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# Assessing Application of Markov Chain Analysis in Nakuru

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## KEYWORDS:

GIS, Land cover, Markov modelling, Nakuru Municipality, Remote sensing, MSS, TM, and ETM

## ABSTRACT

*Land use/cover change is a major global environmental change issue and projecting these changes is essential for the assessment of environmental impacts. In this study, a combined use of satellite remote sensing, geographic information systems (GIS), and markov chains stochastic modelling techniques were employed in analysing and projecting land use/cover changes. The results indicate that there has been a notable and uneven urban growth with a substantial loss in forest land, and that the land use/cover change process has not stabilized. The study demonstrates that the integration of satellite remote sensing and GIS can be an effective approach for analyzing the spatio-temporal patterns of land use/cover change. Further integration of these two techniques with Markov modelling was found to be beneficial in describing, analysing and projecting land use/cover change process. The projected land use/cover for 2015 show substantial increase in urban and agricultural land uses in the study area to a depper extent.*

## 1 Introduction

Urban expansion, particularly the movement of residential and commercial land use to rural areas at the periphery of cities and towns, has long been considered a sign of regional economic vitality. However, its benefits are increasingly balanced against ecosystems including degradation of environmental quality, especially loss of farmland and forests, and also socioeconomic effects (Squires, 2002). The land use/cover changes, associated with rapid expansion of low-density suburbs into formerly rural areas and creation of urban or suburban areas buffered from others by undeveloped land, have ramifications for the environmental and socio-economic sustainability of communities.

Many cities and towns in Africa have seen marked increases in urban growth and the associated impacts of environmental degradation (Kamusoko and Aniya, 2007; Braimoh and Onishi, 2007; Mundia and Aniya, 2005). These changes and their repercussions require careful consideration by local and regional land managers and policy makers in order to make informed decisions that effectively balance the positive aspects of development and its negative impacts in order to preserve environmental resources and increase socio-economic welfare. While regional planners and decision makers are in constant need of current geospatial information on patterns and trends in land use/cover, relatively little research has investigated the potential of satellite data for monitoring land use/cover changes in both rural and urban areas in Africa.

There are various ways of approaching the use of satellite imagery for resolving land use/cover changes. Yuan et al. (1998) divide the methods for change detection and categorization into pre-classification and post classification methods. The pre-classification methods apply a variety of algorithms, including image differencing and image ratioing, to single or multiple spectral bands, vegetation indices or principal components, directly to multiple dates of satellite imagery to create “change” vs. “no-change” maps (Yuan et al, 1998).

This paper describes the approach and results of classifications and post-classification analysis of multi-temporal Landsat data of Nakuru Municipality in Kenya for 1973, 1986 and 2000. The purpose of this study was to measure the land use/cover changes based on multispectral Landsat data and to test a Markov-based model to generate land use/cover change projections in Nakuru municipality, an area characterized by high rates of changes. The approach is based on the quantification of the course of land use/cover in addition to the projection of the process from these observations.

## 2 The study area

Nakuru municipality (Figure 1) lies approximately between 0° 15' and 0° 31' South, and 36° 00' and 36° 12' East, with average altitude of 1,859 meters above sea level, enveloping an area of 290 km<sup>2</sup>. Nakuru town, found within this municipality is the fourth largest town in Kenya. It occupies a pre-eminent position as the administrative headquarters of the Rift Valley Province, and as an industrial, commercial and service centre for the surrounding agricultural hinterland (Odada, et al, 2004). Agriculture and manufacturing are the main economic activities in Nakuru municipality. The area surrounding Nakuru town has vast agricultural potential with numerous farms and many agricultural enterprises. The area is also endowed with vast tourism resources including Lake Nakuru National park. Population in Nakuru has grown substantially over the years from 38,181 in 1962, to 289,385 in 1999, growing at a rate of about 5.6 per annum (Republic of Kenya, 1999). By the year 2015, the population is projected to rise to 760,000, fifty percent above the present levels.

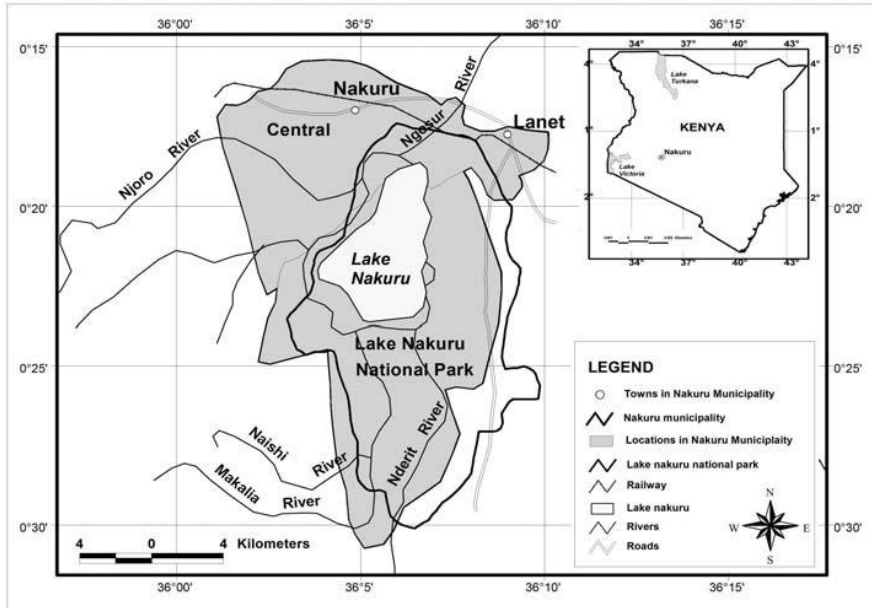


Figure 1: Map showing the extent of the study area

## 3 Methodology

### 3.1 Land Use/cover change analysis

The approach adopted for the analysis of land use/cover involved three sets of clear, cloud-free Landsat images for 1973, 1986 and 2000 where were selected to classify the study area. Nakuru municipality is entirely contained within Landsat TM path 169, rows 60. The data sets comprised of Landsat MSS, TM, and ETM+ images. The three images were rectified using at least 35 well distributed ground control points and nearest neighbour resampling. The root mean square errors were less than 0.5 pixels for each of the images. Reference data were developed for each of the three years and then randomly divided for classifier training and accuracy assessment.

Black and white aerial photos acquired in 1987 and 1995 were used as reference data for the 1986 and 2000 classifications while topographical maps were used as Reference data for the 1973 training and accuracy assessments. Stratified random sampling was adopted for selecting samples. Our classification scheme comprised of six classes namely forest, urban land, agriculture, water, rangeland, barren land, and vegetation, was based on the land use/cover classification system developed by Anderson et al. (1976) for interpretation of remote sensing data at various scales and resolutions.

Several of the factors mulled over during the design of categorization scheme incorporated: the major land use/cover groups within the study area, disparities in spatial decrees of the sensors which varied from 30 to 79

m, and the want to always discriminate land use/cover classes irrespective of seasonal disparities (Anderson et al., 1976). A combination of the reflective spectral bands from images (i.e., stacked vector) was used for classification of the 1973, 1986 and 2000 images. A hybrid supervised-unsupervised training approach referred to as “guided clustering” in which the classes are clustered into subclasses for classifier training was used with maximum likelihood classification (Bauer et al., 1994). Training samples of each class were clustered into 5–10 subclasses.

Class histograms were checked for normality and small classes were deleted. Following classifications, the subclasses were recorded to their respective classes. Post-classification refinements were enforced to diminish categorization errors that were a result of the similarities in spectral responses of certain classes such as bare fields and urban areas and some crop fields and wetlands. Spatial modeller and additional rule based procedures were adopted to overcome these classification challenges and differentiate between classes.

Independent samples of about 100 pixels for each class were randomly selected from each classification category to assess classification accuracies. Error matrices as cross-tabulations of the mapped class vs. the reference class were used to assess classification accuracies (Congalton & Green, 1999). Overall accuracy, user’s and producer’s accuracies, and the Kappa statistic were then derived from the error matrices. The Kappa statistic incorporates the off diagonal elements of the error matrices (i.e., classification errors) and represents agreement obtained after removing the proportion of agreement that could be expected to occur by chance. Following the classification of imagery from the individual years, a GIS based multi-date post-classification comparison change detection strategy was employed to determine changes in land use/cover.

### 3.2 Descriptive modelling of land use/cover change processes

Given the difficulties in designing deterministic models of land use/cover change processes, it is convenient to consider them as stochastic (Lambin 1994). For land use/cover change, one may formulate a principle analogous to one of classical physics: the possibility that the system will be in a given state at a given time  $t_2$  may be derived from the knowledge of its state at any earlier time  $t_1$ , and does not depend on the history of the system before time  $t_1$ —i.e. it is a first-order process (Parzen 1964, Bell). Stochastic processes which meet this condition are called Markov processes and if the Markov process can be treated as a series of transitions between certain values (i.e. the states of the process), it is called a Markov chain (Lambin, 1994).

The number of possible states is either definite or denumerable and for land use/cover change, the states of the system are defined as the amount of land occupied by various land use/covers. To model a process of land-cover change by a Markov chain, the land-cover distribution at  $t_2$  is calculated from the initial land use/cover distribution at  $t_1$  by means of a transition matrix (Lambin 1994). The Markov chain can be expressed as:  $vt_2 = M \times vt_1$

Where  $vt_1$  is the input land use/cover proportion column vector,  $vt_2$  is the output land use/cover proportion column vector and  $M$  is an  $m \times m$  transition matrix for the time interval  $\Delta t = t_2 - t_1$ .

When the transition probabilities depend only on the time interval  $t$ , and if the time period at which the process is examined is of no relevance, the Markov chain is said to be stationary or homogeneous in time (Karlin and Taylor 1975). If two estimates of the transition matrix of a land use/cover change process are available for two calibrations time intervals, these estimates must be adjusted to an equivalent calibration time period to allow for comparisons and to assess the stationarity of the process (Bell and Hinojosa 1977). This operation can be performed by using the matrix analogous of the exponential and logarithmic functions (Petit et al., 2000). For this study, the transition matrices were constructed from the change/no change matrices obtained in the change detection analysis and the modelling processes implemented using algorithms supplied with the Idrisi software.

Although the Markov chain analysis operates under fairly restrictive assumptions such as independence and stationarity, they are scientifically compact and easy to execute with empirical data such land use/cover. In addition, the land use/cover transition probability results can therefore serve as an indicator of the direction and magnitude of land use/cover process.

Markov models have several advantages. Firstly, they are relatively easy to derive from successional data. Secondly, the Markov model does not need deep insight into the system of dynamic change, but it can assist to specify areas where such insight would be important and therefore act as both a stimulant and guide to further research. Thirdly, the basic transition matrix summarises the fundamental parameter of vibrant change in a way that is accomplished by very few other kinds of models. Lastly, the computational requirements of Markov models are self-effacing, and can easily be met by small computers.

Markov models have several disadvantages. Firstly, there is removal from the simple suppositions of stationary, first-order Markov chains while, theoretically possible, results in analytical and computational difficulties. Secondly, in some areas, the data accessible will be inadequate to approximate consistent transfer or probability rates, especially for exceptional transitions. Lastly, the validation of Markov models depends on forecasts of system behaviour over time, and is as a result frequently hard, and may even be unattainable, for really long periods of time (Petit et al, 2000).

## 4 Results

### 4.1 Supervised land use/cover classifications

The three successive supervised land use/cover classifications discriminated six classes: urban land, water, forest land, agricultural land, rangelands and barren land. The accuracy assessment results are provided in Table 1. The overall accuracy of the January 1973 classification, assessed on the basis of topographical maps produced in 1970 was 85%, with a Kappa coefficient of 0.8, while the overall accuracies for the 1986 and 2000 classifications based on black and white aerial photographs were 86% and 92% respectively. These accuracy estimates met the minimum standards as stipulated under USGS classification scheme.

Table 2 : Statistics for Land use/cover for years 1973, 1986, 2000

Year	1973	1986	2000
Land use/cover	Area (km <sup>2</sup> )	Area (km <sup>2</sup> )	Area (km <sup>2</sup> )
Water	39.9	35.0	39.2
Forest	21.1	20.3	19.0
Barren	8.4	2.4	1.9
Urban	19.0	23.5	37.3
Agriculture	71.7	61.1	83.2
Rangeland	131.7	149.3	110.8
Total	291.7	291.7	291.7

### 4.2 Land use/cover changes

The post-classification comparison approach was employed for detection of land use/cover changes, by comparing independently produced classified land use/cover maps. The main advantage of this method is its capability to provide descriptive information on the nature of changes that occurs. The change statistics are summarised in Table 1. The spatial distributions of each of the classes were extracted from each of the land use/cover maps by means of GIS functions. From these results, urban land covered 19 km<sup>2</sup> in 1973 and increased to 24 km<sup>2</sup> in 1988. These areas increased further to 37km<sup>2</sup> by the year 2000. Forest land on the other hand has decreased from 21 km<sup>2</sup> in 1973 to 19 km<sup>2</sup> in year 2000. The agricultural fields occupied 72km<sup>2</sup> in 1973, decreased to 61 km<sup>2</sup> in 1986, but further increased to 83 km<sup>2</sup> in 2000.

Rangelands, consisting of mixed rangeland and shrub/brush rangeland decreased from 131 km<sup>2</sup> in 1973 to 110 km<sup>2</sup> in 2000. These trends in land use/cover changes for Nakuru municipality are summarised in Table 1. The comparison of land use/cover classification results in Table 1 indicates that the rate of encroachment of urban land on other land uses has been rapid, with discontinuous patches of urban development characterizing the urban sprawl. Viewed as a time series, the land use/cover changes have varied substantially over the study period. Urban land in Nakuru Municipality expanded by 6% during the 13-year period from 1973 to 1986 compared to the 13% for about a similar time period between 1986 and 2000. Mundia et al (2008) report that the main driving force of land-cover changes in this region is the growing pressure of population which has more than doubled since 1960.

### 4.3 Land use/cover change projections

Representing the land use/cover change process by a Markov model allows us to address questions such as: How is the land use/cover change process likely to progress in the future? Is it possible to infer future evolutions from observations of recent changes? Land use/cover change projections were generated on the basis of the Markov chain. The transition probabilities produced the projection in Table 2.

In the absence of any major policy, socio-economic or climatic change, future land use/cover changes would continue to affect the natural vegetation, which would continue to decrease over the years by being converted to urban and agricultural lands. The Markov chain analysis for year 2000 and 2015 are summarized in Table 2. From these results, our model predicted that the urban land would increase by 45%; agricultural lands by 28% and the bare land by 196%.

One suspects however that institutional and policy changes will intervene in the study area to modify these trends. Such projections rely strongly on the hypothesis of stationarity of the land use/cover change process. Results reveal that the change process is not stationary since the two projections, based on transition matrices from different time periods, provide divergent equilibrium distributions of land cover.

Table 3: Markov Chain Analysis for year 2000 and 2015

Year	2000	2015	Change (km <sup>2</sup> )	Change (%)
Land use/cover	Area (km <sup>2</sup> )	Area (km <sup>2</sup> )	Area (km <sup>2</sup> )	%
Water	26.7	46.6	19.9	74.7
Forest	22.5	21.7	-0.9	-3.9
Barren Land	2.9	8.7	5.8	196.9
Urban	35.5	51.6	16.1	45.4
Agriculture	74.8	95.8	21.0	28.1
Rangelands	168.6	101.6	-62.0	-37.9

## 5 Conclusion

Monitoring land use/cover changes is necessary for guiding decision making for resource management. We analyzed land use/cover changes between 1973 and 2000 and used the findings to produce a simulated result for Nakuru Municipality for 2015. To achieve this, multispectral Landsat images for 1973, 1988 and 2000 were used in a post-classification analysis with GIS. The Land use/cover results were then employed for predicting land use/cover changes for 2015 using Markov chains. Our results show that land use/cover in Nakuru Municipality has changed. In particular, the urban land has doubled over the period from 1973 to 2000. Loss of forest land and the problem of urban sprawl were noted as serious issues. Markov chains, applied to the remote sensing data by way of transition matrices generated projections of land-cover distributions for the year 2015. The projections of future land use/cover changes on the basis of a Markov chain showed a continuing trend of increase in urban and agriculture land, and the decline in forests and other natural vegetation covers. Our prediction however assumed that the transition probabilities would remain constant. This is unlikely to be the case as the process of land use/cover change does not generally conform to the hypothesis of stationarity and, therefore, Markov chain models may provide unreliable projections.

When facing such severe and rapid land use/cover changes, one requirement for decision-making is to be able project future changes under certain assumptions. Such projections also contribute to increased awareness of the ecological consequences of growing pressures. However, this study only used satellite data which is probably limited and not sufficient to grasp the land use/cover change process in all its complexity. Attempts need to be undertaken to incorporate socio-economic variables to improve the results. The information obtained however, is very useful for planning purposes and for the appropriate allocation of resources and demonstrate the potential of multi-temporal Landsat data to provide a precise and inexpensive means to analyze and map changes in land use/cover over time that can be used as inputs to policy decisions and land management.

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