

A HYBRID IMAGE CLASSIFICATION APPROACH FOR THE SYSTEMATIC ANALYSIS OF LAND COVER (LC) CHANGES IN THE NIGER DELTA REGION

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ABSTRACT:

The landscape of the Niger Delta region of Nigeria is undergoing rapid changes as a result of natural and anthropogenic activities. This necessitates the development of a rapid, cost effective and efficient land cover (LC) classification technique to monitor the biophysical dynamics in the region. Due to the intricate land cover patterns prominent in the study area and the irregularly indistinguishable relationship between land cover and spectral signals, this paper introduces a combined use of unsupervised and supervised image classification for detecting LC classes. The technique utilizes the spectral recognition of the unsupervised classification in the performance mode and the selection of sampling sites from a principal component analyzed image of the supervised classification in the training mode. The unsupervised and supervised classification algorithms used are the generalized form of Heckbert quantization and Maximum Likelihood (ML) respectively. With the continuous conflict over the impact of oil activities in the area, this work provides an initial basis of monitoring LC change, which is an important factor to consider in the design of an environmental decision-making framework. Landsat TM and ETM+ images of 1987 and 2002 were used to test the hybrid classification technique. The overall result indicates the ability to separate more LC classes. Furthermore, the approach provides a means of improving on the deficiencies of the unsupervised and supervised classification methods.

1. INTRODUCTION

The Niger Delta region, known as the economic mainstay of Nigeria is experiencing rapid changes resulting in the alteration of its fragile ecosystem. While the region embarks upon a rapid phase of economic expansion, it faces several environmental challenges caused partly by the pressures induced by anthropocentric activities through petroleum activities, economic development and demographic changes (Osei *et al*, 2006). The severity of the problem has been aggravated due to the absence of proper legislative, regulatory and institutional frameworks to tackle environmental degradation. There is the need to monitor such changes using remote sensing data which has the advantage of synoptic view, repetitive coverage, cost effectiveness and availability. The underlying premise for using remote sensing data is that a change in the status of an object must result in a change in radiance value (Mas, 1999).

Authors such as Yang and Lo (2002), Mundia and Anyia (2005), have conducted land cover classification using unsupervised ISODATA classification algorithm. In Nigeria, supervised classification has been used to monitor land use dynamics in south-western region (Akinyemi, 2005), while Ojigi (2006) compared different supervised classification algorithms to monitor landscape changes in Abuja. His findings reveal that the maximum likelihood algorithm performed better than the other methods used. During the last three decades, a large number of change detection methods have evolved that differs widely in refinement, robustness and

complexity (Hall and Hay, 2003). These methods often involve change extraction and change classification and include, image overlay, image differencing, image ratioing, image regression, tasseled cap transformation, chi-square transformation, post classification comparison and principal component analysis. Ridd and Liu (1998), from their study using some of the above mentioned algorithms, showed that there was no algorithm that had superiority over the others. Environmental change detection of the Niger Delta region using remotely sensed data has been conducted by Niger Delta Environmental Survey, (1997) using a post-classification change detection procedure, while (Osei *et al*, 2006; Omo-Irabor and Oduyemi, 2006), utilized results from unsupervised classification for detecting changes in the region.

Regular and up-to-date information on landscape change is required for planning and land use management. Consequently, the need has arisen to develop a reliable methodology for monitoring the ever changing landscape of the Niger Delta region. This paper therefore, addresses the use of a hybrid classification method to detect changes that have occurred in the study area between 1987 and 2002.

2. STUDY AREA

The area selected for this study covers about 12,000km² of the Niger Delta region of Nigeria (Figure 1). It is located between latitudes 5° 15' and 6° 15' N and longitudes 5° 30' and 6° 30'E.



Figure1. Location of Study area

Four main surface geological units have been identified, consisting of: Fresh water swamp, Coastal Plain Sands, Mangrove swamps, and Sombreiro-Warri plains (Figure 2). Soils are generally hydromorphic and poorly drained. The pristine vegetation has been reduced considerably in the area and replaced by mosaic of secondary re-growth such as arable farmlands (cassava, maize and yam) and tree crops (oil palm, rubber, cocoa and plantain). The remaining natural vegetation occurs as fresh water swamp forest, mangrove swamp forest and ever green lowland rainforest a major source of timber. The River Niger is the major drainage system from which other discrete river systems originate. The region has a humid equatorial climate. The cloud cover is high, with relative humidity and average rainfall above 80% and 3000 mm respectively.

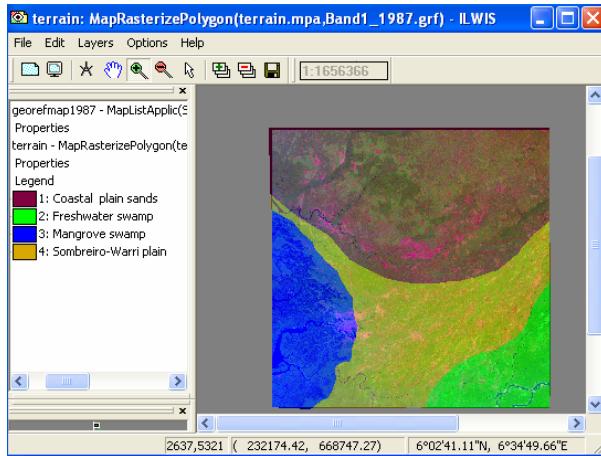


Figure 2: Major terrain units of study area

3. METHODS

3.1 Data sets and image pre-processing

The satellite images used in this study were obtained from the Global Land Cover Facility, (2005), consisting of one scene from the Worldwide Reference System (WRS-2) of path 189 and row 056 (Table 1). The bands used for the analysis include 1-5 and 7. ILWIS 3.3 software was used for image processing and GIS analysis.

Date of acquisition	Type of satellite image	Spatial resolution (m)
21-12-1987	Landsat-5 Thematic Mapper (TM)	30
28-12-2002	Landsat-7 Enhanced Thematic Mapper plus (ETM+)	30

Table 1. Satellite data used for digital image processing

Geometric correction of the images was already conducted producing positionally accurate orthorectified images having root mean square (RMS) geodetic accuracy of better than 50m (Tucker *et al*, 2004). Geocoding is essential for comparing spatially corrected maps of land cover changes through time. An affine transformation was used to rectify the 1987 TM image to the 2002 ETM+ using the UTM map projection (Zone 32), World Geodetic System 1984 datum (WGS 84) co-ordinate system. As the study area has relatively even terrain relief, only the first degree polynomial equation was required for image transformation. The nearest neighbour resampling method was used to avoid altering the original pixel values of the image data. The images were resampled to 28.5 m. The resultant root mean square error (RMSE) was about 0.5 pixels, indicating an excellent registration. According to Symeonakis *et al*, (2006), absolute pixel errors of more than one pixel can also be a cause of concern in multi-temporal studies.

Principal Component Analysis (PCA) was carried out to reduce the dimensionality of the data and improve the spectral information of the band combination. This aided in eliminating redundant information due to inter-band correlation (Lillesand *et al*, 2004). The first PC usually contains the largest amount of information from the original dataset and the transformation of the bands gives rise to a new coordinate system orthogonal to the previous. The calculated variance percentages per band for the images are displayed in Table 2.

	PCA 1(%)	PCA 2(%)	PCA 3(%)	PCA 4(%)	PCA 5(%)	PCA 6(%)
Image 1987	97.65	1.87	0.43	0.30	0.01	0.00
Image 2002	97.38	2.01	0.52	0.04	0.04	0.01

Table 2. Principal component analysis for 1987 and 2002 images

Constant cloud cover is a major problem hindering the use of remote sensing data in tropical regions. In order to improve the misclassification of land cover classes, clouds need to be eliminated from the image. The problems posed by their presence are two fold – firstly, they increase the land cover classes that have high spectral reflectance e.g. sediments and concrete structures. Secondly, they reduce the land cover classes they overlay on the image. Close inspection of the pixel values of the different bands showed that band 4 could be used to differentiate between cloud and other land cover classes effectively. The threshold digital value used for the differentiation was 95.

3.2 Classification system

Before any useful thematic information can be extracted from remote sensing data, a land cover classification system has to be developed to obtain the classes of interest to the analyst (Congalton, 1991). A combination of classification systems used by Forestry Management, Evaluation and Coordinating Unit (FORMECU) and Niger Delta Environmental Survey (NDES) gave rise to 7 land cover classes comprising of - built-up/exposed area, cultivated land, natural forest, water, mangrove (short), mangrove (tall) and palm forest. Within the context of this study, palm forest encompasses secondary growth, palm plantation and scrub.

3.3 Image Classification

The algorithms selected for land cover classification were the unsupervised – Heckbert quantization and supervised - Maximum Likelihood classification algorithms.

3.3.1 Unsupervised Classification

The unsupervised or clustering classification algorithm used is the generalized form of Heckbert quantization. Clustering is the process of identifying pixel possessing the same spectral characteristics. Heckbert quantization is a median cut clustering algorithm that groups image data into spectral clusters based on the statistical properties of all pixel values. TM bands 1, 4 & 5 and ETM+ bands 1, 2 & 5 were used for the three-band combination based on the calculated Optical Index Factor (OIF) of 35.68% and 37.37% respectively. The OIF value is based on the amount of total variance and correlation within and between various band combinations (Jensen, 2005).

This algorithm first builds a three dimensional histogram from the input bands. The histogram representing the feature space is split into many boxes depending on the number of cluster required. Then, appropriate colors are assigned to represent each cluster. The number of clusters used is very important as the number affects the ability of the algorithm to spectrally separate clusters. If the number of clusters selected is small too spectral mixing among land cover classes is obtained and if large, very pure clusters will be generated. To determine the best possible number of clusters to use, different numbers were attempted to spectrally separate classes such as 10, 20, 40, and 50. 50 clusters were finally arrived at as it provided a reasonable separation of the different land cover classes.

3.3.2 Supervised Classification

Maximum likelihood is the most commonly used supervised classification and is it based on the assumption that the training data statistics in each band are normally distributed. Supervised classification begins with defining the areas that will be used as training sites for the different land cover classes. A prior labelling of pixels is then performed on the selected training sites. To avoid the problem of linearity caused by similarity among spectral bands, the first three results from principal component analysis (PCA 1, PCA 2 and PCA 3) were used as band combination for the purpose of creating sample sets.

3.4 Image reclassification

Preliminary examination of the classified images using the two algorithms revealed a wide range of spectral confusion among land cover types. Spectral confusion refers to the fact that several land cover classes have similar spectral response and this poses a major problem of classification inaccuracy (Yang and Lo, 2002). To reduce this problem, close inspection of the classes was executed to highlight major areas of misclassified land cover. This was achieved with the aid of vegetation/land use maps and local knowledge. Most water pixels were classified as mangrove even outside the boundaries of the mangrove swamp. Therefore, to improve on the classification of water, mangrove and water clusters in the unsupervised images were all grouped as water. A resultant attribute map was created for water class only. Additionally, an attribute map was made for natural forest clusters as they were well discriminated from other land cover types in the unsupervised classification especially within the Coastal plain sands. The study area was then sub-divided into 2 main terrain units, whereby the mangrove swamp was separated from the other three terrain units. The attribute maps were then incorporated into to supervised classified maps with the aid of conditional statements. Majority of built-up/exposed areas was separated from other land cover classes especially cultivated by the Normalized Difference Built-up Index (NDBI) (Zha *et al*, 2003).

$$NDBI = \frac{MidIR_{TM\ 5} - NIR_{TM\ 4}}{MidIR_{TM\ 5} + NIR_{TM\ 4}} \quad (1)$$

$$Built-up_{area} = NDBI - NDVI \quad (2)$$

A threshold value of 0.1 was applied to separate Built-up areas from other land cover classes. Smoothening of the classified images to remove the salt and pepper appearance was achieved using a 3x3 majority filter. The reclassified images are shown in Figure 3.

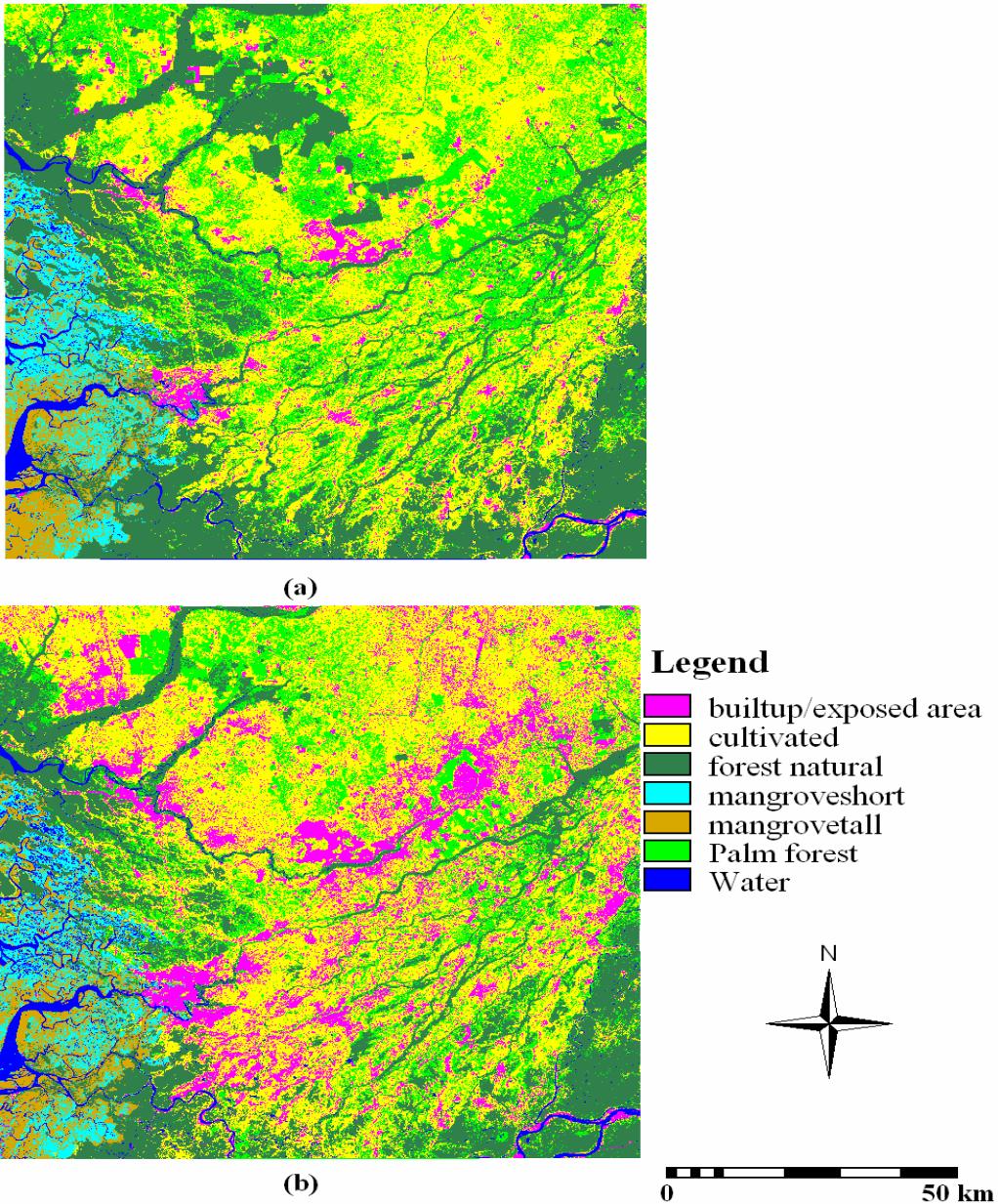


Figure 3. Classified images (a) Landsat TM 1987 (b) Enhanced Thematic Mapper plus (ETM+) 2002

3.5 Land cover classification accuracy assessment

Classification accuracy is necessary to establish the performance of derived thematic map with ground truth or other

reference data set. The confusion matrix is the most frequently used way of expressing classification accuracy. Information in the confusion matrix is evaluated using univariate (e.g. producer's, user's and overall accuracies) (Jensen, 2005).

Digital vegetation and land use maps prepared by the Nigerian Forestry Management, Evaluation and Coordinating Unit (FORMECU) and Niger Delta Environmental Survey (NDES) were used for verifying the accuracy of the classified Landsat TM 1987 image. The verification data for the 2002 classification were biased due to the inaccessibility of majority of the region. Sampling was therefore executed close to roads during field visits in 2006 with the aid of GPS.

3.5 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). Successful use of satellite remote sensing for land cover change detection depends upon an adequate understanding of landscape features, imaging systems, and information extraction methodology employed in relation to the aims of analysis (Yang and Lo, 2002). The selection of an appropriate change detection algorithm is essential because it has a direct impact on the type of classification to be performed and whether important change information can be extracted from the image (Jensen, 2005). A post classification change detection method was applied. Although the accuracy of post-classification methods is dependent on the accuracy of the

individual classifications and is subject to error propagation, the classification of each date of imagery builds a historical series that can be more easily updated and used for applications other than change detection (Yuan *et al*, 2005). Also, this method avoids the problems that arise due to variation in sensor characteristics, atmospheric effects, solar illumination angle sensor view angle and vegetation phenology between dates since each image is independently classified (Chen *et al* 2005).

4. RESULTS AND DISCUSSION

The results of the hybrid classification method for the 1987 and 2002 images are shown in Tables 3 and 4 respectively. The overall accuracy assessment of the 1987 and 2002 images are 83.03% and 76.16% respectively. The misclassification of palm forests affected the accuracy assessment of both 1987 and 2002 images. This could be due to the presence of some amount of palm trees in all land cover classes in the region with the exception of water bodies. The hybrid classification approach in conjunction with NDBI aided the improved performance of built-up/exposed areas, water and natural vegetation.

Land cover classes	BE	CL	NF	MT	MS	PF	W	Total	User's accuracy (%)
Built-up/exposed areas (BE)	183							183	100
Cultivated land (CL)	9	318				27		354	90
Natural forest (NF)			296			127		423	70
Mangrove (tall) (MT)				99	9		2	110	90
Mangrove (short) (MS)				1	117			118	99
Palm forest (PF)	28	82	7			49		116	30
Water (W)							108	108	100
Total	220	400	304	99	126	203	110	1462	
Producer's accuracy (%)	83	80	97	100	93	24	98		Overall accuracy 83.03%

Table 3. Confusion matrix for 1987 image

Land cover classes	BE	CL	NF	MT	MS	PF	W	Total	User's accuracy (%)
Built-up/exposed areas (BE)	46							46	100
Cultivated land (CL)		49				2		51	96
Natural forest (NF)		3	25					28	89
Mangrove (tall) (MT)	2		2	14	6			24	58
Mangrove (short) (MS)			5		17			22	77
Palm forest (PF)	1	7	22			11		41	27
Water (W)		2					11	13	85
Total	49	61	54	14	23	13	11	225	
Producer's accuracy (%)	92	80	48	100	74	85	100		Overall accuracy 76.17%

Table 4. Confusion matrix for 2002 image

Cultivated land occupies more than a third of the total land areas in both years (Table 5). The mainstay of majority of the rural dwellers in the upland region is farming. Since the post classification accuracy is dependent on the initial accuracies of the classified images, this gives a reduced accuracy of 63.24%. The greatest depletion of land cover occurred in Natural forest. An amount of 9.21% equivalent to 1113.00 km² of natural forest disappeared within the 15year period. This result is in line with Osei *et al*, (2006), that forest estate of only about 10 million hectares (10 percent of total land area of Nigeria) is declining at a rate of 3.5 percent annually. The main factor responsible for this decline can be attributed to logging activities especially in the upland regions. Palm forest

comprising mainly of secondary growth, scrub and palm plantations experienced the second largest decline of 7.07% (853.8 km²), arising from the demand for cultivated lands. All other classes showed increase in cover change, with built-up/bare areas and cultivated areas increasing by 10.62% (1282.73 km²) and 5.28% (637.9 km²) respectively. Water bodies increased by 6.7%, this is attributed to the classification of shadow as water bodies in the 2002 image. The increase in short mangrove may be due to the colonization of a wild tree species known as Nypa (Niger Delta Environment Survey, 1997). This species is spectrally indistinguishable from mangrove forest on satellite images.

Land cover classes	Area of 1987 image		Area of 2002 image		Change	
	(km ²)	(%)	(km ²)	(%)	(km ²)	(%)
Built-up/exposed areas	459.1	3.80	1741.8	14.42	1282.7	10.62
Cultivated land	4217.3	34.90	4855.2	40.18	637.9	5.28
Natural forest	3462.8	28.66	2349.7	19.45	1113.0	-9.21
Mangrove (tall)	549.3	4.55	471.3	3.90	78.0	-0.65
Mangrove (short)	501.9	4.15	523.1	4.33	21.1	0.17
Palm forest	2621.5	21.70	1767.7	14.63	853.8	-7.07
Water	270.4	2.24	373.5	3.09	103.1	0.85
Total	12082.3	100	12082.3	100		

Table 5. Change of land cover classes between 1987 and 2002

5. CONCLUSION

The purpose of this work was to develop a rapid method of producing temporal land cover maps for change detection analysis. Although the performance of this hybrid approach improved discrimination of land cover types especially in the upper section of the study area, the misclassification of palm forests affected the accuracy assessment of both 1987 and 2002 images. By combining the results from the two algorithms with knowledge of terrain characteristics, in such a way that only areas that gave acceptable results were combined and used for further analysis, the problem of spectral confusion was significantly reduced in some land cover types such as water, built-up/exposed areas and natural forest.

This paper also revealed the importance of temporal and spatial remote sensing data and GIS tools in detecting the degradation of the environment from development activities in the region. The depletion of forest and mangrove can be attributed to logging, creation of land for farming and oil activities. While the presence of oil companies in the region has attracted labour thus increasing urbanisation. In the absence of an alternative rapid and cost-effective means of obtaining landscape information for monitoring the constant changing environment of the Niger Delta region, this systematic approach becomes necessary although it needs to be continuously revised, as other techniques for improving the accuracy of remote sensing data are developed.

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