ASSESSING APPLICATION OF MARKOV CHAIN ANALYSIS IN PREDICTING LAND COVER CHANGE: A CASE STUDY OF NAKURU MUNICIPALITY

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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 and 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 spatial-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.

Key words: GIS, land cover, Markov modelling, Nakuru municipality, satellite remote sensing.

1.0   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. However, some recent works have shown that satellite remote sensing has the potential to provide accurate and timely geospatial information describing changes in land use/cover. Although land use/cover changes have in the past been monitored by traditional inventories and surveys, satellite remote sensing can be more effective especially for African countries and can provide greater amounts of information along with advantages of cost and time savings for regional size areas. Importantly, remotely sensed imagery provides an efficient means of obtaining information on temporal trends and spatial distribution needed for understanding, modelling, and projecting land change (Elvidge *et al.*, 2004).

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 categorisation 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). These methods establish changes but do not offer information on the nature of change (Ridd and Liu, 1998; Singh, 1989; Yuan *et al.,* 1998). On the other hand, post-classification comparison techniques use separate categorisations of images obtained at altered times to create difference maps from which 'from–to' change information can be generated (Jensen, 2004). Although the accurateness of the change maps is dependent on the precision of the individual classifications and is subject to error propagation, the categorisation of each date of imagery constructs a historical series that can be more easily renewed and used for purposes other than change detection such as modelling. The post-classification comparison approach, adopted for this study, also reimburses for dissimilarity in

atmospheric conditions and vegetation phenology amid dates since each categorisation is separately produced and mapped (Coppin *et al.,* 2004; 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.

2.0 THE STUDY AREA

Nakuru municipality (Figure 1) lies approximately between 0° 15' and 0° 31' South, and 36° 00' and 36° 12' East, with a normal altitude of 1,859 meters above sea level, enveloping an area of 290 km². 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.
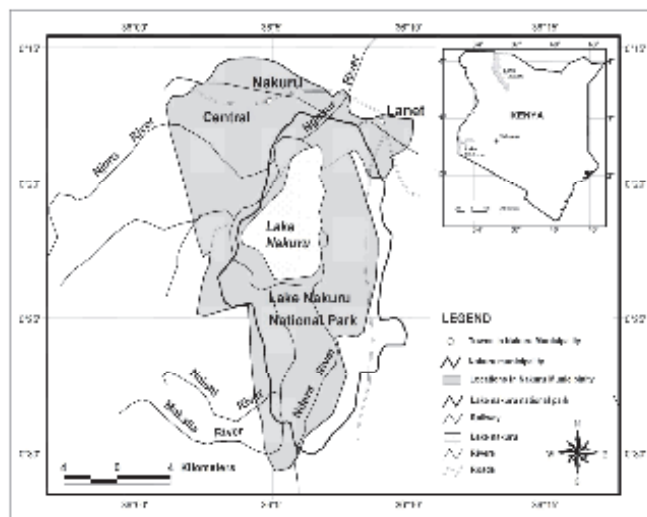

Figure 1 : Map showing the extent of the study area

3.0 METHODOLOGY
3.1 Land Use/cover Change Analysis

The approach adopted for the analysis of land use/cover changes is summarised in Figure 2. Three sets of clear, cloud-free Landsat images for 1973, 1986 and 2000 were selected to classify the study area. The characteristics of these data sets are summarised in Table 1. 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. Image processing was performed using ERDAS Imagine, version 8.5. 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.
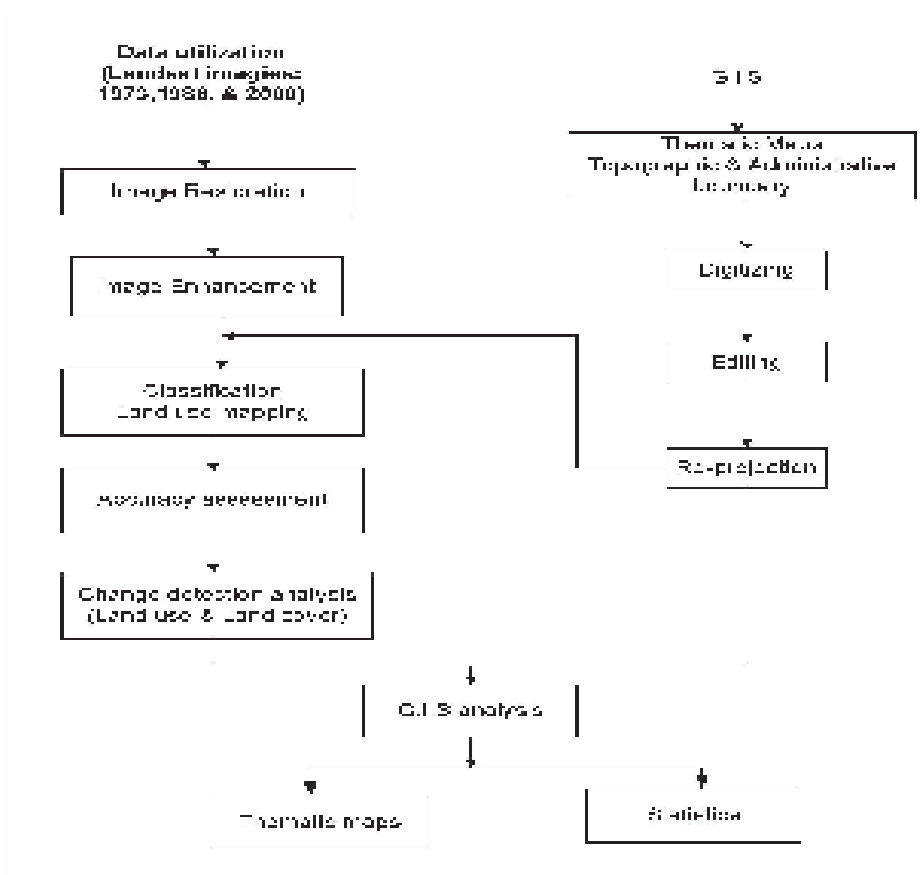

Figure 2: Flowchart for the analysis of land use/land cover changes

Data type	Sensor	Resolution	Coverage	Use
Satellite image	Landsat MSS (31st January 1973)	80 metres	P181r060	Land use/cover mapping for 1973
	Landsat TM (28th January 1986)	30 metres	P169r060	Land use/cover mapping for 1986
	Landsat ETM+ (27th January 2000)	30 metres	P169r060	Land use/cover mapping for 2000
Topographic map				Geometric correction, and ground reference data
GPS points				Ground reference data

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 recoded 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. ERDAS Imagine spatial modeler and additional rule based procedures were adopted to overcome these classification challenges and differentiate between classes.

Table 2: Land use/cover classes for satellite derived land use/cover maps.

Class	Description
Urban land	Residential, commercial and services, industrial, transportation, communication and utilities
Agricultural land	Cropland, plantations, horticultural farms, greenhouses other agricultural crops
Forest land	Acacia, Columbus and euphorbia forests
Rangeland	Sparsely distributed shrubs and bushes with ground layer covered by grass. Species include *Acacia mellifera, Lawsonia inermis*
Bare land	Lake shores, transition areas and bare exposed rocky areas as and quarries
Water	Lake Nakuru, rivers and stream

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. First, 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 forecast's 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).

4.0   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 3. 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 3: Statistics for land use/cover for years 1973, 1986, 2000*

Year	1973		1986		2000	
Land use/cover	Area (km²)	%	Area (km²)	%	Area (km²)	%
Water	39.9	13.6	35.0	12.0	39.2	13.5
Forest	21.1	7.2	20.3	7.0	19.0	6.5
Barren	8.4	2.9	2.4	0.8	1.9	0.7
Urban	19.0	6.5	23.5	8.1	37.3	12.8
Agriculture	71.7	24.6	61.1	21.0	83.2	28.5
Rangeland	131.7	45.2	149.3	51.2	110.8	38.0
Total	291.7	100.0	291.7	100.0	291.7	100.0

land on the other hand has decreased from 21 km² in 1973 to 19 km² in year 2000. The agricultural fields occupied 72 km² in 1973, decreased to 61 km² in 1986, but further increased to 83 km² in 2000. Rangelands, consisting of mixed rangeland and shrub/brush rangeland decreased from 131 km² in 1973 to 110 km² in 2000. These trends in land use/cover changes for Nakuru municipality are summarised in Figure 4. The comparison of land use/cover classification results in Figure 3 indicates that the rate of encroachment of urban land on other land uses has been rapid, with discontinuous patches of urban development characterising 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.

Figure 3: Classified land use/cover maps of Nakuru Municipality for 1973, 1986 and 2000.
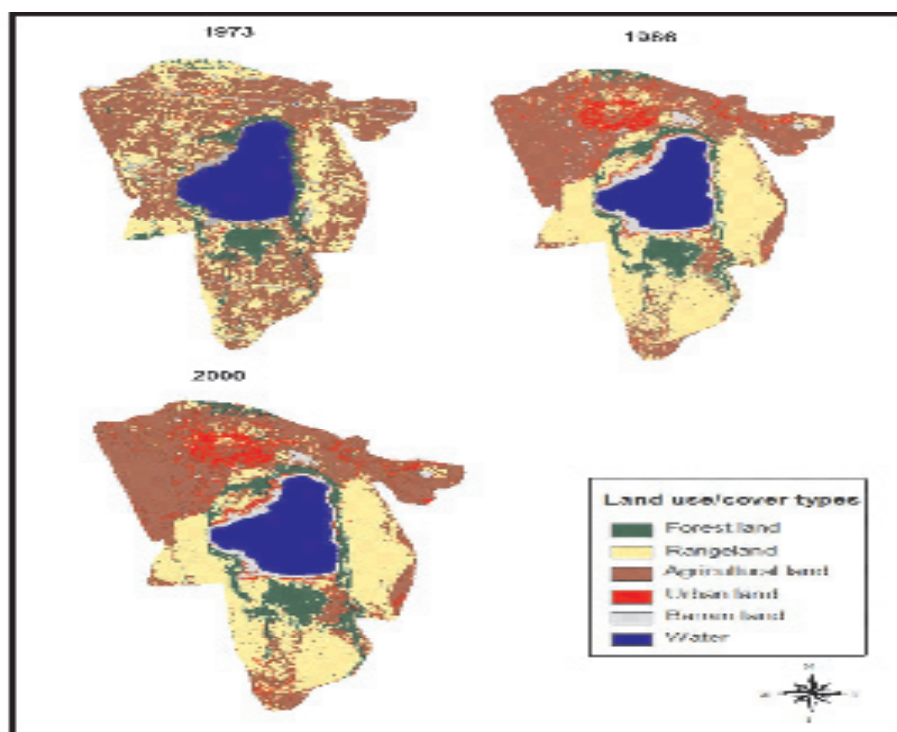
Classified Data	Reference Data							
	Water	Forest	Barren land	Urban	Agriculture	Rangeland	Total	User's Accuracy(%)
Water	282875	0	0	0	0	599	283474	100
Forest	0	89283	0	0	0	24511	113794	78
Barrenland	0	0	43059	0	0	1444	44503	97
Urban	0	0	0	7244	710	29675	37629	19
Agriculture	0	0	290	202	62025	43038	105555	59
Rangeland	0	10423	0	435	4680	335195	350733	96
Total	282875	99706	43349	7881	67415	434462	935688	
Producer's Accuracy (%)	100	90	99	92	92	77		

Overall accuracy = 88%   Kappa = 0.88

(b) 1986 (TM)

Classified Data	Reference Data							
	Water	Forest	Barren land	Urban	Agriculture	Rangeland	Total	User's Accuracy(%)
Water	407312	0	0	0	0	0	407312	100
Forest	0	124237	0	0	0	0	124237	100
Barren land	0	0	5884	81	0	0	5965	99
Urban	0	0	0	21080	0	8050	29130	72
Agriculture	0	142	0	100	248971	26070	275283	90
Rangeland	0	196	0	931	3274	418362	422763	99
Total	407312	124575	5884	22192	252245	452482	1264690	
Producer's Accuracy (%)	100	100	100	95	99	92		
Overall accuracy = 97 %	Kappa = 0.96							

Classified Data	Reference Data							
	Water	Forest	Barren land	Urban	Agriculture	Rangeland	Total	User's Accuracy (%)
Water	337189	0	0	0	0	0	337189	100
Forest	0	60205	0	0	0	0	60205	100
Barren land	0	0	2268	133	0	0	2401	94
Urban	0	0	0	264916	10560	2813	278289	95
Agriculture	0	0	0	21180	410984	62047	494211	83
Rangeland	0	0	0	19780	74564	139466	233810	60
Total	337189	60205	2268	306009	496108	204326	1406105	
Producer's Accuracy (%)	100	100	100	87	83	68		
Overall accuracy = 86 %	Kappa = 0.82							

Figure 4: Trends in Land use/cover for Nakuru Municipality between 1973 and 2015
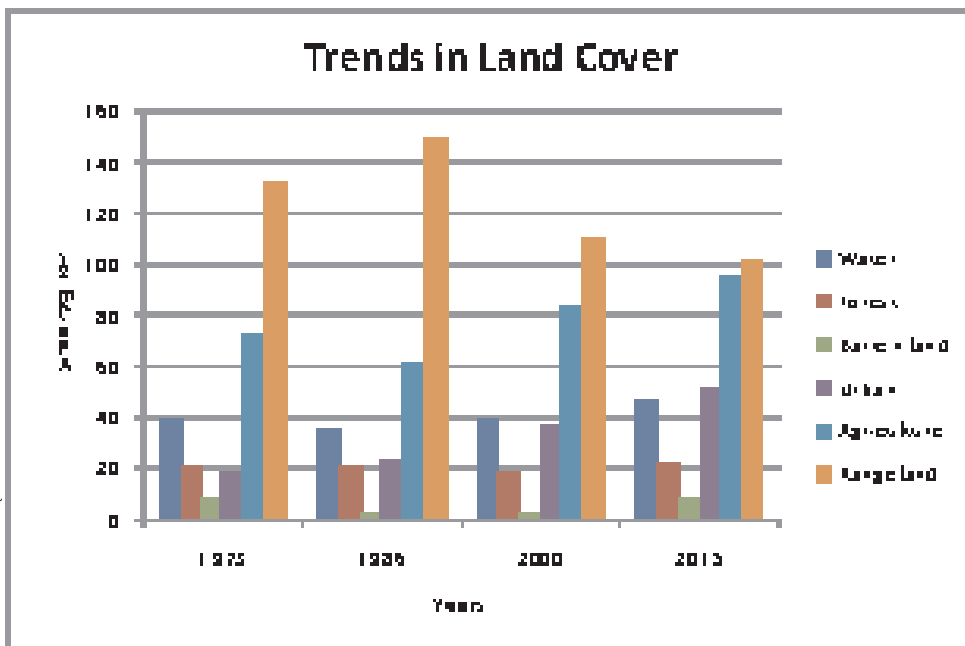
Table 5: Transition probabilities derived from the land use/cover for 1973,

Category	Probability of change					
	Water	Forest	Barren land	Urban	Agriculture	Rangeland
Water	0.49	0.00	0.04	0.15	0.01	0.03
Forest	0.07	0.19	0.01	0.05	0.08	0.31
Barren land	0.02	0.04	0.00	0.08	0.14	0.43
Urban	0.00	0.04	0.00	0.05	0.16	0.47
Agriculture	0.00	0.03	0.00	0.05	0.18	0.45
Rangeland	0.00	0.06	0.00	0.06	0.20	0.38

Category	Probability of changing to :					
	Water	Forest	Barren land	Urban	Agriculture	Rangeland
Water	0.75	0.00	0.00	0.02	0.08	0.04
Forest	0.00	0.52	0.00	0.07	0.01	0.29
Barren land	0.47	0.00	0.07	0.29	0.05	0.00
Urban	0.16	0.00	0.05	0.28	0.26	0.13
Agriculture	0.00	0.01	0.00	0.16	0.33	0.38
Rangeland	0.00	0.03	0.00	0.13	0.36	0.37

$$\underline{p}(n) = (p_1(n) \quad p_2(n) \quad \cdots \quad p_m(n))$$

where pi(n) is the probability that the system is in state i after transition n, given p(0).

If we know the state probability vector at time n, we can compute the *i* th component of the vector at time n +1:

$$p_i(n+1) = p_1(n)p_{1i} + p_2(n)p_{2i} + \ldots + p_m(n)p_{mi}$$

The set of m such equations can be summarized as p(n +1) = p(n)P. These are called forward Chapman-Kolmogorov equations.

Using the equation p(n +1) = p(n)P, the transition probabilities for 1973 to 1986 was normalized to fit 14 years so as to be uniform with the transition probabilities for 1986 to 2000. This was done in Matlab as per the equation p(n +1) = p(n)P

p(0 +1) = p(0)P, is the transition table (1973 to 1986)

p(1 +1) = p(1)P, is the normalized transition table (1973 to 1986)

p(1 +1) = p^2= p(1)P

Table 7: Normalized transition probabilities derived from the land use/cover
for 1973, 1986

Category	Probability of change					
	Water	Forest	Barren land	Urban	Agriculture	Rangeland
Water	0.2385	0.0097	0.0219	0.0842	0.0384	0.1141
Forest	0.0503	0.0604	0.0055	0.0467	0.1015	0.2386
Barren land	0.0116	0.0419	0.0021	0.0423	0.1289	0.2752
Urban	0.0038	0.0426	0.0014	0.0413	0.1342	0.2803
Agriculture	0.0034	0.0409	0.0013	0.041	0.1339	0.2812
Rangeland	0.0067	0.0438	0.0016	0.0403	0.1281	0.2816

process is not stationary since the two projections, based on transition matrices (Table 5 and 6) from different time periods, provide divergent equilibrium distributions of land cover.

Table 8: Markov chain analysis for year 2000 and 2015

Year	2000	2015	Change (km²)	Change (%)
Land use/cover	Area (km²)	Area (km²)	Area (km²)	%
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

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 analyse 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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