LAND USE CHANGES ACROSS RIVER NANYUKI CATCHMENT, KENYA USING CLASLITE AND ENVI

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ABSTRACT

Land use change is a significant factor in environmental conservation and climate change which may be positive or negative depending on how it occurs. The study aimed at examining the land use changes that took place across River Nanyuki catchment from 1984 to 2010. Landsat images of the area were downloaded from USGS database and processed using CLASlite, a forest monitoring application developed by Carnegie Institute for Science (CIS) and ENVI software for land use classification and change detection. Four predominant land use classes were considered, namely forest, agriculture, uncultivated area, and water. Over the study period, the area was observed to have experienced different modifications, most notable being deforestation in the upper part of the catchment where Mount Kenya Forest extended with an overall accuracy of 80%. Most of the deforestation was understood to have taken place in the 1980s and 1990s with 2.5% forest depletion between 1984 and 1995.

KEYWORDS – Conservation, Deforestation, Land use change, Logging, CLASlite

I. INTRODUCTION

Land use change is arguably the most pervasive socioeconomic force driving changes and degradation of ecosystems. Urban development, agriculture, deforestation and other human activities have significantly altered the Earth's landscape. Such disturbance of the land affects important ecosystem services, which can subsequently have wide ranging and long term consequences [1]. Incremental land use changes are continuing over time and these change patterns play important role in climate change mitigation and adaptation [2]. There are, at anytime, new developments such as pivot irrigation, new areas planted to crop and plantations [3, 4]. Land use change mentoring is widely recognized as a useful scientific tool [5], which plays role on making decisions on land allocation, carbon budgeting, and infrastructural development among others. It is also valuable for study of various aspects of an environmental system, such as energy balance, biogeochemical cycles, climate systems and hydrological cycles [6, 7].

Forests and various agricultural practices play a very important role in climate change mitigation and conservation of biodiversity and therefore require proper management [8, 9]. Forests are considered to be a significant sink for carbon and its destruction substantially alters earth's vegetative cover, thereby, reducing its carbon capture ability [1]. Destruction of natural forests is considered to be a major source of carbon dioxide emissions and leading factor in biodiversity loss [10, 11]. According to a research by Union of Concerned Scientists, agricultural practices that use crop rotations and green and animal manure have shown higher biodiversity by foregoing chemical pesticides, reducing nitrogen pollution and supplying more diverse habitats [12]. Integrating livestock and crops, employment of perennial pastures, and adoption of many of the practices used in organic production (e.g., long crop rotations, leguminous and cover crops, use of manure from livestock as fertilizer)

have also shown potential for improved greenhouse gas balance, higher profitability and pollution reduction.

The different land use changes can undoubtedly not be ranked equally on how they affect energy balance in an ecosystem. Converting a forest to cropland for biofuel production can result in much more global warming pollution than the amount that can be reduced by the biofuel plants grown on that land [8, 12]. There is great deal of unintended green house gas emission due to expansion of crop lands for biofuel production [13]. Intensive farming, which continues to increase, has resulted in fragmentation and loss of natural habitats and species living in them [14]. However, such anomaly would be insignificant compared to the effect of turning it to an urban area. These changes are greatly inter-connected with sectors such as socio-economic development, climate change, and food security [2].

River Nanyuki catchment contains some portion of Mount Kenya Forest, which surrounds Mount Kenya, the highest mountain in Kenya [14]. The forest, which preserves large collection of fauna and flora, has experienced an alarming destruction in past, mostly through illegal logging, as uncovered by an aerial survey undertaken by Kenya Wildlife Service in 1999 [14]. Various conservation policies were taken by the government of Kenya following the report. On a wider note, forests around the world have seen a widespread continuous loss and degradation, which called for adoption of various conservation measures [15, 16]. As Scullion et al. [15] suggested, regular land use change monitoring help in understanding the success or otherwise of conservation policies. The far end of the River Nanyuki catchment covers basically semi-arid lands. Land use change across the region using satellite images would provide a deeper understanding of the catchment's dynamics.

II. STUDY AREA

River Nanyuki catchment is situated between 0° 18.5'N, 36° 54.5'E and 0° 9'S, 37° 21.5'E at lower region of Ewaso N'giro North Catchment in central Kenya. The mean annual rainfall in the region is 800mm in the highlands, to less than 400mm in the ASAL area. Agricultural activities are prevalent in the high rainfall area of the catchment, which also contain part of Mount Kenya Forest, while pastoralism prevails in the drier part.



Figure 1. The study area with two key land use classes digitized from Survey of Kenya topographical maps (1973).

III. METHODS

3.1. Classification and Change Detection

United States Geological Survey (USGS) offers rich resources of satellite images from Landsat Satellites on its Earth explorer online database. Four multi-spectral images from Landsat 5 TM and

Landsat 7 ETM+ with 1G correction level and 30 m resolution were used for the analysis. The images are of the years 1984, 1995, 2002, and 2010 respectively, the 2002 image being from Landsat 7 and the rest from Landsat 5, all with 7 spectral bands. 10 year time spaced was intended from 1973 to 2013, but the choice was constrained by unavailability of clear and cloud free images of the catchment which is covered by raw 168 versus path 60 satellite swathe. That also made the use of images from same season impossible, which would have allowed better understanding of agricultural expansion.

The software packages used for the analysis in this study are CLASlite, ArcGIS, and ENVI. CLASlite, which stands for Carnegie Landsat Analysis System-lite, is a forest monitoring software package that was developed by Carnegie Institution for Science (CIS). It offers automated identification of deforestation and forest degradation of tropical forests using remotely sensed satellite images [17, 18]. It consists of four basic steps: calibration, spectral analysis, classification, and change detection. The outputs of the four steps are: surface reflectance image; image containing fractional cover of photo-synthetic vegetation (PV), non photo-synthetic vegetation (NPV), and bare substrate (S); map of forest cover; and two pair maps containing deforestation and disturbance. Extent of forest change can very easily be inferred from the final output images.

In addition to forest change detection, which only covers the changes across Mt. Kenya forest, general change detection was carried out for the whole catchment using ENVI software. Maximum likelihood supervised classification was performed on all the 4 Landsat images. Atmospheric correction was carried out for each image using the calibration utilities of the software. Four classes were used as regions of interests which are forest, agriculture, uncultivated area, and water class. Built-up areas in the maps have similar reflectance properties with bare soil, so they were classified under uncultivated area. Change detection difference maps and statistics were computed for each time step and for whole period. That is, 1984 to 1995, 1995 to 2002, 2002 to 2010, and 1984 to 2010. ArcGIS was used to extract images using water shade shape file.

3.2. Accuracy Assessment

In the absence of an up-to-date land use map for the study area, compressive accuracy assessment was conducted by means of ground truthing. Survey was carried out during one week in the month of April, which falls within long rainy season in the region. As it is not feasible to observe the thousands of pixels of the land use map, minimum of 50 samples was considered from each land use class. According to Kiptala et al., the general practice is to collect a least 3 samples for each land use category [19]. The accuracy assessment was conducted on the 2010 classified image.

Confusion matrix was generated using the pixel samples observed from the field work and their corresponding classes on the 2010 Landsat image. User's, producer's, and overall accuracies were computed. Omitting a pixel from its designated class is referred to as producer's accuracy, while assigning it to unrelated class is user's accuracy [20]. Kappa coefficient, which checks for random allocation of classes, was also computed.

IV. RESULT AND DISCUSSION

4.1. Deforestation using CLASlite

The final step from CLASI forest monitoring analysis produces deforestation and disturbance maps between set images. Deforestation maps for the three study time steps and that from the start year and end year are presented in Fig. 2. The disturbance image is not included since the change detection process by ENVI would presumably not identify it as land use change.

As it can be observed from the images in Fig. 2, the section of Mt. Kenya forest that falls in river Nanyuki catchment has seen significant deforestation within the study periods. Deforestation is shown by white pixel patches. First time step period experienced the greatest deforestation, which was probably due to absence of conservation strategies. Various forest management policies were constituted following a survey findings by Kenya Wildlife Service uncovering high degree of forest destruction [14]. In all the four images, the deforestation is shown to occur lower section of the forest (away from the mountain), and that is the area experiencing continuous agricultural expansion. It is important to note that, CLASlite uses PV reflectance value to classify forests. Plantations having

dense cover which may result in false positives by CLASlite forest cover mapping algorithms. Deforestation shown might have therefore been from logging and conversion to agricultural lands.



Figure 2. Deforestation of the forested area of the catchment for different time-steps

4.2. Change Detection and Change Statistics Using ENVI

Changes in forest, Agricultural, and uncultivated lands for all the selected periods are shown in the bar charts of Fig. 3 (a), (b), and (c). Each bar represents the total area, in square kilometers, taken by other land use classes. The change for this land use class is given in Fig. 3 (a), with highest conversion being in 1984 to 1995 time step. This corroborates the changes detected by step 4 of CLASlite. About 50% of the converted area in that time step was taken up by uncultivated land (bare soil, built up area, and man-made structures) which may imply that the change was caused by logging. Other time steps did not experience as much forest depletion but overall, the forest has seen significant degradation most of which was as a result of pressure from agriculture development and other human activities. This illustrated more clearly in Table 1, where forest has negative net changes in all the periods.





Figure 3. Transition of various land use types

Agricultural and uncultivated lands have also seen significant changes as shown in Fig. 3 (b) and (c). The high value observed in 1984 to 1995 interval is possibly due to difference of time in which the satellite images were acquired. The 1995, 2002, and 2010 images' acquisition dates falls within the last week of January and first week of February which happens to be in the rainy season. 1984 image was acquired in August, and there were probably no agricultural plantations at that period across most part of the catchment. Similar studies show that variation in image acquisition dates influences the accuracy of change detection [21–23]. The information from the figures and that from table 1 indicated expansion of agriculture and water bodies and depletion of forests and uncultivated lands on the other hand.

Land use type	1984 Land cover area in (km ²)	Net Change (%)					
		1984-1995	1995-2002	2002-2010	1984-2010		
Forest	167.53	-2.5	-6.57	-2.63	-4.03		
Agriculture	111.03	5.83	8.31	15.12	22.56		
Uncultivated Area	5127.14	-1.29	-3.6	-0.39	-3.2		
Water	2.55	257.23	85.3	63.62	345.86		

Table 1. Percentage changes of selected land uses

Fig. 4 (c) is a sample result of the change detection analysis from ENVI for the 1984 to 2010 interval. Two natural color images, (b) and (c) are added to provide better understanding of the analysis. The clouds in the 1984 image were classified as uncultivated area because most of them are on the bare land. Large percentage of the depletion (blue color) and the expansion (red color) fall close to the forested area where most of land use change activities take place.



Figure 4. Natural color images for 1984 and 2010 with the detected land use changes

Summary of the accuracy assessment result is shown in Table 2. Overall accuracy and kappa coefficient are 80% and 0.63 respectively. This indicates that the classification is significantly accurate compared to random chance classification.

Land use type	Reference da	Total	User's Accuracy			
	Forest	Agriculture	Uncultivated Area	Water		
Forest	163	23	14	0	200	82
Agriculture	14	98	15	3	130	75
Uncultivated Area	8	31	175	6	220	80
Water	2	0	3	45	50	90
Total	187	152	207	54	600	
Producer's Accuracy	87	64	85	83		80

Table 2. Classification error matrix(Overall accuracy = 80%; Kappa Coefficient = 0.6326)

V. CONCLUSION

Nanyuki river catchment presents a suitable study area with varying landscape and climatic condition. The four classes of land use studied between 1985 and 2010 revealed different forms of land use conversion. It was clearly observed that agricultural lands and water bodies expanded significantly over the period while forest and uncultivated land experienced depletion. The depletion of Mt. Kenya forest may be as a result of the agricultural expansion and logging. With the detection of forest loss corroborated by ENVI, CLASlite application by Carnegie Institute for Science proved to be important in identifying areas of deforestation even for forest that is not fully tropical.

VI. FUTURE WORK

Information on land uses obtained from this phase would be used to examine how their changes affect soil organic carbon stock across the catchment. This will be done by testing organic carbon in soil samples distributed across the catchment and generating a map to be compared with the land use map. The work will fade way other possible future studies such as investigation of ecosystem payment potentials and studying other soil dynamics.

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