Land-Cover Dynamics in an Urban Area of Ghana

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ABSTRACT: The objectives of this study were to quantify land-cover changes. A short-term projection of land-cover distribution in a 2400-ha (1 ha = 10 000 m^2) area of northern Ghana was generated. Landsat Thematic Mapper images acquired in 1984, 1992, and 1999 were used for land-cover mapping, whereas land-cover projections were carried out using transition probability techniques. Remote sensing analyses showed that in the first period (1984–92), the dominant land-cover change process was the expansion of the built-up area (26 ha yr^{-1}) as a result of an increase in demand for housing by the increasing population. Expansion of the built-up area continued at the rate of 35 ha yr^{-1} in the second period (1992–99), as well as development of peri-urban agriculture (24 ha yr^{-1}) to meet the food demand of the rapidly growing population. Projection of land-cover distribution showed that the built-up area would further increase at the expense of cropland and natural vegetation, covering about 39% of the landscape by 2006. Policy implications of this trend are discussed.

This paper is part of a special theme issue on land use and ecosystems.

KEYWORDS: Land use

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1. Introduction

Expansion of urban areas is currently a ubiquitous phenomenon in developing countries of Africa. The region has the highest rate of urbanization in the world, though unaccompanied by economic growth (World Bank, 1995). Out of the estimated population of 18.6 million in Ghana, 37% live in urban areas. The rate of urban growth is estimated at more than 4% (Ghana Statistical Service, 2002). More than half of Ghana's urban population is concentrated in Kumasi, Sekondi-Takoradi, Accra, and Tamale (Figure 1). Dramatic acceleration in urban growth and the associated "ecological footprint" (Rees, 1992) have serious implications for land-cover change on the one hand, and sustainability of urban and peri-urban livelihoods on the other.

Tamale, the largest city in northern Ghana and one of the fastest growing cities in West Africa, has undergone a tremendous change in population, experiencing an increase of more than 4000 people every year from 1960 to 2000 (Figure 2). The city is composed of a blend of modern buildings and traditional shelters made of clay; seasonal farming is the major occupation of the inhabitants (Braimoh, 2003). The city is the hub of intense settlement in northern Ghana for the following three reasons.

- As the administrative capital of the northern region of Ghana, rural populations move to Tamale in the hope of raising their standard of living.
- It is the commercial center for agricultural input and output in northern Ghana. It also offers opportunity for international trade with neighboring Burkina Faso.
- It offers nonfarm employment for migrants from smaller localities.

These same reasons have made Tamale and its environs a hotspot of land-cover change. Demand for housing is ever increasing, whereas food requirement for the increasing population has made urban and peri-urban agriculture increasingly important. In the face of competing demands for land resources, there is a need to understand the state and dynamics of land use/land cover in the area for land-use planning and environmental management purposes. The objectives of this study are to quantify changes in land cover, to evaluate the suitability of Markov chain analysis for descriptive land-cover modeling, and to generate a short-term projection of land-cover distribution in Tamale by 2006. Policy implications of the findings will be highlighted.

2. Methods

2.1. Land-cover mapping

Land-cover mapping was carried out using multitemporal Landsat Thematic Mapper (TM) images. The Landsat TM is a multispectral scanner imaging system on board the *Landsat-5* and *-7* satellite systems. The TM imaging system acquires data in six nonthermal bands and one thermal band ranging from visible to thermal infrared radiation. The spatial resolution of the thermal band is 120 m, whereas the nonthermal bands have a spatial resolution of 30 m. The nonthermal bands of Landsat TM images acquired on 5 November 1984, 21 December 1992, and 7

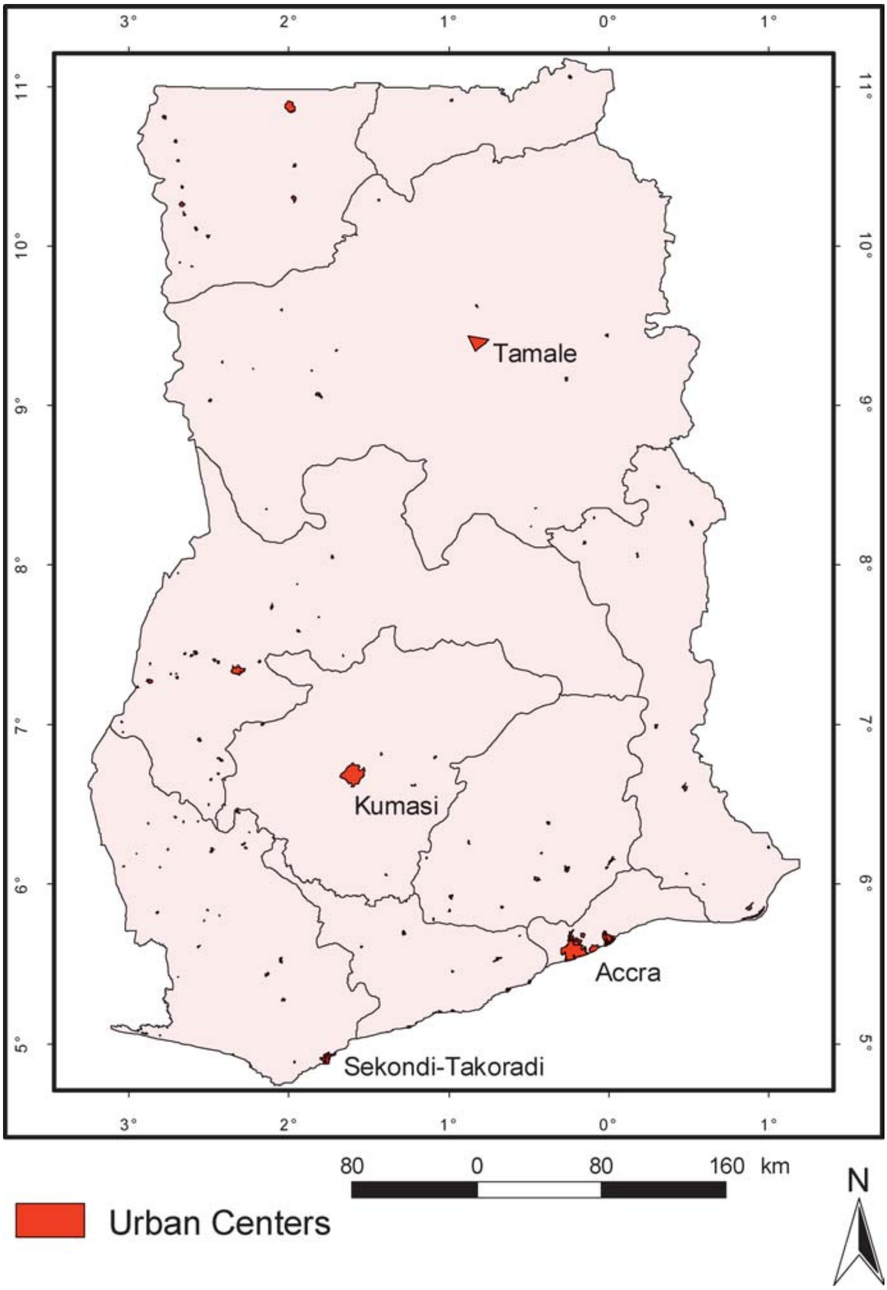

Figure 1. Map of Ghana showing the four major urban centers including Tamale, the study area.

November 1999 were used in this study. Image-to-image geometric projection was performed on a 169 × 156 pixels subset of the images using the 1999 image as the master. A first-order affine transformation was applied, resulting in a root-mean-square error (rmse) of 0.25 and 0.19 for 1984 and 1992, respectively. Radiance

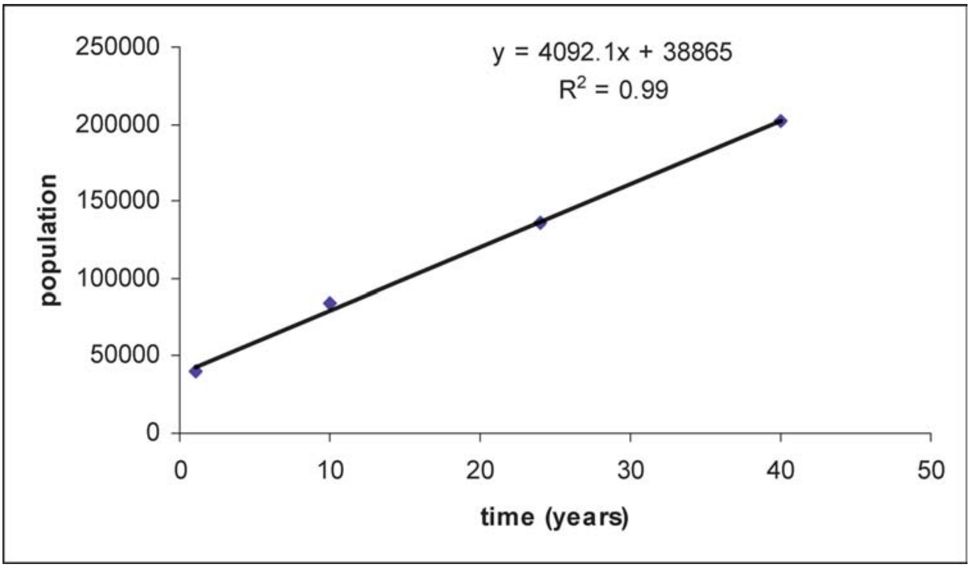

Figure 2. Population trend of Tamale (1960–2000). In the figure, year 1960 = 1, while year 2000 = 41. (Data source: Ghana Statistical Service, 1989, 2002.)

values of the 1984 and 1992 images were normalized to those of the 1999 image following Hall et al. (Hall et al., 1991). Three image transformation techniques were performed prior to image classification. These were the normalized difference vegetation index (NDVI) as a measure of biomass over the landscape; the tasseled cap transform to produce orthogonal soil, vegetation, and water-related bands; and principal component analysis to reduce data redundancy. The first two principal components were combined with NDVI and tasseled cap bands to generate a six-band image for training signature development and classification. Ground truth data for image classification using supervised maximum likelihood algorithms were obtained from the interpretation of 1:10 000 panchromatic air photos acquired in 1992, and global positioning satellite (GPS)-assisted field surveys were carried out between August and December 2001. Five classes were determined: woodland, grassland, cropland, water, and the built-up area. The built-up area refers to all categories of buildings in major and peri-urban Tamale and constructed surfaces (i.e., paved roads).

2.2. Land-cover modeling techniques

Land-use change models can be either prescriptive or descriptive in scope. Prescriptive models (van Ittersum et al., 1998) aim at the determination of the optimum land-use patterns that satisfy a set of goals and objectives. Descriptive models (Lambin, 1997), on the other hand, aim at the simulation of current and near-future land-use patterns. The overall utility of any land-use change model is to guide land-use planning and policy formulation. In line with the objectives of this study, attention is focused on descriptive models of land-use change.

Descriptive models of land-use change consist of three components: multi-temporal land-cover maps, a change function that modifies the values and spatial arrangement of the initial land-cover map, and the resulting prediction map of land-cover change (Lambin, 1994). The land-cover maps are usually derived from remote sensing at spatial resolutions compatible with the study objectives, whereas change functions can be created by mathematical functions that describe processes of change (Lambin, 1997). Depending on the type, descriptive models help to answer the following important questions (Lambin, 1997).

- What biophysical and socioeconomic variables explain land-cover changes?
- At what rate does land-cover change take place?
- Where are the locations (likely to be) affected by change?

Several descriptive modeling techniques have been used to study urbanization. One such technique is the cellular automata approach (e.g., Clarke and Gaydos, 1998). Cellular automata are modeling techniques in which the behavior of a system is generated by a set of deterministic or probabilistic rules. These rules in turn determine the discrete state of a cell based on the states of the surrounding cells (Irwin and Geoghegan, 2001). While the model is useful to formulate scenarios for planning, it requires enormous data for calibration and is also highly computationally intensive. Another limitation is that "growth rules" imposed by the analyst, rather than the actual driving forces of change, govern land-use transitions. This may therefore lead to the wrong policy conclusions.

Another technique of modeling urbanization is the economic approach based on the land-rent theory. Also referred to as the monocentric model, this approach assumes that the distance to the market center is the major determinant of land-use change (Mills, 1967). The primary limitation of this model is that it is not spatially explicit. It treats space as a featureless entity and does not account for interaction among other landscape features that determine the overall spatial structure of land use (Irwin and Geoghegan, 2001).

Another variant of the economic approach models the decision of land owners in a spatially explicit framework (Bockstael, 1996). Such models predict the probability that a land parcel will be developed as a function of hypothesized variables (e.g., location characteristics and/or economic value) affecting development in the area. A limitation of the model is that the spatial distribution of the probability of development does not necessarily explain the amount of land that will be developed. Furthermore, as the prediction map only represents changes taking place within the time interval of the images used to calibrate the model, such econometric models often fail to unravel the dynamic evolution of urbanization. Finally, because the unit of observation is the individual with different goals, aggregation of patterns and processes at the detailed level may not lead to a proper representation of the change processes at the regional level.

Another alternative to the above methods is the Markov chain analysis (Muller and Middleton 1994). Markov chain analysis is a modeling technique in which predictions of future change are based on changes that have occurred in the past

(Turner, 1987; Muller and Middleton, 1994). Markov chain analysis belongs to a group of stochastic techniques that treat land covers as random variables that move in a sequence of steps through a set of ordered states. A sequence of random variables is called a Markov chain if the past and future of the process are conditionally independent given the present. This implies that "the conditional probability of land-use at any time given all previous uses at earlier times depends most upon the most recent use and not upon any earlier ones" (Bell and Hinojosa, 1977). This condition is referred to as first-order stationarity, and stochastic processes that meet the condition are referred to as Markov processes. Brown et al. (Brown et al., 2000) provide a recent example of the application of Markov analysis in modeling land-cover change.

Let $\boldsymbol{c}_t$ be the vector of land-cover distribution at time t. The land-cover distribution at time t+1, $\boldsymbol{c}_{t+1}$ is given by

$$\boldsymbol{c}_{t+1} = \mathbf{M} \cdot \boldsymbol{c}_t, \tag{1}$$

where $\mathbf{M}$ is an $m \times m$ transition matrix whose elements p_{ij} are the probability of transition from land-cover i to j within the interval t to $t+1$. The p_{ij}s are usually derived by dividing each element x_{ij} in the change/no-change matrix by its marginal row total:

$$p_{ij} = \frac{x_{ij}}{\sum_{j=1}^{q} x_{ij}}. \tag{2}$$

The distribution of land cover after n time periods is made by powering matrix $\mathbf{M}$:

$$\boldsymbol{c}_{t+1}^{n} = \mathbf{M}^{n} \cdot \boldsymbol{c}_t. \tag{3}$$

A major advantage of the Markov modeling technique is its operational simplicity and the ability to provide projection of land-use change with minimum data requirements. This is particularly relevant for the study area because historical data on land use is virtually nonexistent. Once a transition matrix has been constructed, it only requires the current land-use information and not old land-use data to project the future land-use distribution.

Markov chain analysis was used 1) to predict land-cover distribution in 1999 using the transition matrix derived from land-cover maps for 1984 and 1992 and 2) to generate land-cover projections for 2006 using the transition matrix from the 1992 and 1999 images. The outputs of the Markov chain analysis include the quantity of pixels expected to transition to various land covers (i.e., simulated quantity), and the conditional probability images showing the likelihood that each land cover would be found at each pixel at the end of the simulation period. The accuracy of the Markov model was evaluated with relative operating characteristics (ROCs). The ROC technique compares observed values over the whole range of predicted conditional probabilities of the transition in 1999. It aggregates into a single index of agreement, the ability of the model to predict the probability of transition at various locations on the landscape. If the model assigns the probability of transition at random across the landscape, the ROC will be equal to 0.5; more generally, the ROC increases as the model assigns higher probabilities to sites that are changed than sites that are not (Pontius and Schneider, 2001).

3. Results

3.1. Data on land-cover change

Land-cover maps are presented in Figure 3. The overall classification accuracies using 116 ground truth samples (measuring approximately 50 m $\times$ 50 m each) from aerial photos and field surveys were 88%, 83%, and 85%, respectively, for the 1984, 1992, and 1999 images. Change was unidirectional for all land covers except cropland. In 1984, cropland occupied over 57% (about 1400 ha) but decreased to about 51% in 1992 (Figure 4). The initial decrease in cropland was a result of the displacement of many farmers, and conversion of their farmlands to buildings (Abudulai, 1996). Cropland increased to about 58% again in 1999. The observed increase in the second period was a result of the expansion of agriculture in the peri-urban area necessary to feed the increasing population. The built-up area increased steadily from 16% (380 ha) in 1984 to 35% (837 ha) in 1999, with migration to Tamale being the major cause of the increase. Other land covers experienced a gradual decrease from 1984 to 1999.

Rates of change are shown in Figure 5. In the first period (1984–92), croplands experienced the highest decrease of 19 ha yr^{-1}, whereas the built-up area increased by over 26 ha yr^{-1}. In the second period, grasslands experienced the highest decrease of 40 ha yr^{-1}, whereas the built-up area again experienced the highest increase of 35 ha yr^{-1}. The overall rate of change (1984–99) was highest for the built-up area (over 30 ha yr^{-1}) and lowest for water bodies (a decrease of about 1 ha yr^{-1}).

3.2. Transition probabilities and Markov models of land-cover change

In Table 1, the main diagonal elements represent the no-change conditional probabilities. Conditional probability of the transition from woodland to cropland increased from 0.42 in the first period to 0.63 in the second period (Table 1). Similarly, conditional probability of the transition of grassland to cropland increased from 0.44 to 0.57. This indicates pressure on natural vegetation cover as a result of the increased demand for food. In both periods, grassland was most likely to be converted to cropland. The conditional probabilities of the conversion of woodland to the built-up area increased in the second period. The conditional probabilities of the transition from cropland to natural vegetation (woodland and grassland) were lower in the second period. This indicates either a reduction in fallow length or the absence of fallow as a result of increasing pressure on land. Under the traditional farming system, fallow is the primary means of rejuvenating soil fertility. It is the period of time the farmers allow the soil to rest after successive years of cropping. Fallow length is inversely proportional to the intensity of pressure on land resources in northern Ghana. The probability of the transition from cropland to the built-up area increased in the second period, indicating that more farmlands were converted to residential uses between 1992 and 1999.

Relationships between observed and Markovian land-cover distributions in 1999 are shown in Figure 6. Correlation between the two datasets is very high and

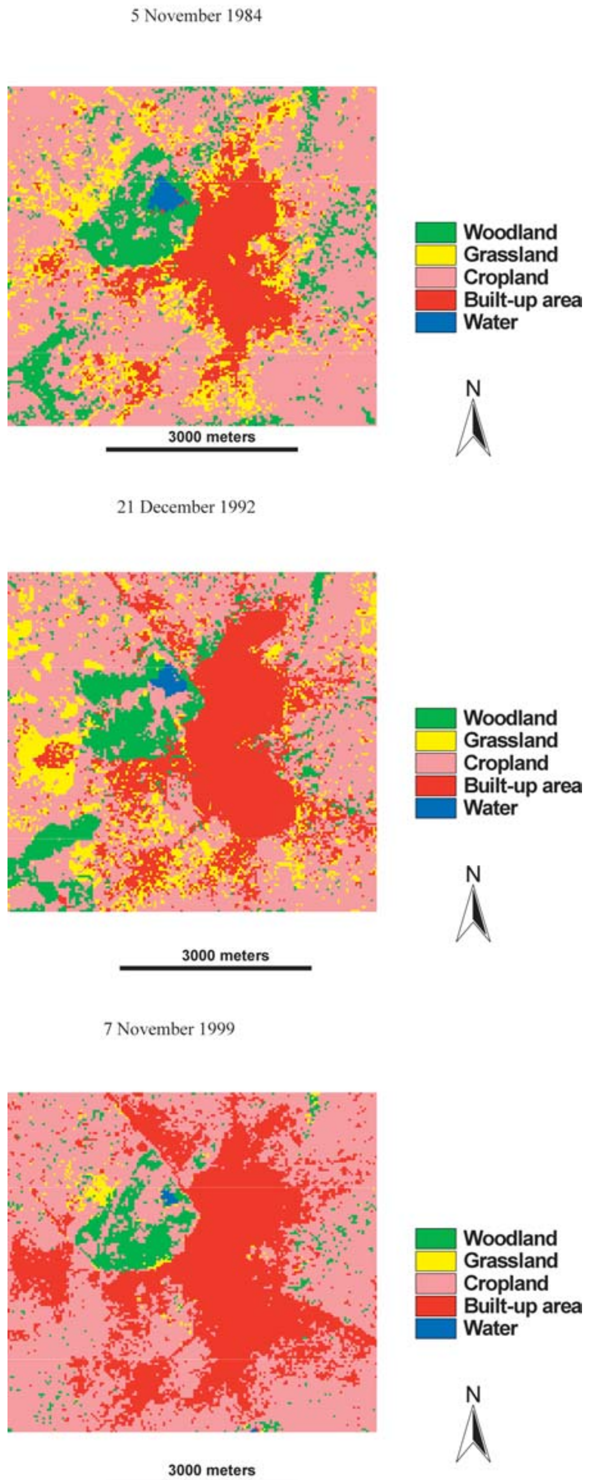

Figure 3. Multitemporal land-cover maps.

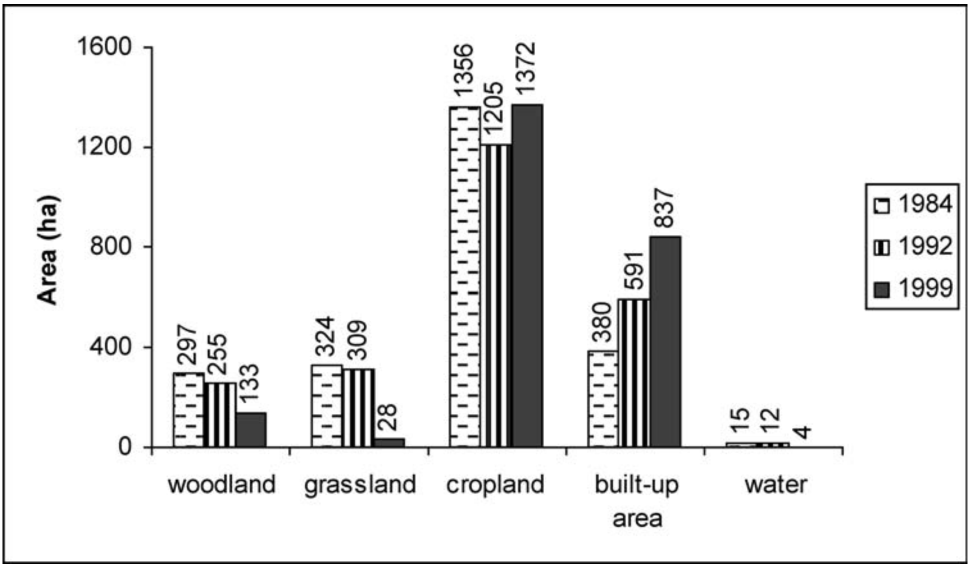

Figure 4. Land-cover statistics.

significant at $p < 0.01$ (Figure 7). This suggests the suitability of the Markov technique in modeling land-cover projections in the study area. As expansion of the built-up area was clearly the dominant change process in the two periods, further discussions on the results of the Markov chain analysis will be limited to the built-up area. The conditional probability image for built-up areas is shown in

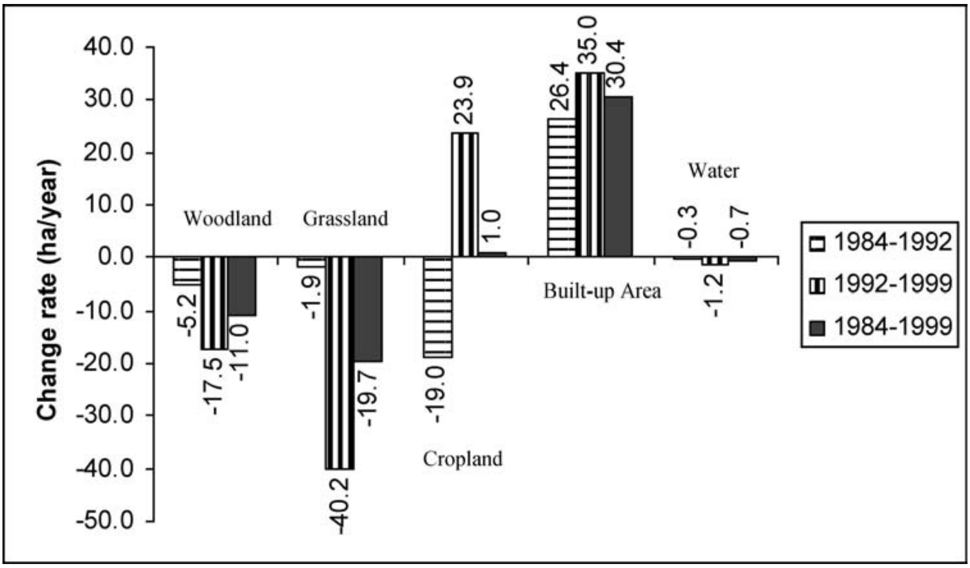

Figure 5. Rates of land-cover change.

Table 1. Transition probability matrices.

Given	Probability of change to: Woodland	Grassland	Cropland	Built-up area	Water
a) 1984–92					
Woodland	**0.41**	0.05	0.42	0.07	0.05
Grassland	0.08	**0.16**	0.44	0.32	0.00
Cropland	0.07	0.15	**0.66**	0.12	0.00
Built-up area	0.03	0.11	0.10	**0.77**	0.00
Water	0.14	0.00	0.16	0.00	**0.70**
b) 1992–99					
Woodland	**0.18**	0.02	0.63	0.17	0.00
Grassland	0.01	**0.01**	0.57	0.41	0.00
Cropland	0.05	0.01	**0.75**	0.19	0.00
Built-up area	0.01	0.00	0.24	**0.75**	0.00
Water	0.20	0.04	0.50	0.00	**0.26**

Figure 8. Comparison of the conditional probability map with the actual built-up area in 1999 yields an ROC of 0.76 (Figure 9), indicating a reasonably good fit.

Projected land-cover distributions in 2006 and observed land-cover distributions in 1999 are shown in Table 2. In the absence of any formal countervailing land-use planning policies, the Markov model predicts that future land-cover change processes would lead to a decrease in natural vegetation, water, and cropland, while the built-up area would increase to 924 ha (about 39% of the landscape).

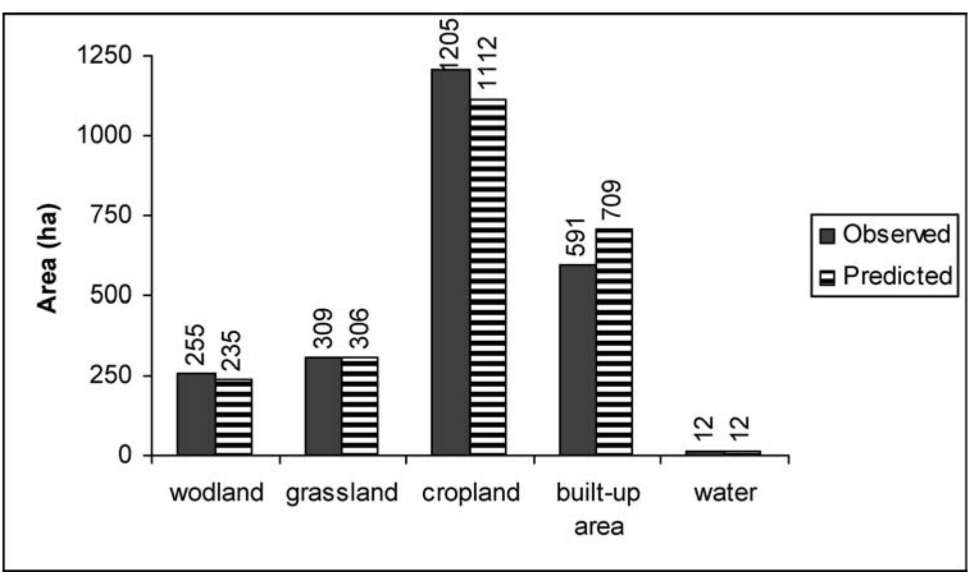

Figure 6. Comparison of observed and Markovian land-cover distribution in Tamale in 1999.

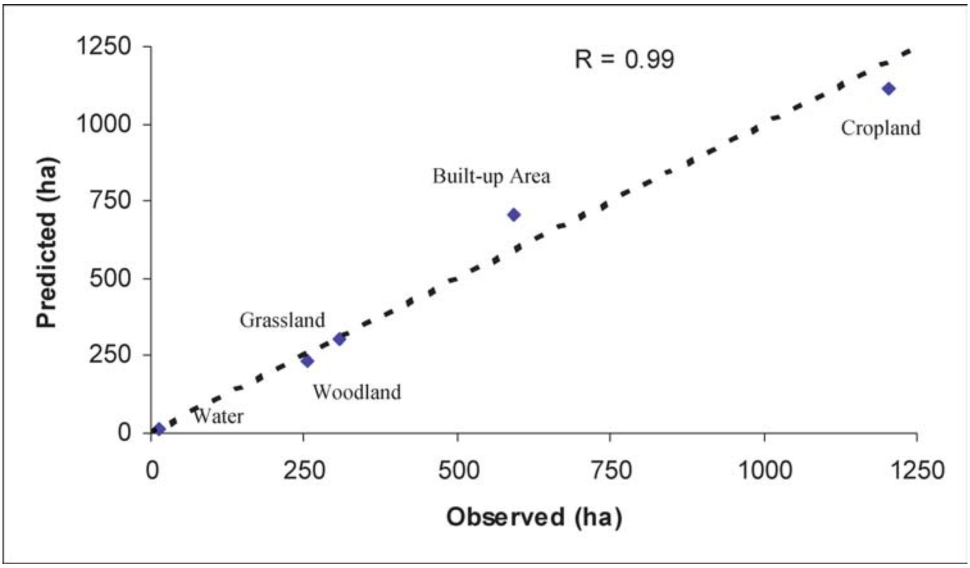

Figure 7. Correlation between observed and Markovian land-cover distribution the hypothetical 1:1 association is shown as a dashed line.

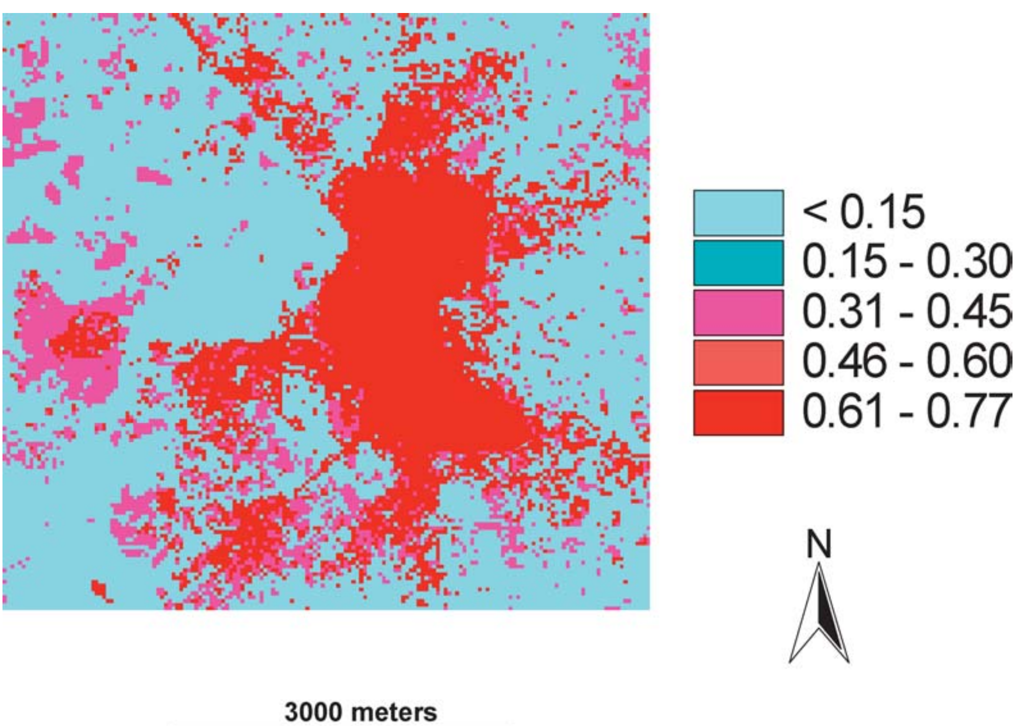

Figure 8. Markovian conditional probability of being the built-up area in 1999.

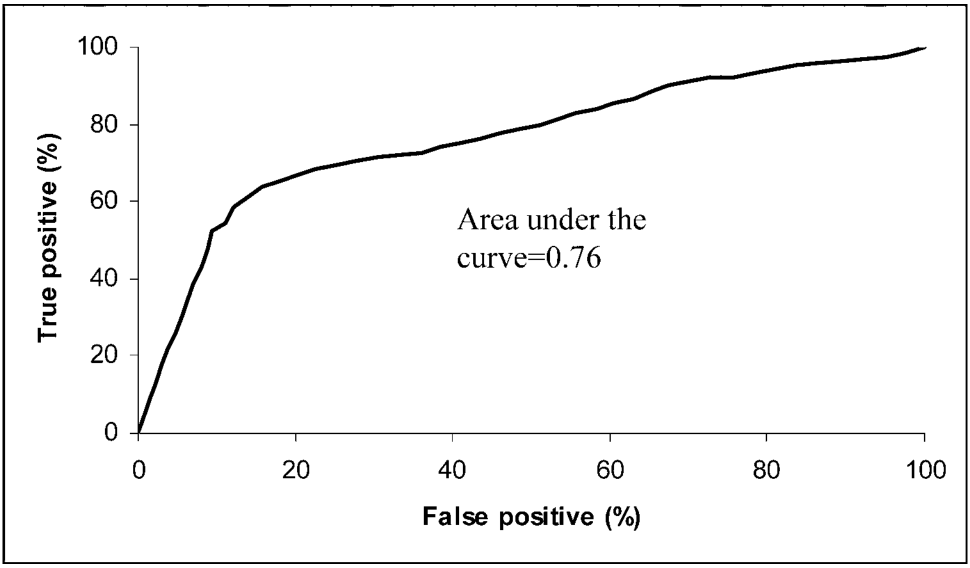

Figure 9. Relative operating characteristic curve to validate observed and the predicted built-up area in 1999.

3.3. Simulation of the impact of urbanization

Overlaying the map of predicted probabilities of the built-up area in 2006 (Figure 10) on the 1999 land-cover map enabled us to assess the level of risk of losing other land covers (Table 3). All grasslands in 1999 are most likely to be converted to the built-up area in 2006, whereas about 44% of the woodland area has a medium risk of being converted to the built-up area in 2006. Similarly, all croplands have a medium risk of being converted to the built-up area.

4. Discussion and conclusions

This research applies Landsat dataset and probability techniques to predict land change in a major city in Ghana. Transition probabilities highlighted the highly dynamic nature of land-use change. The major change between 1984 and 1992 involved a decrease in cropland and natural vegetation, and a corresponding expansion of the built-up area. Between 1992 and 1999, the decrease in natural vegetation continued, whereas cropland and the built-up area experienced an increase. The projection of future changes in land cover using Markov chain analyses showed a continuing trend of increase in the built-up area at the expense of croplands, natural vegetation, and water.

Table 2. Observed and Markovian land-cover proportions (ha).

	Woodland	Grassland	Cropland	Built-up area	Water
Observed 1999 (ha)	133	28	1372	837	4
Predicted 2006 (ha)	103	22	1322	924	1
Change (%)	−23	−21	−4	10	−75

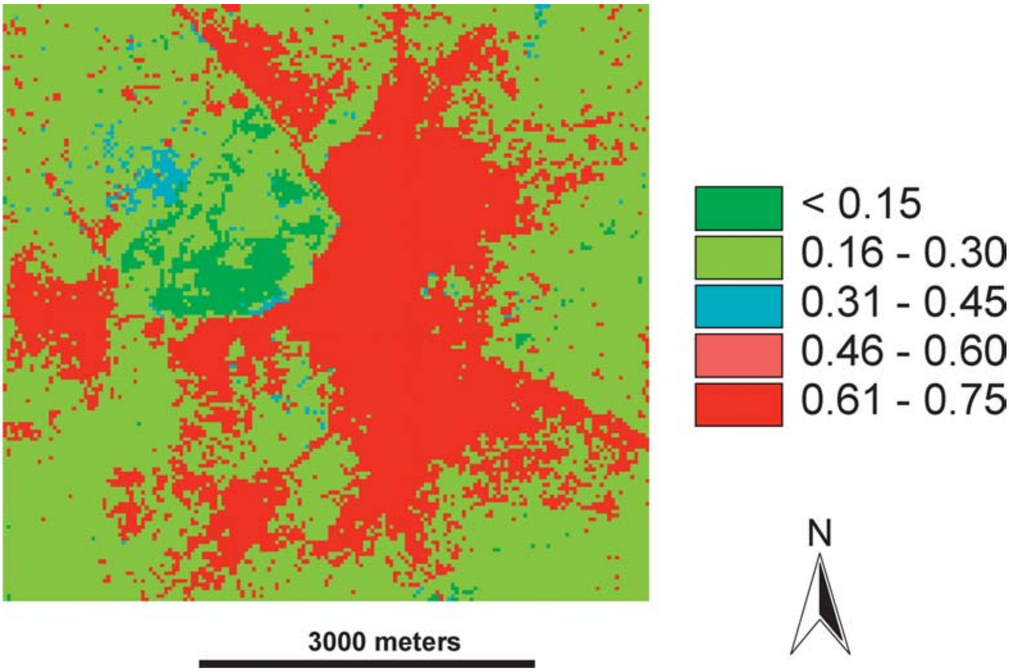

Figure 10: Markovian probability of being the built-up area in 2006.

The study exemplifies how developing countries might use remote sensing and statistical techniques to assess land change and impact policy given otherwise minimal financial resources. The techniques presented are straightforward and inexpensive, as they require minimal dataset and affordable hardware and software to analyze land change.

Markov chain analysis is, however, not an explanatory model of land-use change. It only predicts future distribution of land covers but does not explain the causal factors of change. Furthermore, it is based on the assumption of stationarity of the transition matrix in time and space, which may not always hold. A suitable technique to address these limitations involves calculating dynamic transition probabilities as a function of exogenous variables known to drive land-use change in the study area (Baker, 1989). Equation (1) can then be written as

$$\boldsymbol{c}_{t+1} = \mathbf{M} \cdot [f(t,x)]\boldsymbol{c}_t, \tag{4}$$

Table 3. Amount of land covers (ha) in 1999 in different conditional probability classes of being the built-up area in 2006.

Probability class	Low (<0.15)	Medium (0.15–0.30)	High (0.31–0.45)
Woodland	75	58	0
Grassland	0	0	28
Cropland	0	1372	0
Water	4	0	0

where the $f(t,x)$ notation indicates that the exogenous variables could vary in both time and space. The elements of the transition matrix **M** is then calculated as

$$p_{ij} = \sum_{i=1}^{n} \beta_n x_n, \tag{5}$$

where β_n are the parameters relating the p_{ij} to the exogenous variables x_n.

Finally, the Markov technique assumes spatial independence of the transitions among land-cover type; that is, it does not take spatial influence into account. A recent approach to deal with the issue of spatial interaction involves the use of geostatistical techniques (Brown et al., 2002). The method conditions the simulation of land covers based on initial land cover, the probability of transition to other cover types, and the spatial pattern of change measured with the semivariogram.

The analysis of urbanization as carried out in this study has important policy implications. While economic development is often accompanied by urbanization, the rapid increase in the built-up area due to urbanization as observed in this study is cause for great alarm, as infrastructure at Tamale is grossly inadequate to support such a population increase. Unplanned urbanization has already led to loss of agricultural land and green space. The expected decline of agricultural land in 2006 is also of concern, given the role of peri-urban agriculture in meeting the food demand of this growing city. Urbanization could further lead to development of shantytowns and pollution in the form of water contamination and accumulation of solid waste.

This research underscores the need for rural infrastructure development to alleviate Tamale's high population concentration on the one hand, and encourage the spread of economic activities on the other. Second, there is a need for proper monitoring to prevent further development of shantytowns. Capacity development in the use of remote sensing and geographical information system (GIS) for urban planners is also required. Application of GIS and remote sensing is valuable for monitoring urbanization and developing strategies for curtailing unplanned expansion.

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