Greener Journal of Environmental Management and Public Safety
ISSN: 2354-2276

Detection and Prediction of Land Cover Changes in Upper Athi River Catchment, Kenya: A Strategy Towards Monitoring Environmental Changes

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Research Article

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ABSTRACT

The Upper Athi River Catchment is one of the major catchment areas in Kenya which have experienced land cover changes due to changes in land uses and population pressure. The main objective of the study was to determine past spatial and temporal land cover changes and predict future land cover changes in Upper Athi River Catchment as a means of monitoring environmental changes. Landsat TM images of the years 1984, 2000 and 2010 were used to determine spatial and temporal land cover changes in the period 1984-2010 while the Cellular Automat-Markov (CA-Markov) model was used to predict land cover changes between 2010 and 2030 based on 1984-2010 trends. Change detection between 1984 and 2010 revealed that agricultural and built-up lands increased by 8.67% and 23.70%, while closed/open woody vegetation, broadleaved evergreen forest and rangeland decreased by 9.98%, 2.52% and 19.88%, respectively. Between 2010 and 2030, it was predicted that built-up and agricultural lands would increase by 7.66% and 5.61%, while rangeland; closed/open woody vegetation and broadleaved evergreen forest would decrease by 6.42%, 6.62 % and 0.22 %, respectively. The results showed that agricultural expansion and urbanization will be the main causes of land cover and environmental changes within the catchment.

Keywords: Land cover, CA-Markov model, monitoring, prediction, change detection.

INTRODUCTION

Land cover changes have been recognized as important drivers of environmental changes on all spatial and temporal scales (Turner et al., 1994). Identifying, delineating and mapping of the types of land covers are regarded as important activities in support of sustainable natural resource management. According to Giri et al. (2003), time series analysis of land cover changes and the identification of the driving forces responsible for these changes are needed for sustainable management of natural resources and also for projecting future land cover trajectories. Lambin et al. (2003) noted that land cover change information is needed regarding what changes occur, where and when they occur, the rates at which they occur, and the social and physical forces that drive those changes.

The Upper Athi River Catchment is one of the water catchment areas in Kenya that have experienced rapid land cover changes due changes in land uses and population pressure (Lambretchts et al., 2003). Attempts to come up with intervention measures have been hampered by lack of information on the past rates, location and the likely future land cover changes. In addition, recent development strategies such as Kenya Vision 2030 (GOK, 2007) which emphasizes on agricultural expansion and rapid urbanization are likely to cause major land cover and environmental changes. The main thrust of the study was therefore to determine past spatial and temporal land cover changes and use them to predict future land cover changes in order to generate information that would be used in developing intervention measures and for monitoring environmental changes within the catchment.

Detection and prediction of land cover changes as a means of monitoring environmental changes has been subject of research. Macleod and Congalton (1998) listed four aspects of change detection which are important when monitoring natural resources: detecting the changes that have occurred; identifying the nature of the change; measuring the area extent of the change and assessing the spatial pattern of the change. There are a lot of methods used to predict land cover changes that include mathematical equation based, system dynamic, statistical, expert system, evolutionary, cellular and hybrid models (Falahatkar *et al*., 2011). The most abundant methods in recent land use and land cover literature are the cellular and agent-based models or a hybrid of the two (Berger, 2001; Wood *et al*., 1997; Hartkamp *et al*., 1999; An *et al*., 2005; Le Ber *et al*., 2006; Breuer *et al*., 2006). The CA-Markov model is a hybrid of the cellular automata and Markov models. The CA-Markov models have been regarded as suitable for land cover change detection and simulations by many authors because they consider both spatial and temporal components of land cover dynamics. Predictions of future land cover changes by the CA-Markov Models have been reported in several studies (e.g. Wijanarto, 2006; Falahatkar *et al*., 2011). The Cellular Automata-Markov (CA-M) model is regarded as a suitable approach to modeling both spatial and temporal land cover changes (Houet and Hubert-Moy (2006). In the present study, the CA-Markov model was first evaluated for accuracy of prediction and then used to predict future land cover changes. The study was based on the hypothesis that implementation of Kenya Vision 2030 development strategy would lead to major land cover and environmental changes if future land cover trends resemble the recent land cover trends. In this study the periods for recent land cover trends and future land cover trends refer to the 1984-2010 and 2010-2030, respectively.

The results of the study were expected to form a basis for sounder decision making on management of land resources and environmental impact assessment in Kenya.

MATERIALS AND METHODS

The Study Area

The Upper Athi River Catchment is one of the Kenya's "water towers" (a term used in Kenya to refer to the major catchments). It lies between latitudes 0º49'48"S and 1º49'48"S and longitudes 36º34'48"E and 37º17'24"E, with an approximate area of 5697.5 km^2. It has been experiencing land cover changes due to changes in land uses, especially agricultural expansion and urbanization. The major towns within the study area are Nairobi City, Ruiru, Limuru, Kabete, Githunguri, Dagoreti, Athi River, Juja, Ngong, Embakasi, Uplands and Isinya (Fig.1). It is expected that with the implementation of Kenya Vision 2030, these towns will undergo rapid expansion because it emphasizes on agricultural expansion and urbanization. According to Kenya Vision 2030 (GOK, 2007), urbanization is expected to occur at a rapid rate; and by 2030, it is estimated that by 2030 more than 60 per cent of Kenyans will be living in cities and towns. Both agricultural expansion and urbanization are likely to cause significant land cover changes and environmental changes in general. However, quantitative estimates of the future land cover changes and associated environmental changes have not been determined. The main objective of study was to determine spatial and temporal land cover changes and predict future land cover changes as a strategy towards monitoring environmental changes within the catchment by integrating a land cover prediction model with remote sensing and geographic information system.

Image analysis and land cover change detection

Land cover patterns of the study area were first mapped using Landsat Thematic Mapper images, with a 30-m ground resolution (path/row: 168/61). The Landsat images were chosen in the period December to February, during which cloud – free images could be obtained in the study area. The images chosen were for the years 1984 (December), 2000 (February) and 2010 (December). The geometrically corrected images were obtained from Regional Centre for Mapping and Development (RCMD). A supervised signature extraction with the maximum likelihood algorithm was employed to classify the Landsat images. Bands 2 (green), 3 (red) and 4 (near infrared) were found to be most effective in discriminating each class and thus used for classification. The classification scheme system by Anderson *et al*. (1976) was used during the image analysis. Five major land cover categories were identified for classification, namely broadleaved evergreen forest, closed and open woody vegetation, rangeland, agricultural land and built-up land. Ground control points obtained from field reconnaissance and land cover map of the area (for the year 2000), obtained from International Laboratory Research Institute (ILRI) were used during interpretation of the satellite images and classification accuracy assessment. Land cover change was computed as a percentage of the total study area while spatial land cover change was done through cross-tabulation/cross-classification method. The accuracy of classification for each image was assessed using a classification error matrix from which the user's and producer's accuracies for each land cover category; kappa index of agreement and overall accuracy were computed according to the procedures described by Lillesand and Kiefer (2000).

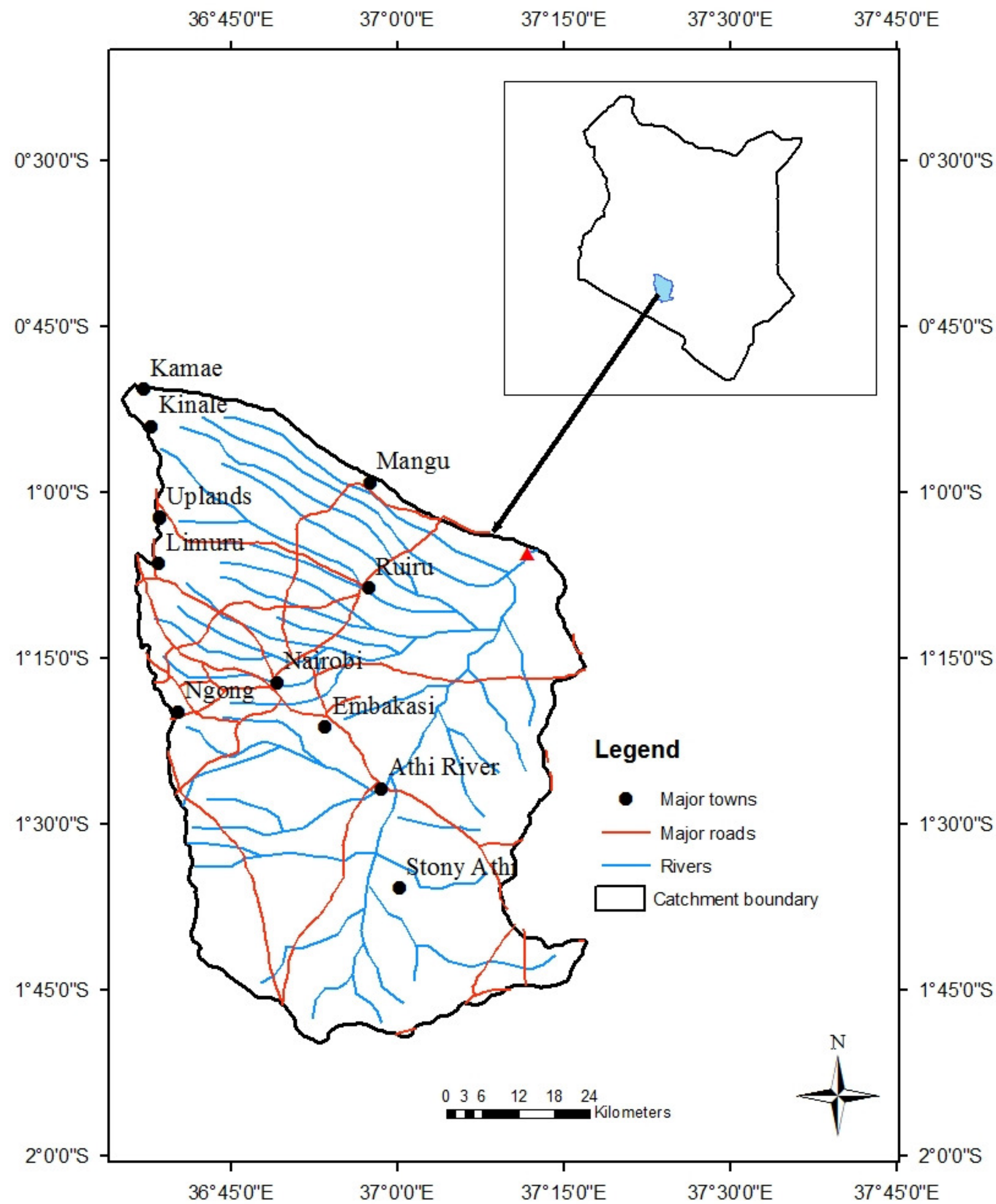

Figure 1: Location of Upper Athi River Catchment, Kenya

Land cover prediction

Land cover predictions were performed using the CA-Markov model. The MARKOV and CA-MARKOV functions available in IDRISI Kilimanjaro software were used to implement the CA-Markov model. The inputs to the model are the earlier image, later image and the number of years of projection in the future with reference to a base year. The earlier and later images provide the trends to be used in projection while the number of years of projection determines the number of iterations.

The first step was to evaluate the accuracy of the CA-Markov model through prediction of land covers of 2010 based on the 1984-2000 land cover trends and 2000 as base year. The predicted land covers of 2010 were then compared to the observed land covers of 2010 as obtained from classification of 2010 Landsat TM image. The accuracy of the CA-Markov model was evaluated using percent error (E) between predicted and observed land cover and the Chi-squared goodness of fit at α =0.01. The percentage error (E) was computed using the formula:

$$E = \frac{(L_{pi} - L_{oi})}{L_{oi}} \times 100 \quad (1)$$

The Chi-square was computed as:

$$\chi^2 = \sum \frac{(L_{oi} - L_{pi})^2}{L_{pi}} \quad (2)$$

Where L_o and L_p are the observed and predicted land cover categories respectively.

The CA-Markov model was then used to predict the land covers of 2030. In the present study, the land cover predictions for 2030 were based on the 1984-2010 land cover trends with 2010 as the base year.

RESULTS AND DISCUSSIONS

Image classification accuracy assessment

The overall accuracies of classification in all the images were greater than 90%, while the overall Kappa Indices of Agreement (KIA) were greater than 0.75 (Table 1), indicating satisfactory accuracy of classification and acceptable level of agreement. The high overall accuracies can be attributed to the good quality ground truth data used during the image classification. The user's and producer's accuracies for each land cover category are presented in Table 1.

Table1: Classification accuracy assessment

Land cover type	1984		2000		2010	
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
Broadleaved evergreen forest	90.34	99.77	96.82	99.77	96.85	93.70
Closed/open woody vegetation	98.56	56.38	95.37	75.87	95.19	41.82
Rangeland	99.62	99.97	98.30	99.93	97.54	98.61
Agricultural land	96.94	49.77	92.16	74.11	78.39	96.18
Built-up land	100.00	77.19	100.00	59.52	95.82	87.22
Overall Accuracy	0.7952		0.7510		0.834	
Kappa Index of Agreement	91.41		92.68		90.01	

PA = Producer's Accuracy, UA= User's Accuracy

In general, the most misclassified land cover categories were agricultural land and closed/open woody vegetation, which were classified as broadleaved evergreen forest. The misclassification led to slightly low user's accuracies of agricultural land and closed/open woody vegetation. The misclassification can be attributed to the almost similar spectral reflectance by broadleaved evergreen forest, agricultural land and closed/open woody vegetation. It could be noted during the interpretation that these land cover categories had a tendency to give similar spectral reflectance and could only be distinguished using the ground truth data. Also, most agricultural land is contiguous with the broadleaved evergreen forest and closed/open woody vegetation categories, leading to the misclassification.

Land cover patterns in Upper Athi catchment

The land cover patterns in Upper Athi River Catchment are presented in Figures 2, 3 and 4 for the years 1984, 2000 and 2010 respectively. It is evident that land cover patterns in the study area are generally controlled by agro-climatic conditions. The broadleaved evergreen forests are concentrated on the highlands in the northwest and southeast. The broadleaved evergreen forest includes the southern slopes of the Abardare Range Forest (indigenous forest) and some plantation forests. The Abardare Range Forest is one of Kenya's major water catchment areas and is the source of Athi River. The agricultural lands are found in high and medium agro-climatic zones, consisting of shrub and herbaceous crops, grown mainly under rain-fed conditions. In the highland, agricultural lands are at the periphery of the forests. The closed/open woody vegetation consists of closed herbaceous forests and open forests. These are found mainly in medium potential areas and in small amounts in highlands. The rangelands are found in medium and low potential areas of the basin, comprising of closed shrubs, open shrubs, shrub savannah and tree savannah. It is dominated by wildlife, cattle grazing and some industrial and agricultural activities. Built-up land category includes towns, urban and rural settlements spread in all parts of the study area. It is evident that most of the growth of built-up land is near existing towns and along main roads. For example, Nairobi City has been expanding while towns such as Athi River have grown along the Nairobi-Mombasa Road.

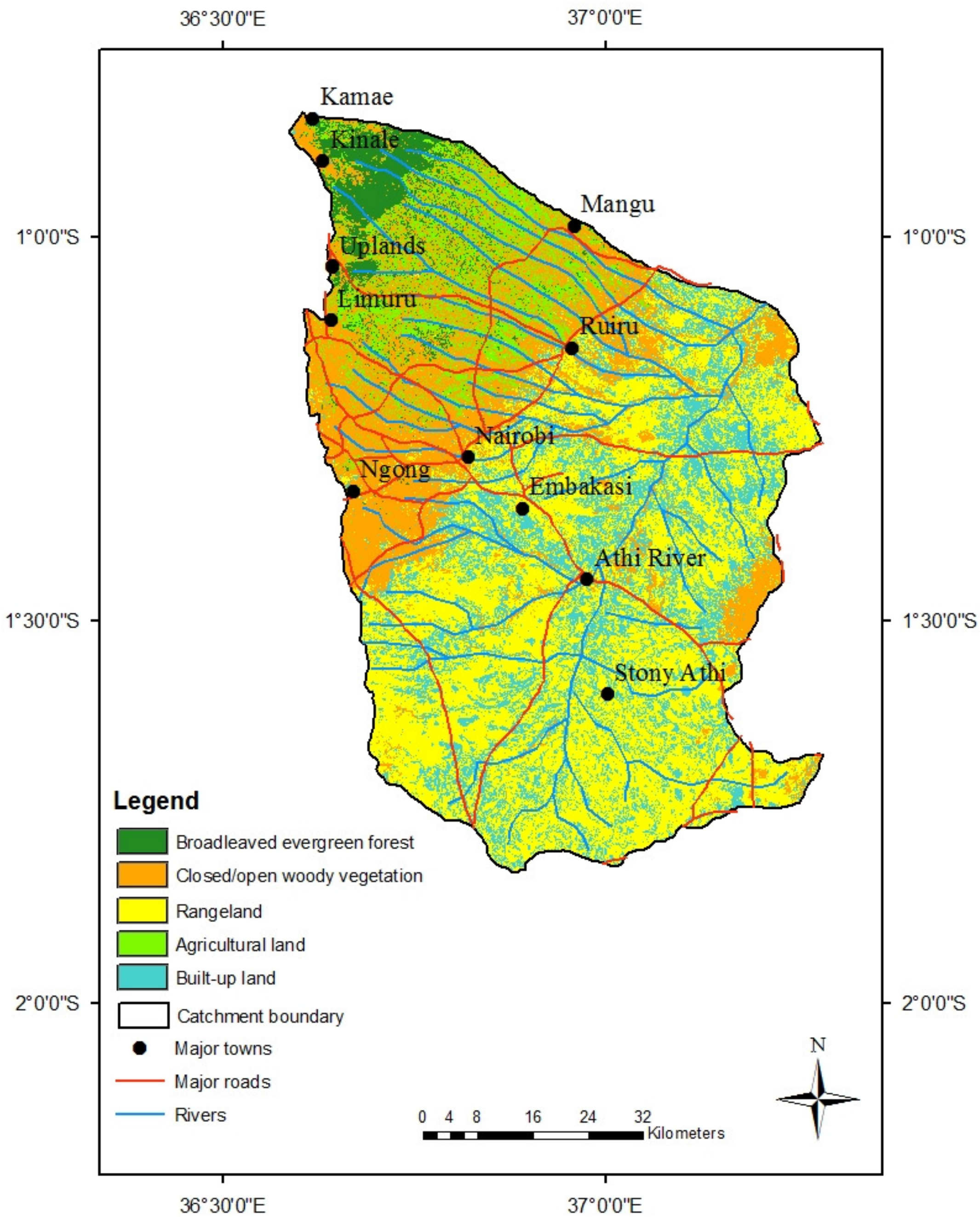

Fig. 2: Land cover types as derived from Landsat TM image of 1984.

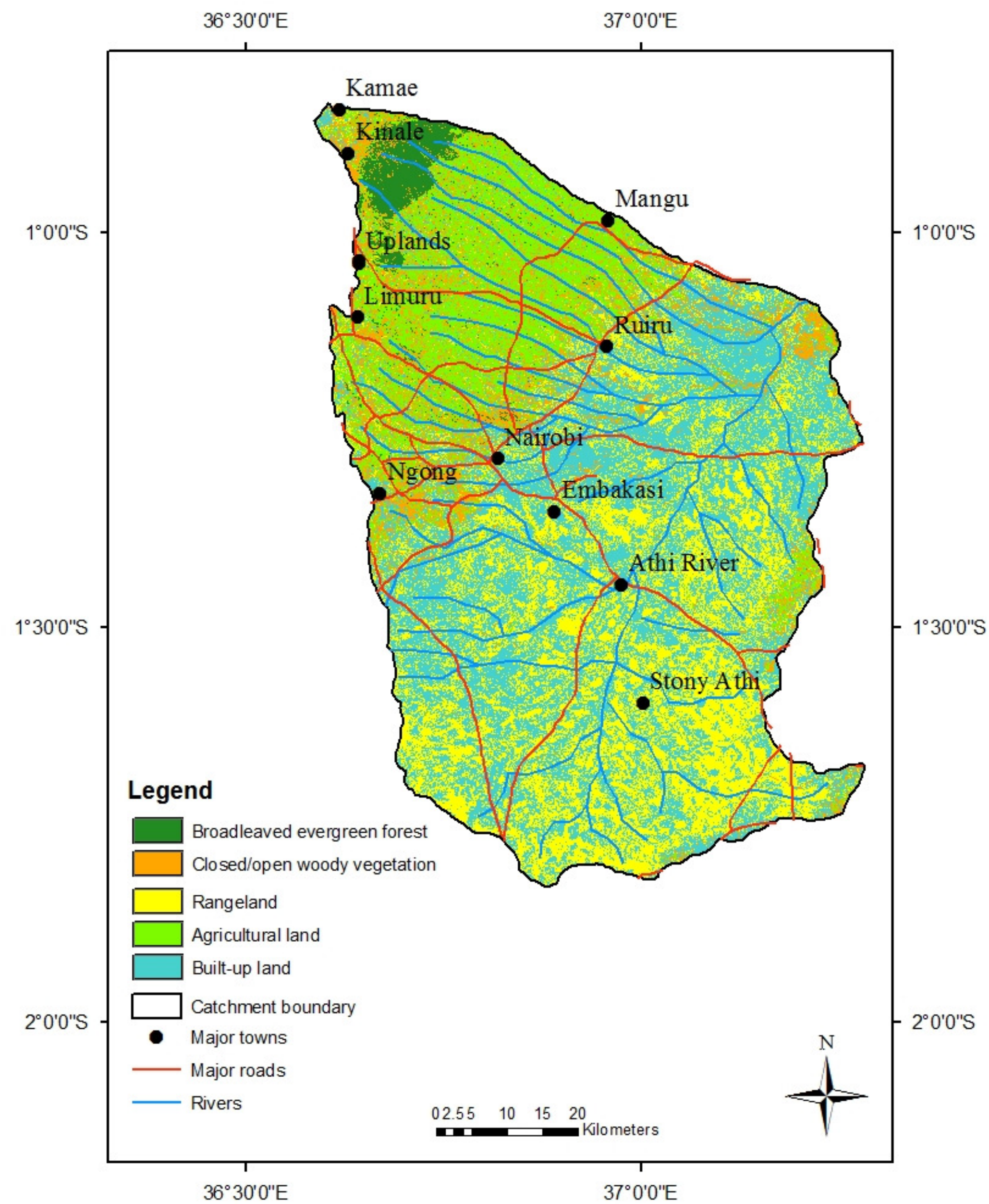

Fig. 3: Land cover types as derived from Landsat TM image of 2000.

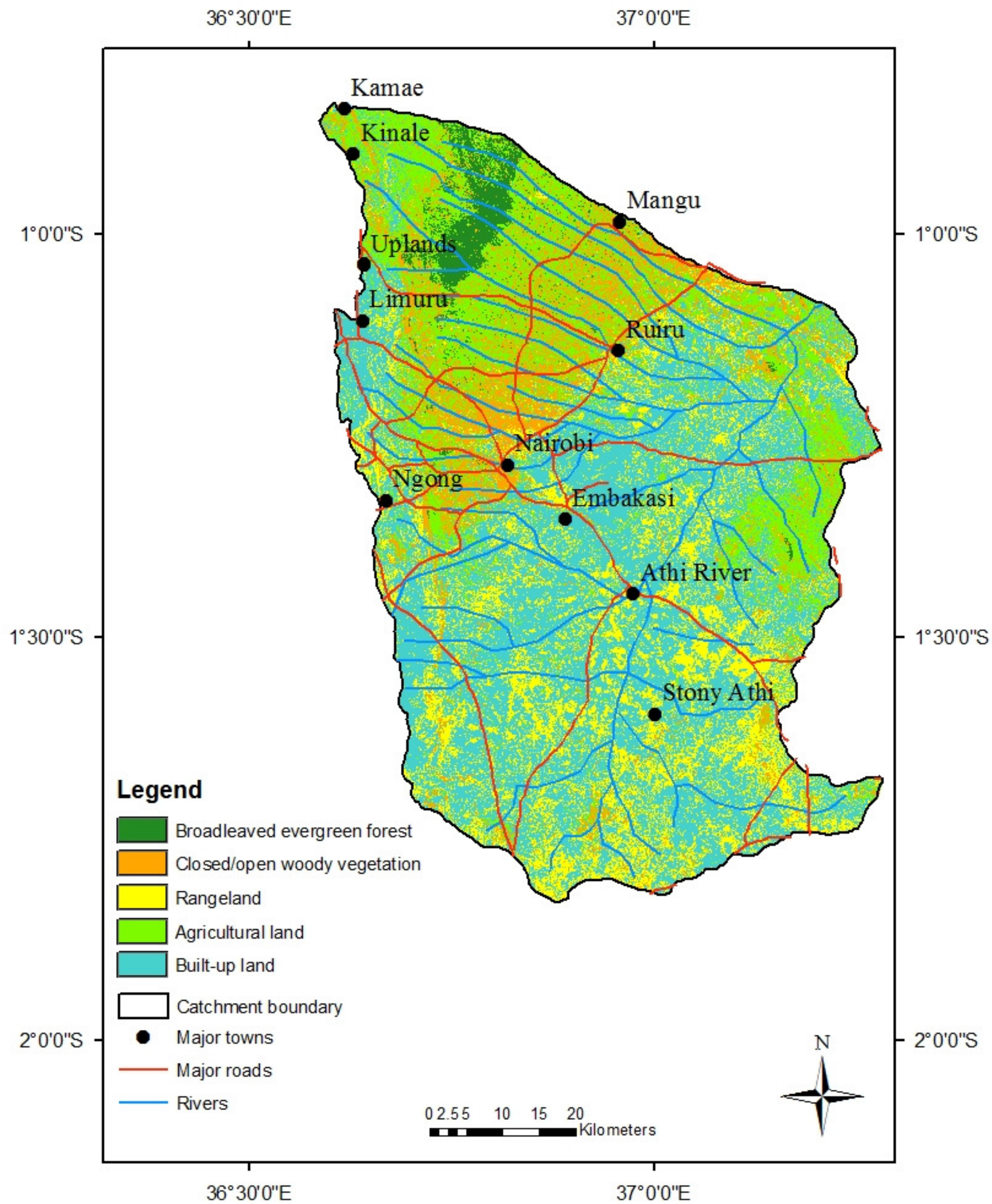

Fig. 4: Land cover types as derived from Landsat TM image of 2010.

Spatial and temporal land cover changes

Table 2 shows the land covers in 1984, 2000 and 2010, while Table 3 shows the cross-classification matrix between land covers of 1984 and 2010.

Table 2: Land cover in 1984, 2000 and 2010

Land cover type	1984		2000		2010		% Change 1984-2010
	Area (km^2)	%	Area (km^2)	%	Area (km^2)	%	
Broadleaved evergreen forest	260.5	4.57	151.3	2.65	117.0	2.05	-2.05
Closed/open woody vegetation	1439.6	25.27	893.94	15.69	871.10	15.29	-9.98
Rangeland	2323.50	40.78	1485.91	26.08	1190.90	20.90	-19.88
Agricultural land	489.6	8.59	949.6	16.67	983.90	17.27	8.67
Built-up land	1184.3	20.78	2216.9	38.91	2534.60	44.48	23.70
Total	5697.5	100.0	5697.5	100.0	5697.5	100.0	

It can be noted that agricultural land increased from 489.6 km^2 (8.59%) in 1984 to 983.90 km^2 (17.27%) in 2010, while built-up land increased from 1184.30 km^2 (20.78%) in 1984 to 2534.60 km^2 (44.48%) in 2010 (Table 2). In the entire period, the agricultural land and built-up land increased by 494.20 km^2 and 1350.30 km^2, representing an increase of 8.67% and 23.70% respectively. On the other hand, broadleaved evergreen forest, rangeland and closed/open woody vegetation decreased between 1984 and 2010. The broadleaved evergreen forest decreased from 260.50 km^2 (4.57%) to 117.00 km^2 (2.05%). The rangelands decreased from 2323.50 km^2 (40.78%) to 1190.90 km^2 (20.90%), while closed/open woody vegetation decreased from 1439.60 km^2 (25.27%) to 871.10 km^2 (15.29%). Overall, the broadleaved evergreen forest, closed/open woody vegetation and rangeland decreased by 143.50, 568.50 and 1132.60 km^2, representing a decrease of 2.52%, 9.98 and 19.88% respectively. The small decrease in broadleaved evergreen forest could be attributed to protection by Kenya Forest Service, since this category of land cover includes part of the Abardare forest, which is a gazetted forest. The decrease of broadleaved evergreen forest agrees with the findings of Lambretchts et al. (2003) who discovered that the Abardare Range Forests were undergoing destruction and degradation due to large-scale uncontrolled and illegal human activities.

Table 3: Cross-classification matrix between land covers of 1984 and 2010 (km^2)

		1984					
		BEF	COV	RL	AL	BL	**Total Area**
2010	BEF	104.47	8.02	0.00	4.51	0.00	117.0
	COV.	57.83	498.09	218.61	96.57	0.00	871.1
	RL	6.49	170.41	991.21	22.79	0.00	1190.9
	AL	83.57	553.91	11.51	334.91	0.00	983.9
	BL	8.14	209.17	1102.17	30.82	1184.30	2534.60
	Total Area	260.50	1439.60	2323.50	489.60	1184.30	5697.50

Where: COV = closed/open woody vegetation; BEF = broadleaved evergreen forest; AL = agricultural land; BL = built-up land; and RL= rangeland.

The cross-classification matrix (Table 3) shows the magnitude of land cover conversions/transitions in terms of areas (km^2). It can be noted that the major land cover transitions between 1984 and 2010 involved conversion of rangeland to built-up land (1102.17 km^2) and closed/open woody vegetation to agricultural land (553.91 km^2). The cross-classification matrix also showed the areas of land cover classes which did not change. These were 104.47 km^2, 498.09 km^2, 991.21 km^2, 334.91 km^2 and 1184.30 km^2 for broadleaved evergreen forest, closed/open woody vegetation, rangelands, agricultural land and built-up land respectively. Based on the major land cover transitions in the 1984-2010 period, it can be inferred that the study area has been experiencing loss of biodiversity and environmental changes in general as the broadleaved evergreen forest and closed/open woody vegetation are converted to agricultural land and rangeland is converted to built-up land respectively.

CA-Markov model evaluation

The percent error (E) and Chi-squared goodness –of – fit test were used to evaluate the CA-Markov model by comparing predicted and observed land covers of 2010. Table 4 shows the predicted and observed land covers of 2010.

Table 4: Comparison of predicted and observed land covers of 2010.

Land cover Class	observed land cover (km^2)	Predicted land cover (km^2)	Absolute Error (%)	Chi -squared
Broadleaved evergreen forest	117.00	123.50	5.56	0.34
Closed/open woody vegetation	871.10	968.70	11.20	9.80
Rangeland	1190.90	1154.64	3.04	1.14
Agricultural land	983.90	960.94	2.33	0.55
Built-up land	2534.60	2489.72	1.77	0.80
Total	5697.5	5697.5		12.63

It can be noted from Table 4 that the percent errors were less than 10% except the closed/open woody vegetation (11.20%), meaning satisfactory performance of the CA-Markov model overall in the present study. The calculated Chi-squared value was 12.63 while the critical value at α =0.01 was 13.30, meaning the hypothesis of no significant differences between predicted and observed land covers was acceptable. Falahaktar *et al.* (2011) also evaluated CA-Markov model using the Chi-squared goodness-of-fit test and a coefficient of agreement. The authors did not find significant difference between observed and predicted land covers areas. In the present study, the CA-Markov model was found suitable and hence used to predict land covers of 2030.

Prediction of land covers of 2030

The probability transition matrix based on 1984 - 2010 trends for prediction of land covers of 2030 is shown in Table 5, while Table 6 shows the predicted land covers of 2030. Figure 5 is a map showing the distribution of predicted land covers in 2030.

Table 5: Probability transition matrix for prediction of land covers in 2030.

		2030				
		BEF	COV	RL	AL	BL
2010	BEF	0.5003	0.0653	0.0798	0.3464	0.0082
	COV	0.0589	0.0516	0.0524	0.6326	0.2045
	RL	0.0206	0.0239	0.3263	0.1900	0.4392
	AL	0.0919	0.0582	0.0273	0.6432	0.1794
	BL	0.0060	0.0120	0.2309	0.2248	0.5263

The probability transition matrix (Table 5) shows the probabilities of each land cover in 2010 changing to other land covers in 2030. It can be noted from Table 4 that the probability of rangeland changing to broadleaved evergreen forest was small (0.0206). This can be explained by the fact that rangeland and broadleaved evergreen forest are found in different agro-ecological zones. On the other hand, the closed/open woody vegetation showed a high probability of changing to agricultural land (0.6326) because they belong to same agro-ecological zone. The agricultural and built-up lands showed high probabilities of not changing to other land covers (0.6432 and 0.5263 respectively). This can be attributed to the permanency nature of built-up land and the perennial crops grown in the study area. The rangeland showed a moderate probability of changing to built-up land (0.4392). This is likely to occur due to the expansion of the existing urban centres, including the Nairobi City and growth of new urban centres as the Kenya Vision 2030 is implemented.

The results also demonstrated that land cover transitions follow the cellular automata proximity rule, which states that land cover changes occur proximate to existing similar land cover classes , and not wholly random . For example, there was high probability of transition from closed/open woody vegetation to agricultural land but small probability of transition from broadleaved evergreen forest to rangeland. In the present study, the agro-ecological zones determined the type of land cover transitions.

Table 6: Predicted land covers of 2030

Land cover category	Area (km^2)	Area (%)	% Change (2030-2010)
Broadleaved evergreen forest	104.28	1.83	-0.22
Closed/open woody vegetation	494.02	8.67	-6.62
Rangeland	825.00	14.48	-6.42
Agricultural land	1303.50	22.88	5.61
Built-up land	2970.70	52.14	7.66
Total	5697.50	100	

It can be noted from Table 6 that built-up land and agricultural land were predicted to increase by 7.66% and 5.61% respectively between 2010 and 2030. On the other hand, rangeland closed/open woody vegetation and broadleaved evergreen forest would decrease by 6.42%, 6.62% and 0.22% respectively in the same period. It should be noted that the predicted land cover trends (2010-2030) resembled those in the period 1984-2010, in which agricultural and built-up lands increased while rangeland, closed/open woody vegetation and broadleaved evergreen forest decreased. The prediction results were in agreement with the major goals of Kenya Vision 2030 of achieving agricultural expansion and urbanization by 2030. However, land cover and environmental changes were expected to occur in the same period. For example, the decrease of the broadleaved evergreen forest, which includes the southern slopes of the Abardare Range Forests, would imply loss of biodiversity and degradation of water catchment areas for the main Athi River and its tributaries. This is because the southern slopes of the Abardare Range Forests are the main catchment areas of the Athi River. The expansion of built-up land at the expense of rangeland is equivalent to loss of biodiversity and destruction of wildlife habitat which could lead to human-wildlife conflicts. This is because the rangeland which includes part of Nairobi National Park is habitat for wildlife. The agricultural expansion at the expense of closed/open woody vegetation could lead to increased rates of soil erosion and pollution resulting from the application of agrochemicals. Based on the results of the study, it could be concluded that significant land cover changes and environmental changes were expected to occur between 2010 and 2030. Therefore, the hypothesis that implementation of Kenya Vision 2030 development strategy would lead to major land cover and environmental changes was accepted in the study. The results of the study can be used by land use planners and environmental managers to develop mitigation measures for sustainable land development in Upper Athi River Catchment. For example, the general increase in built-up and agricultural lands will be accompanied by land cover changes and environmental pollution which require mitigation measures to prevent undesirable effects.

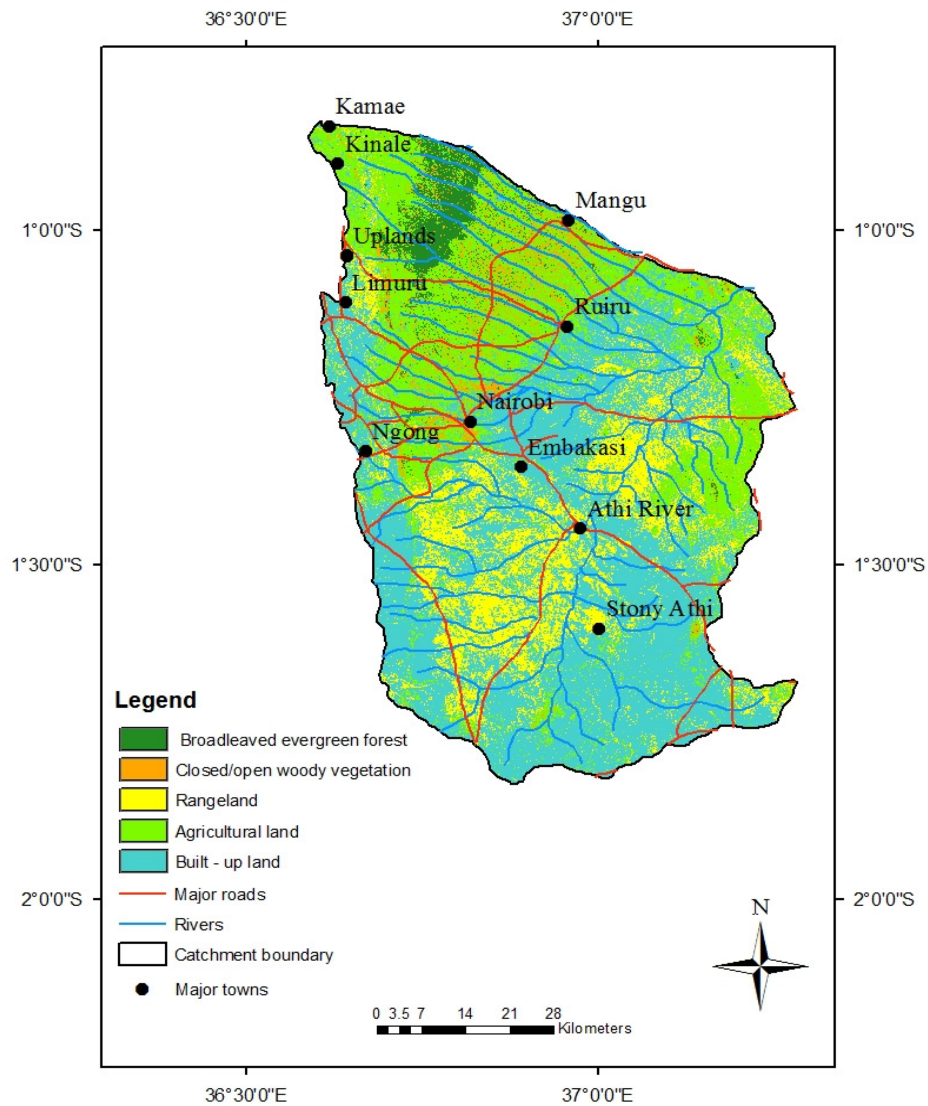

Figure 5: Predicted land cover types of Upper Athi River Catchment in 2030

CONCLUSIONS AND RECOMMENDATIONS

The study was guided by the hypothesis that implementation of Kenya Vision 2030 development strategy would lead to major land cover and environmental changes if future land cover trends (2010-2030) would resemble recent land cover trends (1984-2010) in the study area. Both spatial and temporal land cover changes were observed between 1984 and 2010, with general increase in built-up and agricultural lands; and decrease in closed/open woody vegetation, broadleaved evergreen forest and rangeland. The major land cover transitions were changes from closed/open woody vegetation to agricultural land and rangeland to built-up land. Land cover prediction between 2010 and 2030 revealed that built-up land and agricultural land would increase, while rangeland; closed/open woody vegetation and broadleaved evergreen forest would decrease. This led to the conclusion that the land cover trends in periods 1984-2010 and 2010-2030 were similar. The results of prediction agreed with the major goals of Kenya Vision 2030 of agricultural expansion and urbanization by 2030, implying that the CA-Markov model predictions were realistic and could be relied upon for decision support on land development. Based on the results of the study, it was concluded that agricultural expansion and urbanization will be the main causes land cover and environmental changes within the catchment by 2030 and that mitigation measures were required to avoid undesirable effects; which supported the hypothesis of the study. The study recommends detailed land cover change analysis using high resolution images to identify critical areas for rehabilitation and development of strong environmental laws so as to ensure sustainable land development.

ACKNOWLEDGEMENTS

We wish to acknowledge Regional Centre for Mapping and Development for providing the images used in the study and University of Eldoret for providing office facilities.

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