Assessing Spatio-Temporal Land Cover Changes Within the Nyando River Basin of Kenya Using Landsat Satellite Data Aided by Community Based Mapping – A Case Study

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Abstract

Spatio-temporal land cover changes witnessed within the Nyando River Basin of Kenya were assessed in this study. The land cover changes were mapped by classifying the predominant land cover classes on selected Landsat satellite images. The accuracy of the classifications were assessed using reference datasets developed and processed in a GIS with the help ground based information obtained through participatory community based mapping techniques. The results of the analysis indicated significant deforestation in the headwaters of the basin. Obviously apparent from the land cover conversion matrices was that the majority of the forest decline was a consequence of agricultural expansion. Despite the haphazard land use patterns and uncertainties related to poor data quality for environmental change assessment, the study successfully exposed the vast degradation and hence the dire need for both sustainable landuse planning and catchment management strategies.

1 Introduction

Land cover changes due to anthropogenic interventions remain a major environmental challenge in most river basins in Kenya. One of the basins that epitomize this degradation is the Nyando River Basin. With its headwaters located within the vulnerable Mau Forest currently being threatened by depletion, such changes have led to amplified flood flows during storm events and reduced stream flows during low flows (OLANG & FÜRST 2010). It is hence imperative that such changes are monitored and their sociological, economic and ecological consequences accurately quantified in order to gain valuable information important for management and future restoration efforts (BALDYGA et al. 2007). A common way to map land cover changes is through satellite image classifications. However, satellite classifications require validations through accuracy assessments using historical datasets; a factor which further hinders their applications in areas with limited data. The Nyando Basin lacks consistent and detailed land cover databases. The few existing datasets are generalized maps with inadequate thematic and statistical information essential for authentication purposes (CONGALTON & GREEN 1999).

Furthermore, the existence of amorphous land use patterns and hence lack of a clear definition between areas that intermittently vary between pasture, small scale subsistence agriculture and settlements further complicates accurate monitoring of the changes using satellite images. Previous studies have also shown that spectral signatures acquired from satellite imagery for regions within the tropics display minimal band separabilities amongst the various vegetation types (TATEM et al. 2005, TOTTRUP 2004). With these constraints, it is inevitable to apply an integrated approach that exploits every source of information available to detect and support the classification process. In this contribution, a participatory procedure that integrates rigorous community based information with the commonly used scientific tools involving GIS and RS applications were used to discern historical land cover changes (FÜRST 2004, PELLIKKA et al. 2009). Such a procedure, commonly known as community based GIS, is gaining popularity in most regions in Kenya not only due to data scarcity but also because of the fact that the riparian communities understand and do have some vital information about the environmental changes taking place within their immediate surroundings (RAMBALDI et al. 2007).

2 Study Area

The Nyando basin is located in western Kenya between 0° 25′ S – 0°10′ N and 34° 50′E – 35° 50′ E. It covers an area of about 3550 km^2 within the scarps of the Kavirondo Gulf. The basin is drained by River Nyando with its major tributaries originating from the upland Nandi and Mau Hills. The river drains into the transboundary Lake Victoria at altitudes of about 1300 m *a.m.s.l.* The climate of the basin is largely influenced by the Equatorial Convergence Zone modified by local orographic effects. The land cover types vary principally from forests in the uplands to mixed-type subsistent agriculture in the mid to lowland parts. The human population in the basin currently stands at about 0.8 million and is largely responsible for the majority of the land cover dynamics (Figure 1).

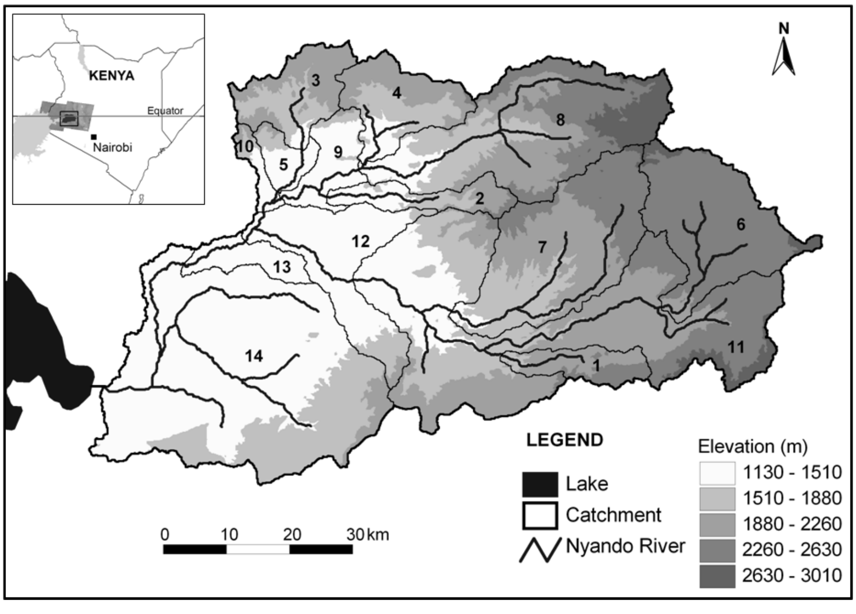

Fig. 1: The study area showing the sub catchments of the basin

3 Datasets

The global Shuttle Radar Topographic Mission (SRTM) digital elevation model (approximately 90m) was processed and used to derive the sub-catchments and their relevant geophysical characteristics. Seven major land cover classes including agriculture, grasslands, forests, wetlands, tea/coffee, shrublands and water were selected for mapping. These classes were selected based on their hydrological significance to allow for subsequent estimation of the effects of the detected land cover change on the hydrological response of the regions. Six Landsat images, two for each year, were acquired for the periods between 1973 and 2000 (Table 1).

Table 1: Characteristics of the selected Landsat images

Date	Landsat sensor	Path/Row	Approx. spatial resolution (m)
27th Jan. 2000	ETM+	169/60	30
05th Feb. 2001	ETM+	170/60	30
28th Jan. 1986	TM	169/60	30
08th Mar. 1986	TM	170/60	30
01st Feb. 1973	MSS	182/60	80
31st Jan. 1973	MSS	181/60	80

The acquired images were already orthorectified and topographically normalized (KUNDU et al. 2008). The images were resampled using the nearest neighbor technique to a common resolution of about 80 m (JENSEN 2005). Ancillary land cover datasets to support the image classifications were also obtained from various sources including the FAO-Africover data available at scale of 1:100000. This database provides good quality geo-referenced land cover data represented by unique attributes based on the FAO/UNEP land cover classification system. The dataset was acquired as vector coverage for Kenya and later processed in conformity with the study demands.

A vectorized land cover dataset for 1987 at a scale of about 1:5M was also obtained from the Ministry of Natural Resources, Kenya. Twelve topographic maps for 1972 at a scale of 1:50000 were also acquired for supporting the image classifications. The maps were digitally processed and geo-referenced based on the third order polynomial transformation (TOA & HU 2001). A general land cover map representing the visible land uses was subsequently delineated from the maps. In overall, the ancillary dataset for 1973 and 1986 did not provide sufficient thematic and statistical detail required for comprehensive authentication purposes. Nonetheless, the datasets were equally important for plausibility checks, understanding the general classification trends and for supporting the adopted proposed community based approach.

4 Methodology

Considering the quality of the available data, the procedure called guided clustering was used to discern the changes (YUAN et al. 2005). This procedure is normally favorable for complex ecological regimes of diverse composition. In principle, guided clustering encompasses the application of unsupervised and supervised classification approaches. In this study, the unsupervised technique was used strictly to identify appropriate clusters to be used as signatures in the subsequent supervised classification process (JENSEN 2005). Due to its relative good data quality of the Africover reference dataset, the study also opted for developing a consistent classification procedure that could be replicated for the other periods.

The Iterative Self-Organizing Data Analysis Technique (ISODATA) unsupervised technique was used to generate about 30 clusters. The generated clusters were carefully identified and labeled, where possible, with the help of the reference datasets. Selected regions with dependable but unidentifiable clusters were highlighted and delineated for auxiliary verification purposes. This was achieved through a comprehensive community based GIS mapping performed through participatory interactions and discussions with the local communities about the historical land cover states of the delineated polygons (RAMBALDI et al. 2007). This rigorous procedure facilitated identification and labeling of selected highlighted areas of uncertainties.

The labeled polygons were compared and carefully evaluated, especially within regions of similar spectral characteristics, and later used as signatures for the supervised classification. The optimal bands for the classification were identified using the statistical transformed divergence technique (ERDAS 2002) due to the amorphous and random land cover patterns in the basin. To discriminate and reproduce the land cover patterns of the area, different classifiers, non-parametric and the parametric, were examined. A 3×3 majority filter was then applied to the classified maps to isolate small pixels arising from the classification, and the individual classified maps mosaicked and clipped to the study area. This approach was preferred to minimize spectral distortions associated with mosaicking multi-date images before classification.

The classification accuracies were later assessed through error matrices developed using auxiliary points generated through stratified random sampling technique. The total numbers of sampling points were established using the Binomial theory, with 5% allowable error being assumed. The expected accuracy of the change maps was also estimated based on a procedure that involved multiplying the individual image classifications accuracy. The procedure is generally based on the premise that when two change maps are overlaid, an accumulation of the overall error occurs leading to the reduction of the estimated accuracy by a factor equal to the product of the individual accuracies (YUAN et al. 2005).

5 Results and Discussion

Generally, the community based approach of identifying and labeling training sites through ground truthing proved sufficient and reliable in assessing the historical land cover states. The best reproducibility of the land cover patterns of the basin was obtained when the maximum-likelihood classifier was used with *a priori* probability weights of cover classes approximated from the reference dataset. Forest and water land cover classes indicated the highest average separability. Grassland and agriculture on the other hand showed the lowest average separability due to their random occurrence and close spectral characteristics. Since, the reference dataset for the year 2000 was the most reliable; it was consequently used to test the accuracy of the classification procedure adopted. Results obtained from the error matrices revealed overall classification accuracy and *Kappa* index of about 84% and 80% respectively. More specifically, higher producers and users accuracies were noted between forests, wetlands and water land cover classes (Table 2).

Table 2: Statistics of the detected land cover changes in the basin

Land cover	**Classified maps**						**Relative change (%)**		
	1973		**1986**		**2000**				
	(km^2)	(%)	(km^2)	(%)	(km^2)	(%)	(73-86)	(86-00)	(73-00)
Agriculture	1564.3	44.1	1432.2	40.4	2002.8	56.5	-4	16	12
Grassland	433.4	12.2	999.0	28.2	617.9	17.4	16	-10	5
Forest	1238.5	35.0	750.6	21.2	514.3	14.5	-14	-7	-20
Shrublands	83.7	2.4	159.4	4.5	234.8	6.6	2	2	4
Wetland	69.2	2.0	118.4	3.3	62.0	1.8	1	-2	0
Tea/coffee	151.4	4.2	80.8	2.3	109.3	3.1	-1	1	-1
Water	2.9	0.1	3.1	0.1	3.0	0.1	0	0	0

During the period of 1973-2000, shrublands increased by 4% representing an area of about 151 km^2. This increase was more prevalent in previously forests regions signifying gradual degeneration through selective logging and re-growths. Agricultural lands expanded by 12% over the same period of time, with the highest increase being observed between 1986 and 2000, due to the seasonal conversions between grasslands and agricultural land cover classes. Between 1973 and 2000, the basin was noted to have observed an upsurge of more than 40% in its human population. This population increase could have exerted sufficient economic pressure on the resources within the vicinity. The land cover conversion matrix for 1973-2000 obtained when the classified images were compared across the years is presented in Table 3.

Table 3: Transition matrices of the land covers in km^2 for 1973-2000

2000 [To]	**1973[From]**							**Total [2000]**
	Agriculture	**Grassland**	**Forest**	**Shrubland**	**Wetland**	**Tea/coffee**	**Water**	
Agriculture	1136.5	305.3	385.4	66.5	53.3	55.0	0.8	2002.8
Grassland	335.1	101.7	111.7	13.3	11.3	44.4	0.5	617.9
Forest	13.0	5.0	490.9	0.5	0.8	4.0	0.1	514.3
Shrublands	48.0	10.5	170.8	1.2	1.0	3.2	0.0	234.8
Wetland	11.9	3.2	41.9	1.9	1.8	1.2	0.1	61.9
Tea/coffee	19.4	7.6	37.4	0.4	0.8	43.6	0.0	109.3
Water	0.6	0.1	0.5	0.0	0.2	0.0	1.5	3.0
Total [1973]	1564.5	433.4	1238.6	83.7	69.2	151.4	2.9	3543.8

With this order of priority, it was noted that the majority of the land cover conversions largely resulted into agricultural expansion. About 305 km^2 of grassland area was converted into agriculture between 1973 and 2000. However, about 13 km^2 of agricultural lands and 5 km^2 of grasslands were converted back to forest in the periods of 1973 – 2000. Considering the rapid population increase demanding more land for subsistence agriculture, the conversion of other land covers back to forests may seem unfeasible. However, from our field surveys, a time span of at least 10 years (between the images selected) is sufficiently long enough to accommodate such magnitude of changes. Tree stands that act as wind breakers for the normally fragile tea crops for instance, are occasionally planted and harvested within the uplands and central parts of the basin. It is also a norm for the riparian communities to plant trees for timber and domestic construction purposes, wherever necessary. Nevertheless, it is also acknowledged that classification or data errors could have possibly led to some fluctuation of the results.

Land cover changes within the sub-catchments of the basin were also evaluated. For instance, in sub-catchment no. 14 located in the downstream of the basin, about 228 km^2 was converted into agriculture. And about 98 km^2 of the previously existing forests in 1973 were completely diminished by the year 2000. The area also witnessed significant decline in the wetlands by a margin of about 25 km^2 within the three decades. From the land cover changes; this sub catchment characterizes an area which has been fully converted into an agricultural sub basin. In sub-catchment no. 6 located in the upstream region, deforestation was noted to have affected an area of about 106 km^2. Agriculture and shrublands on the other hand increased by 69 km^2 and 29 km^2 respectively, with the majority of the changes occurring between 1973 and 1986. This sub-catchment exemplifies a forested region which is slowly being converted into a more or less agricultural sub catchment (Figure 2).

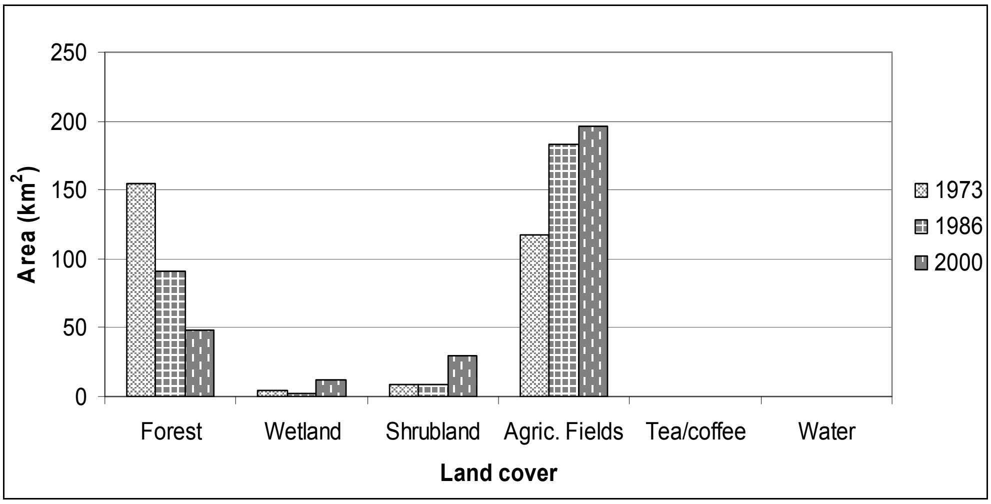

Fig. 2: Land cover changes in sub-catchment No. 6

6 Conclusion and Recommendation

Spatio-temporal changes in the historical land cover states were investigated in this study. The classification results indicated that the basin underwent vast land cover changes over the periods. Apparently clear was the decline in forest coverage with an almost equivalent increase in the agricultural areas. The land cover change results obtained generally depicted similar trends to other studies carried out Kenya. In summary, the study demonstrated the possibility of using multi-temporal Landsat satellite images as a cost effective way of mapping land cover changes. The community based mapping approach used to augment this exercise provided an efficient way to reveal the historical land cover states and trends. Though rigorous in time and cost, such an approach can be used to construct missing information sufficient for mapping of land cover changes in data scarce areas. However, further studies to include other land cover types in future mapping activities are recommended. Such an endeavor will enable extended analysis of the land cover change effects on agricultural and hydrological regimes amongst others. Generally, the agriculture land cover class selected in this study was noted to exhibit immense diversity in terms of their biophysical characteristics. It is hence imperative in future studies to carefully discern these types and assess their spatio-temporal influences on seasonal basis. To achieve this, however, a fully distributed approach involving the application of high resolution spatial datasets may be important.

References

BALDYGA, T. J., MILLER, N. S., DRIESSE, L. K. & GICHABA, N. C. (2007), Assessing land cover change in Kenya's Mau Forest region using remotely sensed data. African Journal of Ecology, 46, pp. 46-54.

CONGALTON, R. G. & GREEN, K. (1999), Assessing the Accuracy of Remotely Sensed Data. CRC Press, Boca Raton, FL, USA.

ERDAS (2002), ERDAS field guide. ERDAS Inc., 6th edition, Atlanta7, USA.

FÜRST, J. (2004), GIS in Hydrologie und Wasserwirtschaft. Herbert Wichmann Verlag, Heidelberg, Germany.

JENSEN, J. R. (2005), Introductory Digital Image processing: A Remote Sensing Perspective, 3rd Edition. Prentice-Hall, Upper Saddle River, NJ, USA.

KUNDU, P. M., CHEMELIL, M. C., ONYANDO, J. O., GICHABA, M. (2008), The use of GIS and remote sensing to evaluate the impact of land cover and land use change on discharges in the River Njoro Watershed, Kenya, Journal of World Association on Soil Water Conservation, J2, pp. 109-120.

OLANG, L. O. & FÜRST, J. (2010), Effects of land cover change on runoff peak discharges and volumes during flood events of the Nyando basin, Kenya. Hydrological Processes (In review).

PELLIKKA, P. K. E., LÖTJÖNEN, M., SILJANDER, M. & LENS, L. (2009), Airborne remote sensing of spatiotemporal change (1955-2004) in indigenous and exotic forest cover in the Taita Hills, Kenya. International Journal of Applied Earth Observations and Geoinformation, 11 (4), pp. 221-232.

RAMBALDI, G., MUCHEMI, J., CRAWHALL, N. & MONACO, L. (2007), Through the Eyes of Hunter-Gatherer: Participatory 3D modelling among Ogiek indigenous peoples in Kenya. Information Development, 23 (2-3), pp. 113-128.

TATEM, A. J., NOOR, A. M. & HAY, S. I. (2005), Assessing the accuracy of satellite derived global and national urban maps in Kenya. Remote Sensing of Environment, 96, pp. 87-97.

TOA, C. V. & HU, Y. (2001), A comprehensive study of the Rational Function Model for photogrammetric processing. Photogrammetric Engineering & Remote Sensing, 67 (12), pp. 1347-1357.

TOTTRUP, C. (2004), Improving tropical forest mapping using multi-date Landsat TM data and pre-classification smoothing. International Journal of Remote Sensing, 25, pp. 717-730.

YUAN, F., SAWAYA, K. E., LOEFFELHOLZ, B. C. & BAUER, M. E. (2005), Land cover classification and change analysis of the twin cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. Journal of Remote Sensing and Environment, 98, pp. 17-328.