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Land-cover binary change detection methods for use in the moist tropical region of the Amazon: a comparative study

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Many land-cover change detection techniques have been developed; however, different conclusions about the value or appropriateness of each exist. This difference of opinion is often influenced by the landscape complexity of study areas and data used for analysis. Which method is most suitable for land-cover change detection in Amazon tropical regions remains unclear. In this paper, 10 binary change detection methods were implemented and compared with respect to their capability to detect land-cover change and no change conditions in moist tropical regions. They are image differencing (ID), modified image differencing (MID), a combination of image differencing and principal component analysis (IDPCA), principal component differencing (PCD), multitemporal PCA (MPCA), change vector analysis (CVA), vegetation index differencing (VID), image ratioing (IR), modified image ratioing (MIR), and a combination of image ratioing and PCA (IRPCA). Multi-temporal Thematic Mapper (TM) data were used to conduct land-cover binary change detection. Research results indicate that MID, PCD and ID using TM band 5 are significantly better than other binary change detection methods and they are recommended specifically for implementation in the Amazon basin.

1. Introduction

Land-cover change detection has been a focus of great interest and research for decades. Many applications require change information to identify the magnitude, direction and rate of land-cover change. For example, in the Amazon basin it is very important to know how much moist tropical forest has been lost during a given period. Land-cover change information can also provide vital data for modelling (e.g. carbon gains/losses) in the Amazon. Analyses of multi-temporal remotely sensed data are prerequisite to understand change processes. The multi-temporal dimension provided by change

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detection data undoubtedly will be increasingly important in a variety of future applications, consequently a better understanding of current change detection techniques and development of new techniques is an important topic of study.

There are two primary categories of change detection. One category focuses on detection of detailed change trajectories, while the other focuses on detection of binary change and non-change features. Post-classification comparison approach is the most often used to detect detailed 'from–to' change trajectory; while image differencing, image ratioing, vegetation index differencing, and principal component analysis (PCA) are often used to detect binary change and non-change information (Lu *et al.* 2004). Although many change detection techniques have been developed, and most have been described in detail in the literature (Singh 1989, Coppin and Bauer 1996, Jensen *et al.* 1997, Yuan *et al.* 1998, Mas 1999, Serpico and Bruzzone 1999, Lu *et al.* 2004), no single method is regarded as optimal or even applicable to all types of study areas. Determining the most suitable change detection method for a study area often is not straightforward due to the differing nature of physical characteristics associated with features of interest and strengths and weaknesses of change detection methods themselves.

Many factors can affect change detection results. They could be the quality of image registration between multi-temporal images, the quality of atmospheric correction or normalization between multi-temporal images, the characteristics of the study areas (complexity of the landscape and topography), analyst's skill and experiences, and change detection methods used. After image data and study areas have been determined, then selection of an appropriate change detection method assumes considerable significance. In many cases, rapidly obtaining land-cover change and non-change information is valuable. However, identifying a suitable approach for land-cover binary change detection is often difficult in the Amazon basin due to lack of knowledge about which approach is most suitable for the moist tropical regions. Hence, this paper aims to identify the binary change detection approaches that are most suitable for moist tropical regions in the Amazon basin through a comparison of the selected binary change detection approaches.

2. Study area

Rondônia experienced high deforestation rates in the Brazilian Amazon during the past two decades (Instituto Nacional de Pesquisas Espaciais (INPE) 2002). Following the national strategy of regional occupation and development, colonization projects initiated by the Brazilian government in the 1970s played a major role in this process (Moran 1981). Most colonization projects in the state were designed to settle landless migrants. Settlement began in this area in the mid-1980s, and the settlers transformed the forested landscape into a patchwork of cultivated crops, pastures and a variety of successional forests. The study area, Machadinho d'Oeste is located in north-eastern Rondônia (figure 1). The climate in Machadinho d'Oeste is classified as equatorial hot and humid, with tropical transition. The well-defined dry season lasts from June to August, the annual average precipitation is 2016 mm, and the annual average temperature is 25.5° C (Rondônia 1998). The terrain is undulating, ranging from 100 m to 400 m above sea level.

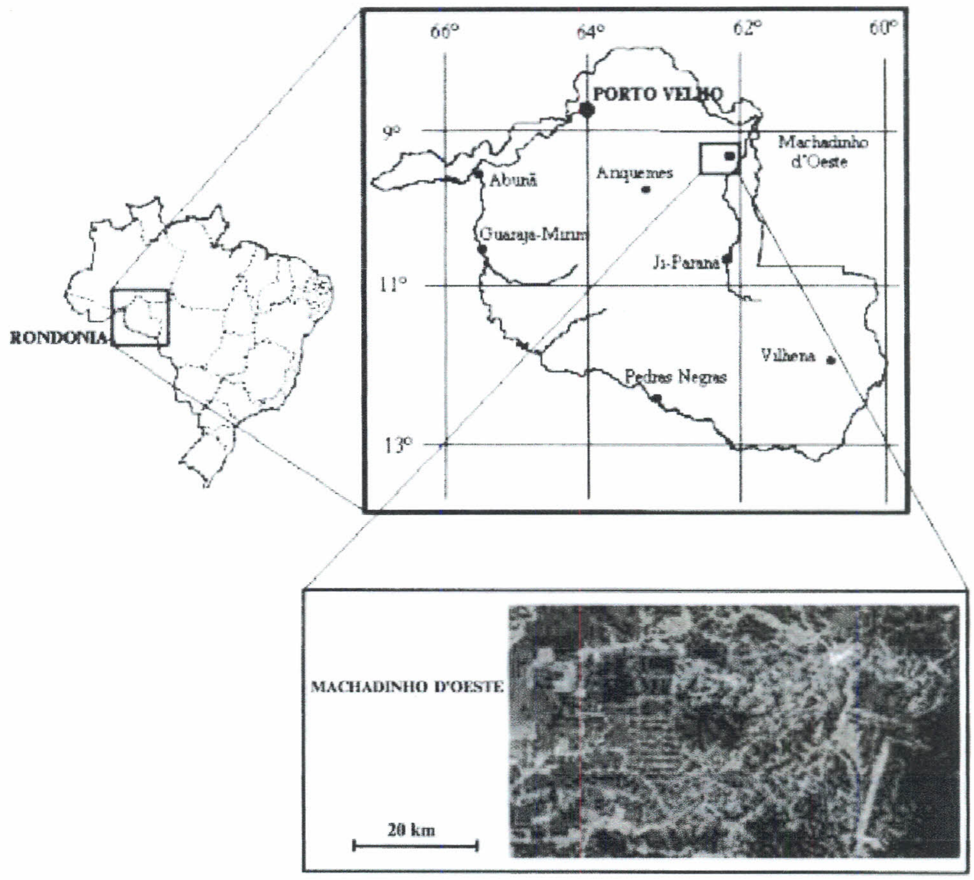

Figure 1. Location of Machadinho d'Oeste in the State of Rondônia, Brazil.

3. Methods

3.1 *Data collection and pre-processing*

Fieldwork was conducted in August 1999 and August 2000. Preliminary image classification and band composite printouts identified candidate areas to be surveyed and a flight over the areas provided visual insights about the size, condition and accessibility of each site. After driving extensively throughout the settlements, field observations provided insight into the structure of regrowth stages, mainly regarding total height and ground cover of dominant species. Indicator species, such as *Cecropia* sp., *Vismia* sp., palms, grassy vegetation, and lianas also helped to assign secondary succession (SS) stages (initial or intermediate SS). Every plot was registered with a Global Positioning System (GPS) device to allow further integration with spatial data in Geographical Information Systems (GIS) and image processing systems. Many plots covering different land cover types, such as SS stages, pasture and coffee plantation, were identified and the land-use history was also recorded while doing fieldwork. A detailed description of field data collection can be found in Batistella (2001) and Lu *et al.* (2003).

Of the various elements of pre-processing for change detection, multi-date image registration and radiometric and atmospheric corrections are the most important.

The importance of accurate spatial registration of the multi-date imageries is obvious because largely spurious results of change detection will be produced if there is misregistration between multi-date images (Townshend *et al.* 1992, Dai and Khorram 1998, Stow 1999, Verbyla and Boles 2000). Two dates of Thematic Mapper (TM) images (15 July 1994 and 18 June 1998) were acquired. The TM imagery in 1998 was geometrically rectified using control points taken from topographic maps at a 1:100 000 scale. A nearest-neighbour resampling technique was used and a rms error of less than 0.5 was obtained. The 1994 image was registered to the same projection as the 1998 TM image.

Conversion of digital numbers into radiance or surface reflectance is a requirement for quantitative analysis of multiple images acquired on different dates. Many methods have been developed for radiometric and atmospheric normalization or correction (Markham and Barker 1987, Gilaber *et al.* 1994, Chavez 1996, Vermote *et al.* 1997, Heo and FitzHugh 2000, Yang and Lo 2000, Song *et al.* 2001, Lu *et al.* 2002). Differences in TM image acquisition dates, Sun elevation angles, and atmospheric conditions that affect remote sensing digital number (DN) values were acquired. In this study, both dates of TM data were radiometrically calibrated into apparent reflectance using an image based dark object subtraction (DOS) model (Chavez 1996, Lu *et al.* 2002). The path radiance was identified based on clear water for each band.

3.2 *Change detection analysis*

Many approaches are used to detect binary change and non-change information (Lu *et al.* 2004). In order to identify binary change detection methods that are most appropriate for moist tropical land cover, 10 methods were examined. These methods include image differencing (ID), modified image differencing (MID), a combination of image differencing and principal component analysis (IDPCA), principal component differencing (PCD), multi-temporal PCA (MPCA), change vector analysis (CVA), vegetation index differencing (VID), image ratioing (IR), modified image ratioing (MIR), and a combination of image ratioing and PCA (IRPCA). Table 1 summarizes the characteristics of these methods. This paper mainly focused on the comparison of performance of these methods in detecting binary land-cover change in the Brazilian Amazon basin.

3.3 *Determination of thresholds*

Determination of suitable thresholds is one of the critical steps in change detection. Different methods can be used to determine these thresholds. For example, one method is to select appropriate thresholds in the lower and upper tails of the histogram distribution of the resultant image, representing changed pixel values, based on a trial-and-error procedure. Another method is to use the standard deviation from the mean and test it empirically. The mean and standard deviation of the entire study area are greatly affected by the extreme values. In many cases the histogram of the resultant image is not normally distributed due to the nature of change in the study area. However, the histogram of unchanged pixels in a study area is normally distributed. In this study, training sample datasets of unchanged objects were identified based on field data, and then the threshold was determined using the mean and standard deviation of the unchanged samples. For example, if the pixel value falls within $[m-\gamma\sigma, m+\gamma\sigma]$, then this pixel belongs to the unchanged

Table 1. Change detection techniques used in this paper.

No.	Technique	Code	Characteristics
1	Image differencing	ID	Image differencing involves subtraction of two spatially registered imageries, pixel by pixel. The pixels of changed area are expected to be distributed in the two tails of the histogram of the resultant image, and the unchanged area is grouped around zero. This method is simple and it is easy to interpret the resultant image; however, it is critical to appropri ately define the thresholds to identify the change from non-change areas.
2	Modified image differencing	MID	Different image bands have their own reflectance characteristics for each land-cover type. The image differencing results between image bands of two dates have different capabilities in detecting land-cover changes. Therefore, the majority rule is used in this paper. First, the image differencing was conducted for each band, i.e. ID(TMi)=TMi(t1)–TMi(t2). Thresholds were identified to detect the land-cover change and to produce a binary image for each band, 1 as change and 0 as non-change. Then, the binary images were developed to produce a new summarized image. For a TM image (six bands), if the value of a pixel is greater than or equal to 4, then the pixel belongs to change class; otherwise, it belongs to unchanged class based on the majority rule.
3	Principal component differencing	PCD	PCA is often regarded as an effective transform to extract information and compress dimensions. The majority of information is concentrated in the first two components. In particular, the first component contained the most information. The difference of the first PCA component of two dates has the potential to improve the change detection results, i.e. PCD=PC1(t1)–PC1(t2). The change detection is implemented based on thresholds.
4	Multi-temporal PCA	MPCA	Two dates of image data were superimposed and treated as a single dataset. PCA is implemented on the stacked dataset. The major component images often contain the overall radiation difference that reflects different land-cover types. The minor com ponent images contain land-cover changes between the different dates. Usually, the third and fourth components are used to analyse the land-cover change. However, it is often difficult to identify the change areas without a thorough examination of the resultant image and field data or combined with visual interpretation of the multi-date composite image.
5	Combination of ID and PCA	IDPCA	Similar to the multi-temporal PCA. The only distinction between them is to replace the single image with resultant image from image differencing. The difficulty is to identify which component image represents major land-cover changes. It is required to examine thoroughly the components and multi-date composite image to identify which component provides the best change information.

Table 1. (*Continued*)

No.	Technique	Code	Characteristics
6	Image ratioing	IR	Ratioing is also a simple and rapid means to detect changed areas. It involves calculation of the ratio of two registered images from different dates, on a band-by-band basis. For those changed areas, the ratio values will be significantly greater than 1 or less than 1 depending on the nature of the changes between two dates of images. Ratioing has been criticized due to the non-normal histogram distribution of the resultant image.
7	Modified image ratioing	MIR	Similar method as modified image differencing. The only distinction between them is to replace the differencing images with ratioed images.
8	Combination of IR and PCA	IRPCA	Similar method as the IDPCA. The only distinction between them is to replace the differencing images with ratioed images before implementing PCA.
9	Vegetation index differencing	VID	Vegetation index differencing is often regarded as an effective method to enhance the difference among spectral features and suppress topographic and shade effects. So, the difference of vegetation indices between two dates has the potential to detect land-cover change more effectively. The normalized difference vegetation index (NDVI) is often used in many applications. In this paper, NDVI difference was used for land-cover change detection, i.e. VID=NDVI(t1)–NVDI(t2).
10	Change vector analysis	CVA	CVA generates two outputs: a change vector image and a magnitude image. The spectral change vector describes the direction and magnitude of change from the first to the second date. The total change magnitude per pixel is computed by determining the Euclidean distance between end points through *n*-dimensional change space. An advantage of CVA is its ability to process any number of spectral bands desired and to produce detailed change detection information. A detailed description of this method can be found in Cohen and Fiorella (1998) and Johnson and Kasischke (1998).

class; otherwise it belongs to the changed class. Different γ constants were tested, ranging from 2.5 to 3.5. The m and σ are the mean and standard deviation of the sample data of unchanged objects in the study area.

3.4 *Accuracy assessment*

Accuracy assessment is an important part of classification and change detection processes. A common method for accuracy assessment is through use of an error matrix. Previous literature has provided the interpretations and calculation methods to determine overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA) and Kappa coefficient (Congalton and Mead 1983, Hudson and Ramm 1987, Congalton 1991, Janssen and van der Wel 1994, Khorram 1999, Smits *et al.* 1999). The Kappa coefficient is a measure of overall statistical agreement of a matrix. It takes non-diagonal elements into account. Kappa analysis was recognized as a powerful technique used for analysing a single error matrix and comparing the difference between different error matrices (Congalton 1991, Smits *et al.* 1999). An error matrix for each change detection method was produced. The accuracy measures UA, PA and OA were calculated for each method implemented. The KHAT statistic, Kappa variance and Z statistic were used to compare the performance among different change detection methods. A total of 260 sample plots were randomly allocated and examined through visual interpretation supported by field data and IKONOS satellite data.

4. Results and discussion

Three categories of change detection methods were grouped for the convenience of comparison of performance among different change detection techniques. They are techniques based on image differencing, image ratioing and PCA. Image differencing based methods include image differencing (ID), vegetation index differencing (VID), modified image differencing (MID), combination of ID and PCA (IDPCA), PC differencing (PCD) and CVA. Table 2 provides a comparison of change detection accuracies using these methods. Among the single band image differencing methods, band TM 5 provided the best accuracy. The overall accuracy reached 99% with an associated KHAT value of 0.97. The second best band to use for change detection was TM 3 with 98% accuracy and a KHAT of 0.95. The change detection accuracies using single band image differencing of TM 1, TM 4 and TM 7 respectively were relatively poor with a KHAT of less than 0.88. The methods MID, IDPCA and PCD had overall change detection accuracies greater than 98.5% and had a KHAT greater than 0.96. The CVA approach did not provide a better change detection result than the ID methods using band TM 5 or TM 3. The VID approach provided a poorer change detection result with a KHAT of 0.79.

Table 2. Accuracy comparison of image differencing based change detection methods.

Methods	Change detection	UA	PA	OA	KHAT
ID_b1	change	81.13	87.76	92.00	0.7896
ID_b2	no-change	95.92	93.38		
	change	90.00	95.74	96.50	0.9048
	no-change	98.67	96.73		
ID_b3	change	94.00	97.92	98.00	0.9459
	no-change	99.33	98.03		
ID_b4	change	86.00	93.48	95.00	0.8630
	no-change	98.00	95.45		
ID_b5	change	98.00	98.00	99.00	0.9733
	no-change	99.33	99.33		
ID_b7	change	89.58	91.49	95.50	0.8758
	no-change	97.37	96.73		
MID	change	100.00	98.04	99.50	0.9868
	no-change	99.33	100.00		
IDPCA	change	95.83	97.87	98.50	0.9586
	no-change	99.34	98.69		
PCD	change	98.04	98.04	99.00	0.9737
	no-change	99.33	99.33		
CVA	change	92.31	92.31	96.00	0.8961
	no-change	97.30	97.30		
VID	change	76.00	92.68	92.50	0.7872
	no-change	98.00	92.45		

Image ratioing based methods include simple image ratioing (IR), modified image ratioing (MIR), a combination of image ratioing and PCA (IRPCA), and vegetation index differencing (VID). Table 3 indicates that band TM 3 provides the best accuracy among single band ratioing approaches. The overall accuracy reached 96.5% with a KHAT value of 0.91. Bands TM 1 and TM 4 had the poorest performance with KHAT values of less than 0.78. The second best approach is from IRPCA. Overall, the image ratioing based methods provided poorer change detection results than image differencing based approaches.

PCA based change detection approaches include PC differencing (PCD), multi-temporal PCA (MPCA), a combination of ID and PCA (IDPCA), and a combination of IR and PCA (IRPCA). These approaches can reduce data redundancy and image dimensionality as well as concentrate a vast majority of useful information inherent in the data in a few components. MPCA was often used for change detection analysis in previous research. The first two PCs often contain unchanged information while higher PCs often contained change information. The highest PCs primarily represent noise, thus contain little information. Table 4 illustrates the bitemporal TM image PCA result. The first four PCs accounted for 97.11% of total variance or information. The other eight PCs accounted for only 2.89% of the information in the data with the highest three PCs in this group (PC10–12) mainly representing noise. The first two PCs accounted for a majority of the variance in the data, but they do not contain temporal change information. The third and fourth PCs contained temporal change information. Visual interpretation of these two PCs indicates that the fourth PC provided better change results. Thus, the fourth PC was used to detect land-cover change.

For the PCA of a single date of TM image, the first PC primarily extracts a majority of the information inherent in the original bands. For example, the first PC accounts for 70.1% of the variance in the 1998 TM image and 68.5% in the 1994 TM image. Differencing the first PC from 1994 and 1998 TM images has the potential to provide a good change detection result. Analysing the PCA results from IDPCA and IRPCA indicated that the second PC from IDPCA and the third PC from IRPCA

Table 3. Accuracy comparison of image ratio based change detection methods.

Methods	Change detection	UA	PA	OA	KHAT
IR_b1	change	76.00	86.36	91.00	0.7500
	no-change	96.00	92.31		
IR_b2	change	88.68	94.00	95.50	0.8824
	no-change	97.96	96.00		
IR_b3	change	92.16	94.00	96.50	0.9073
	no-change	97.99	97.33		
IR_b4	change	80.00	88.00	91.50	0.7806
	no-change	95.86	92.67		
IR_b5	change	90.20	88.46	94.50	0.8562
	no-change	95.97	96.62		
IR_b7	change	82.00	91.11	93.50	0.8207
	no-change	97.33	94.19		
MIR	change	90.91	92.59	95.50	0.8865
	no-change	97.24	96.58		
IRPCA	change	90.00	95.74	96.50	0.9048
	no-change	98.67	96.73		
VID	change	76.00	92.68	92.50	0.7872
	no-change	98.00	92.45		

Table 4. PCA loadings for two dates of TM data (1994 and 1998) in the study area.

TM bands	PC1	PC2	PC3	PC4	PC5	PC6	PC7	PC8	PC9	PC10	PC11	PC12
Ron94_b1	0.068	−0.057	0.025	0.118	−0.085	0.167	0.020	−0.047	−0.035	0.051	0.064	0.965
Ron94_b2	0.124	−0.093	0.086	0.184	−0.229	0.468	0.078	−0.225	−0.041	0.015	−0.771	−0.104
Ron94_b3	0.166	−0.164	0.045	0.319	−0.261	0.578	−0.001	−0.095	0.100	−0.013	0.608	−0.225
Ron94_b4	0.273	0.285	0.848	−0.330	−0.056	0.058	−0.034	0.082	−0.006	−0.001	0.049	0.003
Ron94_b5	0.405	−0.190	0.242	0.567	0.311	−0.440	0.087	−0.346	0.043	0.009	0.002	−0.029
Ron94_b7	0.191	−0.149	0.042	0.348	0.061	0.027	−0.266	0.844	−0.114	−0.011	−0.132	−0.013
Ron98_b1	0.095	−0.086	−0.035	−0.065	−0.188	−0.106	−0.009	0.007	−0.111	0.956	0.027	−0.057
Ron98_b2	0.188	−0.136	−0.057	−0.071	−0.467	−0.240	0.211	−0.017	−0.741	−0.245	0.082	−0.036
Ron98_b3	0.224	−0.258	−0.059	−0.146	−0.575	−0.325	0.005	0.093	0.625	−0.131	−0.067	0.032
Ron98_b4	0.506	0.753	−0.383	0.101	−0.089	−0.001	−0.101	−0.025	0.038	−0.004	−0.008	0.002
Ron98_b5	0.515	−0.289	−0.216	−0.423	0.407	0.213	0.444	0.128	0.040	−0.002	0.006	0.001
Ron98_b7	0.250	−0.280	−0.099	−0.281	0.102	0.043	−0.814	−0.270	−0.132	−0.068	−0.007	0.007
Eigenvalues	81.409	25.389	14.099	11.296	1.857	0.779	0.426	0.275	0.208	0.181	0.119	0.089
% variance	59.804	18.651	10.357	8.298	1.364	0.572	0.313	0.202	0.153	0.133	0.087	0.065
% accuracy variance	59.804	78.455	88.812	97.110	98.475	99.047	99.360	99.562	99.715	99.847	99.935	100.000

Table 5. Accuracy comparison of PCA based change detection methods.

Methods	Change detection	UA	PA	OA	KHAT
MPCA	change	89.58	87.76	94.50	0.8503
	no-change	96.05	96.69		
PCD	change	98.04	98.04	99.00	0.9737
	no-change	99.33	99.33		
IDPCA	change	95.83	97.87	98.50	0.9586
	no-change	99.34	98.69		
IRPCA	change	90.00	95.74	96.50	0.9048
	no-change	98.67	96.73		

provided the best change information, respectively. Table 5 shows the comparison of change detection accuracies and KHAT values from these PCA based approaches. The comparison indicates that PCD and IDPCA methods provided better change detection results than MPCA and IRPCA.

Table 6 provides the Kappa analysis results for the 10 methods used. Analysis of this table indicates that MID, PCD and ID_b5 were the best three change detection methods and that they had significantly better accuracies than VID, MPCA, MIR, CVA, IRPCA and IR_b3. These three methods had KHAT values greater than 0.97. The IDPCA was also significantly better to use for change detection than VID, MPCA, MIR and CVA. The IR_b3, IRPCA, CVA, MIR and MPCA did not have a significant difference in accuracies with KHAT values ranging from 0.85 to 0.91. The MID, PCD, ID_b5 and IDPCA also did not have a significant difference with KHAT values greater than 0.96.

5. Discussion and conclusions

Different binary change detection methods have their own merits and thus selecting a suitable method is an important factor for improving change detection accuracy in a study area. For example, various image bands can be used in ID and IR methods, but the results can be different because each band has its own characteristics, representing different capabilities for distinguishing land-cover types. Jensen and Toll (1982) found the usefulness of visible red band data in change detection analysis in both vegetated and urban environments. Chavez and Mackinnon (1994) also indicated that red band image differencing provided better vegetation change detection results than using NDVI in the arid and semi-arid environments of the south-western United States. Pilon *et al.* (1988) concluded that visible red band provided the most accurate identification of spectral change for their sub-Sahelian semi-arid study area in north-western Nigeria. Fung (1990) came to a similar conclusion that the band TM 3 differencing image produced the best vegetation cover change detection results. However, in the moist tropical region of the Brazilian Amazon basin, band TM 5 image differencing provided the best change detection results and band TM 3 provided the second best results. This may be due to the greater amount of water and related opportunities for differential absorption in TM band 5 in the Amazon environment compared to a drier environment.

Only one spectral band is used in the ID and IR methods, thus selecting the best band is crucial. When it is difficult to identify the best band to use for change detection, then MID is usually the most appropriate method to use. This research indicates that using image differencing based change detection methods are more