geo-referencing.

2.3 High Resolution Images

Since there was no updated map for the case study area, in order to evaluate the accuracy of the method, we used Geoeye high-resolution images for 2010. The mosaic Geoeye images have been cut to the thresholds of Landsat images' latitude and longitude (Figure 3).



(a) (b)

Figure 2: Landsat images (false colour composites), of the study area (a) August 1998 and (b) August 2010.

3 CHANGE DETECTION ALGORITHM

This method consists of four main steps. Pre-processing level as the first step, includes obtaining images and reference maps, image registration and normalization. The purpose of this step is to prepare the images for the next step.

In the second step, thematic map is produced from satellite images and available maps of the area, by clustering an image as the baseline (master) image and labelling the clusters based on the reference maps. Then based on the post- classification comparison method, the changes' nature are labelled. Post-classification comparison applies a comparison between the feature vector of each changed pixel and the centre of the labelled clusters. Based on this comparison the changed pixels will be labelled (change map).

Finally in the last step, a reference map is produced using the high-resolution Geoeye image which is needed for accuracy assessment.

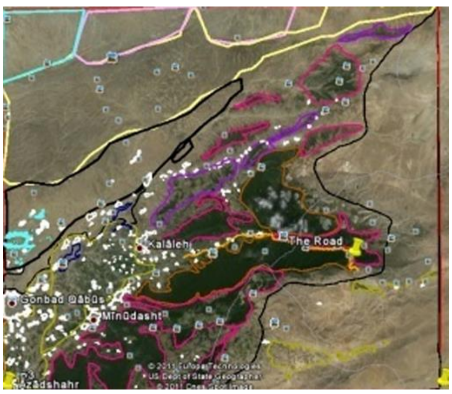


Figure 3: Mosaic Geoeye image of the study area, 2010.

3.1 Pre-processing

Image pre-processing stage, includes both the geometric correction and normalization of images that have been taken at different times from the same area. Pre-processing consists of the following operations.

3.1.1 Geometric Correction

In this study, the geo-referencing of the 1998 image is performed using the 1:250,000 topographic maps. After geo-referencing of 1998 image, the 2010 image is registered to 1998 image. Sub-pixel accuracy for image registration is obtained.

3.1.2 Image Normalization

After a careful image-to-image spatial registration the images must be radiometrically normalized. Accurate normalization is essential for the combined CVA and post classification comparison change detection approach, since both methods assume that a pixel's reflectance is stable through time unless a land cover change occurs (Fraser, Olthof and Pouliot, 2009). Histogram Matching is a common technique for this reason which uses the histograms for image processing and colour adjustment between images.

3.2 Thematic Map Generation

The change detection procedure requires a baseline land cover classification from which changes are detected at nominal 12-year intervals. The thematic map is produced using an unsupervised clustering approach that combines features of the Enhancement Classification (ECM) and Classification by Progressive Generalization (CPG) methods.

The enhanced imagery is clustered to a number of spectral clusters. Visual quality checking is an important part of this and each subsequent generalization step, and is performed by comparing the previous generalization with the current one to ensure that no significant land cover information is lost. The overall coverage of the Earth's classes such as soil, water, plant and etc., are determined. Generalization proceeds by progressively merging spectrally similar and spatially adjacent clusters to generate conceptual classes. Final cluster merging and labeling to a land cover classification is based on expert image interpretation and available reference data (Fraser, Olthof, and Pouliot, 2009).

In this research the 1998 Landsat image is divided into 22 clusters using Iso-data clustering method. The number of clusters is chosen to be twice as the number of conceptual classes which are 11 in the case of this study area. The output for this level is a clustered image (22 clusters), which is labelled based on 1:250,000 topographic map and converted to 11 conceptual classes.

3.3 Change Detection Process

In this section, the sub-steps of change detection process will be explained in the following stages.

3.3.1 Tasseled Cap Transformation

Tasseled Cap transformation is a well-known methods of enhancing spectral information content for Landsat TM data. Tasseled Cap transformation especially optimizes data viewing for vegetation studies. Tasseled Cap index was calculated from data of the related six TM bands (King and O'Hara, 2001). Three of the six tasseled cap transform bands are often used:

- Band 1, brightness as a measure of soil
- Band 2, greenness as a measure of vegetation
- Band 3, wetness as interrelationship of soil and canopy moisture

This transformation is used to calculate brightness and greenness of both images (1998 and 2010), which are the input for CVA analysis.

3.3.2 Applying Change Vector Analysis

A change vector can be described by an angle of change (vector direction) and a magnitude of change from date 1 to date 2 (Fraser et al., 2009), (Chen, Gong, He, and Shi, 2003). We used brightness and greenness as inputs of CVA to measure and monitor reforestation and deforestation of the region of study. The bands are observed in measurement space with brightness placed along the X-axis and greenness placed along the Y-axis.

Change direction is achieved by measuring the angle between corresponding pixels in different times (1998 - 2010) and the magnitude of change is achieved using Euclidean distance between vectors.

Magnitude of change vector and its direction are described by Eq. (1) and Eq. (2) respectively.

$$S = \sqrt[2]{(G_2 - G_1)^2 + (B_2 - B_1)^2} \quad (1)$$

$$\tan\alpha = \frac{G_2 - G_1}{B_2 - B_1} \quad (2)$$

G1, G2, B1, and B2 are values of greenness and brightness in two images, which are obtained from Tasseled cap transformation. To specify the reforestation and deforestation of the jungles, greenness and brightness values should be compared (Kuzera, 2005). Angles measured between 90 and 180 degrees, show reduction in brightness and increase in greenness, this change is considered as reforestation. Angles measured between 270 and 360 degrees, show reduction in greenness and increase in brightness, this change is considered as deforestation (Kuzera, 2005). Angles measured from 0 to 90 and 90 to 180 degrees, show reduction or increase for both greenness and brightness, respectively. This is known as a stable condition, indicating no change in the vegetation of the area (Kuzera, 2005).

According to the magnitude of change vectors, damaged pixels are categorized into 4 levels of low, moderate, severe and very severe deforestation. For this reason four equal intervals are applied as below:

- Interval [1-100]: Low change
- Interval [100-200]: Moderate change
- Interval [200-300]: Severe change
- Interval [300-400]: Very severe

Values less than 1 are considered as noise and values higher than 400 as outlier. The thresholds defined are quite tentative. In Figure 4, the various degrees of grayscale represent different degrees of degradation, the darker shades show more severe deforestation and vice versa.

3.3.3 Post Classification Comparison

Change labeling is accomplished by iteratively updating land cover starting from the baseline classification for only those pixels identified as

changed in the CVA change mask. Post-classification comparison method involves comparison of the new feature vector of each changed pixel with the major feature vector of the cluster centres (determined in the first image). New classes of land cover pixels are determined by assigning a pixel to the most similar cluster and corresponding existing land cover maps, so the new cluster of changed pixels are achieved.
Figure 4: Result of applying the CVA method to two Landsat images of the study area, for 1998 and 2010.

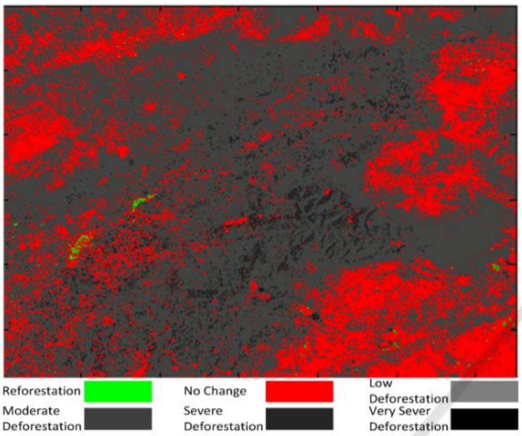


Figure 4: Result of applying the CVA method to two Landsat images of the study area, for 1998 and 2010

To understand the change trends, the feature vector of each changed pixels of 2010 image, is compared with feature vector of classification cluster centres of 1998 image. The changed pixel is assigned to the cluster with the most similarity with cluster centre. Since in 1998 image, each cluster has a distinct relation with an information class, finding the most similar cluster is the same as labelling changed pixels in 2010 image with a new information class.
This model is used for cost-effective classification in large and remote areas and regions where it is difficult to collect data. The main benefit of this approach is that by using post-classification comparison method and a strong knowledge of land cover data the labelling process will be done automatically.

3.4 Accuracy Evaluation

Since there is no updated reference map available for the area, in order to evaluate the accuracy of the obtained change detection results, a reference map is produced by using both the Landsat (2010) and a high-resolution Geoeye image. Geoeye image is taken at the same time as the Landsat image (2010) and covers the whole Golestan national park. It is later cropped so it covers the same latitudes and longitudes that Landsat image covers.

To produce the reference map, Landsat 2010 image is first clustered into 33 clusters. The obtained clusters are compared to the information classes recognized from the high-resolution Geoeye image. In this way the correspondence between clusters and conceptual classes are determined which leads to the classification of 2010 Landsat image. This image is used as the reference map to evaluate the change detection results. We gained 85% accuracy for the proposed change detection method.

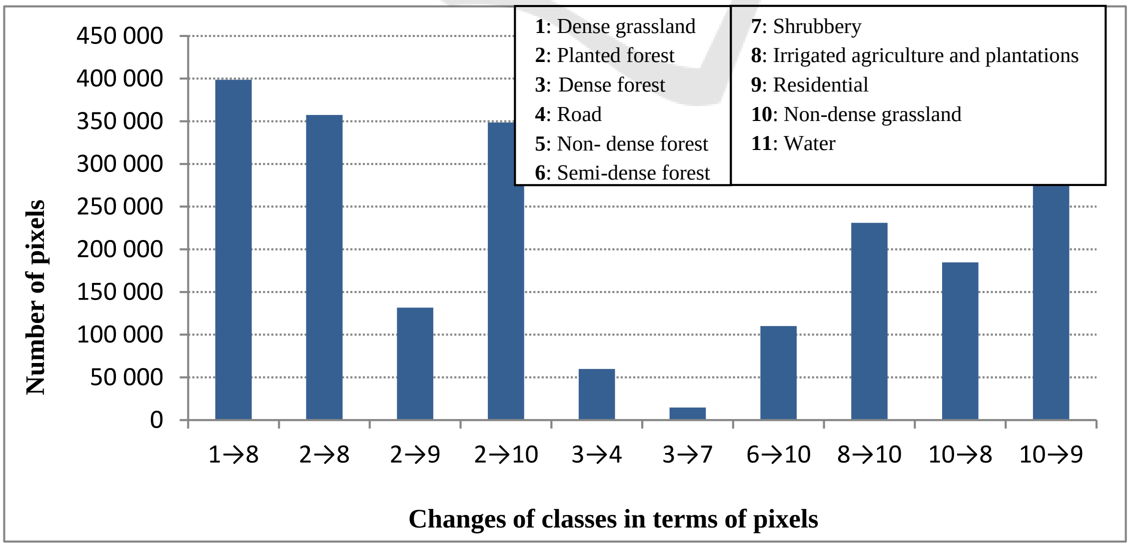


Figure 5: Changes of classes in terms of pixels

4 ENVIRONMENTAL ANALYSIS

Figure 5 shows the classes which have the most change rate and magnitude of their change in terms of pixels. As the statistics show from 1998 to 2010 the number of pixels which converted from planted forest, semi-dense forest, dense forest, and dense grassland classes to road, residential, low density grassland, irrigated agriculture, plantations, shrubbery and non-dense forest classes is very high and this represents a serious degradation in this area. Road construction in forests regardless of its negative effects on the forest, inappropriate urban development, human progression in nature, cutting trees for fuel, human farming in the forests to provide food supply, and etc. are some main reasons for degradation in this area.

A similar research was developed and demonstrated by Fraser using six national parks in Canada. It covered a range of geographical and ecological conditions and was subject to a variety of change agents including forest harvesting, wildfire, land use development, and climate/weather (Fraser, Olthof and Pouliot, 2009). In contrast to Golestan National Park area that is located on one Landsat scene and there is no need to mosaic Landsat images, the area of Fraser's study was vast and required more than one Landsat frame to provide complete coverage. They used 30m resolution Landsat EM and ETM+, from 1990 to 2005 to generate baseline land cover classification at five years intervals. Due to huge height difference, removing haze and topographic effects for Canada's national parks was necessary. However in Golestan National Park, topographical elevations are fairly smooth and there was no need to apply topological corrections in pre-processing. Moreover, radiometric normalization in Canada national parks was done by using filtering, while for Golestan National Park it was done by histogram matching. In both methods, identifying the changed pixels and labelling them, were determined using CVA and signature extension. Finally in Canada baseline land cover and changes were validated by updated available maps and in Golestan National Park by high-resolution Geoeye images (due to the lack of updated maps). Fraser reported 92% correctly identified changed pixels and 8% omission error rate in Canada's parks.

5 CONCLUSION

Timely and accurate change detection of Earth's surface features is extremely important for understanding relationships and interactions between human and natural phenomena in order to promote better decision making. Remote sensing data are primary sources extensively used for change detection in recent decades and many change detection techniques have been developed based on them. The common goal of all these algorithms is to improve the accuracy of the information extracted from remote sensing images. In this paper, a change detection method was proposed to determine changes in the forests of Northern Iran (Golestan National Park). Using the combination of spectral and classification methods lead to an acceptable accuracy.

In comparison with the conducted research on national parks of Canada, lack of updated reference maps, has a direct impact on the final accuracy. The results of the assessment indicated that change detection method should be developed based on local knowledge. While this method provides a set of generic procedures and tools for change detection, its successful application requires an analyst experienced in land cover interpretation and image processing. In particular, the baseline land cover labeling, assessing results from the image correction methods, determining a CVA change threshold, and development of signature extension rules, are subjective and will determine the final accuracy of the land cover change products. This algorithm is a cost-effective change detection method in large areas and tries to minimize the role of the human operator. It can be implemented for most forests regardless of their vegetation. This study is intended to explorer use of high resolution images in the future in order to investigate its capabilities to determine the change of plant species. In future this method also can be elevated using optimisation methods to find the best values for CVA thresholds, number of clusters, and similarity measure and result in an extended intelligent version of current change detection method.

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