INT. J. REMOTE SENSING, 1999, VOL. 20, NO. 1, 139–152

Monitoring land-cover changes: a comparison of change detection techniques*

J.-F. MAS

Laboratory of Remote Sensing and Geographic Information Systems, Centre of Ecology, Fisheries and Oceanography of the Gulf of Mexico (EPOMEX), University of Campeche, AP 520 24030 Campeche, CAMP, Mexico; e-mail: jeanfmas@epomex.uacam.mx

(*Received 20 May 1997; in final form 20 May 1998*)

Abstract. Six change detection procedures were tested using Landsat Multi-Spectral Scanner (MSS) images for detecting areas of changes in the region of the Términos Lagoon, a coastal zone of the State of Campeche, Mexico. The change detection techniques considered were image differencing, vegetative index differencing, selective principal components analysis (SPCA), direct multi-date unsupervised classification, post-classification change differencing and a combination of image enhancement and post-classification comparison. The accuracy of the results obtained by each technique was evaluated by comparison with aerial photographs through Kappa coefficient calculation. Post-classification comparison was found to be the most accurate procedure and presented the advantage of indicating the nature of the changes. Poor performances obtained by image enhancement procedures were attributed to the spectral variation due to differences in soil moisture and in vegetation phenology between both scenes. Methods based on classification were found to be less sensitive at these spectral variations and more robust when dealing with data captured at different times of the year.

1. Introduction

Several regions around the word are currently undergoing rapid, wide-ranging changes in land cover. Much of this activity is centred in the tropics in such countries as Brazil, Columbia, Indonesia, Mexico, the Ivory Coast, Venezuela and Zaire (FAO 1995). These changes in land cover, in particular tropical forest clearing, have attracted attention because of the potential effects on erosion, increased run-off and flooding, increasing CO_2 concentration, climatological changes and biodiversity loss (Myers 1988, Fontan 1994). Remote sensing provides a viable source of data from which updated land-cover information can be extracted efficiently and cheaply in order to inventory and monitor these changes effectively. Thus change detection has become a major application of remotely sensed data because of repetitive coverage at short intervals and consistent image quality.

The basic premise in using remote sensing data for change detection is that

*Presented at the Fourth International Conference on Remote Sensing for Marine and Coastal Environments, Orlando, Florida, 17–19 March 1997.

International Journal of Remote Sensing
ISSN 0143-1161 print/ISSN 1366-5901 online
http://www.tandf.co.uk/JNLS/res.htm
http://www.taylorandfrancis.com/JNLS/res.htm

changes in land cover result in changes in radiance values and changes in radiance due to land cover change are large with respect to radiance changes caused by others factors such as differences in atmospheric conditions, differences in soil moisture and differences in sun angles. Vegetation diversity and interspersion of land cover is high in the humid tropics, and spectral reflectance characteristics of mixed vegetation are often not distinct, causing problems in digital classifications (Roy *et al.* 1991, Sader *et al.* 1991). For example, workers have reported spectral confusion between undisturbed and disturbed forests (Franklin 1993) and between successional forest classes and pasture containing trees (Sader *et al.* 1990). Similar confusion is also expected when trying to discriminate natural grassland (savannah) from pasture lands. Therefore, change between land covers which present similar spectral signatures is difficult to detect.

The impact of sun angle differences and vegetation phenology differences may be partially reduced by selecting data belonging to the same time of the year (Singh 1989). However, it may be extremely difficult to obtain multi-date data of the same time of the year, particularly in tropical regions where cloud cover is common. For example, one of the objectives of the North American Landscape Characterization (NALC) Project was to produce 'triplicates' consisting of Landsat Multi-Spectral Scanner (MSS) images for the years 1973, 1986 and 1992 (plus or minus one year) for the USA and Mexico. In Mexico, because of the low number of good quality scenes, images of the triplicate often do not belong to the same time of the year. Moreover, in many cases it had even been necessary to get images dated outside the 3-year intervals previously defined and to mosaic various images to obtain a cloud-free scene. Table 1 shows that differences between the dates of the NALC triplicate images for southern Mexico (path 18 to 25) are, on average, higher than 2 months. The problem of availability of cloud-free images in tropical regions is very common and has been reported by many authors (Jha and Unni 1982, Ducros-Gambart and Gastellu-Etchegorry 1984, Nelson and Holben 1986, Pilon *et al.* 1988, Alwashe and Bokhari 1993). Consequently, the identification of a robust change detection-methodology is essential for dealing with multi-date data in these regions.

An analysis of the literature reviewed indicates that (1) there are very few studies concerned with comparative evaluation of change detection techniques, (2) the majority of these comparative studies have not supported their conclusion by quantitative analysis of the results (Singh 1989) and (3) many studies have been carried out with images of the same time of the year. The purpose of this study is to compare the relative effectiveness of different techniques in detecting land cover changes in a tropical coastal zone using images captured at different times of the year.

Table 1. Differences in the dates of NALC triplicate images of south-eastern Mexico. Values are expressed in number of days of difference.

	Decades		
	1970–1980	1970–1990	1980–1990
Mean	68.2	81.3	59.2
Maximum	182	177	154
Minimum	1	2	3
SD	51.9	50.6	48.7

SD, standard deviation.

2. Study area

The area of study covers a part of the Términos Lagoon region, State of Campeche, Mexico. It is located in the south-east of Mexico, between 18° 00′ and 18° 55′ N latitude and 90° 55′ and 92° 06′ W longitude (figure 1). Land use within this area is divided principally among mangrove, evergreen tropical forest, wetlands, pasture-land and agriculture. Rates of deforestation in Campeche are high, particularly in the coastal zone (Mas 1996, Mas *et al.* 1997). Much of the land surrounding the lagoon has been deforested for cattle ranching and rice farming (Isaac-Márquez 1993), and, recently, aquaculture and petroleum exploration have begun in the region. A large part of the study area has been protected since 1994 (Yáñez *et al.* 1993). The climate is hot and humid with annual rainfall ranging from 1300 to 1800 mm and average temperature of about 26° C (CNA 1995). Based on precipitation, river discharge, winds and temperature, three seasons were identified: the dry season from February to May, a tropical rainy season from June to October, and the nortes season with periodic rains from October to February (Yáñez-Arancibia and Day 1988).

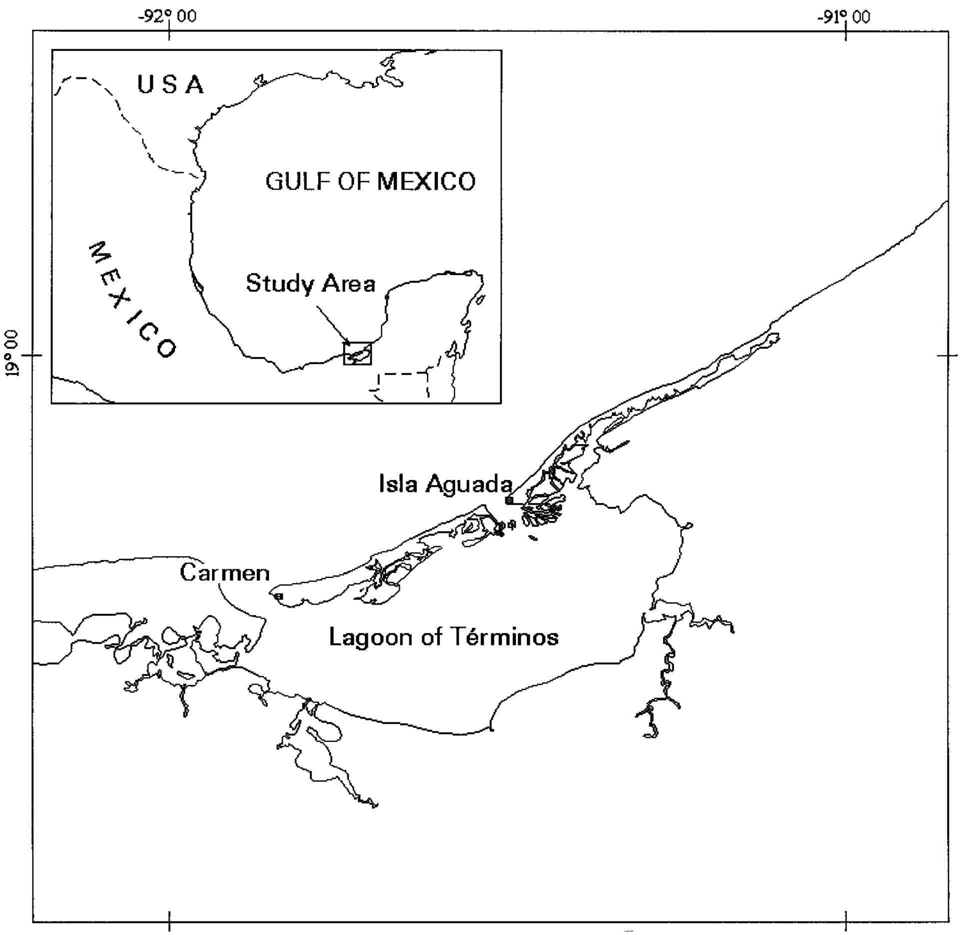

Figure 1. The study area.

3. Data and methodology

The Landsat MSS images used in the present study belong to the NALC triplicate dataset and have been geometrically and radiometrically corrected by the EROS Digital Image Processing Centre. The 1970s scene was 'destriped' to compensate for variations in the radiometric response of the individual detectors. The images were corrected and resampled, using cubic convolution, to a UTM projected output image composed of 60 m × 60 m pixels, with an root mean square error (rmse) of less than 1.0 pixel. A 2045 columns by 1687 lines sample subsection corresponding to the Lagoon of Términos and its surrounding area was extracted from 15 February 1974 and 29 April 1992 Landsat MSS scenes (path 21, row 47). Digital image processing was performed on a SUN workstation using ERDAS software.

3.1. *Radiometric normalization*

Dealing with multi-date image datasets requires that images obtained by sensors at different times are comparable in terms of radiometric characteristics. This usually does not happen even for images generated by the same sensor for several reasons such as change in radiometric performance over time, variation in solar illumination conditions, atmospheric scattering and absorption and changes in atmospheric conditions (presence of clouds). Therefore, if any two datasets are to be used for quantitative analysis based on radiometric information, as in the case of multi-date analysis for detecting surface changes, they ought to be adjusted to compensate for radiometric divergence. There are two ways to achieve these radiometric compensation: (1) performing radiometric calibration, converting the entire dataset from digital number values into ground reflectance values and, (2) performing a relative radiometric normalization between the multi-date images. The first way is generally more complex than the second and is usually unnecessary for the simple purpose of change detection. Conventional techniques for applying relative radiometric normalization use statistical parameters of the whole scene or selected subsets believed to be spectrally stable. However, these techniques do not compensate all atmospheric effects, particularly when clouds are present in one of the images, or require some degree of human intervention in selecting control pixels. For this reason, we used a method based on the Automated Scattergram-Controlled Regression developed by Elvidge *et al.* (1995) and successfully applied in identifying cover changes in the Amazon by Crósta *et al.* (1995). The same spectral band of two dates was used in order to produce a scattergram and define the regression line. The following step was to define the regions of 'no-change' using the scattergram. As both images were taken during the dry season, spectral changes due to phenological differences of vegetation such as mangroves, evergreen forest, pasture land and wetlands were expected to be lower than changes due to land cover transformation or to the presence of clouds. For this reason, the pixels close to the regression line were assumed to be the ones without changes between the two dates and therefore used to perform the radiometric normalization. A histogram-matching procedure was performed in order to carry out the relative image-to-image radiometric normalization. Histograms of the digital numbers within the two multi-date images, master and slave, were computed. Histograms were based on values from pixels belonging to the subarea that has been selected and labelled as 'unchanged' on the scattergram analysis.

3.2. *Change detection*

Researchers involved in change detection studies using satellite images data have conceived a large range of methodologies for identifying environmental changes.

Change detection procedures can be grouped under three broad headings characterized by the data transformation procedures and the analysis techniques used to delimit areas of significant changes: (1) image enhancement, (2) multi-date data classification and (3) comparison of two independent land cover classifications (Mas 1998). The enhancement approach involves the mathematical combination of imagery from different dates such as subtraction of bands, rationing, image regression or principal components analysis (PCA). Thresholds are applied to the enhanced image to isolate the pixels that have changed. The direct multi-date classification is based on the single analysis of a combined dataset of two or more different dates, in order to identify areas of changes. The post-classification comparison is a comparative analysis of images obtained at different moments after previous independent classification. In the present study, six change detection procedures were tested.

3.2.1. *Image differencing*

In this method, registered images acquired at different times are subtracted to produce a residual image which represents the change between the two dates. Pixels of no radiance change are distributed around the mean, while pixels of radiance change are distributed in the tails of the distribution (Singh 1986). Two subtracted images were created for bands 2 and 4, respectively. Data transformations were confined to these bands because they are considered to be the most useful for discriminating forest canopy and vegetation alterations (Nelson 1983).

3.2.2. *Vegetation index differencing*

This technique used a data transformation shown to be related to green biomass (Tucker 1979). The Normalized Difference Vegetation Index (NDVI) is calculated by $NDVI = (NIR—RED)/(NIR + RED)$ where NIR is the near-infrared band response for a given pixel, MSS band 4 and RED is the red response, MSS band 2. The vegetation index was calculated for both dates and then subtracted (Nelson 1983, Singh 1986).

3.2.3. *Selective Principal Components Analysis*

In the Selective Principal Components Analysis (SPCA), only two bands of the multi-date image are used as input instead of all bands. By using only two bands, the information that is common to both is mapped to the first component and information that is unique to either one of the two bands (the changes) is mapped to the second component (Chavez and Kwarteng 1989). Principal components are usually calculated from a variance–covariance matrix. The standardization of the covariance matrix into a correlation matrix by dividing by the appropriate standard deviation reduces all the variables to equal importance as measured by scale. Singh and Harrison (1985) compared standardized and unstandardized PCA and reported substantial improvement of signal-to-noise ratio and image enhancement by using standardized variables. Selective standardized principal components analysis was performed using bands 2 and 4.

3.2.4. *Direct multi-date classification*

The direct multi-date classification is based on the single analysis of a combined dataset of the two dates in order to identify areas of changes (Singh 1986). Classes where changes are occurring are expected to present statistics significantly different from where change did not take place and so could be identified. Unsupervised classification was carried out using the ISODATA method of the ERDAS software which uses spectral distance and iteratively classifies the pixels, redefines the criteria for each class, classifying again, so that the spectral distance patterns in the data gradually emerge (ERDAS 1991).

3.2.5. *Post-classification analysis*

The most obvious method of change detection is a comparative analysis of spectral classifications for times t_1 and t_2 produced independently (Singh 1989). In this context it should be noticed that the change map of two images will only be generally as accurate as the product of the accuracies of each individual classification (Stow *et al.* 1980). Accuracy of relevant class changes depends on spectral separability of classes involved. In the present study, Landsat MSS data of both dates were independently classified using the maximum likelihood classifier.

3.2.6. *Combination image enhancement/post-classification analysis*

In this method, the change image produced through an enhancement procedure is recoded into a binary mask consisting of areas that have changed between the two dates. The change mask is then overlaid onto the date 2 image and only those pixels that were detected as having changed are classified in the date 2 imagery. A traditional post-classification comparison can then be applied to yield from-to change information. This method may reduce change detection errors and provides detailed from-to change information (Pilon *et al.* 1988, Jensen 1996).

3.3. *Accuracy assessment*

In order to determine the accuracy of each change image a random sample of 180 points was selected within the study area. Points which fell in areas corresponding to clouds, to the lagoon or to the border between different land covers were eliminated resulting finally in 106 points. The nature of change within an area of 200 m around the selected points were determined by comparing 1972 and 1990 aerial photographs scale 1:75 000, 1978 and 1992 vegetation maps and colour composites of the two images. For each point, two levels of information were determined: the first level involved only 'change/no change' binary information and the second level described the nature of change (from-to information). This information was compared to the change detection techniques results through confusion matrices.

In the application of digital change detection techniques based on image enhancement, it was necessary to establish a thresholding level in order to define land cover change. All histograms were examined and the mean and standard deviation values for each dataset were calculated. Various standard threshold levels were applied to the lower and higher tail of each distribution in order to find the threshold value that produced the highest change classification accuracy. The relationship between change classification accuracy and threshold for a given transformed band was studied by generating change images for thresholds ranging from 0.25 to 2.00 standard deviations, at 0.25 standard deviation intervals. As a following step, thresholds every 0.1 standard deviation around the initial empirical maximum were tested. If the distributions are non-normal and functions of the standard deviations are used to delimit change from no change, the areas delimited on either side of the mode are not equal. Therefore, the error rates on either side of the mode are not equal. For this reason, an attempt was made to determine the two threshold boundaries using two independent steps. In order to establish the optimal threshold value applied to the lower tail of the distribution, pixels which value was lower than the threshold level L_1 were considered as changed, pixels whose value ranged between the threshold level L_1 and the mean M were classified in the no-change category and pixels whose value was higher than the mean were classified as no data (figure 2, step 1). Various threshold levels were applied in order the find the threshold value that produced the highest change classification accuracy. A similar procedure was applied to determine the threshold value of the higher tail of the distribution L_2 (figure 2, step 2).

Most accuracy indices are biased and affected by the ratio between the number of reference data points of the change and the no-change category (Nelson 1983). Fung and Ledrew (1988) examined the use of different accuracy indices, including overall, average and combined accuracies and the Kappa coefficient of agreement to determine an optimal threshold level for changes detection images. They recommended the Kappa coefficient because it considers all elements of the confusion matrix.

4. Results

4.1. *Radiometric normalization*

Statistics of the subscenes were calculated. It must be noted that the 1992 image presented some clouds and that there were significant radiometric differences between both dates (table 2). The values of 1974 band 2 were regressed against 1992 band 2 using a least-squares regression. The predicted values of 1992 obtained from the regression line were then compared with real 1992 band 2 values by subtraction. If the difference was higher then a threshold value, pixels were considered as changed and were excluded from the histogram calculation. A threshold value of 10 allowed the isolation of 5% of the pixels which present more important spectral variation

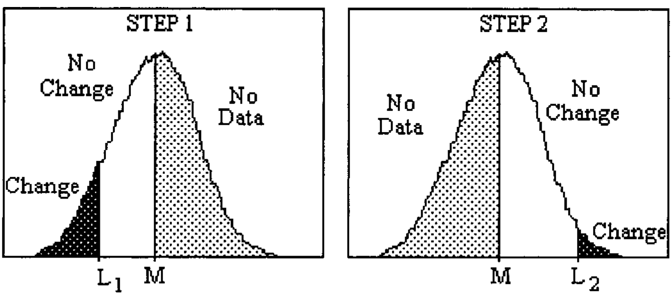

Figure 2. Two-step thresholding method.

Table 2. Statistics of the 1974 and 1992 images before and after radiometric normalization.

	Band 1	Band 2	Band 3	Band 4
Before radiometric normalization				
Mean 1974	25.51	15.20	13.14	26.84
Mean 1992	32.52	28.18	37.15	38.24
SD 1974	8.01	5.23	13.14	17.82
SD 1992	9.20	7.74	17.44	22.33
After radiometric normalization				
Mean 1974 matched	32.21	28.01	36.91	36.91
SD 1974 matched	9.55	8.51	16.56	23.32

SD, standard deviation.

between the two dates. These pixels corresponded mostly to the clouds of 1992 image and to some areas of the lagoon which presented a different grade of turbidity between the two dates. The histogram of the 1974 image was matched to that of the 1992 image because it presented a significantly smaller range of data values than the 1992 image. The histogram matching was carried out using histograms based only on values from pixels classified without change in the regression analysis. After normalization, statistics of the 1974 image were very similar to the 1992 image (table 2).

4.2. *Change detection*

4.2.1. *Image enhancement procedures*

The vegetation index was calculated for both dates. Then three residual images were produced by subtracting band 2, band 4 and vegetation index of both dates. Two selective standardized PCAs were applied to bands 2 and 4 producing two second components. All histograms were examined. The values of the images produced by image subtraction of band 2 and by PCA presented a normal distribution, the differenced image based on band 4 had a non-normal distribution and the vegetation index differencing image presented two separate peaks. Non-normal distributions were mainly due to different spectral responses in the lagoon. For this reason, pixels corresponding to the water and to the clouds were excluded from the histogram and statistics calculation through a masking technique. After masking, all histograms presented a normal or a near-normal distribution and the mean and standard deviation values for each dataset were calculated.

Threshold levels were determined using both one-step and two-step thresholding methods in order to compare them. Table 3 shows that independent two-steps thresholding of the high and low levels allowed only limited accuracy improvement. Moreover, the two-step thresholding procedure presents some limitations: (1) the determination of each threshold level is based only on a reduced subset of the sample points set, and (2) the optimal threshold levels selected independently are not always the most accurate when assessing accuracy with both levels and the entire sample points set because the Kappa coefficient takes into account chance agreement. However, two-step thresholding can be useful to threshold asymmetric distribution.

Table 3. Standard deviation thresholds and classification accuracy achieved using image enhancement procedures.

	One-step thresholding		Two-step thresholding		
Image enhancement procedure	Optimal SD threshold	Kappa coefficient	Optimal threshold low	Optimal threshold high	Kappa coefficient
Band 2 differencing	1.10	0.4100	1.10	1.10	0.4100
Band 4 differencing	1.00	0.2196	0.80	1.00	0.2210
NDVI differencing	1.10	0.3831	1.10	1.20	0.3981
SPCA band 2	1.20	0.4109	1.20	1.25	0.4155
SPCA band 4	0.90	0.2225	0.90	1.00	0.2222

SD, standard deviation.

4.2.2. *Procedures based on classifications*

Unsupervised classification was carried out using the eight bands of the multi-date image in order to classify the image into 35 clusters and to identify potential change classes. The resulting classified image of the clustering was displayed and examined in order to determine the land covers which corresponded to each cluster for both dates. Land cover classes considered were forest cover, nonforest natural vegetation, pasture land/agriculture, water and urban area. It can be noticed that some spectral classes corresponded to various covers with spectral similarities. These spectral classes were then assigned to the land cover which was the more important. As a following step, accuracy of the change image was estimated at change/no change detection and from-to change detection level. At level 'change/no change' detection the Kappa coefficient was 0.2850 (with a global accuracy of 80.71% of the pixels correctly classified) and was 0.3886 in the identification of the nature of the changes (global accuracy of 61.78%).

A post-classification analysis procedure was carried out using supervised classification. Both images were classified into 10 thematic classes (primary forest, secondary forest, mangrove, wetland, pasture land, agriculture, water, urban area and clouds). As a following step, mangroves, primary and secondary forests were grouped into a single 'Forest' class. Also pasture land and agriculture were grouped to finally obtain the same thematic classes as considered in the unsupervised classification. Classified images of 1974 and 1992 were then overlaid in order to generate a change image and accuracy was determined. At level change/no change detection the Kappa coefficient was 0.6191 (and the global accuracy 86.87%) and at level from-to change identification it was 0.7070 (global accuracy 82.41%). Table 4 shows the confusion matrix of the change image.

In order to carry out the combination between post-classification comparison and image enhancement, the change image produced through SPCA of band 2 was recoded into a binary mask consisting of areas that have changed between the two dates. The change image obtained by SPCA using band 2 was chosen because it was the most accurate (table 4). The change mask was then overlaid onto the classified images and date 2 classified image was taken into account only for those pixels that were detected as having changed. In the present study this method did not reduce change detection errors and the classified image is not as accurate as the image generated by simple post-classification comparison (Kappa coefficient of 0.6414).

5. Discussion and conclusion

A summary of the results obtained by using these six techniques is given in table 5. The results of the study can be summarized as follows.

The highest accuracy was obtained using the post-classification comparison based on supervised classification of the two images. The good performance of this approach can be attributed to the high classification accuracy of 1974 and 1992 classified images and to the fact that accuracy has been improved by grouping classes which presented the most common spectral confusion such as mangrove, secondary and primary forest.

In single band analysis band 2 data proved to be superior to band 4 for detecting changes in land cover. The reason for the poor performance using band 4 data is to be found in the high infrared return from the herbaceous understorey in cleared areas which produces classifications errors (Singh 1986). Vegetation index calculations allowed similar results as compared to band 2. Based on the same band, the

Table 4. Confusion matrix of the post-classification comparison change image.

Classified data (post-classification comparison)	Reference data (aerial photographs): No change classes				Change classes							Accuracy
	FF	NN	UU	PP	FN	FP	FW	NF	NP	PF	PN	
Forest/forest (FF)	57.0	–	–	0.2	–	3.5	–	–	–	–	–	93.4
Natural vegetation/natural vegetation (NN)	1.0	5.8	–	1.0	–	0.9	–	–	–	–	–	67.4
Urban/urban (UU)	–	–	1.0	–	–	–	–	–	–	–	–	100.0
Pasture–agriculture/pasture–agriculture(PP)	–	–	–	5.4	–	0.1	–	–	–	–	–	96.4
Forest/natural vegetation (FN)	0.3	–	–	–	–	–	–	–	–	–	–	0.0
Forest/pasture–agriculture (FP)	1.7	–	–	0.9	–	7.6	–	–	–	–	–	76.0
Forest/water (FW)	0.1	–	–	–	–	–	–	–	–	–	–	0.0
Natural vegetation/forest (NF)	–	1.1	–	0.1	–	0.4	–	–	1.0	0.1	–	0.0
Natural vegetation/pasture–agriculture (NP)	–	1.4	–	0.3	–	0.5	–	–	2.9	–	–	58.0
Pasture–agriculture/forest (PF)	0.8	–	–	1.7	–	0.2	–	–	–	2.7	–	50.0
Pasture–agriculture/natural vegetation (PN)	–	0.3	–	–	–	–	–	–	–	–	–	0.0
Accuracy (%)	93.4	67.4	100	56.3	–	58.5	–	–	74.4	93.1	–	82.4

Table 5. Comparison of the performances of the change detection procedures.

Change detection procedure	Change no change level		From-to change level	
	Kappa	Global accuracy	Kappa	Global accuracy
Band 2 differencing	0.4100	80.40	–	–
Band 4 differencing	0.2210	73.90	–	–
NDVI differencing	0.3981	81.84	–	–
SPCA band 2	0.4155	82.05	–	–
SPCA band 4	0.2222	73.20	–	–
Multi-date classification	0.2850	80.71	0.3886	61.78
Post-classification comparison	0.6191	86.87	0.7070	82.41
Masking + post-classification comparison	0.4201	84.52	0.6414	79.58

SPCA offered better accuracy than the image differencing procedure. It seems that SPCA removed inter-images variability due to the sensor and to atmospheric conditions which still remained after radiometric normalization.

Some authors carried out comparative studies of change detection techniques and generally found that post-classification comparison was less effective than enhancement procedures such as image regression (Singh 1986) or image differencing and PCA (Muchoney and Haak 1994). An attempt was made to analyse the potential effect of the differences in soil moisture and vegetation phenology due to the difference between the dates of capture of the two images (15 February 1974 and 1 April 1992) in the poor performances obtained by image enhancement procedures. Climatological data from Isla Aguada were examined for the years 1973, 1974, 1991 and 1992. The rainfall diagram (figure 3) shows that the 1974 and the 1992 images were captured in the middle and at the end of a dry season, respectively. Daily rainfall data show that there was no significant rainfall during the week previous to the capture of both images. A similar difference of time (2 or 3 months) between the dates of capture of the two images could have resulted in significantly higher difference of climatological features as, for example, the difference between April and June. Rojas-Galaviz *et al.*

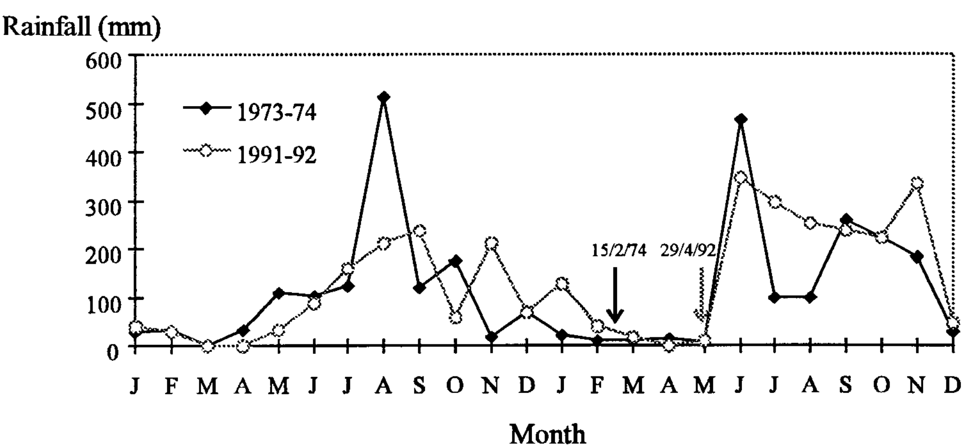

Figure 3. Rainfall diagram for Isla Aguada (1973–1974 and 1991–1992).

(1992) measured the seasonal average of total mangrove litterfall in the Lagoon region, giving values significantly different between February and April. Nevertheless there were significant differences in soil moisture and vegetation phenology between both dates. Therefore a large amount of variation of spectral responses was attributed to these differences. Also, it is important to notice that there are important variations in rainfall from one year to another and that soil moisture and vegetation can be significantly different at the same time of the year.

Image enhancement procedures were not able to differentiate accurately the variations of soil moisture and vegetation phenology from variations due to land cover changes. The use of classification techniques avoided this problem. When carrying out independent supervised classifications, classes which present very different spectral signatures at the different dates can be classified into the same land cover. When using unsupervised multi-date classification, classes which present spectral variation between both dates, but where change is not occurring, can also be identified although, in the present study spectral classes corresponded to different classes of changes and, multi-date unsupervised classification did not allow the accurate identification of the land cover changes. Thus the procedure based on the comparison of independent supervised classifications was found less sensitive to radiometric variations between the scenes and is more appropriate when dealing with data captured at different dates. Post-classification comparison also presents the advantage of giving information about the nature of the changes. Results suggest that the principal land cover changes in the study area (e.g., deforestation for pasture development, forest regeneration and conversion of wetlands to agriculture of rice) can be monitored accurately by remote sensing. In the present study, no attempt has been made to calculate the rate of change of the different covers from the air photographs. However, changes such as rapid deforestation are confirmed by other studies based on the comparison of land cover maps (Sorani and Álvarez 1996, Mas 1996) and on Landsat TM visual interpretation and intensive field work (Benítez *et al.* 1992, Issac Márquez 1993).

Acknowledgments

Landsat images were provided by the NALC project through the Institute of Geography of the National University of Mexico (UNAM). Image processing was performed in the Laboratory of Remote Sensing and Geographic Information Systems of the Centre EPOMEX, University of Campeche. Supervised classifications were carried out by G. Palacio and D. Zárate. I gratefully thank Dr J. Lauga, Dr J.L. Palacio, Dr H. Puig, Dr V. Sorani and two anonymous referees for their valuable comments on the manuscript.

References

Alwashe, M. A., and Bokhari, A. Y., 1993, Monitoring vegetation changes in Al Madinah, Saudi Arabia, using Thematic Mapper data. *International Journal of Remote Sensing*, **2**, 191–197.

Benítez, J., Zárate, D., and Issac Márquez, R., 1992, Avances en la evaluación ambiental de la planicie costera asociada a la Laguna de Términos, Campeche. *Jaina*, **2**, 24.

Chavez, P. S., and Kwarteng, A. Y., 1989, Extracting spectral contrast in Landsat Thematic Mapper image data using selective principal components analysis. *Photogrammetric Engineering and Remote Sensing*, **3**, 339–348.

CNA, 1995, Precipitación media anual y temperatura media anual (Período 1974–95).

Comisión Nacional del Agua (CNA), Gerencia Estatal de Campeche, Estado de Campeche, México.

Crósta, A. P., Roig, H. L., and Elvidge, C. D., 1995, Multitemporal image analysis applied to environmental monitoring in the Brazilian Amazon. *Memorias del VII Simposio Latinoamericano de Percepción Remota, Puerto Vallarta, Mexico, 5–10 November 1995*, pp. 25–30.

Ducros-Gambart, D., and Gastellu-Etchegorry, J. P., 1984, Automatic analysis of bitemporal Landsat data: an application to the study of the evolution of vegetation-covered areas in a tropical region. *Proceeding IGARSS Symposium* edited by T. D. Guyenne and J. J. Hunt (Paris: European Space Agency), pp. 187–192.

Elvidge, C. D., Yuan, D., Weerackoon, R. D., and Lunetta, R. S., 1995, Relative radiometric normalization of Landsat Multispectral Scanner (MSS) data using an automatic-controlled regression. *Photogrammetric Engineering and Remote Sensing*, **10,** 1255–1260.

ERDAS, 1991, *ERDAS Field Guide*, 2nd edn, version 7.5 (Erdas), Atlanta, USA.

FAO, 1995, Evaluation des ressources forestières 1990, Pays tropicaux. Etude Forêts no. 112.

Fontan, J., 1994, Changement globaux et développement. *Nature–Sciences–Sociétés*, 2, 143–152.

Franklin, J., 1993, Discrimination of tropical vegetation types using SPOT multispectral data. *Geocarto International*, **2,** 57–63.

Fung, T., and Ledrew, E., 1988, The determination of optimal threshold levels for changes detection using various accuracy indices. *Photogrammetric Engineering and Remote Sensing*, **10,** 1449–1454.

Isaac-Márquez, R., 1993, Evaluación del cultivo de arroz como fuente de contaminación e impacto ambiental para la Laguna de Términos, Campeche, México. Tésis profesional, Escuela de Biología, Universidad Autónoma de Guadalajara, México.

Jensen, J. R., 1996, *Introductory Digital Image Processing, A Remote Sensing Perspective*, 2nd edn (Upper Saddle River, New Jersey: Prentice Hall).

Jha, C. S., and Unni, N. V., 1994, Digital change detection of forest conversion of a dry tropical Indian forest region. *International Journal of Remote Sensing*, **13,** 2543–2552.

Mas, J. F., 1996, Estimación preliminar de las tasas de deforestación en el Estado de Campeche. *Jaina*, **7,** 7–8.

Mas, J. F., Pérez Vega, A., Palacio Aponte, G., and Zárate Lomelí, D., 1997, Assessing deforestation in the coastal zone of the Campeche State, Mexico. *Proceeding of the IV International Conference on Remote Sensing for Marine and Coastal Environments, Orlando, Florida, 17–19 March 1997*, vol. I, pp. 593–602. http://epomex.uacam.mx/erimdef.html.

Mas, J. F., 1998, Une revue des méthodes et des techniques de télédétection du changement. *Journal Canadien de télédétection*, accepted.

Muchoney, D. M., and Haack, B. N., 1994, Change detection for monitoring forest defoliation. *Photogrammetric Engineering and Remote Sensing*, **10,** 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*, **9,** 1303–1314.

Nelson, R., and Holben, B., 1986, Identifying deforestation in Brazil using multiresolution satellite data. *International Journal of Remote Sensing*, **3,** 429–448.

Pilon, P. G., Howarth, P. J., and Bullock, R. A., 1988, An enhanced classification approach to change detection in semi-arid environments. *Photogrammetric Engineering and Remote Sensing*, **12,** 1709–1716.

Rojas-Galaviz, J. L., Yañez-Arancibia, A., Day, J. W., and Vera-Herrera, F. R., 1992, Estuarine primary producers: Laguna de Terminos, a study case. In *Coastal Plant Community of Latin America* (New York: Academic Press), pp. 141–154.

Roy, R. S., Ranganath, B. K., Diwakar, P. G., Vohra, T. P. S., Bhan, S. K., Singh, J. J., and Pandian, V. C., 1991, Tropical forest mapping and monitoring using remote sensing. *International Journal of Remote Sensing*, **11,** 2205–2225.

Sader, S. A., Stone, T. A., and Joyce, A. T., 1990, Remote sensing of tropical forests: an overview of research and applications using non-photographic sensors. *Photogrammetric Engineering and Remote Sensing*, **10,** 1343–1351.

SADER, S. A., POWELL, G. V. N., and RAPPOLE, J. H., 1991, Migratory bird habitat monitoring through remote sensing. *International Journal of Remote Sensing*, **3,** 363–372.

SINGH, A., 1986, Change detection in the tropical forest environment of northeastern india using Landsat. In *Remote Sensing and Land Management*, edited by M.J. Eden and J.T. Parry (New Zealand), pp. 237–253.

SINGH, A., 1989, Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing*, **6,** 989–1003.

SINGH, A., and HARRISON, A., 1985, Standardized principal components. *International Journal of Remote Sensing*, **6,** 883–896.

SORANI, V., and ALVAREZ, R., 1996, Hybrid maps: updating Mexico's forest cartography using landsat TM imagery and land use information. *Geocarto International*, **4,** 17–23.

STOW, D. A., TINNEY, L. R., and ESTES, J. E., 1980, Deriving land use/land cover change statistics from Landsat: a study of prime agriculture land. *Proceedings of the 14th International Symposium on Remote Sensing of Environment, Vol. 2 (Environmental Institute of Michigan), San José, Costa Rica, 23–30 April 1980*, pp. 1227–1237.

TUCKER, C. J., 1979, Red and photographic infrared linear combinations for monitoring vegetation. *Remote Sensing of Environment*, **8,** 127–150.

YAÑEZ-ARANCIBIA, A., and DAY, J. W. (eds), 1988, *Ecology of Coastal Ecosystems in the Southern Gulf of Mexico: The Terminos Lagoon Region* (Mexico: UNAM Press).

YÁÑEZ ARANCIBIA, A., ROJAS GALAVÍZ, J. L., VILLALOBOS ZAPATA, G. J., ZÁRATE LOMELÍ, D. J., LARA DOMÍNGUEZ, A.L., RIVERA ARRIAGA, E., FLORES HERNÁNDEZ, D., ARREGUÍN SÁNCHEZ, F., SÁNCHEZ GIL, P., SÁNCHEZ CHÁVEZ, J., RAMOS MIRANDA, J., BENÍTEZ TORRES, J., BÁRCENAS PAZOS, C., SANTISBON MONTES DE OCA, C., TERAN CUEVAS, A., ROBERTS, M. J., SAÍNZ HERNÁNDEZ, E., GUTIERREZ LARA, J., VERA HERRERA, F., SAAVEDRA VÁZQUEZ, T., and GOUDEA, T., 1993, Estudio de Declaratoria como Área Ecológica de Protección de Flora y Fauna Silvestre y Acuática de la Laguna de Términos, Campeche. Instituto Nacional de Ecología, Secretaría de Desarrollo Social, Gobierno del Estado de Campeche, Universida Autónoma de Campeche, Programa EPOMEX, Vol. I, II, III.