# FOREST COVER CHANGE ANALYSIS BY OBJECT BASED METHOD USING SPOT AND RAPIDEYE IMAGES

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**ABSTRACT:**

In this paper we present forest cover change analysis by object based method with SPOT-5 (2007) and RapidEye (2013) images for an Ejido in the state of Jalisco, Mexico. We identified three classes in images of each date: 1) forest 2) degraded forest and 3) non-forest. An object based image analysis was applied to first segment the images into objects, and then classify the objects into the above three classes. We compared the results from this object based model with a model based on pixel based method. Classified images from both methods were evaluated with verification data composed of 254 random points and object based methods obtained slightly higher overall accuracy than the pixel based methods. Forest cover changes were analysed by constructing a model in DINAMICA (3.0.6) in which the forest classes of two dates were compared, and the forest cover changes were derived including deforestation, degradation, regeneration, and revegetation. The results show that although the overall accuracies of the classifications show no significance difference by McNemar's test, except the classifications between MLC and MD for 2007, the obtained forest change results show big variance between adopted methods and it is rather difficult to compare them. The future study will apply test data for forest change classes and decide the best change results with the highest accuracies.

## 1. INTRODUCTION

### 1.1 Background

Forest covers about 30% of the land area of the Earth. Changes of forest cover can affect many environmental processes and quantifying forest cover change plays an important role to address issues such as global carbon budget, ecosystem dynamics, etc. Satellite images are important data sources for reliable forest cover mapping and forest cover change quantification. For example, the combination of coarse spatial resolution images, e.g. from MODIS sensor with images of finer spatial resolution such as SPOT, or Landsat can be very useful in identifying and quantifying forest cover change of large area (Gao et al. 2011). One of the relatively simple change detection methods generates change classes by comparison of multi-temporal image classification results. The multi-temporal satellite images were first classified into forest cover types, and then compared pixel by pixel to form spatially explicit forest cover change data. This method requires accurate classification results due to that the accuracy of the forest cover change results depends on the accuracy of the classification results.

Image classification assigns the image pixels into land cover categories by certain algorithm. Pixel base classification usually only implements spectral information of the images. It encounters problems when classifying high resolution satellite images with the increased noise-signal ratio. Besides, there are often spatial characteristics in image segments (groups of pixels) that are useful in the classification especially of high spatial resolution satellite images. Object based classification groups similar and adjacent pixels into objects based on both spectral and spatial information and classifies the segmented image by objects. Both pixel based and object based image classification methods have been proved successful, depending on the study area and sensor choices. This paper tested both pixel based and object based methods for forest cover change analysis with the purpose to find out which method could achieve results with higher accuracy. The assumption is that the multi-temporal classifications with high overall accuracies also lead to change map with high overall accuracies.

## 2. STUDY AREA, DATA, AND METHODOLOGY

### 2.1 Study area

The test area, el "ejido" la Laja, is a village with 760 habitants (INEGI, 2010), located in the Mixtlan municipality in the west of Jalisco state, west Sierra Madre region. The dominant climate is humid and semi-humid, with an altitude of 1440 meters above sea level, and an average annual temperature of 19.8 degrees. The main forest types are pine and oak (Gobierno de Jalisco 2010) (Figure 1).

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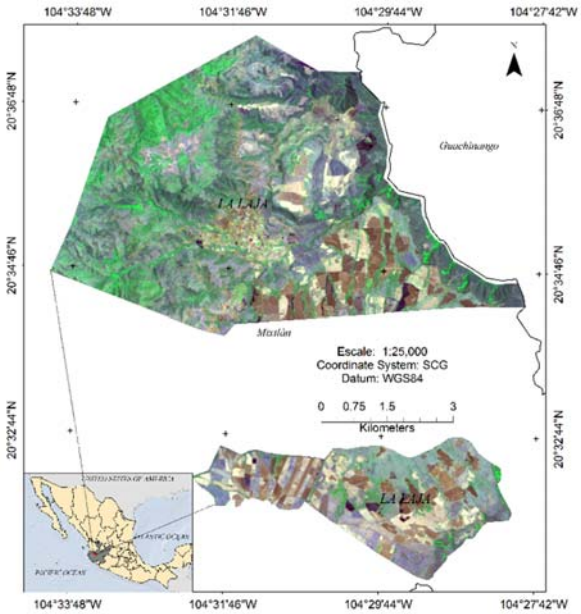


Figure 1. The study area

## 2.2 Data

The data for this analysis include SPOT 5 (for image analysis of 2007) and RapidEye images (for image analysis of 2013). SPOT-5 satellite sensor functioned from May 2002 to March 2015. Its applications include medium-scale mapping (1:25000 and 1:10000), urban and rural planning, and natural disaster management, among others (http://www.satimagingcorp.com/satellite-sensors/other-satellite-sensors/spot-5/).

RapidEye sensor was launched in August 2008 and offers image data with large-area coverage, frequent revisit intervals, high resolution, and multispectral capabilities. Its capabilities can be applied to agriculture, forestry, cartography, and mining, among others. The specifications of SPOT-5 and RapidEye sensor are summarized in table 1.

| | Image bands (nm) | | Spatial Resolution (m) | |
|---|---|---|---|---|
| | SPOT | RapidEye | SPOT | RapidEye |
| Pan | 480 – 710 | / | 5 (nadir) | |
| Blue | / | 440 – 510 | / | 5 |
| Green | 500 – 590 | 520 – 590 | 10 | 5 |
| Red | 610 – 680 | 630 – 685 | 10 | 5 |
| Red Edge | / | 690 – 730 | / | 5 |
| Near IR | 780 – 890 | 760 – 850 | 10 | 5 |
| Shortwave IR | 1580 – 1750 | / | 20 | / |

Table 1. Specifications of SPOT-5 and RapidEye satellite sensor (adapted from http://www.satimagingcorp.com/satellite-sensors/other-satellite-sensors/spot-5/)

For carrying out the classifications, the training data were selected for three classes: forest, degraded forest, and non-forest, for images of 2007 and 2013, respectively. The selection is based on the visual inspection of the classified satellite images. For the accuracy assessment of the classifications, two sets of test data with random points for both 2007 and 2013, were created by visual interpretation.

## 2.3 Methodology

**2.3.1. Multi-temporal image classifications**: Object based classification was carried out in SPRING which requires two parameters for image segmentation: area and similarity. The decision for those parameters was based on a trial and error method by visual inspection of the segmentation results. The segments were classified into thematic classes in SPRING. Pixel based MLC classifies based on the probability function constructed training data, and a pixel will be classified to the class to which it has the highest probability. Pixel based MD classifies a pixel to a land cover category to which it has the shortest distance.

**2.3.2. Accuracy assessment:** Two sets of test data were created for the study area for both 2007 and 2013 by visual interpretation of random points. Error matrix was built with the classification data and the test data, based on which the overall accuracy, the use's and producer's accuracies were calculated. The overall accuracy calculates the proportion of the assessed area that is classified correctly. The user's accuracy calculates the proportion of pixels classified as a class that truly belong to that class, and the producer's accuracy calculates the proportion of pixels from a class that are classified as that class. User's and producer's accuracies are related to commission and omission errors. Kappa coefficient was not used since it may underestimate classification accuracy by overestimating the chance agreement (Pontius et al. 2011).

**2.3.3. The statistic of the McNemar's test:** Because the same set of reference data was used in accuracy assessment for both pixel-based and object-based classification, dependency may exist among the resultant confusion matrices. The McNemar's test was applied to test the statistical significance of the difference between those classifications. McNemar's test is based on an assumption that different classification approaches have the same number of correctly and incorrectly classified pixels. It is a non-parametric test and the statistic follows a chi-square distribution of one freedom degree. The formula for the statistic of the McNemar's test is presented in equation 1:

$$X^2 = \frac{(f_{12}-f_{21})^2}{f_{12}+f_{21}} \quad (1)$$

Where $f_{12}$ represents the number of pixels correctly classified by one method but misclassified by the other, while $f_{21}$ for reverse. For this test, an overlay analysis was carried out with the two classifications in comparison and the test data.

**2.3.4. Post-classification comparison for change detection:** The two-date (2007 & 2013) change detection was carried out by comparing the classification results of the corresponding dates. A model was constructed in DINAMICA EGO to analyse forest cover change. Deforestation is defined as changes from forest to non-forest, and from degraded forest to non-forest; forest degradation is defined as changes from forest to degraded forest; reforestation is defined as changes from non-forest to forest, and to degraded forest; and revegetation is defined as changes from degraded forest to forest. A change matrix 2007 – 2013 is presented in table 2.

| | | Forest cover 2013 | | |
|---|---|---|---|---|
| | | Forest | Degraded forest | Non-forest |
| | Forest | Permanence | Degradation | Deforestation |

| | | | | |
|---|---|---|---|---|
| Forest cover 2007 | Degraded forest | Revegetation | Permanence | Deforestation |
| | Non-forest | Reforestation | Reforestation | Permanence |

Table 2. Change matrix 2007 – 2013.

## 3. RESULTS

This part presents the results of classification and change detected based on the post-classification analysis.

### 3.1 Multi-temporal classifications

The multi-temporal classifications (2007 and 2013) were carried out with object based, pixel based MLC, and pixel based MD classifiers. Training data were created for three categories: forest, degraded forest, and non-forest for the images of 2007 and 2013, respectively.

### 3.2 Accuracy assessment

The accuracy of the classifications was evaluated by test data comprised of 250 random points using error matrix. The results of the overall accuracy, user's and producer's accuracies for the individual classes are summarized in the table 3.

| Accuracy (%) | Forest | Degraded forest | Non-forest |
|---|---|---|---|
| Object based 2007 / 2013: Overall accuracy = 68.5 / 70.2 | | | |
| User's accuracy | 73.3 / 66.3 | 53.3 / 63.2 | 76.4 / 81 |
| Producer's accuracy | 76.7 / 88.4 | 57.1 / 52.7 | 69.4 / 73.9 |
| Pixel based MLC 2007 / 2013: Overall accuracy = 68.1 / 69.8 | | | |
| User's accuracy | 72.7 / 63.6 | 50 / 67.7 | 82.5 / 78 |
| Producer's accuracy | 74.4 / 91.3 | 61.4 / 46.2 | 67.3 / 77.2 |
| Pixel based MD 2007 / 2013, Overall accuracy = 63.8 / 69 | | | |
| User's accuracy | 74.4 / 65.5 | 41.7 / 58.9 | 93 / 85.3 |
| Producer's accuracy | 70.9 / 82.6 | 68.6 / 58.2 | 54.1 / 69.6 |

Table 3. results of accuracy assessment for 2007 and 2013 for the tested classifications.

### 3.3 Results of the statistic of the McNemare's test

The McNemar's test was applied to evaluate if there is significant difference between the classification results by different methods. As an example, between the classifications by pixel-based MD and by object-based method, the $X^2$value from the McNemar's test was 3.6. With one degree of freedom, this result has a p-value greater than 0.05, indicating a statistically no significant difference. In a similar way, the McNemar's test was applied to the classifications of 2007, and those of 2013. The results are summarized in the table 4.

| Comparisons (2007 / 2013) | | $X^2$ | $P$ | Significance |
|---|---|---|---|---|
| Object based | MD | 3.6 / 0.21 | $P < 0.1$ / $P < 0.75$ | No / No |
| Object based | MLC | 0.03 / 0.04 | $P < 0.90$ / $P < 0.90$ | No / No |
| MLC | MD | 4.17 / 0.11 | $P < 0.05$ / $P < 0.75$ | Yes / No |

Table 4. The result of the statistic of the McNemar's test.

### 3.5. Change matrices by post-classification comparison

Forest cover change from 2007 – 2013 was analysed by the comparison of the post-classifications with the methods of object based, the pixel based MLC, and the pixel based MD. The results are presented in change matrices in the table 5, 6, and 7.

| Object based (ha) | | Forest cover 2013 | | |
|---|---|---|---|---|
| | | Forest | Degraded forest | Non-forest |
| Forest cover 2007 | Forest | 1534.2 | 265.9 | 111.4 |
| | Degraded forest | 378.4 | 1115.9 | 379.1 |
| | Non-forest | 115.5 | 242.2 | 1313.1 |

Table 5. Post-classification comparison by object based method.

| Pixel based MLC (ha) | | Forest cover 2013 | | |
|---|---|---|---|---|
| | | Forest | Degraded forest | Non-forest |
| Forest cover 2007 | Forest | 1529.5 | 194.1 | 164.3 |
| | Degraded forest | 425.6 | 1116 | 411.5 |
| | Non-forest | 103.2 | 203.7 | 1408 |

Table 6. Post-classification comparison by pixel based MLC classifier.

| Pixel based MD (ha) | | Forest cover 2013 | | |
|---|---|---|---|---|
| | | Forest | Degraded forest | Non-forest |
| Forest cover 2007 | Forest | 1298 | 293.5 | 55.3 |
| | Degraded forest | 353.4 | 1624.3 | 656.1 |
| | Non-forest | 145.2 | 199.7 | 830.3 |

Table 7. Post-classification comparison by pixel based MD classifier.

### 3.6 Forest change 2007 – 2013

Based on the results of the change matrices, quantities of the forest changes, including deforestation (DEF), forest degradation (F-DEG), reforestation (REF), and revegetation (REV) were obtained. The results are summarized in table 8 (ha).

| (ha) | DEF | F-DEG | REF | REV | Total |
|---|---|---|---|---|---|
| Object based | 490.5 | 265.9 | 357.7 | 378.4 | 1492.5 |
| MLC | 575.8 | 194.1 | 306.9 | 425.6 | 1502.4 |
| MD | 711.4 | 293.5 | 344.9 | 353.4 | 1703.2 |

Table 8. The obtained forest cover changes in quantity (ha) 2007 – 2013.

## 4. DISCUSSION AND CONCLUSION

This study performed forest cover change analysis by post-classification comparison method. The classification was carried out by three different methods: object based method, pixel based MLC and MD methods. The objective was to evaluate if object based method could outperform pixel based method.

The classifications did not show big difference in the overall accuracies. By the McNemar's test, there is significant difference only between the pixel based MLC and MD classifications for the images of 2007. As for the accuracies of the individual classes, degraded forest has the lowest user's and producer's accuracies for both 2007 and 2013. At the same time, non-forest has the highest overall accuracies. Degraded forest covers a wider spectral range than that of the forest and non-forest categories, which makes it difficult to be separated from other classes. There is no significant difference in the classifications by the pixel based method and the object based method for the selected study area using SPOT-5 images. Since the change analysis result

depends on the accuracies of the classification results, this seems to suggest that the change results by those three methods would also be similar. In table 8, the obtained forest change results in total are similar by the post-classifications of object based method and pixel based MLC method. The change results in quantities for the individual categories have the same tendencies: deforestation > revegetation > reforestation > forest degradation. This result makes it difficult to decide which method is more suitable for the forest change analysis. For future study, it is needed to derive test data for change categories and perform accuracy assessment for change maps.

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