Geospatial monitoring and evaluation of UNESCO world heritage forest areas in the Tropics

Mukesh Kumar

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Handledare:
Mikael Egberth

Sveriges lantbruksuniversitet
Institutionen för skoglig resurshushållning
S-901 83 UMEÅ
www.srh.slu.se
Tfn: 018-671000

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Supervisor: Mikael Egberth, SLU, Dept of Forest Resource Management, Remote Sensing
Examiner: Håkan Olsson, SLU, Dept of Forest Resource Management, Remote Sensing

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ABSTRACT

This Study aimed at providing a better understanding for monitoring the status, change and threats to UNESCO world heritage areas that are present in the tropical forest. Three change detection techniques were tested using Landsat images for detecting area of changes in the region of the Rio Platano biosphere reserve, a tropical rain forest in Honduras. The change detection techniques considered were image differencing, post classification analysis using supervised classification and vegetation index differencing (NDVI differencing).

Two Landsat scenes recorded on 28th January 1986 and 18th December 2002 were downloaded from USGS. Images were geometrically and radiometrically corrected and the three change detection techniques were tested. Change maps obtained from each technique were visually interpreted. In order to determine the accuracy of each change maps random points were generated using systematic sampling. For each random point, change/no change were separately evaluated by using high resolution data (Google earth data) through a confusion matrix method. Image differencing for band 2 was found to be the most accurate followed by supervised classification and NDVI. Image differencing using band 3 was found to be less accurate than supervised and NDVI differencing. Supervised classification was selected for calculating area statistics inside and outside the UNESCO protected boundary because of the advantage of indicating the nature of changes. The study revealed two important changes which are clear-cut and some changes (regrowth). Clear-cut have been found to be much higher outside than the inside the protected boundary of UNESCO world heritage forested site.

Key words: NDVI, Landsat, Image differencing, supervised classification

Dedication

To my beloved Father Late Yugal Kishor Yadav to whom I owe a great debt of gratitude.

Inspiration from my father has always been a key to any success in my life.

I know papa aap meray sath hamesa hai.

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Place: Umeå

Date: 20090611 Mukesh Kumar

Contents

ACRONYMS

DN	Digital Number
ETM+	Enhanced Thematic Mapper plus
GCP	Ground Control Point
IR	Image Regression
LULUC	Land Use Land Use Change
NDVI	Normalized Difference Vegetation Index
NIR	Near Infra-Red
PCA	Principle Component Analysis
PIF	Pseudo Invariant Feature
RCS	Radiometric Control Set
RS	Remote Sensing
SPCA	Selective Principal component Analysis
TM	Thematic Mapper
UTM	Universal Transverse Mercator
WGS	World Geodetic System

Introduction

Background

The Remote Sensing unit of UNESCO in Paris has invited SLU to contribute to the development of routines for monitoring the status, change and threat to UNESCO world heritage areas that are present in the tropical forest. UNESCO is also interested in developing and evaluating methods for assessing the status and evaluation of forest cover extent, especially regarding the impact of their inscription as world heritage area. It is also of interest to map the forest cover both inside the protected areas as well as in the vicinity of these areas.

In addition to the technical remote sensing image processing work, it is also of interest to evaluate the feasibility of obtaining a suitable image material, as well as to develop suitable ways to illustrate the analysis. The free release of all Landsat data from the US archives as from January 1, 2009, makes this project especially timely.

Tropical Forest

Tropical forests are located between the latitudes 23.5^{o} North and South of the equator. There are many type of tropical forest, growing on a wide range of soil types in South and Central America, Africa and Asia. According to UNESCO International classification (1973) tropical forest types belongs to Tropical Ombrophilous Forest (Tropical Rain Forest), Tropical and Subtropical Evergreen Seasonal Forest, Tropical and subtropical Semi deciduous low land forest and Mangrove Forest. According to May (1975) tropical rain forest is rich in species composition, it is a complex ecosystem and likely to be more fragile than the temperate ecosystem. Although their habitats cover only 7% of the earth's land surface, they contain more than half the species in the entire world biota. Apart from this, these forests have numerous social and economic values. This includes ecological functions, such as soil and watershed protection and the economic value of the numerous products that can be extracted from the forest (Goldsmith, 1998). Despite its ecological, social and economic importance, tropical forests are being destroyed at an alarming rate. Deforestation rate of tropical forest in 1990 was about 12.3 million hectares per year (FAO, 2001). Deforestation and forest degradation began 20,000 years ago and still continue in modern days (Brown and Brown, 1992; FAO, 2005; Butler and Laurance, 2008). Change in land cover due to tropical deforestation has drawn the attention of the world community because of their potential effect on soil erosion, run-off and carbon dioxide level (Myers 1988, Fontan 1994, Joshi *et al*., 2008).

The need for monitoring the changes in these ecosystems has become a focus in current strategies for managing natural resources and environmental change. The understanding of land cover change help the policy maker, and resource manager to decide where the action should be taken and what kind of intervention is needed.

Review of Literature

Monitoring the land use dynamics in tropical regions has long been in practice but after the launch of first civilian earth observing satellite (Landsat 1) in 1972, there has been significant activity related to mapping and monitoring the change of the natural forest landscape. Satellite remote sensing offers a potentially powerful method of monitoring changes at higher temporal resolution and with lower costs than those associated with traditional methods (Martin, 1989). Detection of land-cover changes, by comparing the images acquired of the same area at different times, is one of the major applications of remotely-sensed images acquired by earth orbiting satellites (Singh, 1989). In general, change detection involves the application of multi-temporal datasets to quantitatively analyze the temporal effects of the land cover change (Lu *et al*., 2004) and its drivers.

Miller *et al*. (1978) applied Landsat image differencing successfully to the mapping of changes in tropical forest cover in northern Thailand. Singh (1984; 1986) used the image differencing technique for monitoring changes due to shifting cultivation in a tropical forest environment. Post classification comparison based on visual delineation and interpretation (Roy and Tomar 2001) as well as on digital techniques (Mas, 1999; Tucker and Townshend, 2000; Zhang *et al.*, 2005) has reported changes in tropics with the use of remote sensing data. Multi-data classification using NDVI (Hayes and Sader, 2001) or tasseled cap (Guild *et al*., 2004) are reported more straightforward to detect changes in tropical forest. Principal component analysis has been assessed for change detection by Singh (1984), Mas (1999), Lu *et al*. (2005) in tropical forest.

Many other studies such as those by Iverson *et al.* (1989), Hansen *et al.* (2000), De Fries *et al*. (2005) have monitored the change in tropical forested landscape, its consequences and change analysis by using satellite remote sensing. An analysis of the literature reviewed indicates that there are very few studies concerned with comparative evaluation of change detection techniques in tropics. Singh (1986; 1989) objectively evaluated automated methods for forest change detection in tropical forest. An Univariate Image differencing, Image ratioing, normalized vegetation index differencing, image regression, PCA, post classification comparison and multi-data classification were compared and found that image regression and image differencing has higher accuracy than any other methods. Mas (1999) carried out comparative studies of six change detection techniques considered were image differencing, vegetative index differencing, selective principle component analysis (SPCA), direct multi data unsupervised classification, post classification change differencing and a combination of image enhancement and post classification comparison for detecting areas of changes in a coastal zone of the state of Campeche, Mexico. Post- classification comparison based on supervised classification was found to be most accurate procedure followed by SPCA which offers slightly better accuracy than the image differencing procedure.

According to Coppin and Bauer (1996), image differencing appears to perform generally better than other methods of change detection. Coppin *et al*. (2004) summarises some previous work and reported that Univariate image differencing is one of the preferred change detection algorithms. Singh (1989) in his review article reported that Univariate image differencing is more effective than post classification, NDVI, bi- temporal PCA for tropical deforestation monitoring. Image differencing is probably the most widely applied change detection algorithm for a variety of geographical environments (Singh, 1989). Lu et al. (2004) has provided a detailed review of the various change detection techniques (table 1).

Table 1: List of change detection techniques (Lu et al., 2004):

Categories	**Techniques**	**Example**
Algebra	Image differencing	Forest defoliation (Muchney and Haack, 1994) Land cover change (Sohl, 1999)
	Image regression	Tropical forest change (Singh, 1986) Forest conversion (Jha and Unni, 1994)
	Image ratioing	Land use mapping and change detection (1998)
	Vegetation index differencing	Vegetation change (Guerra *et al.*, 1998 ; Lyon *et al.*, 1998) Forest canopy change (Nelson, 1983)
	Change vector analysis (CVA)	Disaster assessment (Johnson, 1994; Schoppmann and Tyler, 1996) Change detection of landscape variables (Lambin, 1996)
	Background subtraction	Tropical forest change (Singh, 1989)
Transformation	Principal component analysis (PCA)	Land cover change (Byrne *et al.*, 1980) Forest defoliation (Muchoney and Haack, 1994)
	Tasselled cap	Monitoring green biomass (Coppin *et al.*, 2001) Land use change (Seto *et al.*, 2002)
	Gram-Schmidt	Monitoring forest mortality (Collins and Woodcock, 1994 and 1996)
	Chi-square	Urban environmental change (Ridd and Liu, 1998)
Classification	Post-classification comparison	Land use/ land cover change (Mas, 1997; Castelli *et al.*, 1998) Urban expansion (Ward *et al.*, 2000)
	Spectral-temporal analysis	Changes in coastal zone environments (Weismiller *et al.*, 1977) Forest change (Soares and Hoffer, 1994)

	EM detection	Land-cover change (Serpico and Bruzzone, 1999)
	Unsupervised change detection	Forest change (Hame *et al.*, 1998)
	Hybrid change detection	LULC change (Pilon *et al*., 1988) Vegetation change (Petit *et al.*, 2001)
	Artificial neural network (ANN)	Forest change (Woodcock *et al.*, 2001) Urban change (Liu and Lathrop, 2002)
Advanced models	Li-Strahler reflectance model	Mapping and monitoring conifer mortality (Macomber and Woodcock 1994)
	Spectral mixture model	Seasonal vegetation patterns using AVIRIS data (Ustin *et al.*, 1998) Vegetation change using TM data (Rogan *et al.*, 2002)
	Biophysical parameter method	Tropical successional forest detection in Amazon basin (Lu, 2001)
GIS approach	GIS approach	Urban change (Lo and Shipman, 1990) Landscape change (Taylor *et al.*, 2000)
	Integration of GIS and remote sensing	Urban sprawl (Yeh and Li, 2001) Landscape change (Taylor *et al.*, 2000)
Visual analysis		Land cover change (Slater and Brown, 2000) Land use change (Sunar, 1998)
Other methods	Measures of spatial dependence	Henebry, 1993
	Knowledge-based vision system	Wang, 1993
	Area production method	Hussin *et al.*, 1994

	Combination of three indicators (vegetation indices, land surface temperature and spatial structure)	Lambin and Strahler, 1994
	Change curves	Lawrence and Ripple, 1999
	Generalized linear models	Morisette *et al.*, 1999
	Curve-theorem-based approach	Yue *et al.*, 2002
	Structure based approach	Zhang *et al.*, 2002
	Spatial statistics based method	Read and Lam, 2002

According to Olsson (1993), change images computed from multi temporal remote sensing acquisitions can be used for updating the GIS data base and for monitoring the forest change. These involve a variety of processes like geometric and radiometric correction, image enhancement, detection of change/no change using Image differencing and mapping. Satellite remote sensing data combined with GIS could be used to find out land cover change over time and varying scale of spatial resolution (Louis R. Iverson *et al.).* Satellite imagery kindred with GIS data make possible of generating relevant and spatially explicit variables for analysis (Geoghegan *et al.* 1997). The GIS is now a widely accepted tool for assessment of land cover dynamics because of its ability to examine spatially referenced objects over time (Lo and Shipman 1990). At times, the GIS overlaying change detection technique has been found to be superior (Lambin 1997, Malila 1980, Ludeke *et al*. 1990,).

There are three main ways in which remote sensing and GIS technologies are complementary to each other (Wilkinson, 1996)

i) Remote sensing can be used as a tool to gather data sets for use in GIS;

ii) GIS datasets can be used as ancillary information to improve products derived from remote sensing and

iii) RS data and GIS data can be used together in resource analysis and modeling.

The integration of RS and GIS known as Geospatial Analysis is crucial tool for researcher, resource manager, and policy maker to allow developing, analyzing, and displaying spatially explicit to deal with larger spatial scales such as regional landscapes. At its most fundamental level, RS provides a means by which data can be produced and analyzed for an area and then incorporated in decision making or procedures (Colwell, 1983) GIS may be the most important technology for resource management that have evolved in the recent past. Geospatial analysis involves interaction of a variety of data and derived parameters in desired fashion.

Aims

The aims of the study are

1. To test and recommend feasible methods for change detection in tropical forests.
2. Identify and monitor the forest change in UNESCO world heritage site, inside and outside the protected boundary to see boundary effect by using remote sensing and GIS techniques.

With this background research question for the present investigations are:

1. Which Image processing methods could be recommended?
2. Which change detection techniques or TM band could be recommended to detect change in tropical forests?
3. Could pattern of deforestation or reforestation be detected, inside and outside of the protected areas?

Materials and Methods

Materials

Study Area

The study area is located in the Rio Platano Biosphere Reserve of Honduras 15° 44′ 40″ N, 84° 40′ 30″ W, a UNESCO world heritage areas that mainly consists of tropical forest. The Rio Platano Biosphere Reserve is one of the largest protected areas in Central America with 5, 200 square kilometers and has been a World Heritage site and biosphere reserve since 1982. The reserve covers both mountainous and low land tropical rain forest with full of diverse wildlife and plant life. The reserve is mostly mountainous, including Pico Dama, a giant granite formation, and Punta Piedra. The highest peak of the mountain is 1326m. The low land areas are covered with water in the winter.

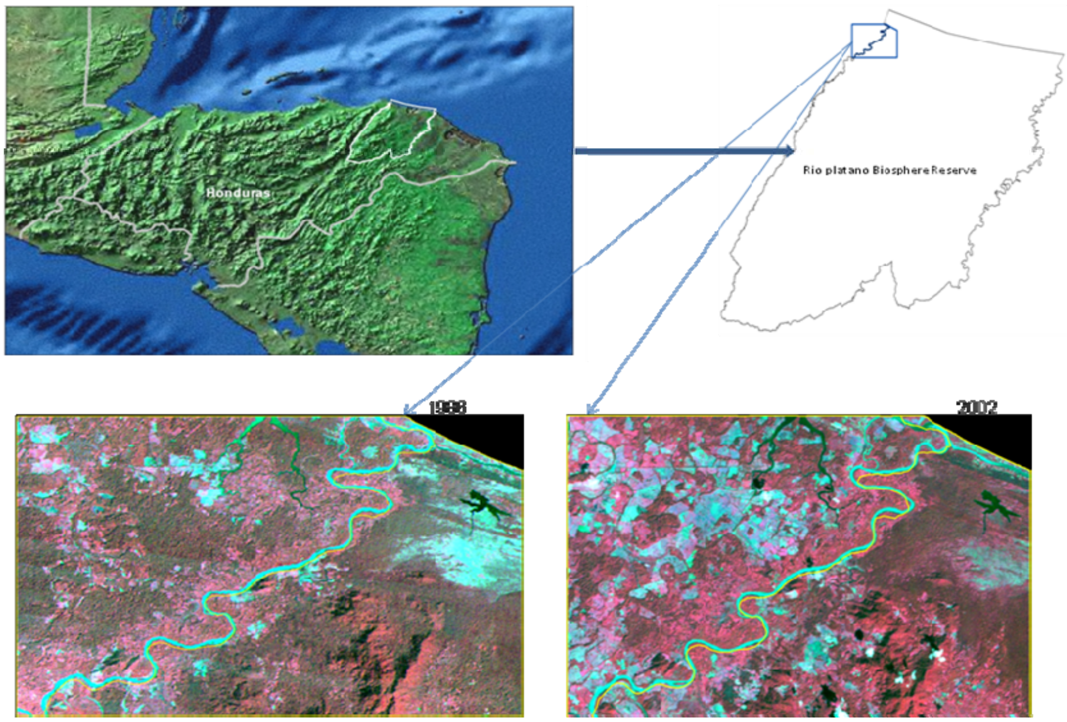

Figure 1. *Study area and its location*

Date of Establishment

1969: Established as an archaeological national park.

1982: Protected as a Biosphere Reserve under the UNESCO Man and the Biosphere Programme

Natural Environment

Rio Platano Biosphere Reserve is a part of the largest undisturbed tropical rain forest in Honduras. The natural vegetation cover of the study area and the surrounded hills is broad leaf rain forest. The rain forest of the region is composed primarily of broadleaf evergreen species such as *Colyphyllum. chiapense, Cedrela odorata, Ceiba pentandra, Ficus* spp., *Luehea seemanii,* and *Virola* spp. (Froehlich and Schwerin 1983:44) with occasional deciduous species like cortes (*Tabebuia guayacan*) and San Juan (*Vochysia hondurensis*) (Agudelo 1987:9). A number of rain forest species, such as mahogany (*Swietenia macrophylla*) and rubber (*Castilla elastica*), have been economically important to the region during the last two centuries (Floyd 1967, Naylor 1989). It has more than 2, 000 species of vascular plants. According to Herrera-MacBryde (1995) the main ecotypes are estuarine and marine, mangrove swamps, costal savanna, broadleaf gallery forest, humid subtropical forest (10-15% of the area), very humid tropical forest (app. 80% of the area) and on the ridge tops, elfin forest. Fauna of this region is also very high about 39 species of mammals, 377 species of birds and 126 species of reptiles and amphibians have been recorded. The climate of the area is hot and humid, especially from May to November. The annual rainfall is between 2850mm to 4000mm.The mean annual temperature of the area is 26.6°C. It receives an average of four severe tropical storms every ten years.

Threats to the study area

Rio Platano Biosphere reserve is a situated in eastern Honduras within the political department of Gracias a Dios. Among the ethnic groups inhabiting Gracias a Dios, the largest is the Miskito (79%), followed by Mestizo/ Hispanic population from the interior (16%), the Garifuna (3%), the Tawahka Sumu (2%), and the Pech or Paya (<1%)(1988 national census, DGEC 1990A:167). The Miskito population has experienced high rates of population growth during the last four decades, as indicated by a variety of available census information. According to Dodds, 1997 rates of population growth for Gracias a Dios range from 2.79 to 3.94 percent per annum. Miskito practice swidden agriculture in areas of secondary and primary forest which are cleared and burned to create field plots (Conklin 1961, Beckerman 1987). So Agriculture expansion into the western side of the Reserve by small farmers (Mainly Miskito) and cattle is reducing the forest. Uncontrolled commercial hunting of wild animals also occurs in this area.

This study focuses on North West part of the Rio Platano Biosphere Reserve which also covers grounds outside the Biosphere Reserve. One particular area of focus in this thesis is to show how this area has changed inside and outside the protected Boundary after their UNESCO recognition.

Table 2. *Images and maps*

Images required for the study	Path/ row	Date of acquisition	Source	Cloud cover (%)
Landsat-5 TM: Band 1-6	P16/R49	1986 01 28	http://glovis.usgs.gov/	0
Landsat-7 ETM+ Band 1-5, 7	P16/ R49	2002 12 18	http://glovis.usgs.gov/	10
High resolution data	DigtialGlobe ID: 101000100004E0CA01	2006 03 21	Google Earth	2

Methods

Geometric correction

Geometric correction is the process of transforming data from one grid system to another. It is applied to raw data to correct errors of perspective due to Earth's curvature and sensor motion. Satellite image needs to be geometrically corrected to a map coordinate system before geospatial processing. The geometric correction should be highly accurate, because misalignment of features at the same location could render the results useless. High precision geometric registration of the multi-temporal image data is a basic requirement for change detection (Gong *et al*., 1992; Dai and Khorram, 1998; Morisette and Khorram, 2000).

Two Landsat images (TM image, 19860128, pixel size: 28 meters and ETM+ image, 20021218, pixel size: 30 meters) of same area were downloaded from the USGS web-site (http://glovis.usgs.gov/). The satellite image of 1986 was resampled to 30 meters cell size the match with the spatial resolution of 2002 image. Nearest neighbourhood resampling technique was used to ensure minimum changes in the pixel values.

The Landsat data downloaded are geometrically system corrected (UTM Zone 16, WGS 84). However, image to image registration was not satisfactory. To remove this, the satellite image of 1986 was registered based using on the polynomial model implemented in ERDAS IMAGINE 9.3. Uniformly distributed common ground control points (GCPs) were located in distinctive feature such as intersection of the two different feature, stream confluence, and top of hills which were clearly visible in both the image. Landmarks that can vary (e.g., water body, vegetation, edge of lake) have not been used. Total of 25 fixed locations were used to register 1986 image with respect to 2002 image.

GCPs with error more than 15m were discarded before registration. The RMS (root mean square) error of the registration was less than 8 meters (~ 1/3 of a pixel). RMS error is the distance between the input location of a GCP, and the resampled location of the same GCP.

Though, manual selection of GCPs is laborious and time consuming it is still mostly used because of the precise registration and the possibility to use it in any area. In our case we also attempted to identify GCPs manually as the study area was so small.

Radiometric correction

The radiometry of remotely sensed data acquired by satellite sensors is influenced by a number of factors, such as atmospheric absorption and scattering (Song *et al.*, 2001; Yang and Lo, 2000; Du *et al.*, 2002). In order to identify genuine land cover changes as revealed by changes in the spectral surface reflectance from multi-date satellite images, it is recommended to carry out radiometric correction. Broadly, the radiometric correction approaches can be classified as absolute and relative techniques respectively. The *Absolute* approach is not only costly but also impractical since for most of historical satellite images correct sensor calibration data are not available (Du *et al.*, 2002) furthermore, accurate atmospheric data from the timepoint of data acquisition is also needed. In the *relative* approach, digital numbers of multi-date images are normalized on the band to band basis to a reference image selected by the analyst (Yang and Lo, 2000). A number of relative radiometric correction methods have been developed for land cover change detection such as statistical adjustments, histogram matching, image regression (IR), pseudo-invariant feature (PIF), radiometric control set (RCS), and no change set determined from scatterogram (NC) (Yang and Lo, 2000).

In this study, band to band histogram matching has been chosen as the most appropriate method. Radiometric correction with band to band histogram matching has proven to be a useful tool in correcting differences between atmospheric and scene characteristics with multi-temporal images taken at different times (Yasuoka, 1988). Histogram matching is a relative calibration process. A look up table is created that convert the histogram of one image (slave) so that it resembles the histogram of another image (master) called the reference image. In this case satellite image of 1986 was used a slave (also called input) and 2002 image was chosen as a master (also called reference).

Change detection

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). Several researchers have worked in tropical forest ecosystems, for change detection studies using satellite data (Miller *et al*, 1978, Singh, 1986, Mas, 1998, Roy and Tomar, 2001). A variety of change detection method have been developed and successfully used to detect the changes. Different change detection algorithms have their own merits/demerits 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). In the present study, changes have been evaluated using different change detection techniques *viz*., (i) image differencing of TM bands; (ii) difference of normalized difference vegetation index (NDVI differencing) and (iii) supervised classification of later data to map the change non change areas.

Image Differencing

Image differencing is a common change detection approach for forested areas and the most widely use algorithm (Nelson, 1983; Singh, 1989; Fung, 1990; Coppin and Bauer, 1996; Cohen *et al*., 1998). In this technique, precisely registered image of time t_1 and time t_2 are subtracted, pixel by pixel, to produce a further image which represents the change between the two times. Mathematically, it can be represented as follows:

$$Dx_{ij}^{k} = x_{ij}^{k}(t_2) - f\{x_{ij}^{k}(t_1)\} + C$$

where x_{ij}^{k} = pixel value of band k and i and j are line and pixel numbers in the image, t_1 = first data, t_2 = second data and C = a constant to produce positive digital numbers.

This procedure yields a difference distribution for each band. In such a distribution, pixels showing radiance change are found in the tail of the distribution while pixels showing no radiance change tend to be grouped around the mean (Stauffer and McKinney, 1978; Singh, 1986), as a normal distribution.

In the present study, we performed Image differencing of respective four bands (green, red, near infrared and mid infrared band 5) of 1986 and 2002 images. The process was carried out in ERDAS IMAGING 9.3. Several thresholds were tested in positive (area that have increase in digital number) and negative (area that have decrease in digital number) radiance change of the digital number (DN) to obtain the reliable “change/no change” image. These threshold values were determined for the each band difference. This was further compared to identify the best band depicting the changes.

Thresholding

Image differencing is the most widely used techniques for change detection but critical element of the methodology is selecting appropriate threshold values in the lower and upper tails of the distributing representing change pixel value. Nelson (1983) selected several different thresholds on the basis of the number of standard deviations from the mean and assessed their relative performance in detecting changes. Woodwell et al. (1983) have advocated a technique in which the analysis sets the cursor thresholds interactively while viewing the result of his decisions on the image display of the processing system.

In the present study thresholds (as %) were selected using ERDAS IMAGING 9.3. Positive and negative change in digital number (DN) greater than the given threshold was considered as change. Other areas of the positive and negative change less than the given threshold were considered as no change. For a consistent result, change images obtain from different threshold value were visually interpreted using both time satellite data, high resolution data (Google earth data) and also inquire cursor.

In image differencing and NDVI differencing change detection method, several attempts were made to identify the threshold to find where the changes have occurred. Different threshold (%) tested in maps are given in table 3

Table 3.*Different tested thresholding (%)*

Satellite band	Band 2	Band 3	Band 4	Band 5	NDVI differencing
Threshold (%)	2,3,4,5,6,	2,3,4,5,6	3,4,10,14,15,16,17	8,9,10,11	3, 8,9,10,11

For TM band 2 and band 3 threshold (4%) provide reliable result. For the band 4 and band 5 different thresholds were tested but no result was found to be satisfactory. However threshold (15%) for band 4 and threshold (10%) for band 5 were selected because result depicted from this threshold value was better than any other result. Similarly for NDVI differencing threshold (10%) was found to be good result.

Vegetative index differencing

Digital spectral radiance value can be analyzed independently on a band by band basis, or in combination of two or more band. One of the most commonly used band combination techniques involves the calculation of vegetation indices. There are number of vegetation indices in use with a common one being the normalized difference vegetation index (NDVI). NDVI is a band ratio calculated using the given formula (Rouse *et al*., 1973).

$$NDVI = \frac{NIR - R}{NIR + R}$$

Where, NDVI is normalized difference vegetation index, NIR is image collected in near infra red radiation; R is image collection in red radiation.

Among many digital change detection methods, NDVI differencing is one of the most frequently used method, especially when changes are from vegetated to non-vegetated areas or vice versa. NDVI image differencing was successfully carried out by (Nelson, 1983; Singh 1986; Lunetta *et al.*, 2002). In this method NDVI was calculated for both dates and then subtracted (Nelson 1983; Singh 1986).

Mathematical image differing was carried out to find out the difference in the NDVI values of two images.

$$D_{NDVI} = NDVI_{t2} - NDVI_{t1}$$

Where, $NDVI_{t2}$ is NDVI image of time 2 and $NDVI_{t1}$ is NDVI image of time 1.

In the present study, NDVI was calculated for 1986 and 2002 image. After that NDVI image of 2002 was subtracted from NDVI image of 1986 and change image was obtained. All this process was carried out in ERDAS IMAGING 9.3. A number of threshold values (in %) were tested in upper and lower tail of the distributing representing change pixel value (DN value).

The NDVI have two important properties:

1. NDVI is highly correlated with amount of green biomass (Tucker, 1979; Hatfield, 1983; Jackson *et al*., 1983; Justice *et al*., 1985).
2. NDVI reduce the variation due to due to surface topography (Holben and Frasher, 1984).
   Studies by Lyon *et al.* (1998), and Lunetta *et al.* (2002) reported that NDVI differencing was the best method for vegetation change detection in biologically complex ecosystems. Furthermore, Lyon *et al.* (1998) indicated that NDVI differencing was least affected by topographic factors.

In this regard it was very interesting to study NDVI differencing in the present study since study area is covered by undisturbed tropical rain forest with high topographic variation.

Supervised Classification

Supervised classification is the process of using a known identity of specific sites in the remotely sensed data to classify the remainder of the image. These known areas are commonly referred to as training sites (Jensen, 1996) and represent homogenous examples of land use/cover types. The status of these sites are derived through combination of ground truth information, analysis of aerial photographs, maps, and personal experience.

In this study, supervised classification was carried out in ERDAS IMAGING 9.3. In this process geometrically corrected images of 1986 and 2002 was opened in the same viewer with the channel combination of 4, 3, and 2 (RGB). Then software’s swipe function was used to view the two scenes (1986 and 2002) images to find the changes between them. As both images were geometrically corrected ‘changes’ and ‘no changes’ was clearly visible. Google earth data was used for known identity to select the training sites. After that uniformly distributed training sets were developed to separate forests, forest blanks (clear cut areas), some change, water body, river and cloud shown in table 4.

Table 4. *Description of cover classes and number of training sites selected*

Classes	Class description
Forest	Represent the geographical locations where no change has taken place between the two time periods.
Some changes	Locations where area has been converted to re-growth or secondary succession.
Forest blank (Clear cut)	clear cut areas are the places with maximum changes, and forest have been converted to blank
Water body	Accumulation of water was also visible in some part of image.
River	Water flowing across the surface of the land comes from Caribbean sea
Cloud	Some small patches of cloud was visible on image

Training sets were selected according to the combination of various classes in the two temporal scenes, such as forest, some change, clear cut, water body, river, cloud. Uniformly distributed training sets for each class (forests-4, some change-4, forest blanks (clear cut areas) -5, water body-2, river-2 and cloud-1) were given on the satellite data. Thus specific signature was set up for different classes. Finally, the Maximum-likelihood classification is employed to attain the classified map.

Accuracy assessment

Accuracy assessment is important for understanding the developed results and using these results for decision-making. The most common quantitative approach consists in the use of confusion matrix as the sole accuracy criteria (Hoffer and Fleming, 1978 and Kalensky et at., 1981). A confusion matrix is a square array set out in rows and a column which expresses the number of observation assigned to a land cover type (classified map) related to the actual land cover (reference map) The columns represent the classified map while rows indicate the reference map. Confusion matrix is used in deriving a summary of overall accuracy, producer’s accuracy, user’s accuracy and Kappa coefficient.

$$Overall\ classification\ accuracy(\%) = \frac{Total\ Number\ of\ correctly\ Identified\ Pixel}{Total\ number of\ \ pixel} \times 100$$

$$\Pr oducers\ accuracy(\%) = \frac{Total\ Number\ of correctly\ Identified Pixel}{Column\ Total} \times 100$$

$$Users\ accuracy(\%) = \frac{Total\ Number\ of correctly\ Identified Pixel}{Row Total} \times 100$$

Previous literature has provided the meanings and methods of calculation for these elements (Congalton et al. 1983, Congalton 1991, Kalkhan et al. 1997, Biging et al. 1999, Foody 2002).

Finally, the contingency table was tested using Kappa Statistics (Khat coefficient) (Lillesand and Kiefer, 1999).

$$\widehat{k} = \frac{N\sum_{i=1}^{r}(x_{ii}) - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}$$

Where, r = no of rows in the error matrix, x_{ii} = the number of observation in row i and column I (on the major diagonal), x_{i+} = total of observation in row I (shown as marginal total to right of the matrix) and x_{+i} = total observation in column i.

In this study all the change maps obtained from image differencing was visually interpreted using Google earth data. In order to determine the accuracy of each change maps systematic sampling (simple random sampling) were determined within the study area. For the change images (which was obtained from image differencing and NDVI) a random sample of 100 points were selected, in the case of supervised classification 120 points were selected within the study area. Some of the points which fell outside study areas, clouds, border between different land cover were removed resulting in 71 remaining points for image differencing, 70 points for NDVI differencing and 85 points for supervised classification change image. ERDAS IMAGING 9.3

provides the function of accuracy assessment by comparing certain pixels in the thematic layer with reference pixel, for which classes is already known. The nature of change in the study area has been determined by (or change image result of study area derived from) high resolution data (Google earth). For each sample point change were separately assessed. This information was compared to the change detection techniques result through error matrices. Four performance indices were derived from the error matrix: overall accuracy, producer’s accuracy, user’s accuracy, and kappa.

Software used:

ERDAS 9.3; ARCGIS 9.3

Microsoft office

Results

Radiometric Normalization

The radiometric variation of the images procured at different dates is a key parameter for interpreting occurred changes. The band to band histogram matching of images procured in 1986 and 2002 was done. After radiometric normalization, statistics of the 1986 image were very similar to the 2006 image (table 5). Except band 2, new mean value of histogram for the year 1986 is closely matched with the year 2002. The new mean value of band 2 is close to year 2002, unlike the value of unprocessed (non radiometric normalization) data.

Table 5. *Statistics of the 1986 and 2002 images before and after radiometric normalization*

	Band1	Band2	Band3	Band4	Band5	Band6
Before Histogram match						
Mean 1986	71	26	20	83	56	14
Mean 2002	60	44	33	77	61	27
SD 1986	2	2	3	17	11	3
SD 2002	4	5	7	14	13	6
After Histogram match						
Mean 1986	60	46	33	77	61	27
SD 1986	4	5	7	14	13	6

Maps of forest areas and changed areas

Change detected by Image differencing

For Image differencing method the map of changed areas were produced based on the thresholding which is described in section 2.2.3a. The pixel value were categorised into the following classes

No change:	Areas with no changes in forest cover.
Change (Increase):	Clearcut forest area.
Change (Decrease):	Area either has weeds, re-growth or secondary succession.

Following are change maps for band 2,3,4,5 produced from Landsat satellite images of 1996, and 2002. The results of change maps (Figure 3) obtained from band 4 and band 5 was not clearly visible.

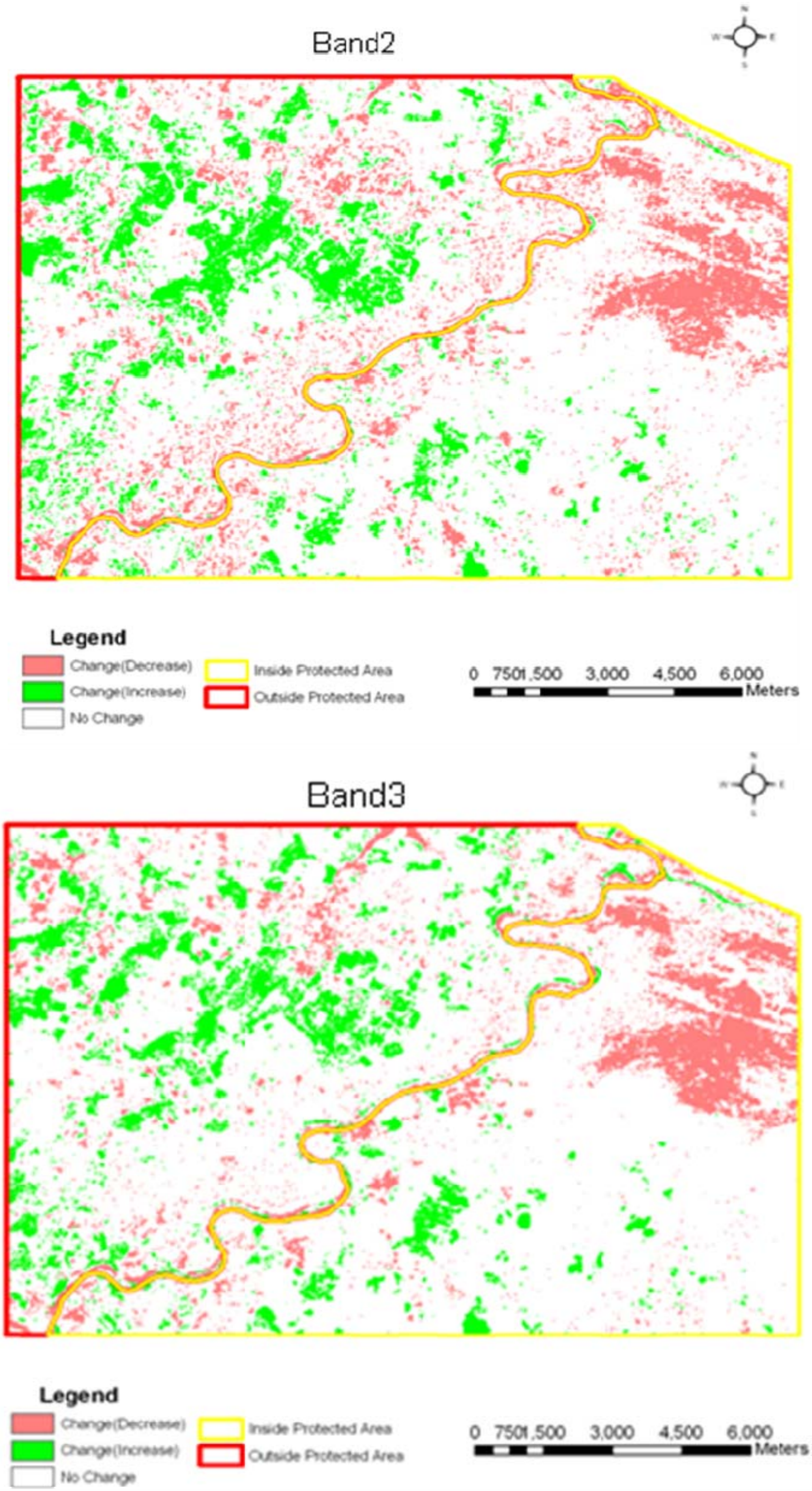

Figure 2. *Change image for band 2 and band 3 using threshold.*

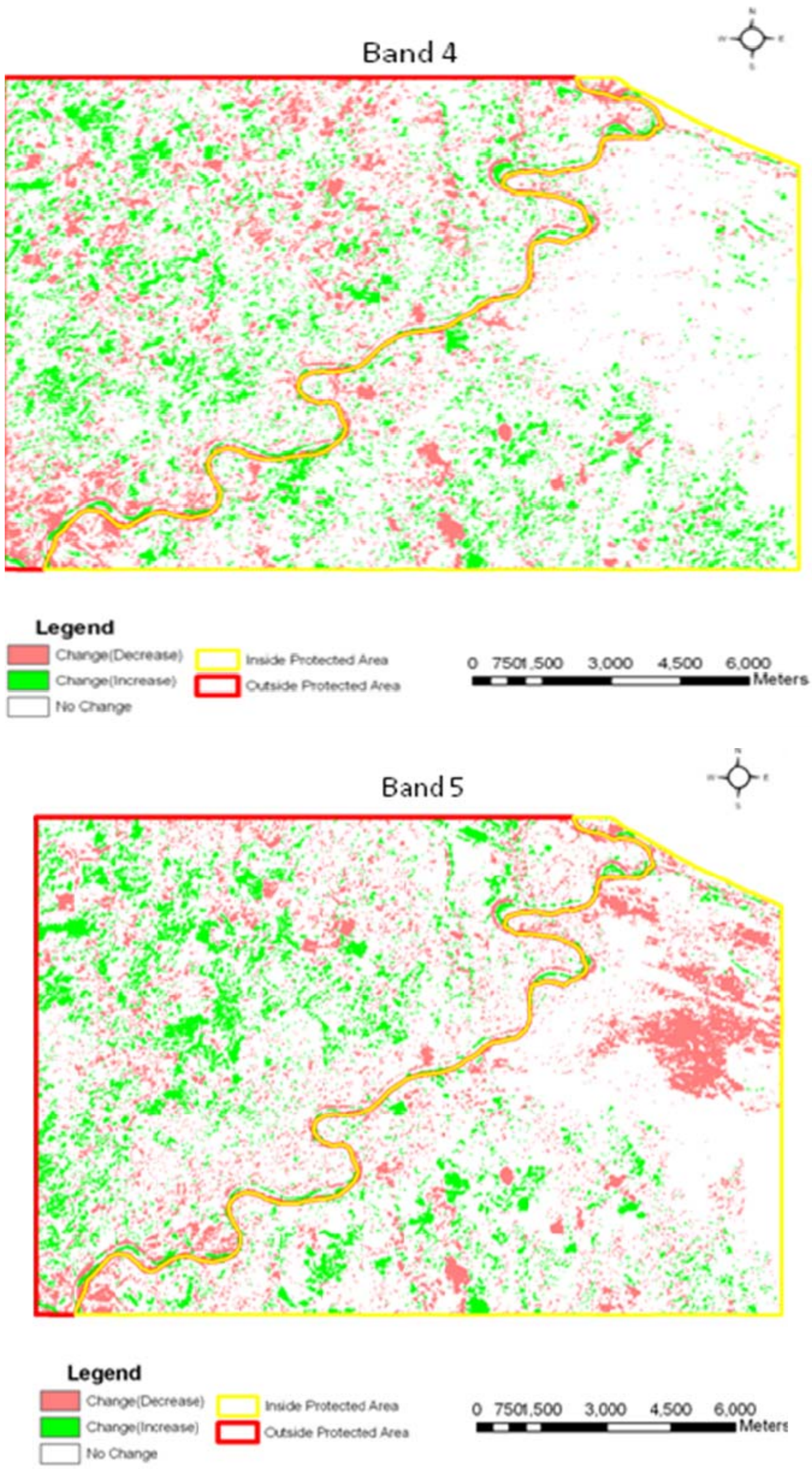

Figure 3. *Change image for band 4 and band 5 using threshold.*

In the figures red and yellow boundaries shows the area outside and inside the Rio Platano biosphere reserve respectively. Area mapped in Green colour has been identified as clear cut areas. “No change” areas in maps represent unchanged forested area.

The result of change map (Figure 3) obtained from band 4 and band 5 was not clearly visible. We found in our study that NIR (band 4) reflectance increase in some part of the clear cut areas. The increase in NIR reflectance is because of some regrowth of vegetation. The regrowth has high NIR reflectance and thus may be compensate for the decrease in NIR (band 4) reflectance resulting from clear cut.

Among all the change images, band 2 depicted the land-cover change matching closest with the ground reality (Google earth data, figure 6). Likewise band 3 also gave a good representation of the changes. However, the change image of band 4 and band 5 was not matching the ground reality. It has also been observed that inside the Rio Platano Biosphere reserve that is UNESCO world heritage tropical forest has less clearcut areas than the outside of the Biosphere reserve.

Change detected by NDVI image differencing

As for the NDVI method the map for changed areas were produce based on the thresholding described in section 2.2.3b. The pixel values were categorised into change and no-change classes.

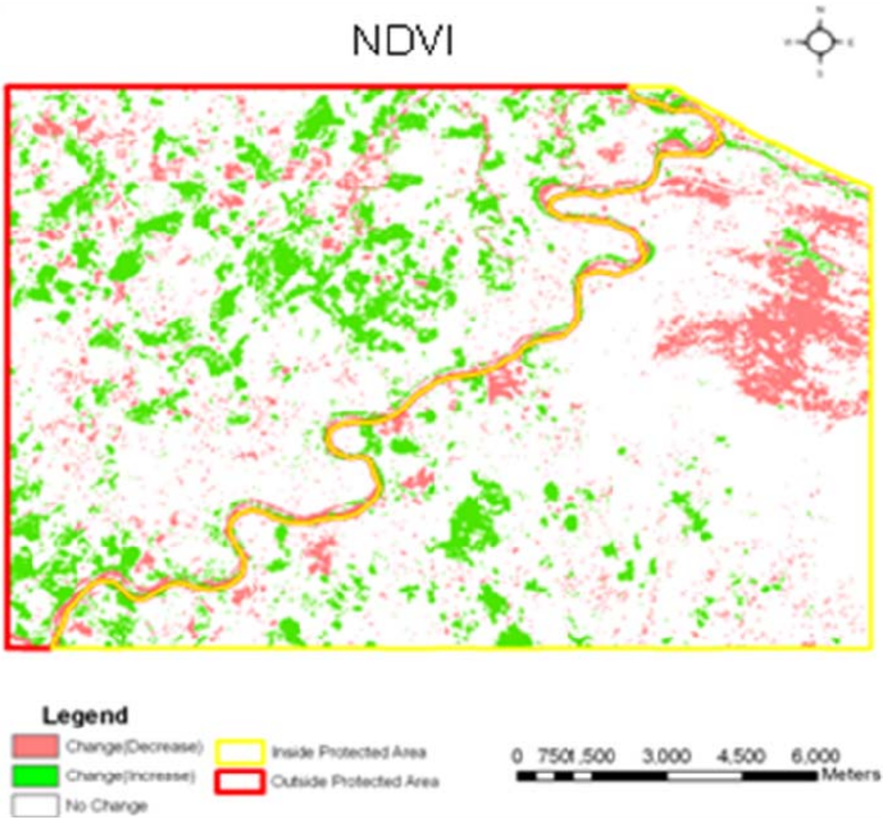

Figure 4. *NDVI difference image using threshold.*

Change detected by Image differencing for different band and NDVI image differencing were shown in table 6.

Table 6 .*Change detected by different band and NDVI image differencing*

	Change (ha)	No change(ha)
Band 2	4424	15447
Band 3	3925	15947
Band 4	4220	16268
Band 5	4505	15995
NDVI	4487	15384

Change detected by supervised-classification

As for supervised classification method the map for land cover change were produce based on the training sets discussed in section 2.2.3d. Land cover map produce from Landsat images of 1996 and 2002 using supervised classification is shown in figure 4.

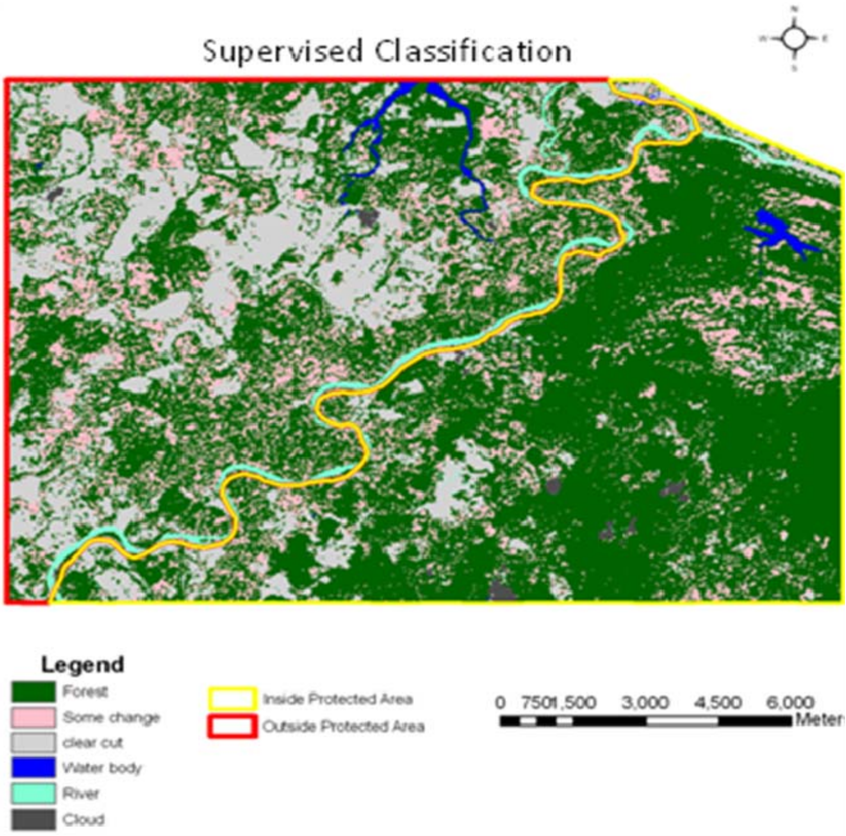

Figure 5. *Map of land cover change classes from Landsat 1996 and 2002*

The classification system used for land cover mapping of the study area consists of six land cover types.

Forest:	Area with no change in forest covers.
Some change:	Area recognized as regrowth or secondary succession.
Clearcut:	Area where maximum change of forest were recognized.
Water body:	Accumulation of water visible in upper part of the classified image. Area mapped in blue colour has been shows water body.
River:	Refers to flowing water which also follow the protected boundary.
Cloud:	Clouds were mapped from 2002 image.

The result of land cover change mapping (table 7) shows that 11987ha (60%) area of forest was mapped as no change in forest cover from the year 1986 to 2002. The land cover changes demonstrate that from the 1986 to 2002, forest clearcut in this study area is 3721 ha (19%). However some changes take place in the study area is 3528 ha that is about 18%, throughout the year 1986 to 2002. Cloud, river and water body change mapped in the area was very small.

Table 7. *Area Statistics of land cover / land cover change*

Land cover	Area (ha)	Area (%)
Forest	11983	60.3
Cloud	111	0.5
River	400	2.0
water body	129	0.6
Some change	3528	17.8
clear cut	3721	18.8
	19872	**100%**

Evaluation of change inside and outside protected Area

Area Statistics inside and outside the UNESCO protected boundary were calculated and presented in table 7. Inside the protected boundary 75% area was mapped as no change in forest cover where as outside only 46% area was mapped as no change in forest. Inside the Biosphere reserve, about 826 ha of forested area that is 8.7% were clearcut, the majority of them in the south-western part. Whereas outside the Biosphere reserve, about 2908 ha of forest 28% were clearcut spread throughout the area. Also change rate outside is 22% higher than inside the protected area where it is only 13.5%.

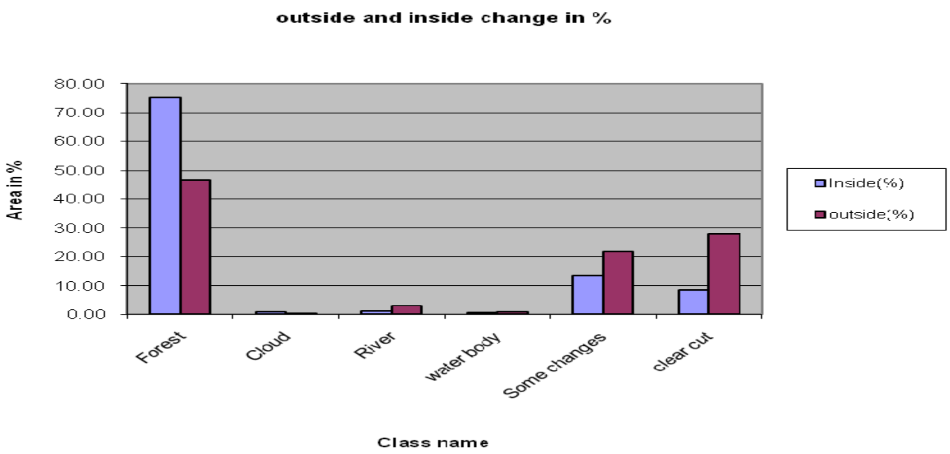

Figure 6.*Graph showing change outside and inside the protected area*

Table 7. *Area Statistics for inside and outside protected Boundary*

	Inside		Outside	
	Area (ha)	Area (%)	Area (ha)	Area (%)
Forest	7188	75.3	4821	46.3
Cloud	77	0.8	34	0.3
River	118	1.2	311	3
water body	50	0.5	80	0.7
Some Changes	1291	13.5	2250	21.7
clear cut	826	8.7	2909	28
	9550	**100**	**10405**	**100**

Accuracy Assessment for change maps

Accuracy assessment for change maps were calculated based on the confusion matrices. In case of image differencing and NDVI image differencing both increase and decrease changes between 1986 and 2002 were grouped together into change classes considered in the analysis. Accuracy assessment for band 4 and band 5 was not assessed because the change image of band 4 and band 5 did not match with the ground reality. The nature of change in the study area has been determined by high resolution data (Google earth, figure 6). Accuracy assessment for changed images was summarized in table 8. Appendix I shows detail about error matrix. The highest change accuracy was obtained using the image differencing for band 2. In single band analysis band 2 proved to be superior followed by supervised classification and NDVI. Band 3 shows relatively poor result in our studies.

Table 8. *Accuracy for change maps produced using different change detection methods*

Method	Overall accuracy	Kappa
Image differencing (Band 2)	87.3%	0.616
Image differencing (Band 3)	75.7%	0.259
Supervised Classification	82.3%	0.599
NDVI image differencing	80 %	0.585

Figure 7. *Google earth image*

Discussion

Clouds are common features of remotely sensed images collected from tropical and mountainous region of the world. The Rio Platano biosphere reserve is a mountainous tropical rain forest where clouds are the main problem. Selecting cloud free data sets are useful for monitoring the change in tropics. Cloud-free data acquisition for a single date is difficult for the whole area, particularly for higher elevations where a high percentage of the protected forest resources are located. To obtain cloud free data for monitor the change, there is a need to search the imagery from different sources. After the free release the all Landsat data from USGS site as from January1 2009 makes present work easier.

Effective image preprocessing is important to detect forest changes. Important keys to this success were the selection of cloud free data, precise registration of two time image, re-sampling, radiometric normalization, and interpreting of the change. High- quality geometric matching of the images is important to ensure that wrong change detection results do not occur.

Spatially accurate forest cover monitoring requires the precise registration of the multidata imagery. Once the imagery has been selected, it is crucial that the imagery has been calibrated to ensure that an observed change in the digital number is true change rather than a change due to atmospheric conditions. The radiometric normalization using histogram matching nearly eliminates the effects of varying atmospheric conditions.

Many change detection techniques have been developed to detect change in tropics. This study compared three techniques for detecting and mapping changes with Landsat data and analyzed three different change detection techniques using confusion matrix. The confusion matrix is a very powerful tool for change detection studies. The confusion matrix provided the means to determine the accuracy of the change detections techniques. Therefore, the confusion matrix allowed the change detection techniques used in this study to be quantitatively assessed and compared. The result obtained by using three change detection techniques (Image differencing, Post classification analysis using supervised classification, NDVI differencing) in present study is summarized in table 8. The image differencing method using band 2 produced the highest overall accuracy followed by post classification analysis based on supervised classification and vegetation index differencing (NDVI differencing).

Image differencing is a very simple method to identify the area covering a large scale. Results obtained from image differencing immediately allowed the observer to locate where changes have occurred. Normally, this technique shows through an increase in the reflectance of the band where the clearing has occurred or through decrease in reflectance where there is an increase in the vegetation cover. The most critical and subjective aspect of image differencing is placement of the threshold level and this depend upon the users preference. After several attempts the difference images with change could be produced with a determined threshold. Image differencing is a most widely used technique (Singh 1984) and extremely straightforward when using a single band (Sunar, 1999). However, some studies suggest that image differencing does not adequately deal with all types of change that are occurring in an area (Sohl, 1999).

Post classification method gives an accurate result for change detection where the user can independently classify the two images in question. Therefore, specific methodology for post classification analysis was carried out using supervised classification. Different steps adopted in this study are, image selection; geo-referencing; co-registration the image; display set up; image overview and input sites for training classification to prepared single classified map. Google earth data was also used for selecting training sites. Post classification comparison can be an effective method when it has to express the specific nature of changes compiled with statistics in terms of tables, graphs or change maps.

The result of this study shows that band 2 has a higher accuracy than the supervised classification. Change (decrease) depicted in the band-2 map inside the protected boundary is more than similar type of change depicted by supervised classification maps. These changes are either some secondary growth or may be some weeds. The depleted and secondary forests are rapidly increasing in extent as a result of human activities all over the tropics (UNESCO, 1978).

The clearcut area was not clearly visible using band 4 and band 5. Disturbance detection may be complicated when the regrowth vegetation from clear cut area is not removed. This is also supported by early studies by Singh (1986). He found in his study that poor performance using band 4 data is due to high infrared return from the herbaceous understory in cleared areas. The study confirms the views expressed by Banner and Lynham(1981) that the sensitivity of the near infrared wavebands to the ingrowth of grass and other vegetation within the clear-cut areas results in higher classification errors rates for the data transforming involving band 5.

The result of this study shows that supervised classification has higher accuracy than NDVI differencing. Lyon *et al.* 1998, and Lunetta *et al*. 2002 found that NDVI differencing is more accurate than post classification but they classify two time data separately. We adopted specific technique where both time images was display in a single viewer and training sets for different land cover classes/ change classes were collected to classify the image giving better result than NDVI differencing. The different classes in the study area can be well detected by supervised classification while, NDVI differencing shows poor performance in detecting change. NDVI image differencing cannot provide detailed information. It can only give the information of increase or decrease NDVI value. NDVI can detect some subtle changes in the forest but some time is more sensitive to small changes in reflectance. Many areas of changes, detected in this study by NDVI differencing are not correct. As for example upper right side in the image shows changes in the water body. Therefore NDVI appears to be less suitable for detecting changes in tropical forest.

Result of forest change analysis by using supervised classification revealed that 40% of forest area have changed over the period analyzed. There are several factors contributing to change in forest cover of the Rio Platano biosphere reserve expansion in agriculture area being one of the major ones. Swidden agriculture and population growth are other major causes of deforestation (David J. Dodds, 1998). The increasing population pressure plays a vital role in triggering deforestation in the study area where, agriculture and animal husbandry play a dominant role in the livelihoods of the local people.

On the other hand, significant difference in clear cut area were found inside and outside the Rio Platano biosphere reserve boundary over the period analyzed. The rate of clearcut area inside the protected boundary was about 9% which is comparatively very less then outside which was 28%.

This can be explained by establishment of the World Heritage site and biosphere reserve since 1982 stop lots of deforestation. Also many local and international agencies have funded several projects to promote sustainable land use and promote biodiversity. Since 1997 Honduran Corporation for forestry development (COHDEFOR) has been responsible for managing the reserve. In 1997 the Rio Platano Biosphere project was initiated in collaboration between COHDEFOR and the German society for Technical Cooperation with the German bank for reconstruction and development to improve the management and conservation of site by providing technical and financial support under the participatory zoning and management component of the social forestry program. Some of the clearcut area has been located inside the protected boundary. This is presumably because area is located on the border of reserve, closer to settlement.

The Cause of deforestation in tropics varies from place to place. The International timber trade has played a major role of deforestation in Southeast Asia but only a minor role in Latin America (Poore, 1989).Whereas agriculture expansion by small farmer for their livelihood play major role of deforestation in tropical rain forest (Tom rudel and Jill roper, 1997). Growth in the size and number of cattle grazing has caused much deforestation in Latin America and little deforestation anywhere else (Shane, 1986). Ricardo *et al* 1997 concluded by discussing of their study that Income, resident duration, age, education, off- farm income, wealth are cause of deforestation in primary rain forest.

Following recommendation can be made based on the result of the study

1. Radiometric calibration using band to band Histogram matching can be used.
2. Tropical deforestation was successfully delineated from Landsat data using Image differencing with high accuracy. Therefore image differencing method using band 2 is recommended for monitoring change in tropical forest as it is simple approach.

Recommendation for further research

1. It would be useful to carry out the study to further explore on placing the threshold value to avoid lots of trial and error.
2. Forest type changes in protected area and how changes occurred could be the topic for a future study.

Reference

Agudelo, C. N.(1987). Ecosistemas Terrestres de Honduras. Association Hondurans de Ecology, Tegucigalpa.

Banner, A. V. & Lynham, T. (1981). Multi-temporal analysis of Landsat data for forest cut over mapping -a trial of two procedures. Proc. 7th Canadian Synp. On Remote Sensing, Winnipeg, Manitoba, pp. 233-240.

Beckerman, S. (1987). Swidden in Amazonia and the Amazon Rim. In Comparative Farming Systems. B.L. Turner II and S.B. Brush, eds. Pp. 55-94. The Guilford Press, New York.

Biging, G. S., Chrisman, N. R., Colby, D. R., Congalton, R. G., Dobson, J. E., Ferguson, R. L., Goodchild, M. F., Jensen, J. R. & Mace, T. H.(1999). Accuracy assessment of remote sensing-detected change detection. Monograph Series, edited by S. Khorram, American Society for Photogrammetry and Remote Sensing (ASPRS), MD, USA.

Brown, K.S. & Brown, G.G. (1992). Habitat alteration and species loss in Brazilian forests. In: Whitmore, T.C. Sayer, J.A. (Eds.), Tropical Deforestation and Species Extinction. Chapman & Hall, London, pp. 119–142.

Byrne, G. F., Crapper, P. F. & Mayo, K. K. (1980). Monitoring land cover change by principal component analysis of multitemporal Landsat data. Remote Sensing of Environment, 10, 175–184.

Butler, R.A., Laurance, W.F. (2008). New strategies for conserving tropical forests. Trends in Ecology and Evolution 23 (9), 469–472.

Castelli, V., Elvidge, C. D., Li, C. S. & Turek, J. J. (1998).Classification-based change detection: theory and applications to the NALC data sets. In Remote Sensing Change Detection: Environmental Monitoring Methods and Applications, edited by R. S. Lunetta & C. D. Elvidge (Chelsea, MI: Ann Arbor Press), pp. 53–73

Cohen, W. B. & Fiorella, M.(1998). Comparison of methods for detecting conifer forest change with Thematic Mapper imagery. In Remote Sensing Change Detection: Environmental Monitoring Applications and Methods, edited by C. Elvidge and R. Lunetta (Ann Arbor: Ann Arbor Press), pp. 89–102

Collins, J. B. & Woodcock, C. E. (1994). Change detection using the Gramm–Schmidt transformation applied to mapping forest mortality. Remote Sensing of Environment, 50, 267–279.

Collins, J. B. & Woodcock, C. E. (1996). An assessment of several linear change detection techniques for mapping forest mortality using multitemporal Landsat TM data. Remote Sensing of Environment, 56, 66–77.

Colwell, R.N. (ed.) 1983. Manual of Remote Sensing. Am. Soc. Photogr. Rem. Sens. Falls Church, Virginia.

Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment, 37, 35–46.

Congalton, R. G., Oderwald, R. G. & Mead, R. A. (1983). Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques. Photogrammetric Engineering and Remote Sensing, 49, 1671–1678.

Conklin, H. (1961). The study of shifting cultivation. Current Anthropology 2:27-61.

Coppin, P. R. & Bauer, M. E. (1996). Digital change detection in forest ecosystems with remote sensing imagery. Remote Sensing Reviews, 13, 207–234.

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

Coppin, P., Nackaerts, K., Queen, L., & Brewer, K. (2001). Operational monitoring of green biomass change for forest management. Photogrammetric Engineering and Remote Sensing, 67, 603–611.

Dai, X. L. & Khorram, S. (1999). Remotely sensed change detection based on artificial neural networks. Photogrammetric Engineering and Remote Sensing, 65, 1187–1194.

DeFries, R., Hansen, A., Newton, A.C. & Hansen, M.C. (2005). Increasing isolation of protected areas in tropical forests over the past twenty years. Ecological Applications, 15, 19–26.

DGEC (Dirección General de Estadística y Censos). (1990a). Characteristics Geográficas, Migratorias, y Sociales de la Población por Departamento. Censo Nacional, 1988, Tomo II. DGEC, Tegucigalpa

Dodds, D.J. (1997). A Multilevel Analysis of Population Growth in Eastern Honduras. CIPEC Working Paper No. CW97-DD2. Indiana University, Bloomington.

Dodds, D.J. (1998). Components of Population Growth among Three Indigenous Peoples of the Río Plátano Biosphere Reserve. Poster presented at the Annual Meeting of the Population Association of America, April 2-4, Chicago.

Du, Y., Teillet, P. M. & Cihlar, J. (2002). Radiometric normalization of multitemporal high-resolution satellite images with quality control for land cover change detection. Remote Sensing of Environment, 82, 123–134.

FAO (2005). State of the world's forests. Forestry Department/FAO, Rome.

FAO. (2001). Global forest resources assessment 2000: main report. Retrieved **4**-June-2003, from the World Wide Web:

Floyd, T.S. (1967). The Anglo-Spanish Struggle for Mosquitia. University of New Mexico Press, Albuquerque.

Foody, G. M. (2002). Status of land cover classification accuracy assessment. Remote Sensing of Environment, 80, 185–201.

Fontan, J. (1994). Changement globaux development. Nature- Sciences- Societies 2,143 152.

Froehlich, J.W. & Schwerin, K.H. (eds) (1983). Conservation and indigenous human land use in the Rio Platano watershed, Northeast Honduras. Research Paper Series No. 12, Latin American Institute, University of New Mexico, Albuquerque. 94 pp

Fung, T. (1990). An assessment of TM imagery for land-cover change detection. IEEE Transactions on Geoscience and Remote Sensing, 28, 681–684.

Geoghegan, J; Wainger, L. & Bockstael, N. (1997). Spatial landscape indices in a hedonic framework: an ecological economics analysis using GIS. Ecological Economics 23, 251–64.

Goldsmith, F. B. (Ed.). (1998). Tropical rain forest. London: Chapman & Hall.

Gong, P. (1993). Change detection using principal component analysis and fuzzy set theory. Canadian Journal of Remote Sensing, 19, 22–29.

Guerra, F., Puig, H., & Chaume, R. (1998). The forest–savanna dynamics from multidate

landsat-TM data in Sierra Parima, Venezuela. International Journal of Remote Sensing, 19, 2061–2075.

Guild, L.S., Cohen, W.B., Kauffman, J.B. (2004). Detection of deforestation and land conversion in Rondonia, Brazil using change detection techniques. International Journal of Remote Sensing, 25 (4), pp. 731- 750

Hame, T., Heiler, I. & Miguel-Ayanz, J. S. (1998). An unsupervised change detection and recognition system for forestry. International Journal of Remote Sensing, 19, 1079–1099.

Hansen MC, DeFries RS, Townshend JRG (2000) Global land classification at 1 km spatial resolution using a classification tree approach. International Journal of Remote Sensing 21**,** 1331–64.

Hayes, D. J. & Sader, S. A. (2001). Comparison of change detection techniques for monitoring tropical forest clearing and vegetation regrowth in a time series. Photogrammetric Engineering and Remote Sensing, 67, 1067–1075.

Henebry, G. M. (1993). Detecting change in grasslands using measures of spatial dependence with Landsat TM data. Remote Sensing of Environment, 46, 223–234.

Herrera-MacBryde, O. (1995). North-east Honduras and Rio Platano Biosphere Reserve. Department of Botany, Smithsonian Institution, Washington, D.C. U.S.A.

Hoffer, R. M. & Fleming, M. D. (1978). Mapping vegetative cover by computer-aided analysis of satellite data. LARS Tech. Rep. 011178., Lab. for Applications of Remote Sensing, Purdue Univ., Indiana, 11 pp.

Holben and Justice, (1980). An examination of spectral land ratioing to reduce the topographic effect on remotely sensed data. NASA/GSFC Tech. Mem. 80640, Goddard Space Flight Center, Greenbelt, MD. 27 pp.

Hussin, Y. A., De Gier, A. & Hargyono, (1994) Forest cover change detection analysis using remote sensing: a test for the spatially resolved area production model. *Fifth* European Conference and Exhibition on Geographic Information Systems, EGIS 94 Proceedings, Paris, France, March 29–1 April 1994 (Utrecht: EGIS Foundation), vol. II, pp. 1825–1834.

Iverson LR., Graham RL., Cook EA. (1989). Applications of satellite remote sensing to forest ecosystems. Landscape Ecology *3***,** 131–43.

Jackson, R.D. (1983). Spectral indices in N-space. Remote sensing of Environment, 13, 409-421

Jensen, J. R. (1996). Introductory Digital Image Processing: a Remote Sensing Perspective (Englewood Cliffs, NJ: Prentice-Hall).

Jha, C. S., And Unni, N. V. M. (1994). Digital change detection of forest conversion of dry tropical forest region. International Journal of Remote Sensing, 15, 2543–2552.

Johnson, R. D. (1994).Change vector analysis for disaster assessment: a case study of Hurricane Andrew. Geocarto International, 1, 41–45.

Joshi, P.K., Kumar, M., Paliwal, A., Midha, N., Das, P.P. (2008). Assessing impact of industrialization in terms of LULC in a dry tropical region (Chhattisgarh), India using remote sensing data and GIS over a period of 30 years**.** Environmental Monitoring and Assessment, DOI 10.1007/ s10661-008-0211-z.

Kalkhan, M. A., Reich, R. M. & Czaplewski, R. L. (1997). Variance estimates and confidence intervals for the Kappa measure of classification accuracy. Canadian Journal of Remote Sensing, 23, 210–216.

Kalkhan, M. A., Reich, R. M., & Czaplewski, R. L. (1997). Variance estimates and confidence intervals for the Kappa measure of classification accuracy. Canadian Journal of Remote Sensing, 23, 210–216.

Lambin, E. F. & Strahler, A. H. (1994). Change-vector analysis in multitemporal space: a tool to detect and categorize land-cover change processes using high temporal resolution satellite data. Remote Sensing of Environment, 48, 231–244.

Lambin, E. F. & Ehrlich, D. (1996). The surface temperature–vegetation index space for land cover and land-cover change analysis. International Journal of Remote Sensing, 17, 463–487.

Lambin, E. F. & Ehrlich, D. (1997). Land-cover changes in sub-Saharan Africa (1982–1991): application of a change index based on remotely sensed surface temperature and vegetation indices at a continental scale. Remote Sensing of Environment, 61, 181–200.

Lawrence, R. L. & Ripple, W. J. (1999). Calculating change curves for multitemporal satellite imagery: Mount St. Helens 1980–1995. Remote Sensing of Environment, 67, 309–319.

Lillesand., Thomas M. & R.W. Keifer. (1999). Remote Sensing and Image interpretation, John Wiley & Sons, Inc. New York.

Liu, X. & Lathrop, R. G. Jr, (2002). Urban change detection based on an artificial neural network. International Journal of Remote Sensing, 23, 2513–2518.

Lo, C. P. & Shipman, R. L. (1990). A GIS approach to land-use change dynamics detection. Photogrammetric Engineering and Remote Sensing, 56, 1483–1491.

Lodwik, G. D. (1979). Measuring ecological changes in multitemporal Landsat data using principal components. Proceedings of the 13th International Symposium on Remote Sensing of Environment held in Ann Arbor in 1979 (Ann Arbor, Michigan: Environmental Research Institute of Michigan), pp. 1-11.

Louis R**.** Iverson, Robin Lambert Graham and Elizabeth A. Cook (1989) Application of satellite remote sensing to forested ecosystem. Landscape Ecology 3, 131-143.

Lu, D. S. (2001). Estimation of forest stands parameters and application in classification and change detection of forest cover types in the Brazilian Amazoˆn basin. PhD dissertation, Indiana State University, Terre Haute, IN, USA.

Lu, D., Mausel, P., Batistella, M., Moran, E. (2005). Land-cover binary change detection methods for use in the moist tropical region of the Amazon: a comparative study. International Journal of Remote Sensing, 26 (1), pp. 101-114

Lu, D., Mausel, P., Brondizio, E. & Moran, E. (2004). Change detection techniques. International Journal of Remote Sensing, 25 (12), pp. 2365-2407.

Ludeke AK, Magio RC, Reid LM (1990) An analysis of anthropogenic deforestation using logistic regression and GIS. Journal of Environmental Management 32**,** 247–59.

Lunetta, R. S., Ediriwickrema, J., Johnson, D. M., Lyon, J. G. & Mckerrow, A. (2002). Impacts of vegetation dynamics on the identification of land-cover change in a biologically complex community in North Carolina, USA. Remote Sensing of Environment, 82, 258–270.

Lyon, J. G., Yuan, D., Lunetta, R. S. & Elvidge, C. D. (1998). A change detection experiment using vegetation indices. Photogrammetric Engineering and Remote Sensing, 64, 143–150.

Macomber, S. A. & Woodcock, C. E. (1994). Mapping and monitoring conifer mortality using remote sensing in the Lake Tahoe Basin. Remote Sensing of Environment, 50, 255–266.

Malila, W. A. (1980). Change vector analysis: an approach detecting forest changes with Landsat. Proceedings of the 6th International Symposium on Machine Processing of Remotely Sensed Data, Purdue University, West Lafayette, IN, USA (West Lafayette, IN: Purdue University), pp. 326–335.

Martin, L.R.G., 1989. Accuracy assessment of Landsat-based visual change detection methods applied to the rural-urban fringe, Photogrammetric Engineering and Remote Sensing, 55:209-215.

Mas, J. F. (1997). Monitoring land-cover changes in the Terminos Lagoon Region, Mexico: a comparison of change detection techniques. Proceedings of the IV International Conference on Remote Sensing for Marine and Coastal Environments, Orlando, FL, USA (Amsterdam: National Aerospace Laboratory), vol. 1, pp. 159–167.

Mas, J. F. (1999). Monitoring land-cover changes: a comparison of change detection techniques. International Journal of Remote Sensing, 20, 139–152.

May, R. M. (1975). Diversity stability and maturity in natural ecosystem with particular reference to the tropical moist forests. F. A. O. Rome. 9 pp.

Miller, L. D., Nualchawee, K. & Tom, C. (1978). Analysis of the dynamics of shifting cultivation in the tropical forests of northern Thailand using landscape modelling and classification of Landsat imagery. NASA Tech. Mem. 79545, Goddard Space Flight Center, Greenbelt, MD. 19 pp.

Miller, A. B., Bryant, E. S. & Birnie, R. W. (1998). An analysis of land cover changes in the northern forest of New England using multitemporal Landsat MSS data. International Journal of Remote Sensing, 19, 245–265.

Morisette, J. T., Khorram, S. & Mace, T. (1999). Land-cover change detection enhanced with generalized linear models. International Journal of Remote Sensing, 20, 2703–2721.

Muchoney, D. M. & Haack, B. N. (1994). Change detection for monitoring forest defoliation. Photogrammetric Engineering and Remote Sensing, 60, 1243–1251.

Myers, N. (1988) Tropical forests: much more than stocks of wood. Journal of Tropical Ecology, 4, 209-221

Nelson, R. F. (1983). Detecting forest canopy change due to insect activity using Landsat MSS. Photogrammetric Engineering and Remote Sensing, 49, 1303–1314.

Olsson, H. (1993). Regression function for multitemporal relative calibration of thematic mapper data over Boreal forest, Remote Sensing of Environment, 46:89-102.

Petit, C., Scudder, T. & Lambin, E. (2001). Quantifying processes of land-cover change by remote sensing: resettlement and rapid land-cover change in southeastern Zambia. International Journal of Remote Sensing, 22, 3435–3456.

Poore, D, (1989). No timber without trees: Sustainability in Tropical Forests (London Earthscan).

Pilon, P. G., Howarth, P. J., Bullock, R. A. & Adeniyi, P. O. (1988). An enhanced classification approach to change detection in semi-arid environments. Photogrammetric Engineering and Remote Sensing, 54, 1709–1716.

Read, J. M. & Lam, N. S.-N. (2002). Spatial methods for characterizing land cover and detecting land cover changes for the tropics. International Journal of Remote Sensing, 23, 2457–2474.

Richards, J. A. (1984). Thematic mapping from multitemporal image data using the principal components transformation. Remote Sensing of Environment, 16, 35–46.

Ridd, M. K. & Liu, J. (1998). A comparison of four algorithms for change detection in an urban environment. Remote Sensing of Environment, 63, 95–100.

Rogan, J., Franklin, J., & Roberts, D. A. (2002). A comparison of methods for monitoring multitemporal vegetation change using Thematic Mapper imagery. Remote Sensing of Environment, 80, 143–156.

Rouse, J. W., Hass, R. H., Schell, J. A. & Deering, D. W. (1973). Monitoring vegetation systems in the Great Plains with E. R. T. S. Proc. 3rd Int. Symp. on Remote Sensing of Environment, Ann Arbor, Michigan, pp. 10-14.

Roy Chowdhury R. (2006). Landscape change in the Calakmul Biosphere Reserve, Mexico: modeling the driving forces of smallholder deforestation in land parcels. Applied Geography 26 (2)**,** in press.

Roy, P. S. & Tomar, S. (2001). Landscape cover dynamics pattern in Meghalaya. International Journal of Remote Sensing, 22 (18), pp. 3813-3825.

Schoppmann, M. W. & Tyler, W. A., 1996, Chernobyl revisited: monitoring change with change vector analysis. Geocarto International, 11, 13–27.

Serpico, S. B. & Bruzzone, L. (1999). Change detection. In Information Processing for Remote Sensing, edited by C. H. Chen (Singapore: World Scientific Publishing), pp. 319–336.

Seto, K. C., Woodcock, C. E., Song, C., Huang, X., Lu, J. & Kaufmann, R. K. (2002). Monitoring land-use change in the Pearl River Delta using Landsat TM. International Journal of Remote Sensing, 23, 1985–2004.

Singh, A. (1984). Tropical forest monitoring using digital Landsat data in northeastern India. Ph. D. thesis, University of Reading, Reading, England.

Singh, A. (1986). Change detection in the tropical forest environment of North-eastern India using Landsat. In Remote Sensing and Tropical Land Management (New York: John Wiley and Sons), pp. 237–254.

Singh, A. (1989). Digital change detection techniques using remotely-sensed data. International Journal of Remote Sensing, 10, 989–1003.

Singh, A. (1989). Digital change detection techniques using remotely sensed data. International Journal of Remote Sensing, 10, 989–1003.

Slater, J. & Brown, R. (2000). Changing landscapes: monitoring environmentally sensitive areas using satellite imagery. International Journal of Remote Sensing, 21, 2753–2767.

Soares, V. P. & Hoffer, R. M. (1994). Eucalyptus forest change classification using multi-data Landsat TM data. Proceedings, International Society of Optical Engineering (SPIE), 2314, 281–291.

Sohl, T. (1999). Change analysis in the United Arab Emirates: an investigation of techniques. Photogrammetric Engineering and Remote Sensing, 65, 475–484.

Song, C., Woodcock, C. E., Seto, K. C., Lenney, M. P., & Macomber, S. A. (2001). Classification and change detection using Landsat TM data: when and how to correct atmospheric effect? Remote Sensing of Environment, 75, 230–244.

Stauffer, M. L. & McKinney, R. L. (1978). Landsat image differencing as an automated land cover change detection technique. Rep. CSCI TM-7816215., Computer Sciences Corporation, Silver Springs, MD.

Shane, D. (1986). Hoofprints in the Forest: Cattle Ranching and the Destruction of Latin America's Tropical Forest (Philadelphia: Institute for the Study of Human Issues).

Sunar, F. (1998). An analysis of changes in a multi-date data set: a case study in the Ikitelli area, Istanbul, Turkey. International Journal of Remote Sensing, 19, 225–235.

Taylor, J. C., Brewer, T. R. & Bird, A. C. (2000). Monitoring landscape change in the national parks of England and Wales using aerial photo interpretation and GIS. International Journal of Remote Sensing, 21, 2737–2752.

Tucker, C. J. (1979). Red and photographic infrared linear combination for monitoring vegetation. Remote Sensing of Environ. Vol. 8,pp. 127-150.

Tucker, C. J. & Townshend, J. R. G. (2000). Strategies for monitoring tropical deforestation using satellite data. International Journal of Remote Sensing, 21, 1461–1471.

Ustin, S. L., Roberts, D. A. & Hart, Q. J. (1998). Seasonal vegetation patterns in a California coastal savanna derived from Advanced Visible/Infrared Imaging Spectrometer (AVIRIS) data. In Remote Sensing Change Detection: Environmental Monitoring Methods and Applications, edited by R. S. Lunetta and C. D. Elvidge (Chelsea, MI: Ann Arbor Press), pp. 163–180.

Wang, F. (1993) A knowledge-based vision system for detecting land change at urban fringes. IEEE Transactions on Geoscience and Remote Sensing, 31, 136–145.

Ward, D., Phinn, S. R. & Murray, A. T. (2000). Monitoring growth in rapidly urbanizing areas using remotely sensed data. Professional Geographer, 52, 371–386.

Weismiller, R. A., Kristof, S. J., Scholz, D. K., Anuta, P. E. & Momin, S. A.(1977). Change detection in coastal zone environments. Photogrammetric Engineering and Remote Sensing, 43, 1533–1539.

Wilkinson, C.R. (1996). Global change and coral reefs: impacts on reefs, economies and human cultures. Global Change Biology 2:547-558

Woodcock, C. E., Macomber, S. A., Pax-Lenney, M. & Cohen, W. B. (2001). Monitoring large areas for forest change using Landsat: generalization across space, time and Landsat sensors. Remote Sensing of Environment, 78, 194–203.

Yang, X. & Lo, C. P. (2000). Relative radiometric normalization performance for change detection from multi-date satellite images. Photogrammetric Engineering and Remote Sensing, 66, 967–980.

Yasuoka, Y. (1988). Detection of land-cover changes from remotely sensed images using spectral signature similarity. Proceedings of the 9th Asian Conference on Remote Sensing, November 1988, pp. G31–G36.

Yeh, A. G. & Li, X. (2001). Measurement and monitoring of urban sprawl in a rapidly growing region using entropy. Photogrammetric Engineering and Remote Sensing, 67, 83–90.

Yue, T. X., Chen, S. P., Xu, B., Liu, Q. S., Li, H. G., Liu, G. H. & Ye, Q. H. (2002). A curve-theorem based approach for change detection and its application to Yellow River Delta. International Journal of Remote Sensing, 23, 2283–2292.

Zhang, Q. F., Devers, D., Desch, A., Justice, C. O., Townshend, J. (2005). Mapping tropical deforestation in Central Africa. Environmental Monitoring and Assessment, 101 (1-3), pp. 69-83.

Zhang, Q., Wang, J., Peng, X., Gong, P. & Shi, P. (2002). Urban build-up land change detection with road density and spectral information from multitemporal Landsat TM data. International Journal of Remote Sensing, 23, 3057–3078.

http://landcover.usgs.gov.prodescription.html.

http://www.fao.org/forestry/foris/webview/forestry2/index.jsp?siteId=101&langId=1

Appendix I

Error Matrix

Band 2

Classified Data	Change	No change	Row Total	User Accuracy (%)	Kappa
Change	10	1	11	90.91	0.88
No change	8	52	60	86.67	0.478
Column Total	18	53	71		
Producer Accuracy (%)	55.56	98.11			

Overall Classification Accuracy = 87.32%

Overall Kappa Statistics = 0.6158

Band 3

Classified Data	Change	No change	Row Total	User Accuracy (%)	Kappa
Change	5	1	6	83.3	0.1559
No change	17	48	65	73.8	0.7585
Column Total	22	49	71		
Producer Accuracy (%)	22.73	97.96			

Overall Classification Accuracy = 74.65%

Overall Kappa Statistics = 0.2587

NDVI

Classified Data	Change	No change	Row Total	User Accuracy (%)	Kappa
Change	19	1	20	95%	0.9079
No change	13	37	50	74%	0.4313
Column Total	32	38	70		
Producer Accuracy (%)	59.38%	97.37%			

Overall Classification Accuracy = 80.00%

Overall Kappa Statistics = 0.5847

Supervised classification

Classified Data	Forest	Degraded forest	Clear cut	Row Total (%)	User Accuracy(%)	Kappa
Forest	45	5	7	57	78.95	0.5526
Degraded forest		9	2	11	81.81	0.7792
Clear cut		1	16	17	94.12	0.9167
Column Total	45	15	25	85		
Producer Accuracy (%)	100	60	64			

Overall Classification Accuracy = 82.35%

Overall Kappa Statistics = 0.2587