LAND USE/LAND COVER CHANGE DETECTION IN METROPOLITAN LAGOS (NIGERIA): 1984-2002

M.O. Adepoju, Presenter
Professor A.C. Millington
Dr. K.T. Tansey

ABSTRACT

This paper examines the land use/land cover changes that have taken place in Lagos for the last two decades due to the rapid urbanisation. Lagos is one of the fastest growing mega-cities in the world; yet it lacks reliable modern, scientific monitoring techniques to effectively monitor and manage the land use changes brought about by urbanization. The capabilities of remote sensing in terms of large spatial coverage, spatial and temporal resolutions adequate for these type of studies as well as the ability of GIS to handle spatial and non-spatial data are the optimal approach for this. A post-classification approach was adopted with a maximum likelihood classifier algorithm. The Landsat TM (1984) and Landsat ETM (2000) were merged with SPOT-PAN (2002) to improve classification accuracies and provided more accurate maps for land use/cover change and analysis. It also made it possible to overcome the problem of spectral confusion between some urban land use classes. The land cover change map revealed that forest, low density residential and agricultural land uses are most threatened: most land allocated for these uses have been legally or illegally converted to other land uses within and outside the metropolis.
Key words: Land Use/Cover; Change Detection; Lagos; Urbanisation; Remote Sensing; GIS.

INTRODUCTION

Lagos is located in Nigeria at latitude 6 27’ N and Longitude 3 24’E. This falls just above the equator on Africa continent. The metropolitan Lagos has an area of 137,460 hectares. Lagos was the formal capital of Nigeria with an estimated population of 14.5million people (UN, 2003). The rapid population growth has brought many environmental, social and economic problems which led to the relocation of Federal Capital of Nigeria in 1991. Despite the various governments effort at decentralisation of activities thought to serve as pull factors for the rapid population growth due to the influx of migrants from the rural hinterland. Lagos still accounted for over 40% of commercial, industrial and institutional activities in Nigeria. The impact of concentration of the above activities in a naturally confined and landlocked area coupled with a rapid urbanisation has put enormous pressure on the land cover and land use in the metropolis and its environs.

Though, there are a lot of efforts at Federal and State Government level to manage and control the situation. But Lagos, been one of the fastest growing urban agglomeration in the world has proved very difficult to manage with the traditional (orthodox) planning techniques. The failure is visibly seen all over the metropolis as the whole city now looks like a mashed spider web, which can only be entangled by sophistication of modern technology. The adoption of technology (RS and GIS) can provide the much needed and missing intelligence which is very important to modern urban management and control. The strategic location of Lagos in Nigeria and the role of attracting direct foreign investment to the Nation and Africa continent make it pertinent for the Government and private sector to have a re-think about the state of Lagos and the challenges facing her at the international level to attract investment for the economic development of the country. Hence, the need to use the cutting edge capabilities of remote sensing and GIS to study the trend and rate of spatial growth and the landscape structural changes.

Urban classifications pose one of the great challenges to remote sensing because of the numerous features that make-up the urban centre. Welch (1982) concluded that only finer resolution satellite imagery could meet the spatial requirement of urban classification accuracy and feature identification and extraction. With the development of third generation satellite sensors, with spatial resolution ranging from 30m to 1m. Welch (1982) prediction for accurate urban classification was finally met. But still this does not automatically remove the classification problems facing the researchers in the field of urban remote sensing studies. As most of the urban features are bigger than the 1 meter, this lead to more pixels been erroneously classified (Aplin, 2003).

DATA

Data are a representation, abstraction or model of reality (Gatrell, 1991; Burrough and McDonnell, 1998; Atkinson and Tate, 1999). In most environmental sciences there are two main strategies for collecting data:

systematic inventory and ad hoc, project-based data collection (Burrough, 1997). Satellite remote sensing falls under systematic surveys. Remote sensing data are primary sources extensively used for change detection in recent decades (Lu D., et al., 2003). Because of the advantages of repetitive data acquisition, its synoptic view, and digital format suitable for computer processing, remotely sensed data, such as Thematic Mapper (TM), Satellite Probatoire d'Observation de la Terre (SPOT), Radar and Advanced Very High Resolution Radiometer (AVHRR), have become the major data sources for different change detection applications during the past decades. In general, change detection involves the application of multi-temporal datasets to quantitatively analyze the temporal effects of the phenomenon.

Satellite images from Landsat TM (1984), ETM+ (2000) and SPOT (2002) panchromatic were used in this study. Careful consideration was given to the images used (spatial, temporal, spectral and radiometric suitability). Table 1, shows detail information about the satellite images used. Lagos State Land Use Map (2001) and photographs taken while on field trip were also used for ease of interpretation of the satellite images and its analysis. Also, population data from United Nations population division was used to show the growth rate of metropolitan Lagos both at national and international level.

Table 1. Satellite Dataset used; Identified by Path/Row, Date and Scene ID for the Study Area

Platform (Sensor)	Path/Row	Date	Scene ID #
Landsat 5 TM	191/055	18/12/1984	P191R55_5T841218
Landsat 7 ETM+	191/055	06/02/2000	0750003230013
SPOT (HRV2)	067-337	17/01/2002	2067-33702-1-1710:25:502 p067-337/0

METHODOLOGY

Principal Component Analysis (PCA)

PCA is a feature space transformation designed to remove spectral redundancy (Schowengerdt, 1997; Ozkan and Erbek, 2005). It allows redundant data to be compacted into fewer bands—that is, the dimensionality of the data is reduced. The bands of PCA data are non-correlated and independent, which makes it more interpretable than the source data (Jensen, 1996; Faust, 1989; ERDAS Imagine, 1997). The purpose of PCA is to define number of dimensions that are present in a data set and to fix the coefficients, which specify the positions of that set of axes that point in the direction of greatest variability in the data (Ozkan and Erbek, 2005). This method was used because its ability to improve the classification accuracy by taken the advantage of the strength of PCA mentioned above. The first few bands account for a high proportion of the variation in the data. PCA was limited to 3 bands to display the image in RGB.

Classification

The objective of image classification is to create cluster classes from multispectral satellite imagery. Image classification is essential in making sense of the many colours present within an image. Supervised classification technique with maximum likelihood classifier was used. The fact that landscape structure and land cover dynamics are very complex in most of African Urban Centres makes Maximum Likelihood Classifier (MLC) an appropriate classification method. This is a sophisticated classifier and considered the most appropriate for the study area. MLC been a per-pixel classifier was able to handle and show the spatial distribution of land uses and land cover types in metropolitan Lagos. Though, this can resulted in what Lu et al., 2004 called "Salt and Pepper" pattern classification. The classification accuracy of 96.6% for level 1 classification and 87% and 83.7% accuracy for level 2 and 3 respectively underline the strength of MLC to handle remotely sensed data from metropolitan Lagos where land use classes have little or no spectral distinction because of organic development due to lack of planning and zoning laws at the initial stage of growth. The MLC effectively handled this problem better than other types of classifiers tried for this research. One of the reasons for the performance of MLC could be attributed to the fact that it is a per-pixel classifier.

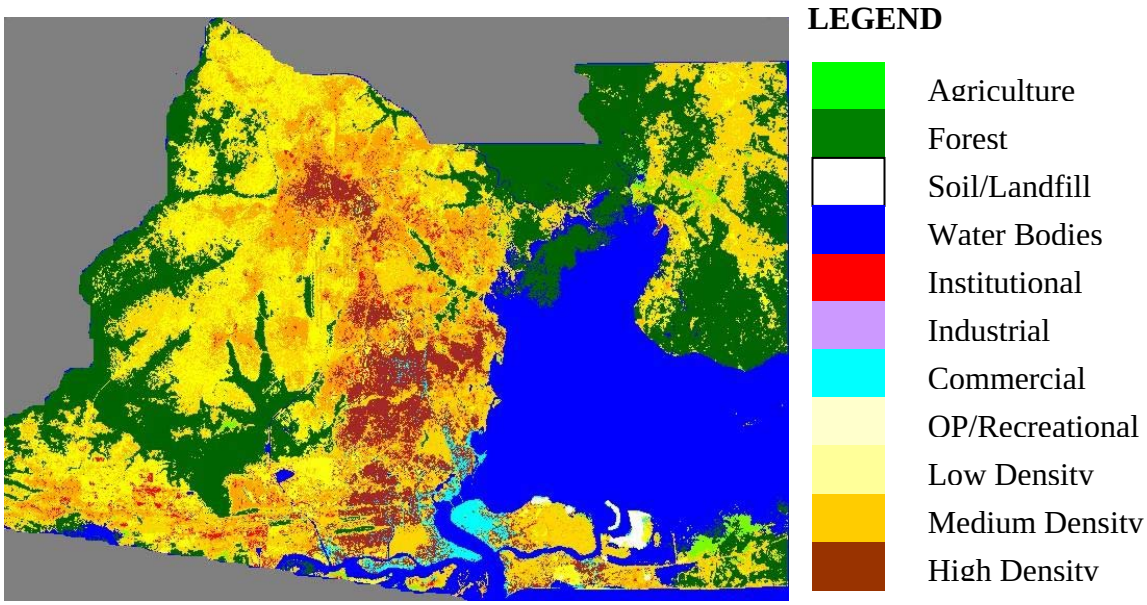


Figure 2. 1984 Land Use/Cover Level III Map

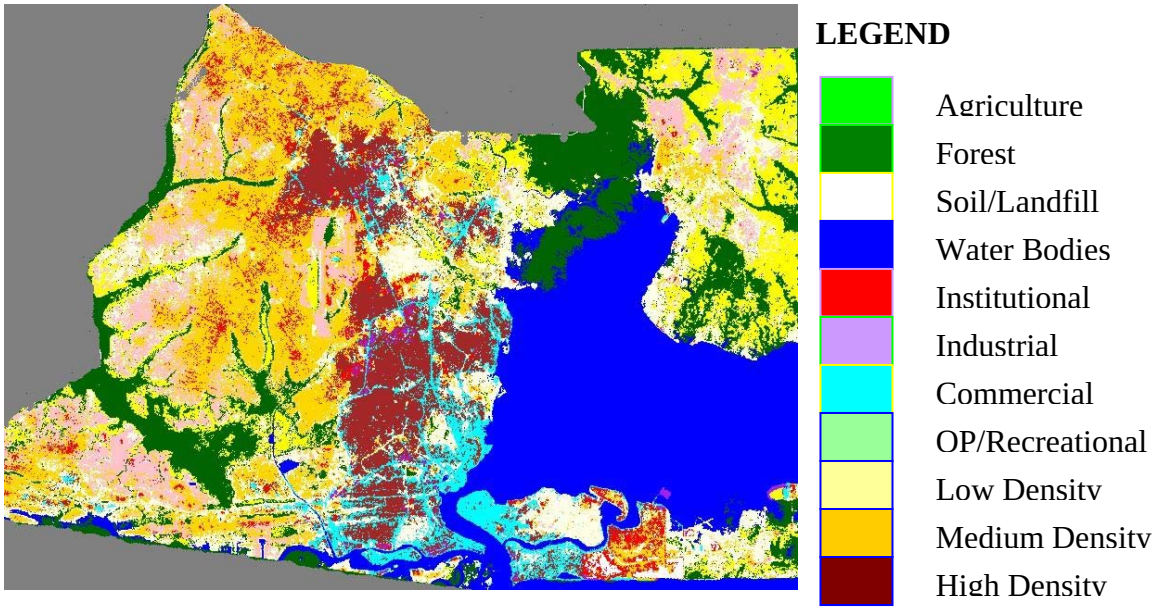


Figure 3. 2002 Land Use/Cover Level III Map.

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; Lu D. et al., 2003). Digital change detection has been divided into two major groups This involves the use of multitemporal data sets to discriminate areas of land cover change between dates of imaging (Lillesand T.M. et al., 2004). This research is focused on the changes between-class (conversion from one land cover class to another) and within-class (changes from one land use to another).
Post-Classification change detection approach was employed due to its ability to bypassed the problems and difficulties associated with analysis of images acquired at different times of the year and sensors (Yuan D. et al., 1998). In this research, land cover change is detected as a change in land cover label between two image dates. It is based on two independent true land cover class classification, which was achieved by supervised classification.

Classification Accuracy Assessment

Campbell J.B. (2002) defines accuracy as “correctness”, which measures the agreement between a standard assumed to be correct and a classified image of known quality. Accuracy is considered an important step in

evaluation of different image processing routines in image classification (Foody, 2002; Lu and Weng, 2005). For any acceptable research findings, there must be a high level of confidence in the result which is what accuracy assessment is all about. Error matrix is used to assess the accuracy of the classified images. Congalton and Green, 1999, present the mathematical representation of error matrix and KHAT as follows:

The KHAT values below are measure of how well remotely sensed classification agrees or accurate with the reference data. Landis and Koch (1977) grouped KHAT

$$\hat{k} = \frac{ObservedAccuracy - ChanceAgreement}{1 - ChanceAgreement}$$

- Shows the extent to which the correct values of an error matrix are due to "true" vs. "chance" agreement.
- Ideal case: c.a. → 0, o.a. → 1, K-hat → 1

$$\hat{k} = \frac{n\sum_{i=1}^{k} n_{ii} - \sum_{i=1}^{k} n_{i+} n_{+i}}{n^2 - \sum_{i=1}^{k} n_{i+} n_{+i}}$$; n_{ii} , n_{i+} , and n_{+i} as previously define above.

k: # of rows, columns in error matrix n: total # of observations in error matrix

n_{ii} : major diagonal element for class I n_{i+} : total # of observations in row i (right margin)

n_{+i} : total # of observations in column i (bottom margin)

The overall accuracy of the classification is 96.6% for level 1 (land cover) and 86.6% for level 2 (land cover/use). Detail of producer's and user's accuracy for level 1 classification is on the table 2.

The Kappa values such as: 0.80 (i.e., 80%) represents strong agreement; 0.40 and 0.80 (i.e., 40–80%) represent moderate agreement; and a value below 0.40 (i.e., 40%) represent poor agreement (Congalton and Ross, 1999). The conditional Kappa values in table 3 shows that water bodies, forest, urban/built-up and bear soil land cover have strong agreement with the classification.

Table 2. 1984 Level I Error Matrix for Land Cover Types

	Referenced Data						
Classified Data	**Water Bodies**	**Forest**	**Urban/Built**	**Bear Soil**	**Row Total**	**Producer's Accuracy**	**User's Accuracy**
Water Bodies	**8**	**0**	**1**	**0**	**9**	**88.89**	**88.89**
Forest	**0**	**10**	**1**	**0**	**11**	**100**	**90.91**
Urban/Built	**1**	**0**	**60**	**0**	**61**	**96.77**	**98.36**
Bear Soil	**0**	**0**	**0**	**8**	**8**	**100**	**100**
Column Total	**9**	**10**	**62**	**8**	**89**		

Overall Accuracy = 96.63%

Table 3. K-hat value for each category

Class Name	Kappa
Water Bodies	0.87
Forest	0.89
Urban/Built Up	0.94
Bear Soil	1.0

Overall Kappa Statistics = 0.93

RESULTS AND DISCUSSION

The post classification comparison of land use/cover classes gives the change that took place between 1984 and 2002 in hectares. Table 2 below shows detail of temporal change between land cover types. The urban/built-

up has 35.5% increases, bear soil nearly double its size with 96.3% increase from the initial area coverage in 1984. There is an increase of 1.6% in water bodies which may be due to sensor difference or canalisation projects in the study area. There is 57.8% decrease in the forest and agriculture land cover. The spatial growth or expansion in other land cover types is directly taken place on the agricultural land and forest as indicated by been the only land cover type with decrease in area coverage for the period under study.

Figure 2 gives a graphical representation of the land cover change in Lagos between 1984 and 2002.

Table 2: 1984 and 2002 Land Cover Change derived from Post-Classification Comparison

Land Cover Type	1984 Area (Ha)	1984 %	2002 Area (Ha)	2002 %	Change Area	% Change
Urban/Built-Up	47728	35	64656	47	+16928	35.5
Bear Soil	1265	1	2483	2	+1218	96.3
Water Bodies	55602	40	56465	41	+863	1.6
Forest & Agric	32865	24	13856	10	-19009	-57.8
Total	137460	100	137460	100		

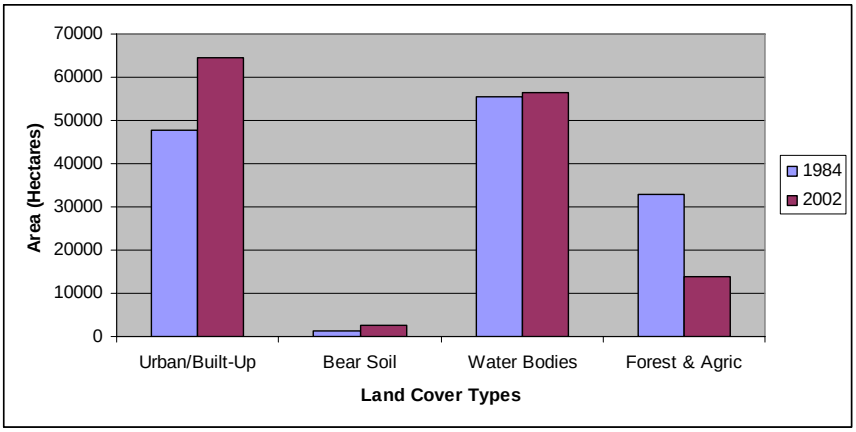


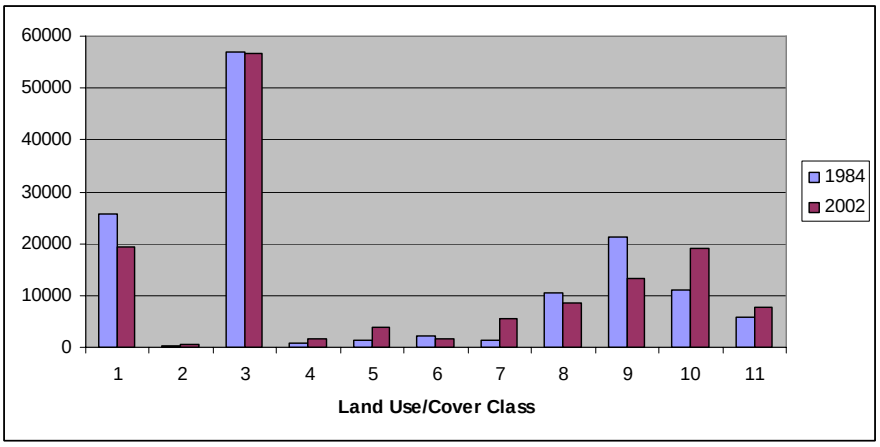
Figure 4. Chart showing Land Cover change between 1984 and 2002.

Figure 3, shows the land cover/use post-classification comparison derived from independently classified images of 1984 and 2002. The change is calculated in percentage and area (hectares) within each land use class. Forest land cover has decreased by 24.8%, agricultural land uses also decrease by almost half (48.1%).

The 32.5% decrease in industrial land use can be attributed to the economic recession during the period under study which led to the conversion of this uses to place of worships (church). This is one of the reasons for the 179.6% increase in the institutional land use. However, the highest increase is in the commercial land use with 273.5%. Most of the change in commercial is the conversion of land use such as residential to commercial notably in the low density areas such as Victoria Island, Ikoyi and along major roads in the metropolis.

Table 3. 1984 and 2002 Land Cover/Use Change derived from Post-Classification Comparison

Land Cover Type	1984 Area	1984 %	2002 Area	2002 %	Change Area	% Change
Forest	25628	18.6	19265	14.0	-6363	-24.8
Bear Soil/ Landfill	274	0.2	459	0.3	185	67.5
Water Bodies	56860	41	56676	41	-184	-0.3
Agriculture	1591	1.6	826	0.6	-765	-48.1
Institutional	1365	1.0	3816	2.8	2451	179.6
Industrial	2342	1.7	1581	1.6	-761	-32.5
Commercial	1477	1.1	5517	4.0	4040	273.5
Open Space/ Recreational	10425	7.6	8570	6.2	-1855	-17.8
Low Density Residential	21306	15.5	13317	9.7	-7989	-37.5
Med. Density Residential	10361	7.5	18958	13.8	8597	83
High Density Residential	5831	4.2	8475	6.0	2644	45.3
Total	137460	100	137460	100		



LEGEND

1	Forest
2	Bear Soil
3	Water Bodies
4	Agriculture
5	Institutional
6	Industrial
7	Commercial
8	Open Space
9	Low Density
10	Medium D.
11	High Density

Figure 5. Land Use/Land Cover change between 1984 and 2002

Population Growth

Lagos is one of the fastest growing urban agglomerations in the world, with a population of 3.3million people in 1975, 13.4millions in 2000 and an estimated 23.2millions by 2015 (UN, 1999). The growth rate of Lagos, 1975 – 2000 was 5.6% which was the highest among the 10 most populous urban agglomerations. And the 3.7% for 2000 – 2015 also remain the highest compared to other urban agglomerations. Table 4 refers. Though, there is a significant reduction in the estimated growth rate for 1975-2000 and 2000-2015 but Lagos still remain the highest when compared with other urban centres. The rapid population growth is one of the major factors that are responsible for the spatial growth and the associated pressure on different land use types leading to conversion of one land use class to another.

Table 4. Urban Agglomeration Population and Growth Rate (UN, 1999)

Urban Agglomeration	World Ranking (2000)	Population in Millions			Growth Rate (%)	
		1975	2000	2015	1975-2000	2000-2015
Tokyo	1	19.8	26.4	26.4	1.2	0.0
Mexico City	2	11.2	18.1	19.2	1.9	0.4
Bombay	3	6.9	18.1	26.1	3.9	2.4
Sao Paulo	4	10.0	17.8	20.4	2.3	0.9
New York	5	15.9	16.6	17.4	0.2	0.3
Lagos	6	3.3	13.4	23.2	5.6	3.7
Los Angeles	7	8.9	13.1	14.1	1.5	0.5
Shanghai	8	11.4	12.9	14.6	0.5	0.8
Calcutta	9	7.9	12.9	17.3	2.0	1.9
Buenos	10	9.1	12.6	14.1	1.3	0.7

CONCLUSION

It is undoubtedly that the rapid population growth in metropolitan Lagos has a great impact on the land use/cover in the area. The reduction in some of the land cover/uses underline the dangerous trend that the pressure poised by population growth and the changing functionality of Lagos and her importance in the world economic globalisation on the land use and land cover. For an effective management and control of the land use/cover there is an urgent need for both state and Federal governments to strengthened and trained planners and related professionals with the modern techniques such as GIS and RS to monitor and manage Lagos with good intelligence provided for effective policy formulation. Otherwise, the much desired safe, healthy, functional and aesthetically pleasing urban environment is becoming daunting by the day.

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