ENVIRONMENTAL LAND USE CHANGE DETECTION AND ANALYSIS USING MULTI-TEMPORAL REMOTE SENSING SATELLITE IMAGERY: A CASE STUDY OF NAKURU MUNICIPALITY

C. N. Mundia, M. K. Gachari and K.W. Mubea
Department of Geomatic Engineering and Geo-spatial Information Systems, Jomo Kenyatta University of Agriculture and Technology, Nairobi
E-mail: charlesndegwam@yahoo.com

ABSTRACT

Land use/land cover in Nakuru Municipality has been changing rapidly because of increased interactions of human activities with the environment as population increases. Multi-temporal Landsat images (1973, 1986 and 2000) together with physical and socio-economic data were used in a post-classification analysis with GIS to map land use/land cover distribution and to analyse factors influencing the land use/land cover changes for Nakuru Municipality. An unsupervised classification approach was first used to get a rough idea of land cover expected. The second approach was supervised classification which was used to generate land covers. Their statistics revealed that substantial land use/land cover changes had taken place with urban land increasing by about 9 km^2 over the study period (1973-2000). Forests decreased substantially after 1986 to 2000 as agricultural land decreased. Water decreased by about 0.15 km^2 over the study period. Rapid urbanisation and deforestation were noted to be the major factors influencing rapid land use/land cover changes. Urban expansion has replaced agricultural farmlands and other natural vegetation, thereby affecting the habitat quality and leading to serious environmental degradation. Successful planning of Nakuru Municipality will require reliable information about land use/land cover changes and factors influencing such changes.

Key words: Land use and cover changes, post-classification analysis, remote sensing, GIS

1.0 INTRODUCTION

During the last 30 years, Nakuru Municipality has been transformed from a sparsely populated and densely forested expanse into a region that is heavily settled, extensively cultivated, and rapidly urbanising. A key driver has been the substantial increase in the human population, resulting from both past and continuing relatively high birth rate and extensive in-migration.

Improper land use planning has been identified as one of the main causes of environmental and land degradation in the Lake Nakuru drainage basin, (Karanja *et. al.*, 1986; China, 1993; Chemelil, 1995). Land fragmentation and deforestation have led to serious soil erosion problems, including gullying and siltation of Lake Nakuru. This has been due to the lack of appropriate land use planning and the inadequate measures for sustainable development leading to environmental degradation.

Nakuru is a rapidly growing centre with varied economic base and unclear urban planning, management. Environmental problems have resulted, particularly impacting on the delicate lake ecosystem adjacent to a fast developing human settlement. Serious land use conflicts have resulted.

Changes in land use/land cover have been accelerated, driven by a host of factors including population and economic growth. Urban sprawl, characterised by random and unplanned growth, has led to loss of forested and fertile agricultural land, and has caused fragmentation, degradation and isolation of remaining natural areas.

Since the dynamics of land use/land cover change affects environmental and social economic conditions, a better understanding of the rate, causes and consequences of the land use/land cover changes is very essential for land use management, formulating sustainable development strategies and in detecting environmental changes (Barnsley and Barr, 1996).

Up-to-date land use inventory is essential when making plans for solving problems associated with the rapidly growing areas. In this context, accurate information on land use changes is needed for documenting growth, making policy decisions and improving land-use planning (Bullard and Johnson, 1999; Gross and Schott, 1998; Jacobson, 2001). It is also a required parameter for predictive land use modelling (Epstein *et al.*, 2002). Remote sensing and GIS technologies are very useful tools for dynamic monitoring of the process of land-use/cover changes (Howarth and Boasson, 1983).

The cost effectiveness of using remote sensing technology and the advancement in computing techniques to extract up-to-date land use/land cover information from digital images has made it more viable for developing countries such as Kenya, and further justifies studying Nakuru Municipality. Thus, the research offered a good opportunity to investigate the appropriateness of available techniques to derive land use/land cover information.

The aim of this study was to investigate various image processing algorithms to generate information from multi-temporal data sets. Moreover, the capability of different classification methods was investigated. To achieve this objective, multi-temporal Landsat data acquired in 1973, 1986 and 2000, and a topographic map compiled in 1997, were used in a post-classification comparison strategy to identify land use/land cover changes.

1.1 Study Area

Nakuru Municipality lies approximately between latitudes 0° 15' and 0° 31' South, and longitude 36° 00' and 36° 12' East, with an average altitude of 1,859 metres above sea level, covering an area of 230 km^2 (Figure 1). Within the municipality lies Nakuru town, Lake Nakuru National Park, and Lanet town. Nakuru town is located 160 km North West of Nairobi, and is the fourth largest urban centre in Kenya after Nairobi, Mombassa and Kisumu.

Lake Nakuru is salt a water and shallow and small compared to other Kenyan Rift Valley lakes. It fluctuates in size, depending on the season, between about 5 km^2 and over 40 km^2. Lake Nakuru is fed by four seasonal rivers and the permanent Ngosur River. The seasonal rivers are the Njoro, Nderit, Makalia and Lamudhiak, all of which originate in the Eastern Mau Forest. (Lake Net, 2004).

Nakuru Municipality is one of the divisions of Nakuru District. It has two locations, namely Central and Lake Nakuru National Park. Nakuru Municipality has two major towns, Nakuru and Lanet. Nakuru occupies a pre-eminent position as the administrative capital of Rift Valley, and as an industrial, commercial and service centre for the surrounding agricultural hinterland. (Odada, *et al.*, 2004).

Agriculture, manufacturing and tourism are the backbone of the economy of Nakuru. The area surrounding the town is known for its vast agricultural potential with numerous small farms and also vast agricultural enterprises.

Within the neighbourhood of Nakuru, nearly 50% of urban farmers use irrigation to support agriculture despite the fact that the use of domestic water for irrigation is illegal. Further, 97.5% of Nakuru's population relies on agriculture for food. (Lake Net, 2004).

Tourism is an important economic activity in Nakuru. The town, and the region, is endowed with vast resources that make tourism a key income generating activity. Nakuru is home to Lake Nakuru, one of the Rift Valley soda lakes, which forms part of the Lake Nakuru National Park. The park is famous for the large numbers of flamingoes that can be seen foraging in the shallow lake.

Nakuru population has been growing at the rate of 5.6% per annum. From a population of 38,181 in 1962, the population reached 163,927 in 1989, and 289,385 in 1999 (Republic of Kenya, 1999). By the year 2015, the population is projected to rise to 760,000, which is approximately 50% above the present level. (Mwangi, 2007).

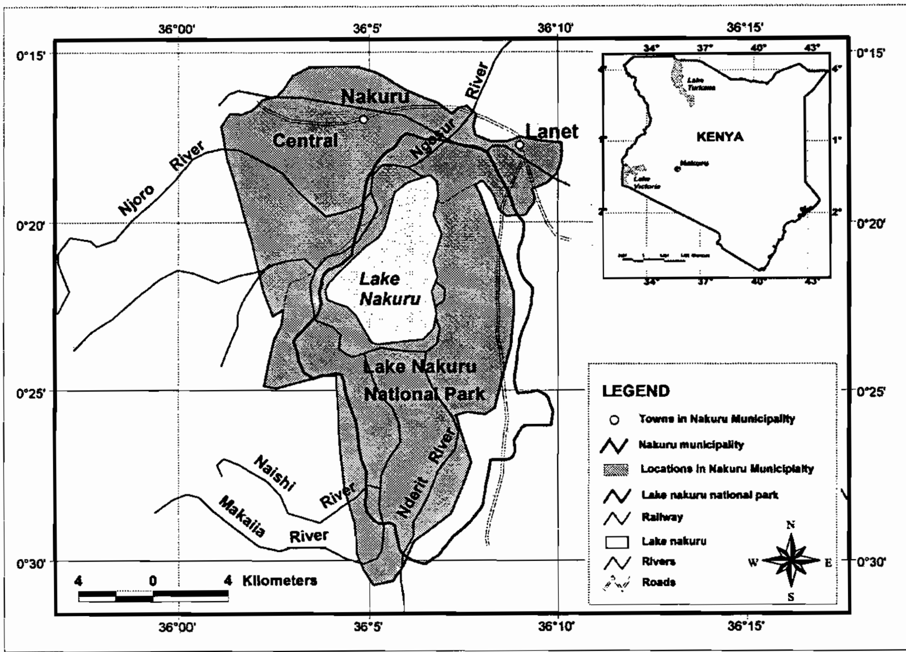

Figure 1: Study area - Nakuru Municipality

2.0 MATERIALS AND METHODS

2.1 Materials - Data

Three Landsat imageries acquired on 31st January 1976 covering scene p181060, 28th January 1986 covering scene p169r060, and 27th January 2000 covering scene p169r060 were selected for this study. Hence, the study period covered about 27 years. A topographic map at a nominal scale of 1:50 000 compiled in 1997 was used as reference data and for accuracy assessment. The image processing and data manipulation were conducted using algorithms supplied with the ERDAS imagine image processing software, which also incorporates GIS functions. Arc GIS 9 and Arc view 3.2a were used for GIS overlay analyses.

2.2 Methodology

There are two basic approaches for land use/cover change detection (Singh, 1989) namely, post classification comparisons and simultaneous analysis of multi-temporal data. Both approaches have their advantages and disadvantages. The first approach has some sources of uncertainty (Aspinall and Hill, 1997). These include locational inaccuracy in the different classifications and the problems derived from classification errors. This approach requires very good accuracy in the classification because the accuracy of the change map is the product of the accuracies of the individual classifications (Singh, 1989). In the case of the second approach, several procedures have been developed, such as multi-date classification, image differencing, vegetation index differencing, principal component analysis and change vector analysis (Fung, 1987). In these procedures, the basic premise is that changes in the land use/cover must result in reflectance values which must be larger than those caused by other factors such as differences in atmospheric conditions, sun angle, soil moisture or precise sensor calibration. Selecting image acquisition dates as close as possible for the different years used minimises problems related to sun position and vegetation phenology (Pilon *et al.*, 1988). Nevertheless, there are some problems related to this second approach:

(i) Most of these procedures provide little information about the specific nature of land use/cover changes,

(ii) threshold technique used to differentiate change from no change is usually not clear (Smits and Annoni, 2000), and

(iii) the number of bands and their wavelengths (spectral information) is different (Fung, 1992), as well as the sensitivity of the sensors. While this is also a problem in the first approach, it is more critical in the second approach.

The first approach (post classification approach) was used, because the data used for this study was acquired using different sensors with different spatial resolutions. Moreover, it is a more common procedure for comparing land use/land cover dynamics (Congalton and Macleod, 1994). The image processing procedures included image pre-processing, the design of classification scheme, image classification, accuracy assessment and analysis of the land use/land cover changes.

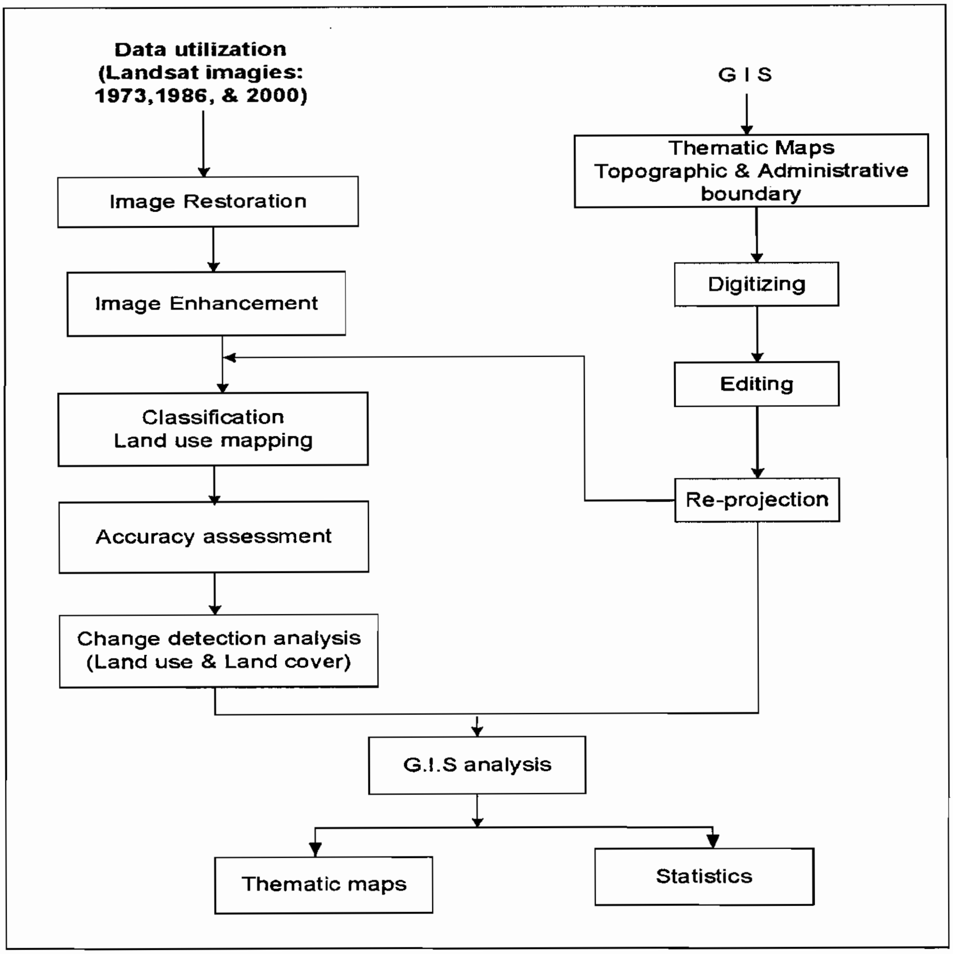

Figure 2: Flowchart for the analysis of land use/land cover changes

2.3 Data Preprocessing

High precision geometric registration of the multi-temporal image data is a basic requirement for change detection (Morisette and Khorram, 2000). First, the 2000 Landsat ETM image was rectified corresponding to the WGS 84 spheroid and UTM projection. Twenty ground control points (GCPs) and five check points, well distributed across the entire image, were located in the image and in the 1:50, 000 topographical map covering the study area. A digitising tablet was used to register the image to the topographical map. A third order polynomial was used, resulting in a root mean square (RMS) error of 0.0121. The image was resampled using the nearest neighbour method in order to maintain the radiometric properties of the original data. The other two images, Landsat MSS and TM, were geo-referenced to the 2000 image using approximately 20 well distributed GCPs. Third order polynomial equations were used and the maximum RMS error with that of MSS image at 0.0279 and TM image at 0.0361. The images were resampled using the nearest neighbour method.

Without radiometric calibration of multi-temporal images, non-surface factors can make it difficult to quantify and interpret change (Chavez and McKinnon, 1994). An absolute correction algorithm can be applied to correct images to absolute surface reflectance only if atmospheric depth and sensor calibration data are available for all dates of imagery. No such data were available for the three images used in this study. Of the three methods developed by Schott *et al.* (1988), Hall *et al.* (1992), Olsson (1993) and Salvaggio (1993), the method of Hall *et al.* (1992), which uses dark objects (e.g., burned area, water) and bright (e.g. bare, rock outcrops) targets for radiometric adjustments was used in this study, because bright and dark targets could easily be found in the images. This method corrects images of a common scene relative to a reference image using dark and bright pixel control sets. Ground targets common to the images, which were considered constant reflectors over time, were selected. For these targets any changes in their brightness values on the multi-temporal image set was attributed to detector calibration, astronomic, atmospheric and phase angle differences.

2.4 Ground Truth

The study area was visited two times with a GPS unit, one before the classification and later after classification. The first visit was a reconnaissance in order to be familiar with the area and to obtain training sites for supervised classification. The later visit involved picking coordinates so as to verify the accuracy of supervised classification.

2.5 Image Classification

A modified version of the Anderson Scheme (Anderson *et al.*, 1976) was adopted for this study. In total, six land use/cover classes were established. Some of the factors considered during the design of classification scheme included the major land use/cover categories found within the study area, differences in spatial resolutions of the three sensors which varied from 30 meters for TM (Thematic Mapper) and ETM+ (Enhanced Thematic Mapper) to 79 meters for MSS (Multi-Spectral Scanner) and the need to consistently discriminate land use/cover classes irrespective of the seasonal differences.

2.5.1 Unsupervised Classification

This approach was first adopted because it allowed spectral clusters to be identified with a high degree of objectivity (Yang and Lo, 2002). This method involved unsupervised clustering and cluster labelling. The ISODATA (Iterative Self-Organising DATA Analysis) algorithms in ERDAS imagine were used to identify spectral clusters. ISODATA method uses a minimum spectral distance to assign a pixel to a cluster. The performance of this algorithm is sensitive to the sampling nature and clustering parameters (Vanderee and Ehlich, 1995). To avoid the impacts of sampling characteristics, the ISODATA algorithm was run without assigning predefined signature sets as starting clusters. The algorithm then treated the entire data set as one cluster and a number of natural spectral clusters could eventually be identified after a number of iterations. The most important clustering parameter is the number of classes. This number affects the performance of an ISODATA classifier in capturing most of the land surface variability for the image data being analyzed (Yang and Lo, 2002). If too small, relatively broad clusters may be generated which may not produce true results. If the number is too big, very pure clusters may be yielded with highly demanding computational resources and substantial increase in time required for cluster labeling. To find the optimum number, different numbers of classes were empirically tried and forty was found to be optimum for TM, ETM+ and MSS data for the study area. All the four bands of radiometrically normalised MSS data, seven bands of the TM and nine bands of ETM+ were used in ISODATA clustering. Other parameters that were specified for ISODATA clustering included convergence value specified at 0.950, the maximum number of iterations at 6 to allow clustering to stop naturally upon reaching the convergence threshold, and true color scheme so that the output could be compared with the original images. Six classes were selected. Histogram equalisation was selected to enhance the appearance of the resulting images.

2.5.2 Supervised Classification

Here, various classifiers, namely, minimum distance, mahalanobis and maximum likelihood classifiers were run on the Landsat scenes (MSS, TM & ETM). Maximum likelihood approach is totally dependent on the spectral pattern recognition (Lillesand, 1994). The supervised classification technique was preferred, because the data of the study area was known and the prior knowledge about the nature of the study area was available. Training sites were used for the supervised classification of each image. These training areas were delineated from a false colour composite image (bands 2, 3 and 4). These training sites represented agricultural areas, rangelands, forests, urban areas, water bodies, and barren land. To avoid misclassification, these training areas must be as homogeneous as possible. Ancillary data such as topographic map, ground truth points, and pan sharpened band 8 of ETM+ were considered during the selection of training areas in order to obtain the greatest accuracy of the classification results.

This involved making signatures for six classes namely, water, forest, urban, agriculture, rangeland and barren land using AOI (Area of Interest) tools. Various signatures were established in each category and later merged into the six categories.

Three classifiers were used for bands 2, 3, 4 for TM and ETM+ and band 1, 2, 4 for MSS. (Erdas field guide, 2002). The first classifier was minimum distance classifier. It is used to classify unknown image data to classes which minimise the distance between the image data and the class in multi-feature space. The distance is defined as an index of similarity so that the minimum distance is identical to the maximum similarity. An overall accuracy of 77.6% and Kappa statistic of 0.6578 was obtained for year 2000.

The second classifier was mahalanobis distance classifier. It's a classifier decision rule that is similar to the minimum distance decision rule, except that a covariance matrix is used in the equation. Maybe more useful than minimum distance in cases where statistical criteria must be taken into account. An overall accuracy of 95.055 and Kappa statistic of 0.9165 was obtained for year 2000.

T he third classifier was maximum likelihood. It is one of the most popular methods of classification in remote sensing, in which a pixel with the maximum likelihood is classified into the corresponding class. It takes the variability of classes into account by using the covariance matrix. An overall accuracy of 95.23% and Kappa statistic of 0.9193 was obtained for year 2000. Maximum likelihood classifier gave the highest accuracy and was used as the basis of this research such as land use/land cover maps and so on.

2.6 Classification Accuracy Assessment

Land cover maps produced using remote sensed data contain some errors that need to be identified in order to establish the appropriateness of specific use of the maps. The basic idea in a thematic accuracy assessment is to compare the mapped category of each pixel with the actual land cover category, as discovered by ground truth or use of other ancillary data such as topographic maps or aerial photography.

The degree of accuracy in the land cover classification was computed statistically by comparing reference categories to those of the classified land cover map. Producers accuracy was obtained from dividing the number of correctly classified pixels in each category (on the major diagonal) by the number of training set pixels used for that category (column total). User's accuracy was obtained from dividing the number of correctly classified pixels in each category (on the major diagonal) by the total number of pixels that were classified in that category (the row total). A confusion matrix was constructed, where the overall accuracy was computed by dividing the total of the correctly classified pixels (major diagonal) with the total number of pixels. Kappa (Khat) statistic was obtained as a measure of the difference between the actual agreement between reference data and an automated classifier and the chance agreement between the reference data and a random classifier.

2.7 Land Cover Mapping and Change Detection

Actual change can be obtained by a direct comparison between classification outcomes from one date with that from the other date. Temporal changes that have occurred between the three dates can be measured by performing change matrix (Howarth and Wickware, 1981 cited in Somporn S., 1995). However, in this study, only direct comparison between the three scenes was performed to identify the temporal affect.

The goal for change detection is to discern those areas on a digital image that depict changes from images acquired at an earlier time. There is a variety of change detection techniques developed since the 1970s which include post-classification (Weismiller *et al.*, 1977), multi-temporal principal component analysis (Byrne *et al.*, 1980), and multidate Kauth-Thomas (Collins and Woodcock, 1996), and ratio vegetation index differencing (Townsend and Justice, 1986).

2.8 Post Classification Comparison

In the post classification comparison approach two or more images are independently classified and registered, and though the use of a pixel-by-pixel comparison algorithm, those pixels that indicate changes between images are determined (Weismiller *et al.*, 1977). Specifically, change matrix statistics were computed to explain the specific changes.

3.0 DERIVING FINAL RESULTS

To investigate the land use change in Nakuru Municipality, intuitive analysis was implemented on the Landsat MSS, TM and ETM+ images. This involved the use of two classification techniques to derive land use/land cover inventories for the three years in order to compare the changes on the spatial trends during twenty seven years.

3.1 Supervised Classification Results

Supervised classification was used to derive general land use/land cover (LULC) of the area. Before starting with the analysis using the above method, unsupervised classification (ISODATA algorithm) was run in order to attain pure spectral signature that represent real LULC categories. The modified signatures obtained from the unsupervised classification were used to derive six LULC classes, namely, water, forest, agriculture, rangeland, urban and barren land.

Table 1: Land use/land cover classes for satellite derived land use/land cover maps

Classes	*Description*
Urban land	This comprised mixed urban land (residential, industrial and commercial) and roads.
Water	This comprised mainly of Lake Nakuru waters, rivers and streams. During ground truthing, rivers noted were Makalia River, Naishi River, Nderit River and Njoro River.
Forest land	Comprised of acacia forest, colobus forest, and euphorbia forest being identified with Lake Nakuru National Park during ground truthing. Acacia forest was also identified to be dominant in other parts of Nakuru Municipality as they survive all seasons in a year
Agricultural land	These are the lands primarily used for farming and for production of food, fiber, and other commercial and horticultural crops. By the help of satellite data, it is possible to identify the various agricultural lands up to level II of USGS image representative formats which use moderate resolution satellite data.
Rangeland	This comprised of mixed rangeland mostly shrub and bush which serve as grazing land for wildlife within Lake Nakuru National Park.
Barren land	This comprised of the lake shore, transitional areas, and bare exposed rock whose spectral reflectance was similar to urban land.

3.2 Database Creation – Exporting to GIS for Final Results Analysis

The extracted land use classes for the three images were exported into a GIS database, where they were coded and attributed. GIS has capabilities of storing large amount of data. Computation of areas for each land cover class was done using the spatial analyst tool in Arc GIS 9. The land use classes would then be attributed for further analysis.

3.3 Accuracy Assessment

Error matrices were generated based on maximum likelihood classifier for the three years. Statistics generated included overall accuracy, producer's accuracy, user's accuracy and Kappa statistic.

Table 3: Error matrices of Land use/land cover maps
a. 1973 (MSS)

	Reference Data							
Classified Data	Forest land	Water	Barren land	Rangeland	Agriculture	Urban land	Row Total	**User's accuracy**
Forest land	**395**	0	0	9	0	0	**404**	97.772
Water	0	**2046**	0	0	0	0	**2046**	100
Barren land	0	0	**238**	254	48	0	**540**	44.074
Rangeland	5	0	4	**5191**	304	0	**5504**	94.313
Agriculture	0	0	0	3463	**2275**	0	**5738**	39.648
Urban land	0	0	1	33	2	**17**	**53**	32.075
Column Total	**400**	**2046**	**243**	**8950**	**2629**	**17**	**14285**	
Producer's accuracy %		98.75	100	97.942	58	86.535	100	

Overall accuracy **71(%)**, Kappa statistic **0.56** *b. 1986 (TM)*

Classified Data	Water	Barren land	Forest land	Rangeland	Agriculture	Urban land	Row Total	**User's accuracy %**
Water	**6555**	0	0	0	0	0	**6555**	100
Barren land	0	**1845**	0	23	23	3	**1894**.	97.413
Forest land	0	0	**1266**	0	1	0	**1267**	99.921
Rangeland	0	0	0	**32137**	286	5	**32428**	99.103
Agriculture	0	1	0	2708	**6437**	0	**9146**	70.380
Urban land	0	98	0	186	24	**217**	**525**	41.333
Column Total	**6555**	**1944**	**1266**	**35054**	**6771**	**225**	**51815**	
Producer's accuracy %		100	94.907	100	91.679	95.067	96.444	

Overall accuracy **94 (%)**, Kappa statistic **0.89**

c. 2000 (ETM+)

Classified Data	*Water*	*Forest land*	*Rangeland*	*Agriculture*	*Urban land*	*Barren land*	*Row Total*	***User's accuracy %***
Water	**5211**	0	0	0	0	0	**5211**	100
Forest land	0	**818**	0	0	0	0	**818**	100
Rangeland	0	0	**18148**	186	2	0	**18336**	98.975
Agriculture	0	0	1076	**4844**	0	0	**5920**	81.824
Urban land	0	0	101	16	**103**	120	**340**	30.294
Barren land	0	0	2	8	4	**1143**	**1157**	98.790
Column Total	**5211**	**818**	**19327**	**5054**	**109**	**1263**	**31782**	
Producer's accuracy %		100	100	93.900	95.845	94.495	90.499	

Overall accuracy **95(%)**, Kappa statistic **0.922000** (ETM+)

3.4 Change Detection Analysis

Change detection analysis entailed finding the type, amount and location of land use changes that have taken place (Yeh *et. al.*, 1996). Various algorithms are available for change detection analysis. In this study, post-classification comparison was used to assess land use/cover changes. The results from the two independently classified images were registered and the pixels that have changed their land cover classification between the two epochs located. The changes in area of land covers clearly indicated change.

The estimation for the rate of change for the different covers was computed based on the following formula:

$$\%\ Change_{year\ x} = \frac{Area_{year\ x+t} - Area_{year\ x}}{Area_{year\ x}} x\ 100\ \% \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(1)$$

$$Rate\ of\ change = \frac{Area_{year\ x+t} - Area_{year\ x}}{Area_{year\ x}\, x\ t_{years}} x\ 100\% \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(2)$$

where: $Area_{year\ x}$ = area of $cover_i$ at the first date

$Area_{year\ x+t}$ = area of $cover_i$ at the second date and

t_{years} = period in years between the first and second scene acquisition dates

Change Detection Final Results and Discussion

Results (quantification) of land cover classes is as illustrated in Table 2, the pie-charts (Figure 4) and Figure 3.

Table 2: Areas of Land use/land cover types for the Nakuru Municipality extracted from Landsat images

a. Distribution of land uses for the three years

Year	**1973**		**1986**		**2000**	
Land cover classes	Area (Km^2)	Percentage (%)	Area (Km^2)	Percentage (%)	Area (Km^2)	Percentage (%)
Agricultural	108.7557	38.35	91.2435	32.17	86.4277	30.47
Barren land	11.8617	4.18	13.0767	4.61	12.9984	4.58
Forest land	18.1042	6.38	22.0140	7.76	21.7328	7.66
Rangeland	101.7724	35.88	100.2890	35.36	103.7658	36.58
Urban land	2.2549	0.80	22.3134	7.87	24.1715	8.52
Water	40.8681	14.41	34.6879	12.23	34.5615	12.18
Total	283.6170	100.00	283.6245	100.00	283.6576	100.00

According to Table 2 (b), change in surface area of water was from 408681 km^2 in 1973, 346879 km^2 in 1986, and 345615 km2 in 2000. Thus the surface area of water has decreased by 6.31 km2 as from 1973 to year 2000.

b. Spatial changes, percentage change and rate of change in land cover classes

Land cover classes	**1973 to 1986**			**1986 to 2000**		
	Change ares in km2	Percentage change %	Rate of change	Change area in km2	Percentage change %	Rate of change %
Agricultural land	-0.16	-16.10	0.00	-0.0528	-5.28	0.00
Barren land	0.10	10.24	0.00	-0.0060	-0.60	0.00
Forest land	0.22	21.60	0.00	-0.0128	-1.28	0.00
Rangeland	-0.01	-1.46	0.00	0.0347	3.47	0.00
Urban land	8.90	889.57	0.05	0.0833	8.33	0.00
Water	-0.15	-15.12	0.00	-0.0036	-0.36	0.00
Total	8.89			0.0428		

Vegetation includes: agriculture, forests, rangeland, and manicured urban vegetation (Jensen, 2003). The amount for vegetation was obtained by aggregating agriculture, forest, and rangeland and re-computing spatial changes and percentage change in area covered by vegetation.

C. Vegetation coverage, spatial changes and percentage change

	1973	73-86		1986	86-00		2000
Category	Coverage area (km2)	change area in (km2)	percentage change %	coverage area (km2)	change area in (km2)	percentage change %	coverage (km2)
Vegetation	228.6323	-0.07	-6.60	213.5465	-0.0076	-0.76	211.9262

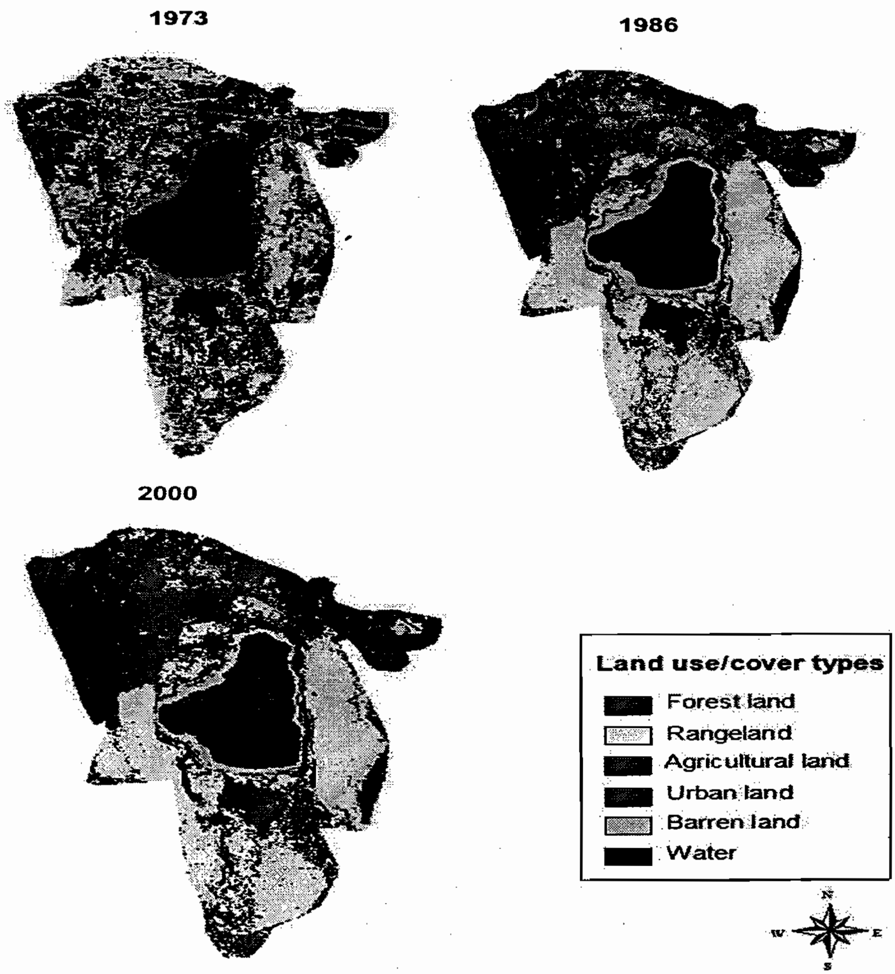

Figure 3: Land use/land cover map for the years 1973, 1986 and 2000

5.0 CONCLUSION AND RECOMMENDATIONS

Increasing land use/land cover changes due to rapid urban growth and concentration of people were observed in Nakuru Municipality during the study period. To investigate the changes, image processing algorithms were used to generate change information from multi-temporal data sets fcr years 1973, 1986 and 2000. The accuracies of three classifiers were also investigated.

Statistics of changes in land cover classes were extracted and thematic maps generated in GIS. Accuracies of three classifiers were generated in form error matrices after supervised classification with maximum likelihood having the highest accuracy in terms of overall accuracy and Kappa statistic.

The land use/land cover in Nakuru Municipality was noted to have changed significantly. Urbanisation began at a very high rate between 1973 and 1986, but still continued into year 2000 at a moderate rate. The surface area of the lake was also noted to have decreased significantly within the study period. Nevertheless, there has been a decrease in agricultural land implying that such land has changed into urban land. Furthermore vegetation has decreased implying destruction of forests through deforestation and changing climatic conditions which inhibit natural growth of vegetation. Economic development and the rising population were noted to be the major factors influencing land use/land cover changes.

This study indicates that urban sprawl and environmental degradation are serious challenges that the local government has to deal with in its effort to realise sustainable development of the municipality. There is urgent need for better urban environmental management that will prevent ecosystem degradation, deal with environmental deterioration and protect the urban poor.

Further research need to be conducted with recent images for example Landsat ETM+ 2006. Moreover, integration of high spatial resolution images into the research would enable classification up to the second level and third level of USGS land cover categories.

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