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Quantifying processes of land-cover change by remote sensing: resettlement and rapid land-cover changes in south-eastern Zambia

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Abstract. The objectives of this study are to quantify, based on remote sensing data, processes of land-cover change and to test a Markov-based model to generate short-term land-cover change projections in a region characterised by exceptionally high rates of change. The region of Lusitu, in the Southern Province of Zambia, has been a land-cover change 'hot spot' since the resettlement of 6000 people in the Lusitu area and the succession of several droughts. Land-cover changes were analysed on the basis of a temporal series of three multispectral SPOT images in three steps: (i) land-cover change detection was performed by combining the postclassification and image differencing techniques; (ii) the change detection results were examined in terms of proportion of land-cover classes, change trajectories and spatio-temporal patterns of change; (iii) the process of land-cover change was modelled by a Markov chain to predict land-cover distributions in the near future. The remote sensing approach allowed: (i) to quantify land-cover changes in terms of percentage of area affected and rates of change; (ii) to qualify the nature of changes in terms of impact on natural vegetation; (iii) to map the spatial pattern of land-cover change. 44% of the area has been affected by at least one change in land cover during the period 1986 to 1997. The average annual rate of land-cover change was 4.0%. Agricultural expansion was the dominant change process. Land-cover change trajectories highlighted the dynamic character of changes. The results obtained by applying a Markov chain for projecting future evolutions showed the continuing upward trend of bare soils and cultivated land, and the rapid downward trend of forests and other natural vegetation covers.

1. Introduction

Land-use/land-cover change is increasingly recognised as being an important driver of global environmental change (Turner *et al.* 1994). To ensure a sustainable management of natural resources, it is necessary to understand and quantify the processes of landscape change. Patterns of landscape modification are the results of complex interactions between physical, biological and social forces (Turner 1987). To understand and predict change processes, one needs to monitor and characterise

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spatial patterns of land-use/land-cover change. Field-based studies allow the observation and description of processes of land-cover change in a detailed and spatially disaggregated way. Such studies describe the interactions between human activities and their environment and thus highlight the driving forces of land-cover change. However, field studies are generally not sufficient to quantify and analyse spatio-temporal patterns of land-use/land-cover changes at an aggregated level (Liverman *et al.* 1998). Moreover, field studies alone cannot provide predictions of future patterns of change.

Remote sensing has emerged as the most useful data source for quantitatively measuring land-cover changes at the landscape scale (Hudak and Wessman 1998). The dynamics of change processes can be investigated through temporal series of remote sensing data and by analysing change trajectories (i.e. sequences of successive changes in land-cover types) (Turner 1987, Turner *et al.* 1989, Singh 1989, Hall *et al.* 1991, Alves and Skole 1996, Coppin and Bauer 1996, Lambin 1996, Guerra *et al.* 1998, Mertens and Lambin 2000). The goal of temporal series analysis is not only to project the likely temporal evolution of a landscape, but also to interpolate land-cover distributions between observation dates (Lambin 1997). Interpolation of temporal data and short-term projections can easily be performed by modelling the change process as a stationary Markov process, as long as this process is homogeneous in time (Bell 1974, Bell and Hinojosa 1977).

It is interesting to monitor and model change processes in locations that are clearly identified as land-cover change 'hot spots' given their high rates of land-cover change (Lambin and Ehrlich 1997). 'Hot spots' may be viewed as models for land-cover changes which could occur in other regions at much lower rates, and thus can be used to test methods for both backward (historical approach) and forward (predictive approach) projections. If projection methods, such as Markov chain models, are validated at the scale of a decade in a land-cover change 'hot spot', the same predictive models could be applied successfully in other less-critical regions over longer periods.

The objectives of this study are to quantify, based on remote sensing data, land-cover change processes and to test a Markov-based model to generate land-cover change projections in a region characterised by exceptionally high rates of changes, the region of Lusitu, in the Southern Province of Zambia (figure 1). The approach is based on the quantification of the process of land-cover change and the descriptive modelling of the process from these observations.

2. Background

To better understand processes of land-cover change, one has to address four questions (Lambin 1994, 1997):

(1) What are the main ecological and socio-economic variables which drive the land-cover change process—*why? (explanatory analysis)*;
(2) Where are the areas most affected by land-cover change located—*where? (spatial analysis)*;
(3) At what rate does the land-cover change progress and when did it start—*when? (temporal analysis)*;
(4) Is the spatial diffusion of land-cover change homogeneous in all directions? Is the change progression constant in time? Are there spatio-temporal sequences of change—*how? (analysis of the change process)*.

Several authors have tried to gain insights into fine spatial and temporal dynamics of land-use/land-cover changes by analysing time series of remote sensing data and using various change detection techniques (e.g. Stone and Lefevre 1998, Mas 1999). Moreover, simple, first-order transition probability models have frequently been applied to model processes of change in vegetation types and land use (e.g. Robinson 1978, Baker 1989). Burnham (1973) used a Markov land use model in the southern Mississippi alluvial valley to study alternative institutional policies in land management to attain specific land use projections. Turner (1987) developed a stochastic land-use transition model by taking explicitly spatial influences into account.

3. Data

3.1. *Study area*

The study area is part of a larger territory in Zambia which has been studied by demographers and anthropologists since 1956 (Clark *et al.* 1995, Scudder and Colson 1997). The region of Lusitu (21 778 ha) is located in Zambia, south-east of Lusaka and on the north of the Kariba Dam (figure 1). The Lusitu river is a tributary of the Zambezi river which marks the border between Zambia and Zimbabwe. This region was resettled in the late 1950s by a portion of the Tonga-speaking population deported after the flooding of the Kariba dam. The region is dominated by savannah deciduous woodlands, with mopane woodland (*Colophospernum mopane*). Scattered scrubs (*Combretum imberbe*) partly cover the exhausted and early fallow lands. There are some natural protected forests (*Acacia heterocantha*). Along the Zambezi and its tributaries, one finds reeds (*Phragmites woodland*) and riverine forest patches (*Acacia*

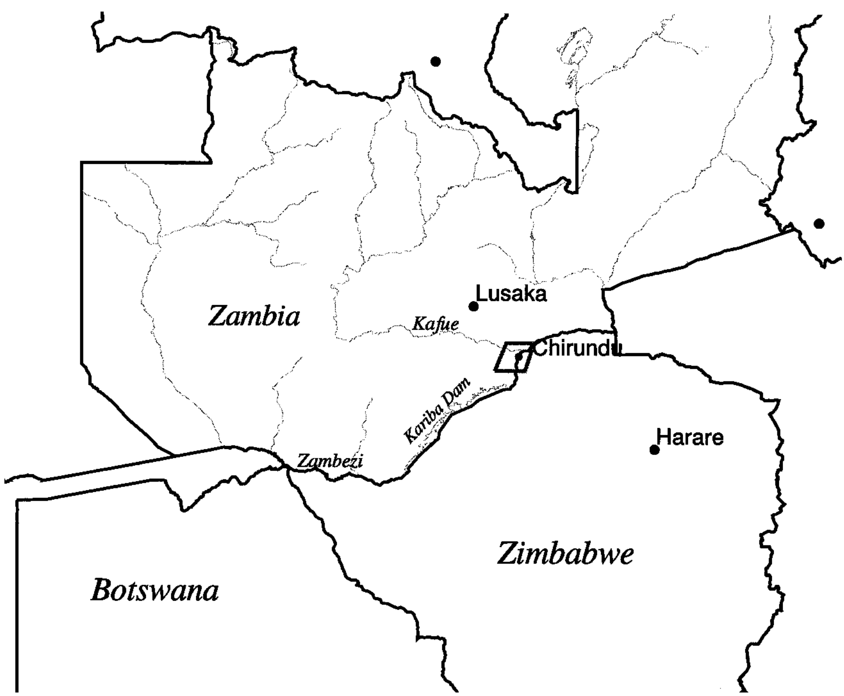


Figure 1. Location of the study area.

albiba and *Tamarindus indica*). Some new forests are formed by a dense woodland of a fruit tree (*Ziziphus mauritania*).

3.2. *Field observations*

Since 1956, long periods of field data collection, approximately five to ten years apart, have been supplemented by short visits lasting from one week to several months (Clark *et al.* 1995). The site was surveyed in 1956–57, 1962–63, 1972–73, 1981–82, 1987–88, 1992, 1997, 1998–99. The fieldworkers analysed the impact on land use of resettlements associated with the creation of Lake Kariba. They collected ecological and demographic data to characterise land-use changes in several villages.

3.3. *Meteorological data*

In the Zambezi Valley, rainfall is characterised by a high interannual variability (figure 2(*a*)) (Scudder 1962). The mean annual rainfall was 593 mm for the 1979–1995

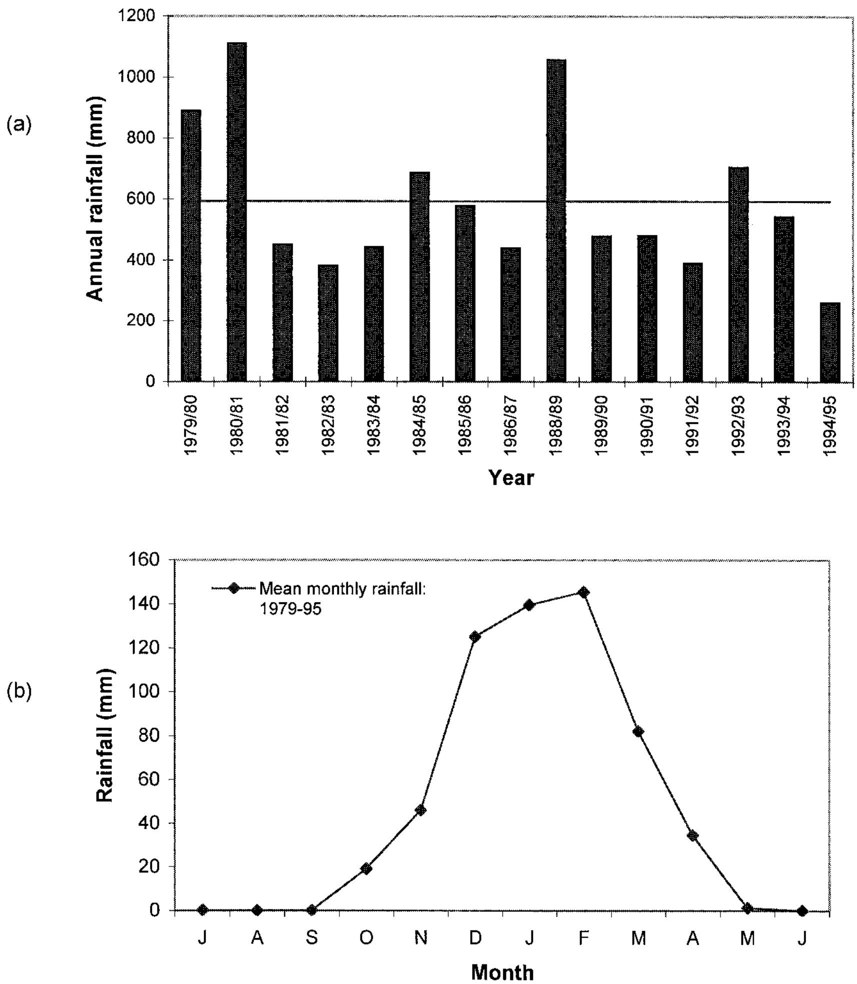


Figure 2. (*a*) Annual rainfall data for Lusitu from 1979 to 1995. The mean annual rainfall (straight line) is 593 mm; (*b*) Mean monthly rainfall data for Lusitu from 1979 to 1995.

period of record at the station of Lusitu. It was 655 mm for the 1932–1956 period at Chirundu, about 15 km north of Lusitu (Scudder 1962), versus 527 mm for the 1980–1995 period. The region of Lusitu is characterised by a single rainy season which extends from October to April (figure 2(*b*)). Droughts have been a frequent occurrence since the early eighties (Dunham 1994, Scudder and Colson 1997). Since 90% of agriculture within the Lusitu area is rainfed, an average of 510 mm of precipitation per annum is required to sustain the region. During eight of the years from 1981 through 1995, the annual rainfall was lower than this level (figure 2(*a*)).

3.4. *Population data*

Before 1958, the area was inhabited by only six small villages of Shona-speaking Goba, with probably no more than 750 inhabitants in total. In 1958, approximately 6000 Tonga-speakers from 35 villages have been resettled into the Lusitu area in connection with the construction of the Kariba Dam. By June 1963, the total population in the area was listed as 8096. By 1994, that population had nearly doubled to an estimated 15 290 (Scudder and Colson 1997). The population continues to increase and significant numbers of people are now leaving the area to pioneer new land elsewhere. Since 1958, agriculture has rapidly expanded. Severe land degradation has been continuously progressing, leading to a bare land situation with a Sahelian appearance (Scudder and Colson 1997).

Because of tsetse fly-carried trypanosomiasis disease in cattle, there were few cattle in the Lusitu area at the time of resettlement (Scudder and Colson 1997). One government resettlement commitment was to initiate a major tsetse control operation which has been quite successful over the years. The livestock population has never stopped to increase, from 562 in 1959 to 26 800 in 1991 (Scudder and Colson 1997). In years of poor rainfall that number of livestock within the Lusitu had grazed and browsed out available food as early as June–July, with deaths from hunger beginning then and increasing especially in the October–November period, just before the start of the rains. Some stock owners had to move their cattle elsewhere.

3.5. *Remotely-sensed data*

Multispectral images from the Système Pour l'Observation de la Terre (SPOT) satellite were obtained for 1986, 1992 and 1997, during the dry season (respectively, 11 August, 23 June and 22 October). No cloud-free data were available at more exact anniversary dates. 1982–83 was a very serious drought year as were 1991–92 and 1994–95. 1992–93 was an average rainy season, as were 1980–1981 and 1988–89 (figure 2(*a*)). Since 1996, no rainfall data were available, but a field survey during the rainy season of 1996–97 revealed that heavy rains and floods had occurred. These interannual variations in rainfall affect the land surface signal measured by the satellite sensor. The satellite images acquired in the dry seasons of 1986 and 1992 followed two low rainfall years, whereas the months preceding October 1997 were relatively wet. Thus, any observation of an increase in vegetation cover from 1986 to 1997, or 1992 to 1997 should be interpreted with caution. Actually, the same trees can be leafless after a severe drought and in leaf on a better rainfall season. On the other hand, any observation of a degradation of the natural vegetation from 1986 to 1997, and 1992 to 1997 is more likely to be real.

All the SPOT images were geometrically co-registered to each other, using up to 100 ground control points and a second-order polynomial transformation (root mean square error of 0.20 pixel). The nearest neighbour resampling method was used. The atmosphere was free of haze when the three images were acquired. Radiometric corrections to compensate for differences in sun elevation angle were applied to the data (Forster 1984). As an important radiometric shift was observed for the 1997 image with respect to the two other images, the former was first corrected by radiometric rectification (Hall *et al.* 1991). The parameters of the reference 1992 image were then applied to the corrected 1997 image to obtain absolute digital numbers.

Panchromatic aerial photographs at a 1:30 000 scale from 1980 and 1991 were also used as reference data. They were interpreted, scanned and assembled in a mosaic.

4. Methods

4.1. *Supervised land-cover classifications*

Land-cover maps for 1986, 1992 and 1997 were produced for the study area by independent supervised classifications using a maximum likelihood classifier. Eleven land-cover classes were intended to be mapped: water, sandy soils, settlements, forests, herbaceous savannahs, bush savannahs, woody savannahs, riverine forests, cultivated land, roads and reeds. The training areas were identified by photo-interpretation on the panchromatic aerial photographs from 1980 and 1991. Several iterations were made to improve the classifications on the basis of field checks. The classification accuracy was assessed on the basis of a stratified random sample of 599 point observations on the aerial photographs, with approximately equal sample size in each land-cover class (Congalton 1991).

4.2. *Land-cover change detection*

Postclassification comparison is often used to detect land-cover changes between two images (figure 3). However, the accuracy of this change detection technique is only as good as the result of the multiplication of the accuracies of each individual classification (Singh 1989). Recent studies have identified image differencing as being the most accurate change detection technique (Singh 1989, Coppin and Bauer 1996, Macleod and Congalton 1998). Image differencing was performed by subtracting the reflectances of the red band of the two dates, as (red reflectance of 2nd date)–(red reflectance of first date) (figure 3). The red spectral band was selected as the study area is located in a semi-arid region and the three images were acquired in the dry season. The vegetation was too low in stature and structure to use the near-infrared (NIR) band, which is mostly related to the amount of green biomass. The spectral contrast between low cover semi-arid vegetation and bare soils is more pronounced in the red band than in the near-infrared band (Franklin *et al.* 1993).

Two thresholds (a positive and a negative one) in the histogram of the difference values were chosen to distinguish between change and no-change areas. The choice of thresholds was guided by field-based descriptions of patches of land-cover change and by a visual interpretation of successive aerial photographs. Asymmetric thresholds around the mean value of the difference image were applied: mean value minus 1.5 standard deviation and mean value for, respectively, negative and positive changes for (1992–1986), and mean value minus 1.5 and plus 1.0 standard deviation for, respectively, negative and positive changes for (1997–1992). The dominant changes showed an increase in the reflectance of the red band, indicating a decrease in vegetation cover. Asymmetric thresholds were required as areas affected by a decrease in vegetation cover were much more widespread than areas affected by an increase

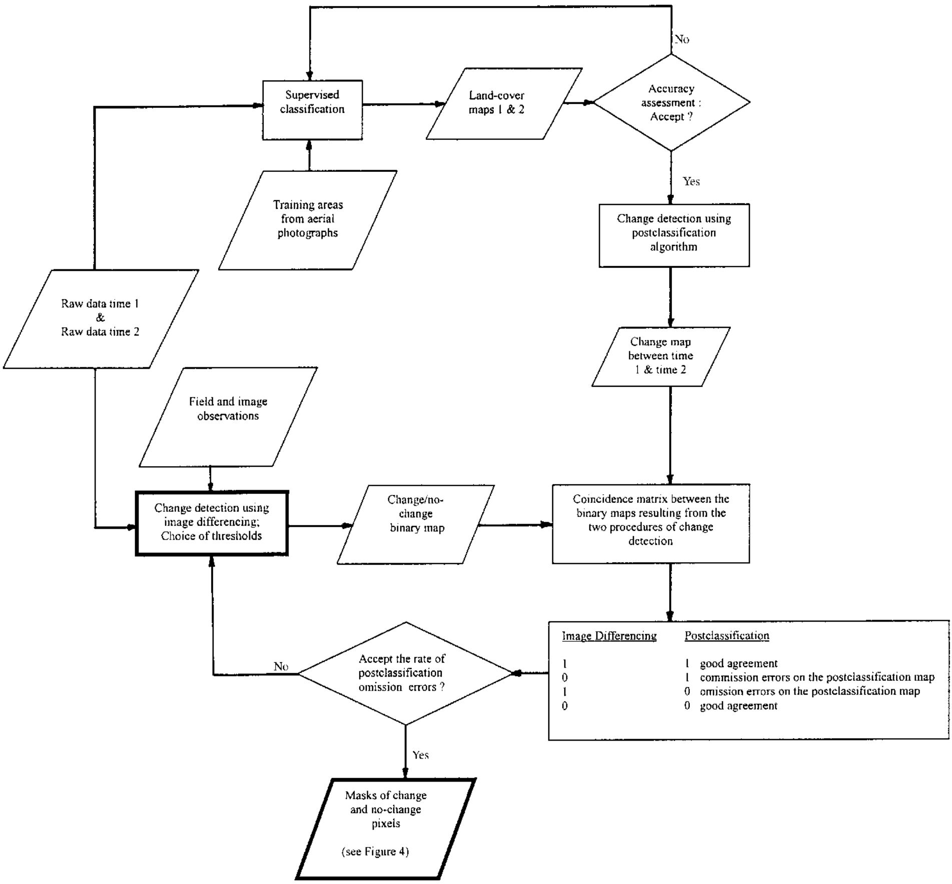


Figure 3. Steps leading to the choice of thresholds in the image differencing procedure for change detection.

in vegetation cover. A (non-random) sample of patches of the more recent change detection (1997–1992) were validated in the field.

The output of the above procedure was a binary change/no-change map. To characterise the nature of land-cover changes, 'from' and 'to' identifiers must be assigned (Macleod and Congalton 1998). The mask of no-change pixels from image differencing was applied to the first date classification and the mask of change pixels to the second date classification. These two masked classifications were combined to obtain an enhanced land-cover map for the second date (Pilon *et al.* 1988, Macleod and Congalton 1998). The land-cover change map with 'from' and 'to' identifiers was produced by combining land-cover map from the first data with the enhanced land-cover map for the second date (figure 4).

This change detection method combining the postclassification and image differencing techniques eliminates commission errors often generated by the postclassification comparison technique. A high omission error in the postclassification change detection technique compared to the image differencing technique indicates either that the threshold values applied to the difference image are too low, leading to an overestimation of changes, or that an important proportion of changes are land-cover modifications (i.e. changes of condition within a land-cover category) rather

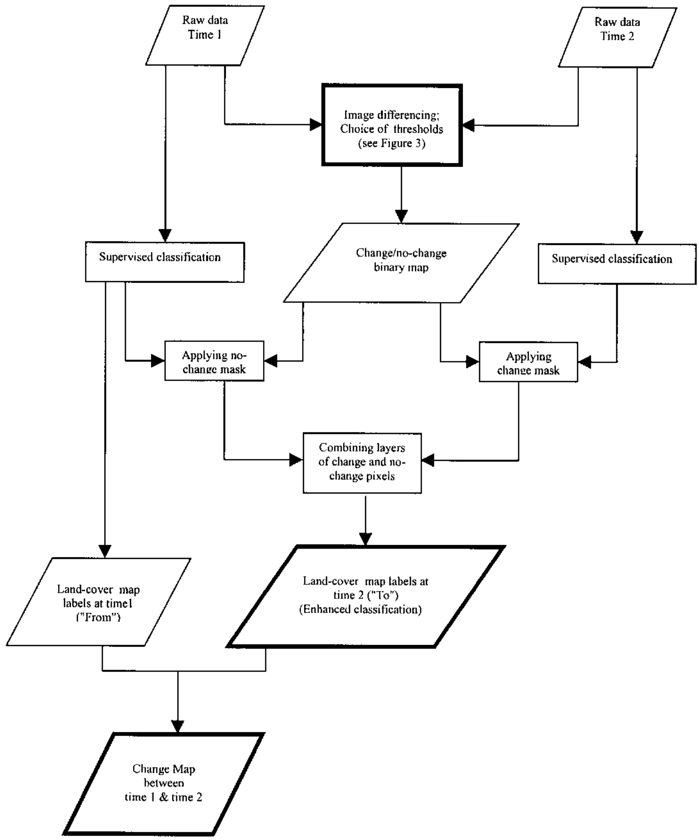


Figure 4. Production of an enhanced classification by image differencing and labelling of land-cover change pixels.

than land-cover conversions (i.e. changes from one class to another). The former are not detected by the postclassification change detection technique, unless each land cover classification identifies a very large number of land-cover classes.

Change/no-change matrices were constructed for the 1986–92, 1992–97 and 1986–97 time intervals. In these matrices, the element in the (i)th row and the (j)th column are the number of pixels of class i from the first image (i.e. initial date) and of class j from the second image (i.e. later date). The land-cover proportion of the (i)th class of the first image corresponds to its relative marginal frequency n'_i:

$$n'_i = \frac{n_{i.}}{n} = \sum_{i=1}^{q} \frac{n_{ij}}{n} \tag{1}$$

where n_i is the marginal frequency of the class i, n_{ij} is the number of pixels of the class i from the first image that were changed to the class j in the second image, n is the total number of pixels of the images.

4.3. *Land-cover change trajectories*

The dynamics of change was analysed in a Geographic Information System on the basis of land-cover change maps, to identify change trajectories (i.e. sequences of land-cover classes for every observation date). The greater the number of land cover classes, the greater is the number of change trajectories, as:

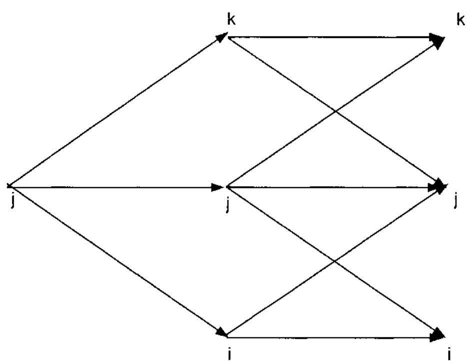
$$m_t = m_c^d \qquad (2)$$

where m_t is the number of trajectories, m_c is the number of land-cover classes and d is the number of images in the temporal series. For three successive land-cover classifications with 10 land-cover classes each, the potential number of land-cover change trajectories is 1000.

To reduce the number of trajectories, we clustered land-cover classes in four aggregated classes of vegetation cover, ordered by their mean normalised difference vegetation index (NDVI) value. The NDVI is sensitive to variations in fractional vegetation cover (Huete *et al.* 1985, Ormsby *et al.* 1987). Finally, the dynamics of the vegetation cover was monitored by aggregating the NDVI change trajectories into a few dominant types (figure 5).

4.4. *Descriptive modelling of land-cover change processes*

Given the difficulties in designing deterministic models of land-cover change processes, it is convenient to consider them as stochastic (Lambin 1994). For land-use/land-cover change, one may formulate a principle analogous to one of classical physics: the probability 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



Category	Trajectory			Categories of changes in vegetation cover
	1986	1992	1997	Description
1	j	j	j	Land-cover class and vegetation cover class unchanged
2	j	j	j	Vegetation cover class unchanged
3	j	k	j	Reversible change in vegetation cover
4	j	j	i	Recent decrease in vegetation cover
5	j	j	k	Recent increase in vegetation cover
6	j	i	i	Early decrease in vegetation cover
7	j	k	k	Early increase in vegetation cover
8	j	k	i	Successive changes in vegetation cover in opposite directions

Where $\overline{NDVI_i} < \overline{NDVI_j} < \overline{NDVI_k}$

Figure 5. Aggregated trajectories of land-cover change, based on changes in vegetation cover as measured by mean NDVI values.

(Parzen 1964, Bell and Hinojosa 1977). Stochastic processes which meet this condition are called Markov processes. 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. For land-cover change, the states of the system are defined as the amount of land occupied by various land covers. The number of possible states is either finite or denumerable.

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-cover distribution at t_1 by means of a transition matrix (Lambin 1994). The Markov chain can be expressed as:

$$v_{t2} = M \times v_{t1} \tag{3}$$

where v_{t1} is the input land-cover proportion column vector, v_{t2} is the output land-cover proportion column vector and M is a $m \times m$ transition matrix for the time interval $\Delta t = t_2 - t_1$. The probability p_{ij} of transition between a pair of states is easily calculated by dividing the cell n_{ij} of the change/no-change matrix by its row marginal frequency, $n_{i.}$:

$$p_{ij} = \frac{n_{ij}}{n_{i.}} \qquad \text{where } n_{i.} = \sum_{j=1}^{q} n_{ij} \tag{4}$$

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-cover change process are available for two calibration 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, Lipschutz 1979). This operation can be performed by using the matrix analogous of the exponential and logarithmic functions. For a calibration period of one year, one can write:

$$M_1 = M_t^{(1/t)} = \exp m\left[\frac{1}{t} \times \log m(M_t)\right] \tag{5}$$

where t is the calibration time interval of the Markov chain, M_t is the transition matrix of the Markov chain for the t time interval, M_1 is the transition matrix for an annual transition rate and $\exp m$ and $\log m$ are the matrix functions analogous to exponential and logarithmic functions. When t approaches infinity, M_t approaches a matrix whose rows are identical and equal to the stationary equilibrium distribution of the process.

For this study, three transition matrices were constructed from the change/no-change matrices obtained in the change detection analysis. The time intervals used for calibration are 6, 5 and 11 years for, respectively, the 1986–1992 transition matrix (M_{86}^{92}), the 1992–1997 transition matrix (M_{92}^{97}) and the 1986–1997 transition matrix (M_{86}^{97}). The stationary equilibrium distribution of the three Markov chains was calculated. The short-term stationarity of the Markov chains was tested by interpolating the land-cover distribution of 1992 (P_{92}) from the 1986–1997 Markov chain and compared with the observed distribution in 1992 (O_{92}). This was done by applying a non-integer exponent of 6/11 to the M_{86}^{97} transition matrix and multiplying the resulting matrix by the initial 1986 land-cover distribution vector. Similarly, the land-cover distribution of 1997 (P_{97}) was extrapolated from the 1986–1992 Markov chain and compared with the observed distribution in 1997 (O_{97}). A fourth transition matrix was constructed from 1997 to 1992 and a backward extrapolation of the land-cover distribution of 1986 (P_{86}) was compared to the observed distribution of 1986 (O_{86}).

5. Results

5.1. *Supervised land-cover classifications*

The three successive supervised land-cover classifications discriminated ten classes: water, sandy soils, settlements, forests, herbaceous savannahs, woody savannahs, riverine forests, cultivated land with crops, harvested agricultural land and reeds. Herbaceous, bush and woody savannahs being difficult to separate spectrally, only herbaceous and woody savannahs were discriminated. Roads were too narrow to be extracted and were thus merged with settlements. Cultivated lands were split in two classes to increase their separability with other land-cover classes. The sandy soils class includes sandy soil banks, sandy outcrops and soils not suitable for cultivation. The settlement class included bare lands associated with villages and their roads, huts, vegetable gardens, thickets and livestock enclosures. The forest class included natural forest areas (*Acacia heterocantha*) and dense cultivated fruit tree areas (*Ziziphus mauritania*). The woody savannahs corresponded to open canopy, deciduous woodlands with scrubs (*Combretum imberbe*). The class 'cultivated land with crops' included highly fertile alluvial soils, which can be cultivated twice annually, in the rainy and dry seasons.

The overall accuracy of the June 1992 classification, assessed on the basis of aerial photographs of 1991 was 83%, with a Kappa coefficient of 80%. This accuracy estimate suffers from the large number of classes, the different spectral resolutions of the SPOT data and aerial photographs, the difference in season between the SPOT image (acquired in June) and the aerial photographs (acquired in January), and some of the land-cover changes that might have taken place between 1991 and 1992. The rate of land-cover change being very high in the eighties, the aerial photographs of 1980 turned out to be unusable to validate the 1986 classification. It was not possible either to assess systematically the accuracy of the 1997 classification as no recent aerial photographs were available. However, the aerial photographs of 1991 were used to check the classification of no-change areas between 1991 and 1997. The classification was also partially validated by non-systematic ground truthing at the end of 1998.

Recent fallows could not be discriminated in a separate class. They belong to three different classes depending on their pedogenesis (hilltop and slope soils) and soil-type (shallow or heavy clay soils). If fallows are covered by little or no vegetation and are dominated by bright soils, they belong to the sandy soils or harvested agricultural land classes. In the case of low vegetation cover and dark soils, they are included in the settlement or harvested agricultural land classes. When they have a more dense vegetation cover, they look spectrally like cultivated lands with crops or herbaceous savannahs. An analysis of images acquired in dry and wet seasons could help to discriminate between uncultivated land and recent fallows.

On the East side of the river, in Zimbabwe, immediately adjacent to the Zambezi floodplain, patches of short grasslands were confused spectrally with cultivated areas and have been classified as agriculture (figure 10). These patches of grassland in the woody Zimbabwean savannah may be explained by the presence of elephants, which are known to destroy riverine forests and convert these to grasslands, and/or the presence of safari camps, which might have led to a decrease in vegetation density in isolated patches since 1980.

5.2. *Quantitative data on land-cover change*

The results of the land-cover change detection can be expressed differently depending on the objective of the study. Land-cover changes can be summarised in a unique change statistics which quantifies the proportion of pixels which have changed in the overall study area independently of their classes. If the study concerns changes in land-cover proportions, the analysis has to deal with n indices, where n is the number of land-cover classes; when the change analysis investigates the 'from' and 'to' changes in land-cover, the number of change indices increases to n^2; when more than two observation dates are taken into account, the number of change indices increases to n^y, where y is the number of images in the temporal series.

As the objective of this study is to demonstrate how a quantification of land-cover change, on the basis of remote sensing data, allows for a better understanding of processes of change, the results are introduced by a set of questions, which are then addressed on the basis of quantitative information. Field-based information is invoked to support the interpretation of the process of land-cover change.

(*a*) At the level of the overall study area, the main research questions on land-cover change processes are: *At what rates did land-cover changes progress from 1986 to 1997? Was the trend in land-cover change the same during the 1986–1992 and 1992–1997 periods?*

The overall rate of land-cover change for the three time intervals (1986–92, 1992–97 and 1986–1997) were 34%, 17% and 44%, respectively. Land-cover changes in this region were extremely important as only 56% of the study area remained unchanged over the 1986–1997 period. The average annual rate of land-cover change between 1986–1997 was 4.0%. Scudder and Colson (1997) report that the main driving force of land-cover changes in this region is the growing pressure of population and livestock, both of which have more than doubled since 1960. The succession of droughts between the two last decades is an additional factor of change in the savannah woodlands, in combination with land use extensification which led to land scarcity (Dunham 1994, Scudder and Colson 1997).

Since the last population census of 1994, the spread of land degradation has been continuing. As a result of this degradation, up to 50% of the population of some villages already moved out of the area to pioneer new land. The remote sensing analysis reveals however that land-cover changes have slowed down in the nineties compared to the eighties. Actually, the annual rate of land-cover change is 5.67% for 1986–1992 and 3.40% for 1992–1997.

(*b*) At the level of land-cover classes, the main questions on land-cover change are: *Which land-cover types were most affected by the change process? What were the rates of conversion from one land cover type to another? Are the rates of change constant for any given class over the period 1986–1997 (i.e. is the change process stationary)?*

From field observations, the most significant changes appeared to be the spread of bare soils and cultivated areas, and the destruction of the forest, which has been serious since 1958 (Scudder and Colson 1997). The vectors of land-cover proportions obtained from the successive (enhanced) classifications reveal that (table 1), in 1986, the study area was dominated by forest and savannah (51% of total area), but also

Table 1. Observed land-cover proportions for 1986, 1992 and 1997 in percentage and annual rates of land-cover changes in per cent for the period of 1986–1997.

	1986 (%)	1992 (%)	1997 (%)	Annual rate of land-cover changes (%)
Water	3.42	3.45	3.28	−0.37
Sandy soils	3.27	6.88	5.78	6.98
Settlements	1.59	4.45	4.63	17.38
Forest	12.04	8.56	6.25	−4.37
Herbaceous savannah	12.55	13.57	13.84	0.93
Woody savannah	20.71	14.13	12.80	−3.47
Riverine forest	5.71	4.54	4.27	−2.29
Cultivated land with crops	19.70	19.92	23.83	1.91
Harvested agricultural land	17.18	20.68	21.99	2.55
Reeds	0.20	0.10	0.41	9.55
Unclassified	3.62	3.73	2.92	−1.76

largely covered by agricultural land (37%). After 11 years, in 1997, forests and savannahs only occupied 37% of the total area, and agricultural land occupied 46%.

The remote sensing analysis confirmed that the major land-cover conversions were from the forest, riverine forest and woody savannah classes, to the sandy soils, settlement and agricultural land classes (figure 6). A decrease in the rate of change is observed after 1992 for all classes, except for the cultivated land with crops (figures 6 and 7). The three higher rates of conversion concern changes from forest,

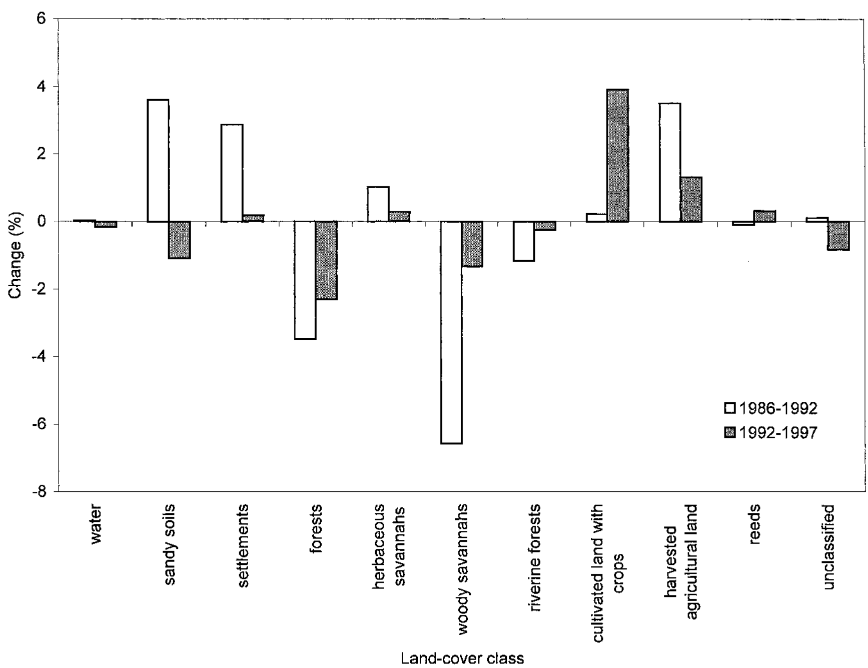


Figure 6. Changes in land-cover proportions over the two pairs of observation years. A positive variation of a land-cover proportion corresponds to an increase in area for the land-cover class from the first to the second date.

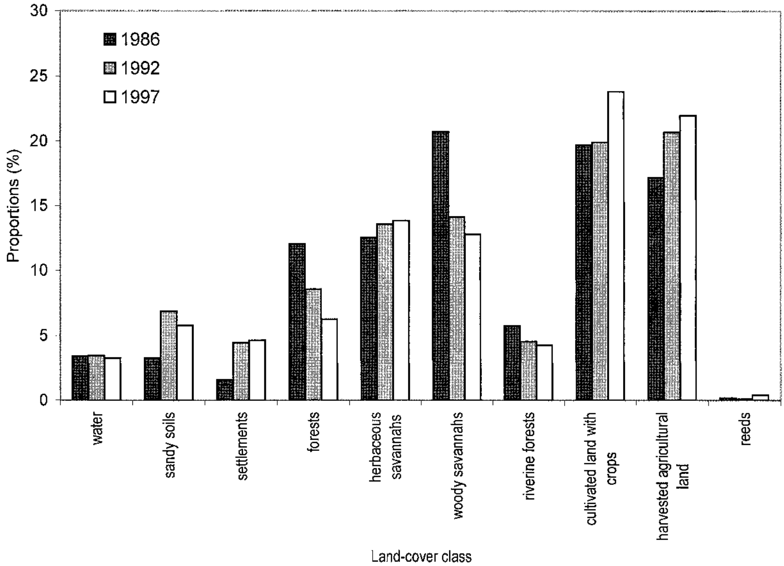


Figure 7. Evolution of land-cover proportions as observed over the three observations years.

herbaceous and woody savannahs to agricultural land (table 2). Thus, clearly, agricultural expansion is the dominant change taking place in the study area.

The conditional probabilities of change are equal to 1 minus the no-change conditional probabilities (i.e. the numbers on the diagonal of the transition matrix); they are lower for all classes between the 1986–1992 period compared to the 1992–1997 period, except for the sandy soils and settlement classes (figure 8). This decrease in the probability of change of a given pixel from one class to another can be explained either by a drastic reduction of the initial land cover (e.g. for the forest class) or by institutional constraints over this land cover (e.g. for protected forests).

5.3. *Land-cover change trajectories*

The main question that can be addressed by an analysis of land-cover change trajectories is: *Were the land-cover changes sudden or progressive, irreversible or reversible?*

Table 2. Annual rates of land-cover conversion for the period 1986–1997.

'From' class	'To' class	Annual rate of conversion (%)
Forests	Cultivated or harvested agricultural land	2.34
Herbaceous savannahs	Cultivated or harvested agricultural land	2.15
Woody savannahs	Cultivated or harvested agricultural land	1.95
Riverine forests	Cultivated or harvested agricultural land	1.09
Forests	Herbaceous savannahs	1.43
Woody savannahs	Herbaceous savannahs	1.16
Riverine forests	Herbaceous or woody savannahs	1.41
Cultivated land with crops	Sandy soils or settlements	0.38
Harvested agricultural land	Sandy soils or settlements	1.07
Herbaceous savannahs	Sandy soils or settlements	0.87
Woody savannahs	Sandy soils or settlements	0.34

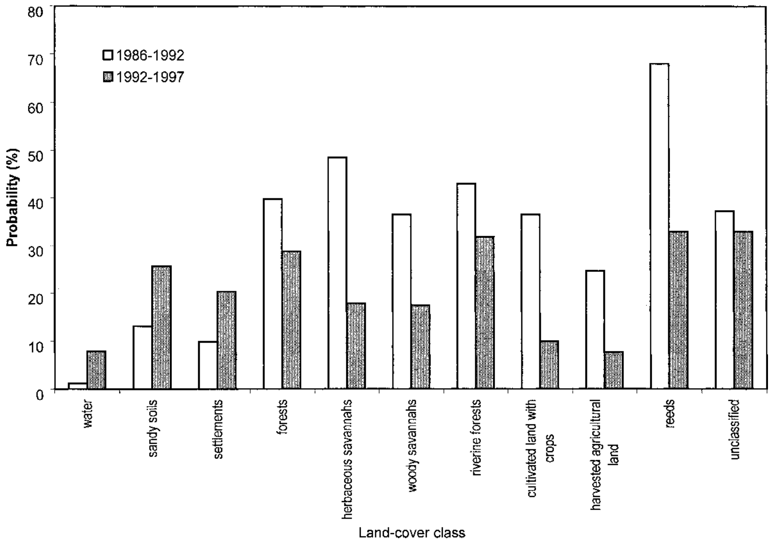


Figure 8. Conditional probabilities of change from a given land-cover class to any other class.

By combining the successive (enhanced) land-cover classifications, 804 land-cover change trajectories were produced. 567 trajectories were left after elimination of the undetermined trajectories (i.e. those that include unclassified pixels). The re-classification of the ten land-cover classes into four vegetation cover classes (based on mean NDVI values) led to a further reduction of the number of change trajectories, which could now be described in terms of increase or decrease in vegetation cover. The aggregated classes are as follows: water (class 1); sandy soils, settlement and agricultural land classes (class 2); natural vegetation, composed by forests, woody savannahs and herbaceous savannahs (class 3); and reeds and riverine forests (class 4). The ordered relation between the mean NDVI value for these classes remains constant for the three dates. Out of the 64 potential NDVI change trajectories, 54 are actually represented in the data. They were summarised in eight types of trajectories of vegetation cover change (figure 5).

The analysis of the area proportion of these eight trajectories of vegetation cover change provides information on the degree of reversibility of changes (table 3). The dominant trajectories of change are characterised by a decrease in vegetation cover,

Table 3. Area proportion of aggregated trajectories of vegetation cover changes.

Category	Description	Area proportion (%)
1	Land-cover class and vegetation cover class unchanged	56.20
2	Vegetation cover class unchanged	10.78
3	Reversible change in vegetation cover	2.52
4	Recent decrease in vegetation cover	6.99
5	Recent increase in vegetation cover	2.63
6	Early decrease in vegetation cover	16.80
7	Early increase in vegetation cover	2.65
8	Successive changes in vegetation cover in opposite direction	1.41

with early changes with biomass loss (16.8%) and late changes with biomass loss (6.99%). The category of no-change in vegetation cover reaches 10.78%. The changes with an increase in vegetation cover are poorly represented (5.3% of the total for both early and late changes). These trajectories correspond to the regeneration of natural savannahs in previously cultivated plots or to natural successions from woody savannahs to forests.

The analysis of land-cover change trajectories within each aggregated category of vegetation cover change (table 4) reveals that, from 1986 to 1992, natural vegetation was converted to agricultural land in a proportion of 10.04% of the total study area, and agricultural land to sandy soils and settlements for 3.35% of the total area. Between 1992 and 1997, similar changes have transformed 4.4% of the total area from natural vegetation to agriculture. Reversible changes are most evident in agricultural lands, which are frequently put into fallows. In this case, the dominant transitions were from cultivated lands to sandy soils or herbaceous savannahs, which indicate the recent abandonment of cultivation and the regeneration of natural vegetation on fallows. Changes between agricultural classes represent 4.87% of the total area while modifications of the natural vegetation cover (e.g. from forest to woody savannah, and from woody savannah to herbaceous savannah) represent 5.47% of the study area.

5.4. *Spatial patterns of land-cover change*

The analysis of the spatial patterns of land-cover changes allows to address the following questions: *Where are the change and no-change areas located? Are there some specific spatio-temporal patterns of land-cover change in the study area?*

Some clear spatial patterns of change are visible on the land-cover change map for the 1986–1997 period (figure 9). On the East side of the Zambezi river, in Zimbabwe, the woody savannah of the safari game management area displays few changes. On the West side of the Zambezi river, the changes have spatially developed by patches in a concentric manner around unchanged land cover areas, which correspond to the initial settlement areas. On the lower left corner of the land-cover change map, the white unchanged patches correspond to a protected indigenous forest. The areas which have changed to agricultural land are located around areas which have changed to sandy soils and settlements. Changes to natural vegetation

Table 4. Area proportion of some of the detailed trajectories of land-cover changes.

Category	Trajectory 1986	1992	1997	Total surface area (%)	Annual rate (%)
6	Natural vegetation	Agriculture	Agriculture	10.04	2.01
6	Agriculture	Sand—settlement	Sand—settlement	3.35	0.83
6	Natural vegetation	Sand—settlement	Sand—settlement	1.37	0.27
4	Natural vegetation	Natural vegetation	Agriculture	4.40	0.88
4	Natural vegetation	Natural vegetation	Sand—settlement	0.87	1.63
3	Agriculture	Sand—settlement	Agriculture	1.79	0.44
7	Agriculture	Natural vegetation	Natural vegetation	1.56	0.38
5	Agriculture	Agriculture	Natural vegetation	1.10	0.27
2	Degradation of the natural vegetation			5.47	1.10
2	Changes within agricultural classes			4.87	1.20

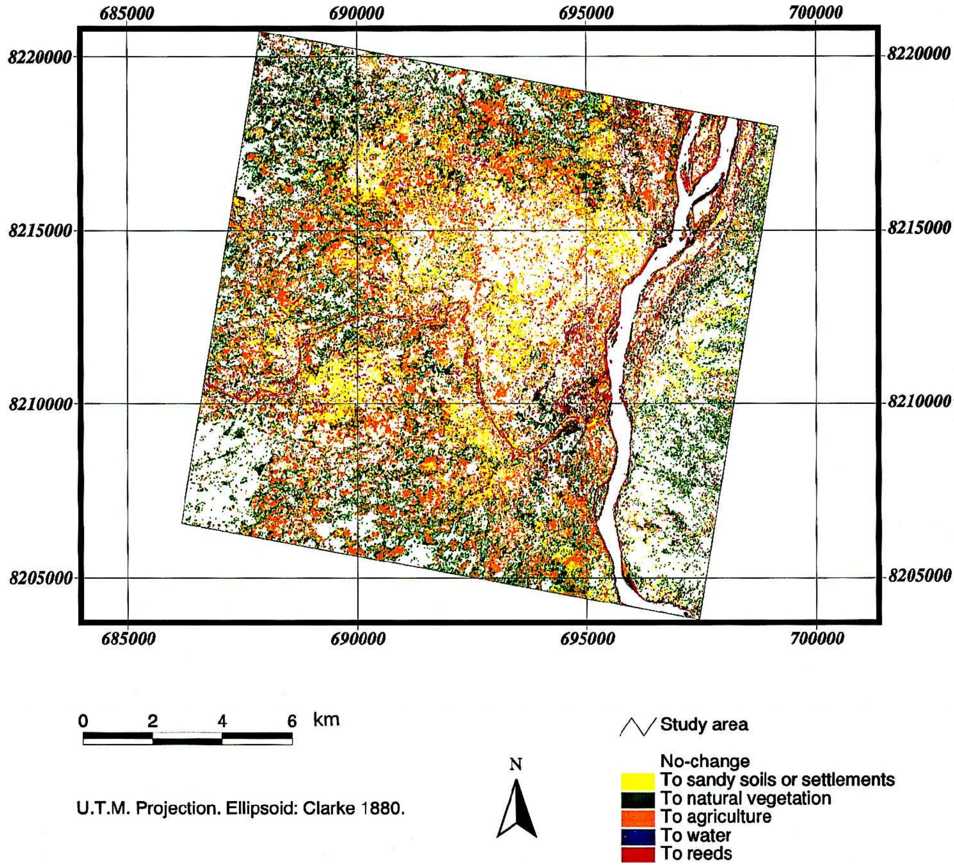


Figure 9. Land-cover change map for the period 1986 to 1997.

include an increase of vegetation on fallows and modifications of the natural vegetation.

Recent changes involving a decrease in vegetation cover have mostly developed in the southern part of the study area (figure 10) and correspond to patches of deforestation. The agricultural expansion clearly shows a pattern of centrifugal diffusion at the expenses of woody savannahs and forests. Patches of modifications of the natural vegetation are found at the edges of the most recently converted agricultural lands. These are probably early signs of new land-cover conversions to come. Sandy soils and settlements are expanding in a similar manner, at the expense of agricultural land; they do not replace forests or other natural vegetation covers but rather the agricultural classes, either because the population tends to move closer to cultivated fields, or because the oldest agricultural lands are over-exploited and become barren soils.

5.5. *Land-cover change projections*

Representing the land-cover change process by a Markov model allows us to address questions such as: *How is the land-cover change process likely to progress in the future? Is it possible to infer future evolutions from observations of recent changes?*

Land-cover change projections were generated on the basis of the Markov chain

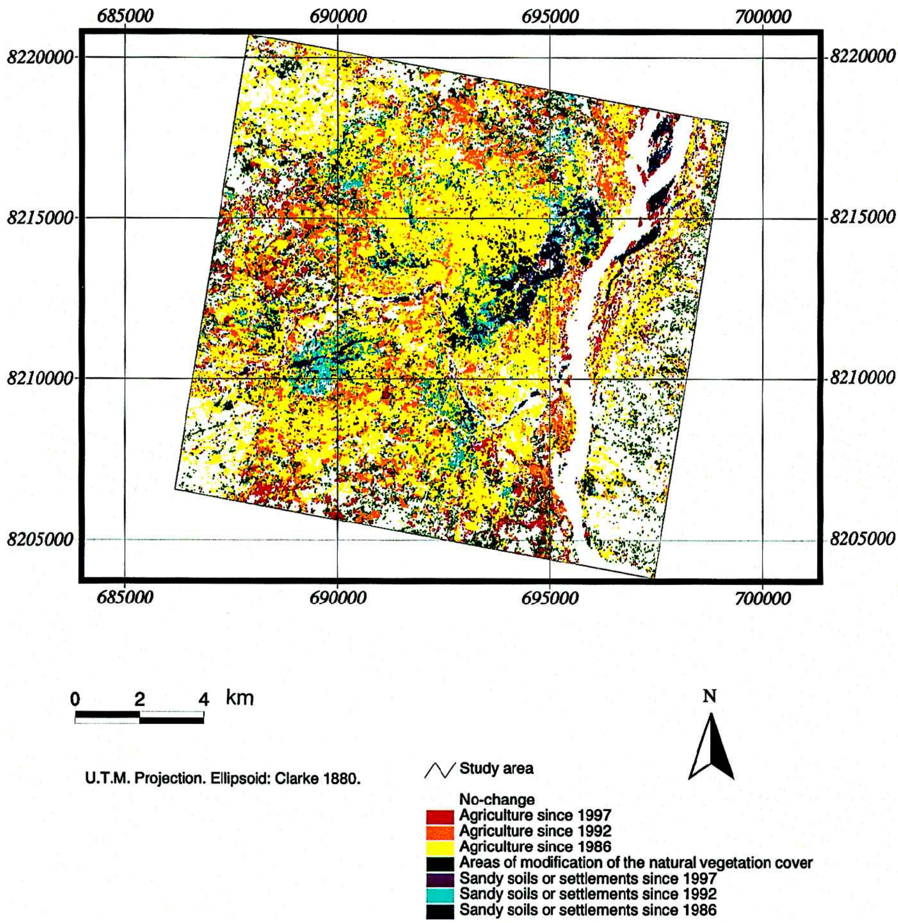


Figure 10. Trajectories of land-cover change for the 1986–1992–1997 time series.

M_{86}^{92} (figure 11). In the absence of any major policy, socio-economic or climatic change, future land-cover changes would continue to affect the natural vegetation, which would continue to decrease over the years by being converted to agricultural lands and, eventually, bare soils. From 1986 to 2010, this model predicted that the natural vegetation could drop from 45.3% to 21.5% of the study area; the agricultural lands could increase from 36.9% to 41.6% and the bare soils could increase from 4.9% to 26.52% of the total area. These projections are indeed alarming, especially concerning the expansion of bare soils which are prone to wind and water erosion. One suspects however that institutional and/or technological changes will intervene in the study area to modify these trends.

Such projections rely strongly on the hypothesis of stationarity of the land-cover change process. As the time t approaches infinity, M^t approaches a matrix whose rows are identical and equal to the stationary equilibrium distribution. Results reveal that the change process is not stationary since the three projections, based on transition matrices from different time periods, provide divergent equilibrium distributions of land cover (figure 12).

The interpolation (P_{92}) (figure 13(*b*)) shows the best agreement between predicted

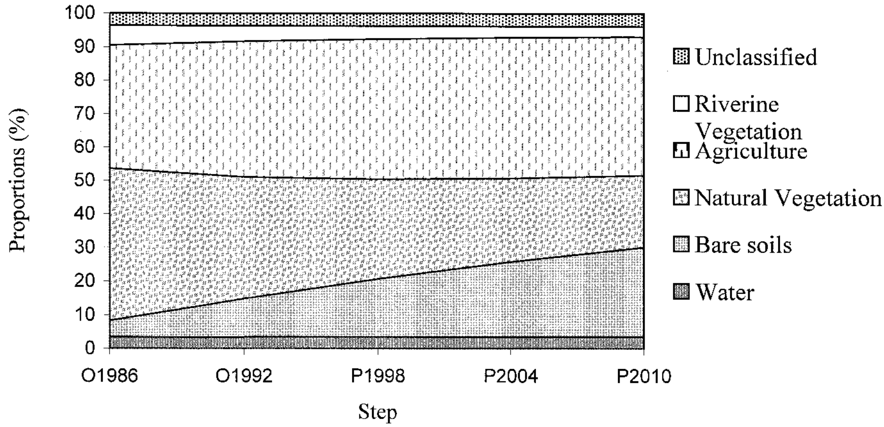


Figure 11. Evolution of land-cover proportions projected (P) by a Markov model based on observed (O) land-cover proportions in the recent past.

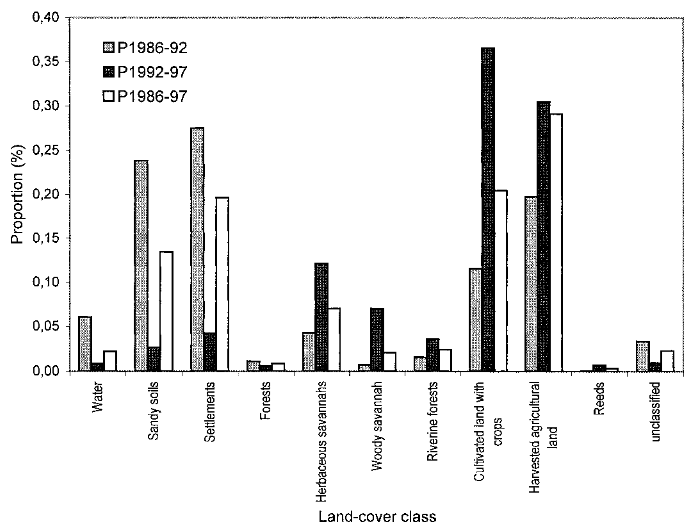


Figure 12. Equilibrium distributions of land-cover proportions projected (P) by the three Markov chains.

and observed values, whereas the two extrapolations (P_{86} and P_{97}) (figures 13(a) and 13(c)) are most poorly estimated. The land-cover proportions of the classes sandy soils, settlements, woody savannahs and cultivated land with crops are the most poorly estimated by the different models (figure 13). These results show that the change process is not stationary mostly for these land-cover classes, probably because conversions to these classes did not occur continuously but rather in abrupt steps. The herbaceous savannahs and harvested agricultural land classes would probably follow the same behaviour for longer term extrapolations as, for these two classes, the difference between the conditional probabilities of change between the 1986–1992 and 1992–1997 periods are also high (figure 8).

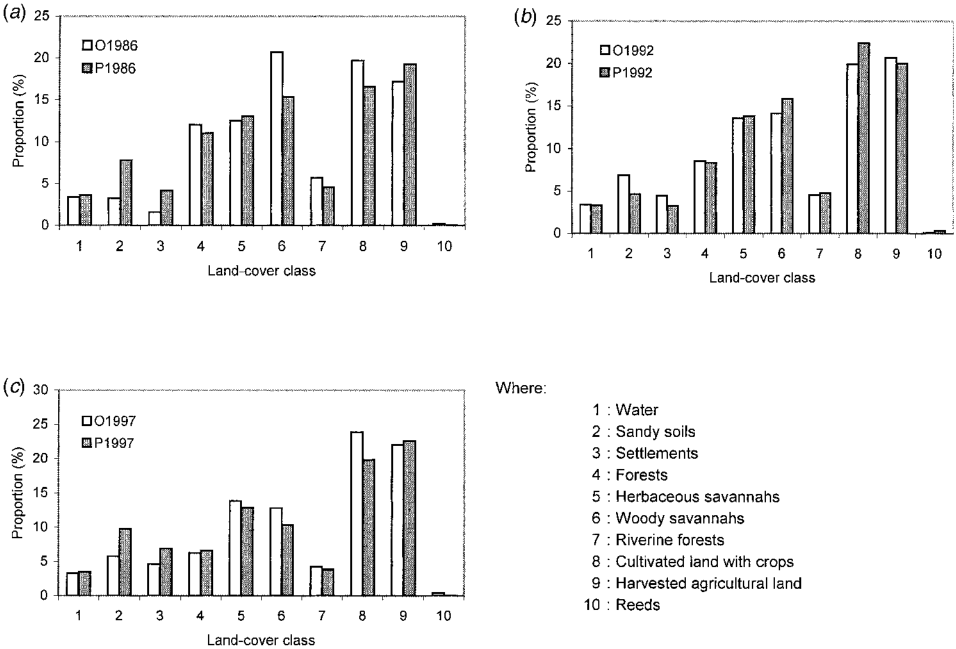


Figure 13. Comparisons between: (*a*) Land-cover proportions projected (P^{1986}) by extrapolation from the 1992–1997 transition matrix (M_{92}^{97}), and the observed (O^{1986}) land-cover proportions; (*b*) Land-cover proportions projected (P^{1992}) by interpolation from the 1986–1997 transition matrix (M_{86}^{97}), and the observed (O^{1992}) land-cover proportions; (*c*) Land-cover proportions projected (P^{1997}) by extrapolation from the 1986–1992 transition matrix (M_{86}^{92}), and the observed (O^{1997}) land-cover proportions.

6. Conclusion and discussion

The analysis of a temporal series of medium-resolution satellite data improved the quantification and, therefore, understanding, of a process of land-cover changes. Land-cover changes were quantified in terms of percentage of area affected and rates of change. Moreover, the nature of the changes were described in terms of impact on the natural vegetation, and the spatial patterns of land-cover change were detected and mapped. Land-cover change trajectories—defined as sequences of successive changes in land-cover types—highlighted the dynamic character of land-cover change. Markov chains, applied to the remote sensing data by way of transition matrices, generated projections of land-cover distributions in the near future and for periods between observation years.

Since the resettlement of 6000 people in the Lusitu area and the succession of several droughts, the conversion of forest to cultivation has been serious. The region of Lusitu was characterised by an average annual rate of land-cover change of 4.0% over the last two decades, thus deserving the attribute of 'land-cover change hot spot'. The major changes in the region occurred during the 1986–1992 period and led mainly to the conversion of natural vegetation into agricultural lands and then bare soils. More subtle land-cover changes were also identified, such as modifications of natural vegetation and crop-fallow cycles. Since 1992, a decrease in the rate of change was observed. The agricultural expansion from the core resettlement area to the West and Southwest of the study area is rapid and should be monitored in the future. Spatially, the changes expanded in a centrifugal manner, with the diffusion of cultivated fields in the woody savannah and the forest.

The projections of future land-cover changes on the basis of a Markov chain showed a continuing trend of increase in bare soils and cultivated land, and the rapid decline in forests and other natural vegetation covers. This assumed however that the transition probabilities would remain constant. This is unlikely to be the case as, for periods longer than a decade, the process of land-cover change does generally not conform to the hypothesis of stationarity and, therefore, Markov chain models provide unreliable projections.

When facing such severe and rapid land-cover changes, one requirement for decision-making is to be able project future changes under certain assumptions. Such projections also contribute to increase awareness of the ecological consequences of growing pressures. However, this study focused on a period of time which is probably too short to grasp the land-cover change process in all its complexity. Attempts must now be undertaken to increase the period of observation toward the past (i.e. before the resettlement) by analyzing longer temporal series of land cover data. This requires methods to integrate, in a homogeneous database, data coming from a variety of sources, such as old aerial photographs and remotely sensed data.

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