Assessing the Impacts of Land Use Land Cover Change in Mutama Bweengwa Catchment of Southern Province, Zambia

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Abstract

Climate change and land use land cover directly impact the alteration of hydrological cycles, making water more unpredictable and increasing the frequency and intensity of floods and droughts. However, proper planning of adaptation and mitigation options is hampered by inadequate up-to-date information on land use/Land cover in many catchments and sub-catchments of Zambia and other developing countries. This study assessed the land use change in the Mutama Bweengwa River Catchment of Southern Zambia. The objective of the study was to investigate land use land cover changes (LULCC) in the Mutama Bweengwa Catchment in the Southern Province of Zambia from 2000 to 2021. The data used for the study were satellite images of the area downloaded from the United States Geological Survey (USGS). Specifically, the Landsat images were from path 172/row 71 and path 172/row 72 for the period 2000, 2007, 2014 and 2021. The methods used included data identification and acquisition, image pre-processing, image processing, accuracy assessment, validation and presentation. Image pre-processing was used to correct distortions during image acquisition. The techniques used were: image enhancement for extracting useful information, which involved carrying out band combination and brightness and contrast adjustment when conducting the mosaicking process using ERDAS imagine 2014. Supervised classification based on the maximum likelihood algorithm in ERDAS Imagine was employed to generate the land use land cover classification and later exported in ArcMap 10.7.1 for map creation. The image classification was based on six different LULC classes, which were: water body, build-up/settlement, forest, cultivated land-rainfed/bare land, cultivated land-irrigated, and grasslands. Preliminary results of this study have shown a decrease in the classes of water bodies and forest areas by 0.34% and 55.5%, respectively, over the 21-year period. The accuracy of the resultant land use/land cover maps was evaluated with the kappa statistic and error matrix. The preliminary results have also shown an increase in the land use land cover class categories of cultivated land-irrigated, grassland, cultivated land-rain fed/bare land and built up/settlements by 0.13%, 46.7%, 14.6% and 8.4%, respectively.

In conclusion, the supervised classification of the Landsat images indicated pronounced land cover changes over the 21-year period. Although this provides preliminary conclusions,

it indicates that immediate actions should be taken to protect the sub-catchment from further loss of land cover by strengthening the regulatory framework. Further work on the project is expected to bring out some of the factors that have contributed to this change.

Keywords: *Land use land cover (LULC), change detection, Landsat images, Data, Classification*

Introduction

Land use and climate change are global issues, and a detailed study to determine their relationship and impact on the future is of great importance. However, the causes and consequences of human-induced climate change and land use activities are rarely studied interdependently.

Land use describes any physical and biological or chemical change to the physical and biological attributes of land that may be attributed to management(1). Land use change is responsible for increases in the human population, deforestation, food types, and demand for energy and fibre (2). Climate change involves global warming, precipitation, natural disasters like floods, storms, and droughts(3). Land-use impacts climate through deforestation and rapid population growth, whereas climate change impacts land use through unpredictable heavy rainfall and increasing temperature. For instance, climate change affects crop production, which leads to land-use change from agriculture to another land-use type.

It should be noted that drivers of climate change and land use vary in time and space. It is, therefore, important to have information on the temporal variation of land use to guide decision-makers. This is particularly important for the land use/land cover change that occurs across water catchment areas, as this can adversely impact the water balance. This means that adequate and accurate information on land use/land cover is key for the sustainability of the catchments. In Zambia, extensive work has been done in delineating catchments and water protection areas to be protected by law(4). However, for several catchments and sub-catchments, the question of how land use/land cover has changed over time requires constant updating as this information is relevant for use in climate simulation models and future planning about their sustainable use. Against this background, this study was undertaken in the Mutama Bweengwa catchment of the Southern Province, of Zambia. The objective of the study was to conduct a land use/cover classification for the Mutama-Bweengwa catchment for the last 21 years (2000, 2007, 2014 and 2021).

Materials and Methods

Description of Study Area

The Mutama-Bweengwa Basin is located in the administrative districts of Monze, Pemba, Choma and Kalomo in the Southern Province of Zambia. It covers an area of approximately 41,9974 hectares and is hydrologically located in the Lower Kafue sub-basin (Figure 1). This sub-micro-catchment is located in the lower Kafue catchment, which is geographically located between 24^{o} 42’E, 11^{o} 30’S and 28^{o} 30’E, 17^{o} 30’S. The hydrological sub-catchment area for Mutama-Bweengwa has a corresponding river length of 99 km from headwaters to their respective confluence (5).

In terms of livelihood, local communities inhabiting the sub-catchments are largely subsistence farmers depending on rain-fed agriculture. However, the headwater streams of the sub-catchments support a number of commercial farmers. Land use activities such as industrial, brick-moulding, sand mining, logging and charcoal production exist in the sub-catchments mainly at a small-scale(5).

Data

Multi-temporal Landsat satellite data of the Mutama Bweengwa catchment were acquired for the years 2000, 2007, 2014, and 2021 to carry out the LULC classification. Images of the same season (July to August)) free from cloud cover and identifiable features not affected by seasonality were considered in the selection. Table 1 shows the images acquired from the United States Geological Survey (USGS), an open source available at (https://earthexplorer.usgs.gov/).

Image Pre-processing

The satellite image was imported in ERDAS imagine software and geo-referenced to Universal Transverse Mercator (UTM) system in World Geodetic System (WGS) 1984 zone 35 S. Layer stack operations were used to combine the different spectral bands in multiband composite images (the bands used were 4,3 and 2). Mosaicking of the images was conducted, which involved the process of joining the two geo-referenced images into one using ArcMap 10.7. Lastly, A shapefile of the study area was then used to clip out a subset from the merged image as the Area of interest (AOI).

Image Classification

Prior knowledge from field surveys was used to select training sites for the land cover categories listed in the classification scheme shown in Table 2. Using the basic colours red, green and blue (RGB), we used false colour composites (FCC) images. These false colour composite images are suitable to distinguish between different land cover types or ground objects like built-up forests (6). The FCC band combination of RGB is bands 4, 3 and 2, respectively. The dataset was trained using the pixel colour and tone of specific land use classes, with each individual training site created by drawing polygons containing at least 50 pixels. To train a single land use class, polygons of pure pixels for that class were drawn. This procedure was repeated for all 6 land use classes and saved as a signature file using the signature editor in ERDAS imagine software. This signature file was then used during the supervised classification stage. A supervised digital image classification based on the maximum likelihood classifier (MLC) was done to categorise all pixels in the image into land use/land cover classes (7). Supervised classification enabled the assigning of each pixel in the image to a class to which it had the highest probability of being a member, thus, generating land use/land cover categories(8). The classified image was then vectorised and exported as a shape file from which a land use/ land cover map was generated for overall visualisation. This procedure was repeated for all the images.

Accuracy Assessment

Accuracy Assessment was done by an error matrix using the Kappa coefficient (9). The Kappa (k) coefficient is a strong and widely used statistical measure to assess the inter-raster agreement between variables. The Kappa coefficient lies between 0 and 1, which is often multiplied by 100 to give a percentage measure of classification accuracy. Kappa values are also characterised into three groupings: Strong Agreement (Kappa > 80%), Moderate Agreement (40% ≤ Kappa ≤ 80%), and Poor Agreement (Kappa< 40%) (9).

Ground Truth

In this study, 279 ground control points were used to validate the classified image for the 2000 and 2021. This was achieved using a stratified random sampling design. The reference data for this study was obtained from field visits and high-resolution Google Earth Pro images.

Change Detection

Land use and cover area distribution results were used to compute land use and cover trends, net change, percentage change and rate of LUCC between the years 2000 and 2007, 2007 and 2014, 2014 and 2021 and for the period 2000 and 2021. The changes in magnitudes for each land use class were calculated by subtracting the area coverage of the second year from the initial year, as shown in the following in equation 1. Magnitude = Areas (Ha) of the new year – Areas (Ha) of the previous year (1)

Results

The Extent of Land Use/land Cover Classes in Mutama Bweengwa

The six LULC classes observed and recorded were water body, cultivated land-rain fed/ bare land, forest, built-up, cultivated land-irrigated and grassland in the study area (Table 2). Figure 2 shows the extent of LULC maps in the study area for the years 2000, 2007, 2014 and 2021. The land use patterns (six categories) identified for all years are shown in Table 3 and Figure 2. After image classification, 41,9974 hectares of land area was estimated for the Mutama Bweengwa catchment.

Accuracy assessment was conducted based on the Kappa coefficient, and the accuracy assessment results for 2000 and 2021 LULC maps are shown in Table 4 and Table 5. The overall accuracy for 2000 and 2021 was 84.58% and 89.4%, with a Kappa coefficient of 0.82 and 0.81, respectively, suggesting accurate classification.

Land Use/cover Change Over Time (2000 - 2021)

As shown in Table 3, forests had the highest LULC in 2000 and were constantly changing throughout the study period. Nevertheless, forest area steadily decreased from 275,256.7 ha (65.5%) in 2000 to 41,958 ha (10%) in 2021. In 2000, forest area accounted for 65.5% of the total area, but by 2021 it decreased to 10%. The water body was another LULC that continued to decline from 1942.52 ha (0.5%) in 2000 to 505.7 ha (0.12%) in 2021, a net decrease of 1436.8 ha (-0.38) in the water area during the study period. However, some LULC, such as cultivated land irrigated, cultivated land - rainfed/ bare land, grassland and built-up areas, experienced an increase in its coverage throughout the study period, 2005 with an area. In 2000, the LULC areas cultivated land irrigated, cultivated land - rainfed/ bare land, grassland and built-up area covered 2.52147 ha (0.0006%), 52717.04 ha (12.6 %), 89851.85 ha (21.4%) and 203.3165 (0.004%) respectively. In 2021, cultivated land irrigated, cultivated land -rainfed/bare land, grassland and built-up area increased in area and covered 546 ha (0.13%), 87991 ha (21.0 %), 286392 ha (68.2%) and 2582 ha (0.6%) respectively.

Discussion

The land use change matrix (Table 3) shows the conversion of one land cover class to another. The decrease in magnitude in a water body from 2000 to 2021, while not common, can be attributed to the disappearance of seasonal streams due to drier years experienced in the recent past, which could have led to a change to this class to either grassland or cultivated land areas. Equally, forest areas were among the main land cover classes that converted to grassland, built up and cultivated land from 2000 to 2021, resulting in a net increase in these classes. The increase in cultivated land irrigated and rainfed/bare land mainly comes from forest cover. Cultivated land is also converted to other land cover classes, namely, built-up and grasslands. However, forest area lost a greater part of its cover to grassland (286392 ha), cultivated land, rainfed/ bare land (87991 ha), built up (2582 ha) and water body (505.7 ha). The different land cover classes also converted to forest areas during the study period. The increase in the built-up area mainly came from the conversion of forest areas, grasslands and cultivated land-rain-fed area.

Much of the land in Mutama Bweengwa Catchment was a forest. However, over time, the land cover has been turned into grasslands and cultivated land areas. This can be mainly attributed to an increase in population which has consequently led to increased human activities in the catchment(5). Literature indicates that the loss of forest cover could be specifically due to the unsustainable cutting down of trees in forest cover for settlements expansion, urbanisation, and infrastructure development (10,11). Further, the communities within the catchment depend on agricultural activities for their livelihoods, which explains the increase in agriculture areas during the study period. Other drivers of loss in forest cover are the rising demand for farmland for agricultural production large number of poor local people living in and around the forest and dependent on the forest for their subsistence(12), and charcoal production. The water body was reduced compared to an increasing trend of the bare land and cultivated land close to the resource. This suggests that changes in land use and land cover are negatively impacting the water body leading to a reduction in the aerial coverage of the water body(8).

An increase in built-up area was also observed during the study period. This increase could result from the construction of some facilities, road infrastructure development, and settlements from the high demand for land by the growing population in the study area(13). A population increase within the study area entails converting LULC classes into built-up and bare land areas, which can explain the increase in a built-up area in catchments during the study period(14). As local communities are close to natural resources, such as forests, an increase in the number and lengths of roads in the study area could promote economic development and facilitate forest degradation and deforestation(15).

Conclusions

This study has demonstrated analytically that Mutama Bweengwa experienced major LUCCs from 2000 to 2021. The analysis of sources and trends of LULCs show a decline in forest area and water bodies, and an increase in agriculture activities (cultivated rain-fed/cultivated irrigated), grassland and built-up. The forest area is likely to decrease further due to the high population growth rate, and increased settlements leading to a high demand for land for agricultural purposes to meet the needs of the local people. The increase in the other land use classes, such as agricultural land (cultivated land rain fed/ irrigated), built-up, and grassland will lead to more deforestation and forest degradation, with implications on the livelihoods of the local communities and ecosystem services. This will also negatively affect food security in the area within the catchment as increasingly more land will be needed for settlements and infrastructure development. This study brings out relevant lessons to aid in policy and environmental management strategies regarding catchment protection and mitigation measures.

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Tables

Table 1: Characteristics of Image Data Used in the Study

Sn	Data Type	Year of Production	Worldwide Referencing System		Resolution
			PATH	ROW	
1	Landsat imagery	2000	172	71	30 m
			172	72	
2	Landsat imagery	2007	172	71	30 m
			172	72	
3	Landsat imagery	2014	172	71	30 m
			172	72	
4	Landsat imagery	2021	172	172	30 m
			172	172	

Table 2: Classification Scheme for Training Site

Classes	Description
Forest	All forest cover
Built-Up	Urban areas and rural dwellings and associated structures
Cultivated land-rain fed/ bare land	Areas cultivated annually during the rainy season, areas of exposed soil and barren area influenced by human impact
Cultivated land-irrigated	Areas with cultivated crops using irrigation systems
Water body	All rivers and water bodies
Grassland	Area covered with grass and mainly used for grazing

Table 3: Land Use and Cover Change Assessment of Mutama Bweengwa from 2000 to 2021

Classification Scheme	2000		2007		2014		2021		Change Difference% (2000 and 2021)
	Area (Ha)	Area%	Area (Ha)	Area%	Area (Ha)	Area%	Area (Ha)	Area%	
Built up	203.3	0.05	992	0.24	1308.694	0.31	2582	0.61	-0.57
Cultivated-irrigated	2.5	0.0006	338	0.08	227.1318	0.05	546	0.13	-0.13
Cultivated-rain fed	52717.0	12.6	81130	19.3	137543.4	32.6	87991	21.0	-8.4
Forest	275256.7	65.5	122838	29.25	88643.95	21.1	41958	10	55.5
Grassland	89851.85	21.4	213896	50.9	191666.1	45.6	286392	68.2	-46.7
Water body	1942.52	0.5	780	0.19	585	0.14	505.7	0.12	0.34
Total	419974	100	419974	100	419974	100	419974	100	

Table 4: Accuracy Assessment for 2021

Classes	Cultivated land-rain fed	Grass land	Forest	Water body	Build up	Cultivated land-irrigate	Total	Commission	User Accuracy
Cultivated land-rain fed	54	0	0	0	18	0	72	0.25	0.75
Grassland	0	32	0	0	1	7	40	0.2	0.8
Forest	0	0	34	2	0	2	38	0.106	0.895
Water body	0	0	0	16	1	0	17	0.059	0.941
Build up	0	0	0	0	18	0	18	0	1
Cultivated land-irrigated	0	0	0	0	0	16	16	0	1
Total	54	32	34	18	38	25	279		
Omission	0	0	0	0.111	0.526	0.36			
Producer Accuracy	1	1	1	0.889	0.474	0.64			
Overall Accuracy	0.846								
Kappa	0.82								

Table 5: Accuracy Assessment for 2000

Classes	Water body	Cultivated land-rain fed	Cultivated land-irrigated	Grassland	Built up	Forest	Total	Commission	user accuracy
Water body	6	0	0	0	0	7	13	0.538	0.461
Cultivated land-rain fed	0	23	0	3	2	0	28	0.179	0.821
Cultivated land-irrigated	0	3	10	1	0	0	14	0.286	0.714
Grassland	0	2	0	48	0	2	52	0.077	0.923
Built up	0	4	0	0	8	0	12	0.333	0.667
Forest	4	0	0	2	0	154	160	0.039	0.961
Total	10	32	10	54	10	163	279		
Omission	0.4	0.281	0	0.111	0.2	0.055			
producer accuracy	0.6	0.718	1	0.889	0.8	0.944			
overall accuracy	0.892								
Kappa	0.81								

Figures

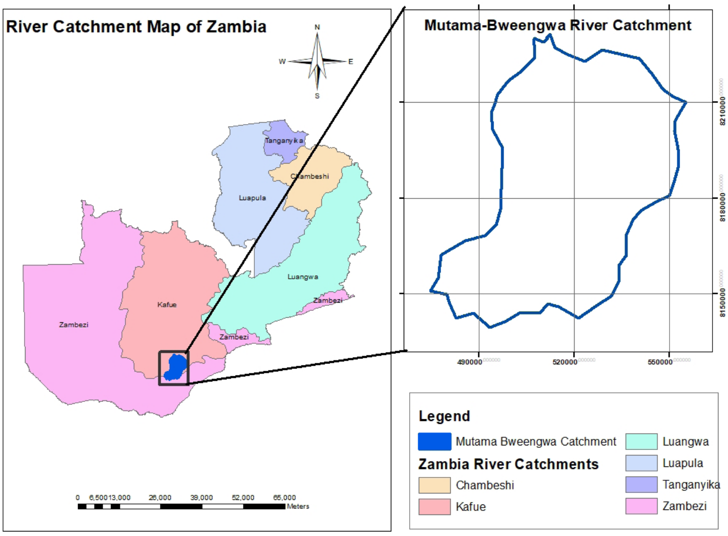

Figure 1: *Location Map*

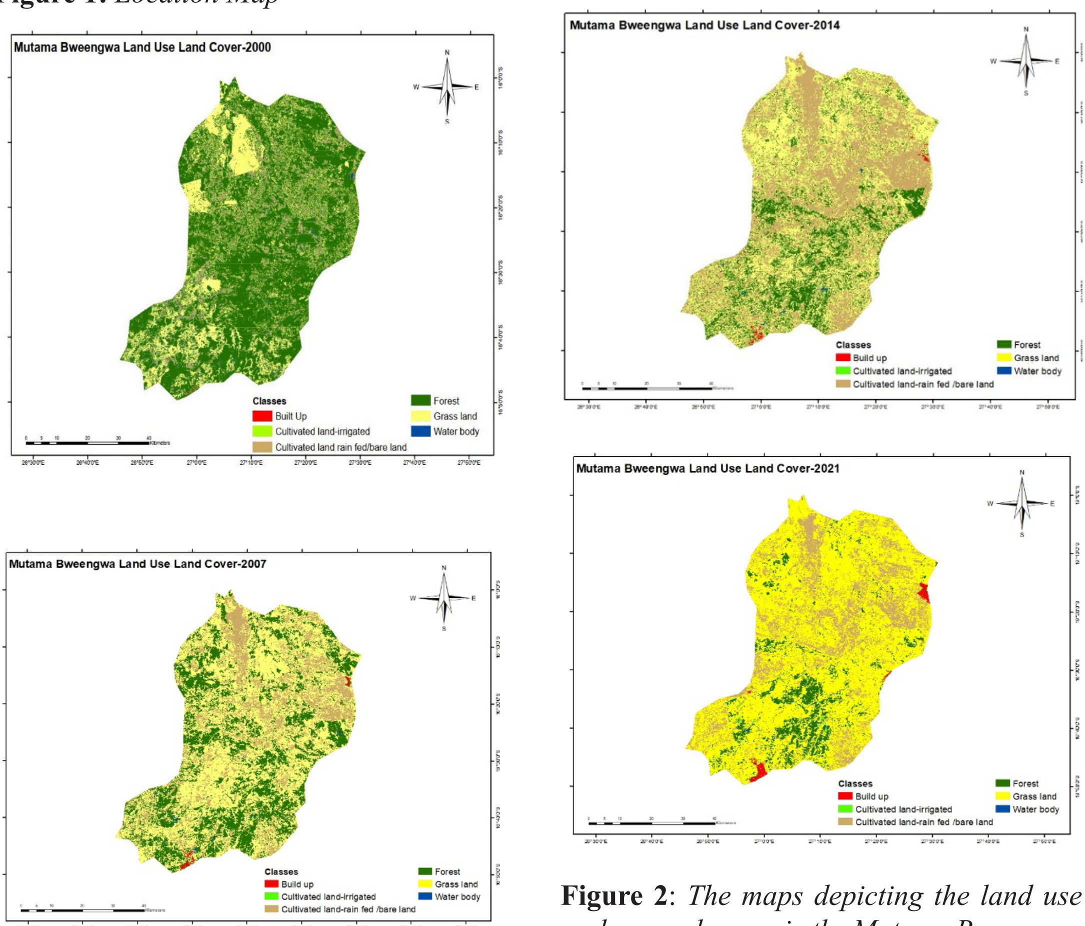

Figure 2: *The maps depicting the land use and cover changes in the Mutama Bweengwa catchment during the study period from 2000 to 2021*