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Research Article

Identification and Mapping of Land Use Land Cover Variations Using Time-Series Landsat Data in MBOMIPA Wildlife Management Area

Solomon Sembosi

Department, Protection, Southern Tanzania Elephant Program, Iringa, TANZANIA

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Abstract

Since the 1990s, MBOMIPA has experienced changes in land use. This study used Landsat data to assess land use and land cover changes from 1997 to 2021. The processing of satellite images and evaluation of variations in land use and land cover was done using ArcGIS and ERDAS. The supervised land use classification was created using a maximum likelihood method. The findings of this study assessed the area of closed forests declined by about 186.04 ha over a period of 24 years (1997–2021), with a 14.8% annual rate of change, and 327.08 ha of open woodlands had undergone a 15.88% annual rate of change to other land use land cover types. All these conversions of woodlands were highly detected to be converted to shrubland, grassland, and bare land. With Kappa values of 0.90, 0.90, 0.83, and 0.93 for 1997, 2002, 2007, and 2021, respectively, the total supervised classification accuracy was found to be 91% for 1997, 91% for 2002, 86% for 2007, and 97% for 2021. The findings of this study will be valuable in assisting to plan and carrying out significant management strategies to safeguard the MBOMIPA Wildlife Management Area's rich biodiversity.

Keywords: Land use, landcover, Landsat, MBOMIPA, WMA

Introduction

Accurate detection of changes in the landscape is essential for understanding the evolution of natural resources over time. Time series datasets are crucial for quantifying and analyzing changes in land use or land cover (Mas, 1999; Afify, 2011). Remote sensing data has revolutionized the way land use and land cover changes are monitored by providing updated and high-resolution information on environmental changes (Yuan et al., 2019). Land use and land cover analysis have become essential tools for assessing environmental changes over the space-time continuum (Kaya et al., 2015; Chen et al., 2021). These changes are accelerating, mainly driven by human activities such as urbanization, deforestation, and agriculture expansion (Burak et al., 2004; Islam et al., 2018; Fazal et al., 2022). Hence, timely and accurate detection of these changes is crucial for the sustainable management of natural resources and the environment.

The impact of environmental changes on wildlife and their resources has become a critical area of concern in global environmental studies. Land use and land cover changes, driven mainly by human activities; have a profound impact on wildlife resources (Crouzeilles et al., 2021). Studies across different regions of the world report change in land use and land cover, which have significant impacts on wildlife resources (Settele et al., 2019). These changes in land use and land cover alter environmental processes, impacting their function and structure and imposing contrasting effects on species diversity, abundance, and general wildlife habitats (Bouyer et al., 2021). Human activities such as deforestation, mining, urbanization, and agriculture expansion are known to be significant drivers of land use and land cover changes, impacting wildlife and their resources (Wilkie et al., 2016; Braga et al., 2020). Therefore, mitigating the negative impacts of human activities on wildlife resources requires effective conservation strategies that consider both the ecological and socio-economic factors that influence land use and land cover changes.

The management and conservation of wildlife areas and their natural resources heavily rely on the study of land use and land cover changes (Kuemmerle et al., 2011). Traditional methods, such as vegetation surveys and demographic studies, are still used in many community wildlife management areas, but they are not as efficient as modern technologies like remote sensing and Geographic Information Systems (GIS) in studying wildlife and their environment or resources. Remote sensing and GIS are capable of addressing complex environmental issues that require advanced data processing techniques, thereby providing the necessary data for better wildlife resource management, especially in community-owned wildlife areas. Additionally, the use of GIS and remote sensing has become essential for studying various Earth processes, and the availability of geographic data has increased due to the use of time-series Landsat data, which GIS aids in their interpretation and understanding "(Kjelland et al., 2021; Reynolds et al., 2020)".

The MBOMIPA WMA is a community-owned wildlife area that is critical for the protection of animals from big mammals to small ones and wildlife in general in the Southern Highlands of Tanzania. This area was set aside by the community living nearby Ruaha National Park in Tanzania to promote sustainable use of natural resources through effective management and anti-poaching efforts to prevent the loss of wildlife habitats and vegetation degradation. It represents a fragile wildlife landscape near the Ruaha National Park, which if not conserved soon, may be lost for the future generation to benefit directly from wildlife. Anthropogenic pressures including increased fire incidence as a result of honey poachers, increase in human population from the proximity villages, illegal deforestation for charcoal production and cattle herds destructs lead to an extensive decrease in vegetation which in turn eventually converts the natural land cover to diverse land uses. This study aims to map, quantify and assess land use or land cover changes that occurred from 1997 to 2020. This work aimed to assess apparent LULC changes during the observed time frame mainly concerning forests and other vegetation in general.

Materials and Methods
Description of the Study Area

The study was conducted in a community-based organization of 21 villages, Matumizi Bora ya Malihai Idodi na Pawaga (henceforth referred to as MBOMIPA), Swahili for "Sustainable Use of Wildlife Resources in Idodi and Pawaga,". MBOMIPA comprises an area of about 777 hectares and it was founded in 1994. It comprises the communities living next to Ruaha National Park in Tanzania promoting wildlife-based livelihoods as a means to ensure biodiversity conservation, anti-poaching efforts, and sustainable natural resource management. The area is located in the Idodi and Pawaga Divisions of Iringa District in Iringa Region, Tanzania. The study area is located in the southern highlands of Tanzania's mainland as seen in figure 1 between 6.9º and 8.0ºS and between 34.8º and 35.7ºE (WMA, 2006). The Northern and eastern boundary of the WMA is formed by the Ruaha National Park boundary while to the west and south, it is bound by the grazing lands, farms, and settlement of the villages in Idodi and Pawaga Division.

In general, the weather of the area differs from the northern part which is drier than the south and with an average rainfall of greater than 500mm per annum whereas the southern area gets an average of 750mm to 1000mm of rain per year. The western part of the WMA which is adjacent to the Mtera dam obtains 450mm of rain (SWECO, 1985; John, 2022). More than that Rainfall data collected at Ruaha National Park in Msembe which is the park's headquarters located to the north of the WMA gives an average rainfall of 500mm yearly (TANAPA GMP, 1997).

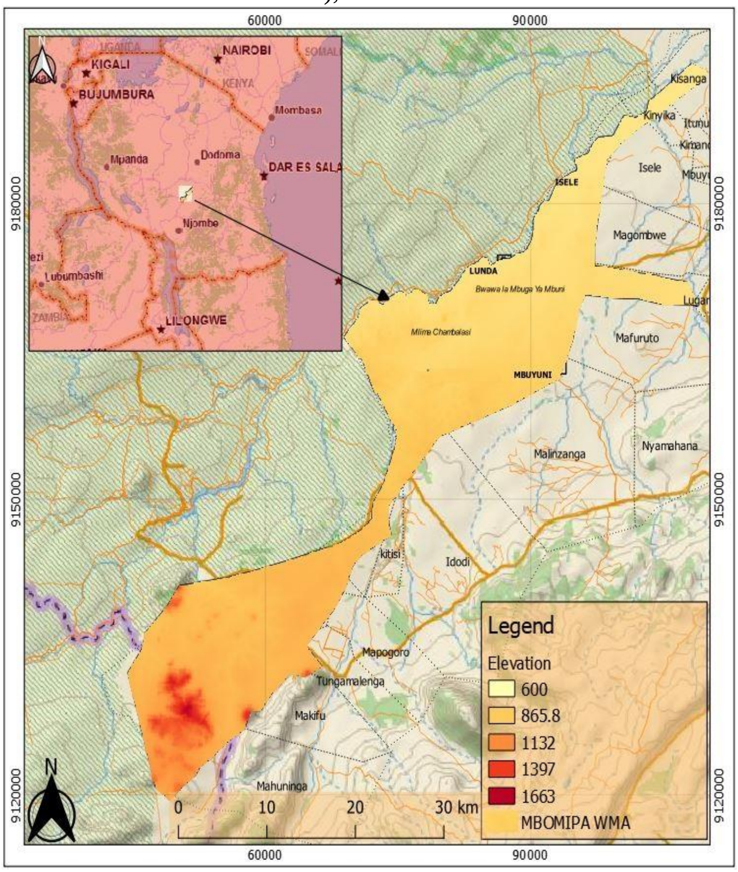

Fig. 1. Map of the study area.

The WMA is covered dominantly with vegetation type of open woodlands, a mixture of shrubland, grassland, and closed forest as well as riparian vegetation along the river streams running in and along the boundaries of the WMA. It's a home for a variety of Insects, spiders, fishes, amphibians, reptiles, birds, Elephants, leopards, cheetahs, African wild dogs, hippopotamus, buffalo, giraffe, zebra, impala, eland, giant pangolin, jackal, hyena, waterbuck, warthog, greater and lesser kudu (recognized as one of the areas in the world where they are found together), Impala, aardvark, mongoose and bat-eared fox, Nile crocodile, monitor lizard and snakes (UNDP, 2015).

Image Acquisition

Time series images for the years 1997, 2002, 2007, and 2021 were used to investigate the historical changes in land use and land cover in the study area. All the images have a resolution of 30 and correspond to path 168 and rows 65 and 66 of the Landsat Worldwide Reference System (WRS) and were downloaded from the United States Geological Survey (USGS) website (https://earthexplorer.usgs.gov/). Table 1 summarizes the details of the Landsat images used in this study.

Table 1. Source and details of the satellite imagery used in this study.

Satellite	Sensor	Acquisition date
Landsat-5	TM	30-07-1997
Landsat-7	ETM	04-07-2002
Landsat-5	TM	26-07-2007
Landsat-8	OLI/TIRS	29-07-2021

To assure the best comparison and to minimize seasonal variation in plant phenology between the study periods, images were captured on related satellites and during the dry season when the sky is usually clear, which enabled obtaining of lower or free cloud imagery with the best visibility.

The periods of imagery were designated based on events that had considerable impacts on the establishment of the WMA. The image of Landsat 5 Thematic Mapper (TM) captured in 1997 was used to represent the status of the study area when it was founded and when Tanzania experienced a rash of illegal activities, causing a reevaluation of the nation's wildlife management practices and policies. Enhanced Thematic Mapper (+ETM) of 2002 represents the year when MBOMIPA was legally recognized as a community-based organization under the Societies Ordinance in 2002, becoming the first indigenous conservation and development organization of its kind in Tanzania (UNDP, 2015). The image of Landsat 5 Thematic Mapper (TM) captured in 2007 symbolizes the year when the MBOMIPA wildlife management area was legally gazette and it was used as a model for repetition in other areas as a way to safeguard wildlife and encourage sustainable livelihoods to the community adjacent to protected areas. The image Landsat 8 (OLI/TIRS) of 2021 marks the current condition of the study area.

Image Processing and Analysis

Earlier the processing of satellite imagery started, and an extensive ground survey was done throughout the study area using GPS MAP 64SX equipment. This assessment was crucial for the creation of training spots and signature generation as well as to acquiring precise locational point data for respective land use and/or land cover class encompassed in the classification system. The acquired images were processed using ERDAS Imagine 2015 and ArcGIS 10.8 software packages.

Image Preprocessing

Actual analysis using Landsat data from different sensors can be arduous due to the associated errors related to geometric and/or radiometric effects (Giri et al. 2015) therefore doing geometric and radiometric corrections for the satellite images is vital to building a clear association between ground biophysical features and downloaded satellite images and therefore removing false signs of objects, making the corrected images adequately for quality analysis (Coppin et al. 2004, Pons et al. 2014). This study considered several consecutive steps of data preprocessing including geometric, radiometric, and atmospheric corrections using Arc GIS 10.8 and ERDAS IMAGINE 2015 software packages. In this stage of data preprocessing sub-setting, gap-filling, enhancement as well as a selection of the suitable bands was blended for the actual classification process.

To minimize radiometric errors, the radiometric tool in ERDAS IMAGINE 2015 was used to calibrate the satellite images. This process involved the conversion of the digital number (DN) as raw data from sensors to top-of-atmosphere reflectance as actual ground surface reflectance (Amro et al. 2011). Atmospheric effects can cause satellite images to have a restricted dynamic range, usually perceived as haziness or reduced contrast. The atmospheric effects on the satellite images were corrected using a haze reduction tool in ERDAS as this function improves the images using either a Tasseled Cap for the Landsat 5 TM only due to the sensor algorithm and Point Spread Convolution approach for ETM and OLI satellite images. As a part of atmospheric correction, topographic normalization is very important as it involves the use of a digital elevation model (DEM) to minimize sun-angle shading effects present in most satellite aerial imageries and therefore helps in presenting the original image and thus clear spectral signature as well as high accuracy during classification process (Amro et al. 2011). The DEM for the study area was obtained from SRTM (Shuttle Radar Topography Mission). The satellite images that are Landsat level-1are terrain corrected and therefore geometric correction was not compulsory (Young et al. 2017).

Image Classification

Different features on the earth's surface have different remittance properties and spectral reflectance and thus making the idea of recognizing them through the classification process possible. The process of image classification in remote sensing involves the categorization of pixels of a raw satellite image to produce land use and/or Land cover classes as a result useful thematic maps are prepared (Lillesand and Keifer 1994, Boakye et al. 2008).

For this study of land use, land cover classes have been developed based on field visits, knowledge of the study area, and other studies. Therefore, 7 land use land cover classes including riverine vegetation, grassland, open woodland, closed woodland, bare land, river/water bodies, and shrubland were developed to form a general classification scheme for this study. This study used a supervised method as it produces a more accurate classification together with a maximum likelihood classifier as it allows good interpretation of the results and brings good accuracy (Krishna et al. 2009, Peacock, 2014, Ren et al. 2019). To delineate different land use land cover classes, this study employs both false and true color combinations to aid a clear visualization of features. Based on the knowledge of the study area, and ground control points collected during field observations several training sites were selected for each land use land cover class for all the satellite images followed by the application of a maximum likelihood classifier to generate spectral signatures for classification of images (Figure 2).

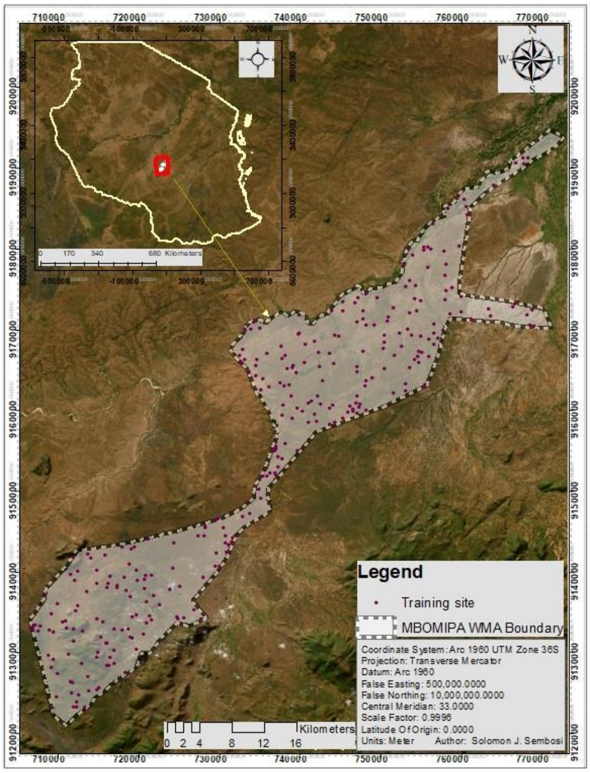

Fig. 2. Distribution of training sites in MBOMIPA Wildlife Management Area

Accuracy assessment

Accuracy assessment is one of the crucial stages in the classification process. For this study, accuracy assessment was done in ERDAS IMAGINE 2015 using high-resolution Google images obtained from Google Earth Pro. Random points with a specific color and pixel value were generated for the classified images and then identified by the user and allocated to different classes. A minimum of 50 samples were selected randomly for each class in ArcGIS 10.8 using the “create random points” tool. Accuracy assessment was done based on error matrices (overall accuracy and kappa coefficient). More than that producer’s and user’s accuracies were also acquired for each class, which quantify the omission and commission errors. According to “Lillesand et al. (2008), an accuracy assessment greater than 70% is an acceptable accuracy in classification studies”, and “Fleiss et al. (2008) identified a more than 0.75 kappa statistic value as an excellent agreement while the values between 0.40 and 0.75 are considered fair whereas a value of less than 0.4 is measured poor correspondence”.

Change Detection

Different objects and/or phenomena at different periods tend to display changes and the process of identifying these changes is termed change detection. Exploration of changes in land use and or land cover studies using change detection identifies more than just changes and tends to provide further information on the spatial extent, pattern as well as nature of respective changes (Gallego, 2004). Given there are different methods of change detection, this study used the post-classification method or technique as one of the proven and most acceptable ones (Foody, 2002).
Through the post-classification method, thematic maps are generated from the classification of multiple date images separately followed by a pixel-based comparison of the corresponding land use land cover classes. The post-classification approach involves the classification of multiple date images separately to generate thematic maps, after which a pixel-based comparison of the corresponding classes is used to produce tables and maps of changes that have occurred (El-Hattab, 2016). Although good change detection depends on the accuracy of the classification process, post-classification has some benefits and this includes, detailed information covered from the changes in land use land cover matrix, quantification in magnitude and rates of the respective changes as well as minimization in the likely effects of sensor, atmospheric and environmental alterations among imageries as they are individually classified (Alawamy, 2020). Due to the high accuracy attained by different studies (Islam, et al. 2016-2018, Matlhodi, et al. 2019) that employed this method and its capability of determining the direction of change in land use land cover, this study involves a post-classification method in identifying the changes between the study periods.

Results
Land Use and Land Cover Types

Figures 3, 4, 5, and 6, respectively, show the spatial distributions of LULC categories in the MBOMIPA Wildlife Management Area in 1997, 2002, 2007, and 2021. For 1997, 2002, 2007, and 2021, the classified maps' overall accuracy was 91%, 91%, 86%, and 94%, while the associated Kappa Indices of Agreement were 90%, 90%, 83%, and 93%, respectively. Table 2 provides an overview of the areal and percentage coverages of the various LULC classes.

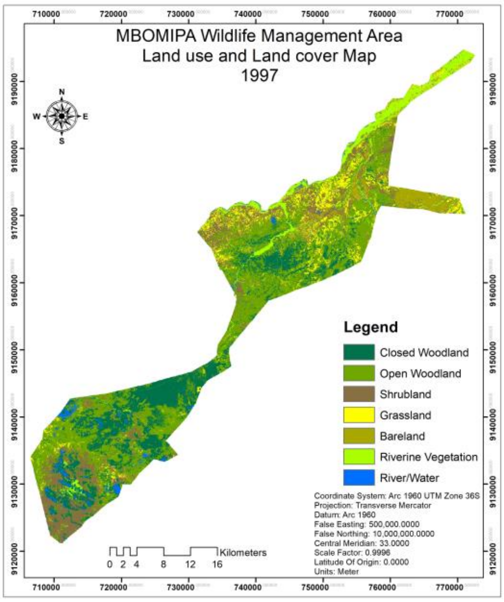

Fig. 3. Distribution of LULC types in the MBOMIPA Wildlife Management Area in 1997.

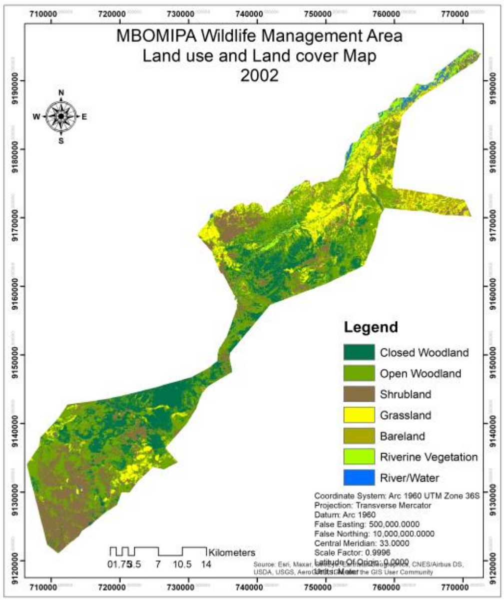

Fig. 4. Distribution of LULC types in the MBOMIPA Wildlife Management Area in 2002.

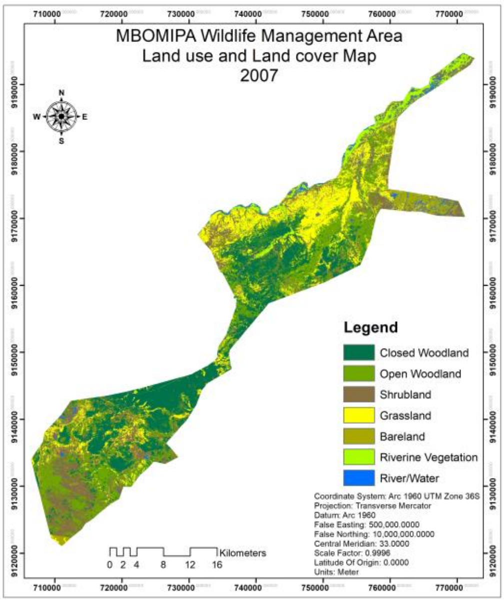

Fig. 5. Distribution of LULC types in the MBOMIPA Wildlife Management Area in 2007.

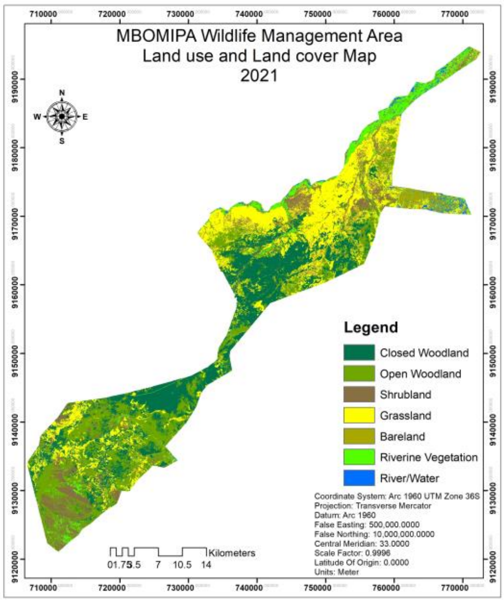

Fig. 6. Distribution of LULC types in the MBOMIPA Wildlife Management Area in 2021.

Table 2. The size and percentage of the MBOMIPA WMA that was covered by LULC classes in 1997, 2002, 2007, and 2021.

Land Use Land Cover Category	**1997**		**2002**		**2007**		**2021**	
	Area (Km^2)	% Of Land	Area (Km^2)	% Of Land	Area (Km^2)	% Of Land	Area (Km^2)	% Of Land
Closed Woodland	186.04	23.94	165.38	21.28	163.10	20.99	157.97	20.33
Open Woodland	327.08	42.10	339.52	43.70	296.13	38.11	267.31	34.40
Shrubland	111.63	14.37	123.28	15.87	129.61	16.68	136.41	17.56
Grassland	71.17	9.16	100.75	12.97	120.96	15.57	125.85	16.20
Bare-land	9.65	1.24	11.84	1.52	17.94	2.31	25.21	3.24
Riverine Vegetation	54.44	7.01	16.68	2.15	31.86	4.10	52.54	6.76
River/Water	16.98	2.19	19.54	2.52	17.40	2.24	11.70	1.51
Total	777	100	777	100	777	100	777	100

Open forest and closed woodland were the two main land cover types in the management area, respectively, whereas shrubland, grassland, bare land, riverine vegetation, and river/water had comparatively low coverages between 1997 and 2021. (Table 2).

The WMA had a higher proportion of open woodland, closed woodland, and shrubland coverages throughout the study periods 1997, 2002, 2007, and 2021. Throughout the study area, there have been changes in areas covered with grassland and bare land from 1997 to 2021 as reflected in table 2. Open woodland was the most dominant land cover type from 1997 to 2021. It had the highest proportional coverage around the protected area followed by closed woodland. Shrubland revealed slight changes from 1997 to 2021 while riverine vegetation indicated different changes from 1997 to 2002 and 2007 to 2021. On the other side, rivers and/or water sources indicated a slight change throughout the study period.

LULC Cover Change from 1997 to 2021

Between 1997 and 2002, closed woodland and riverine vegetation coverages had the largest net declines in the study area. But grassland, open, woodlands and shrubland coverage expanded the most followed by bare land and river/water (figure 7). During the 2002 -2007 period, the coverages of shrubland, grassland, bare land, and riverine vegetation increased but those of closed woodlands, open woodlands, and river/water decreased (figure 8).

For the period 2007 and 2021, open woodlands had a sharp decrease compared to closed woodland and river/water. Generally, for the whole study period from 1997 to 2021, there is a sharp decline in open woodland followed by closed woodland and a slight decline in river/water and riverine vegetation. On the other side, there is a sharp increase in grassland followed by shrubland and bare land (figure 8).

LULC Cover Change Courses (1997-2021)

During the 1997-2002 period, significant riverine vegetation was converted to river/water and bare land while on the other side closed woodland was converted to open woodland, shrublands, and bare land. From 2002 to 2007, open woodland underwent the highest conversion to other land use types while little river/water was converted to other categories. Most of the open woodland was converted to grassland, bare land, and shrublands while some parts were detected to have water/river transformed into riverine vegetation. Despite the various conversions, grassland increased consistently for the whole study period while closed woodlands and open woodlands decreases.

From 1997 to 2021, extreme changes happened in open woodlands, followed by grasslands, closed woodland, and shrubland (See figure 9 and 7 for transformation of LULC). Much of the open woodlands was transformed into shrubland and grasslands while extensive closed woodland was transformed to open woodlands and shrubland. Particularly, the remaining cover classes showed little transformations as low as 1% (table 2). The greatest transformations of grassland were recorded in the northern-central of the protected area and woodland was noticed in the southern part of the WMA.

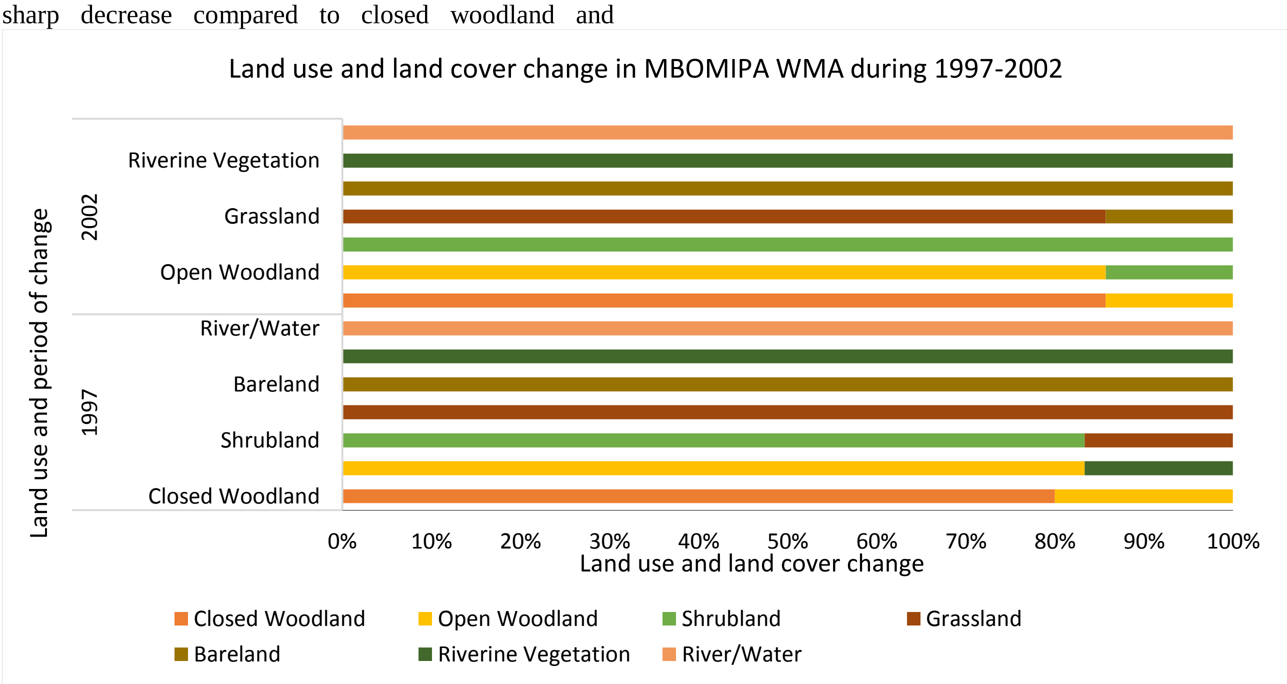

Fig. 7. LULC change (%) of the protected area from 1997 to 2002.

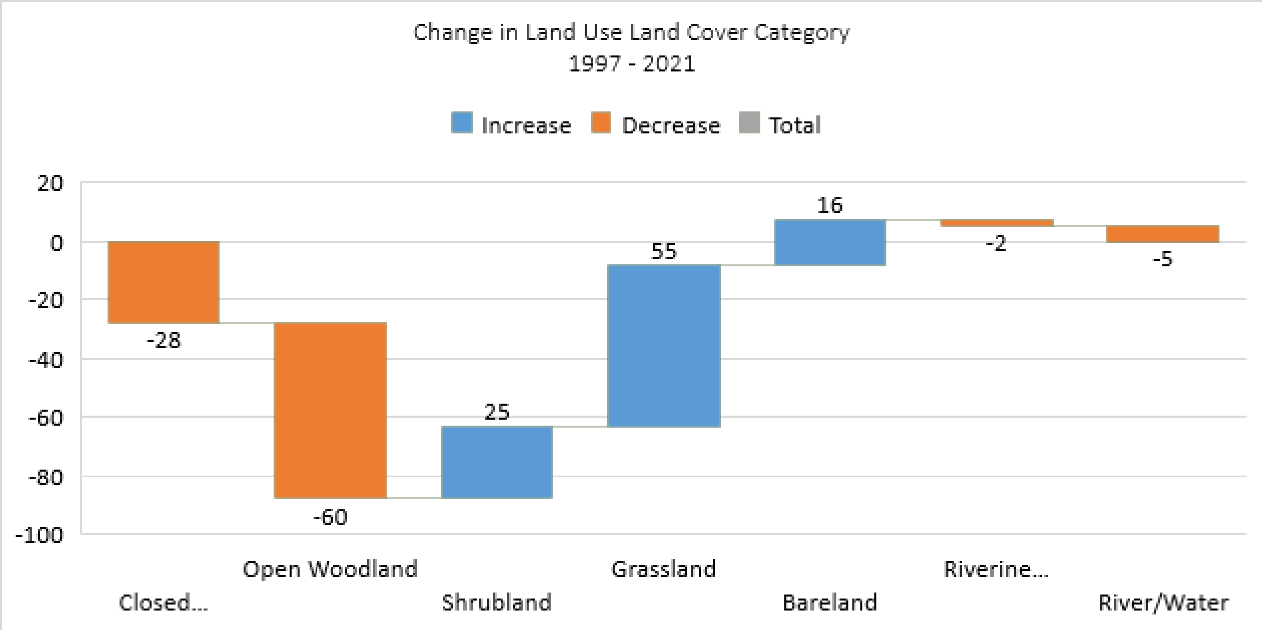

Fig. 8. Increase and decrease of LULC classes of the protected area from 1997 to 2021.

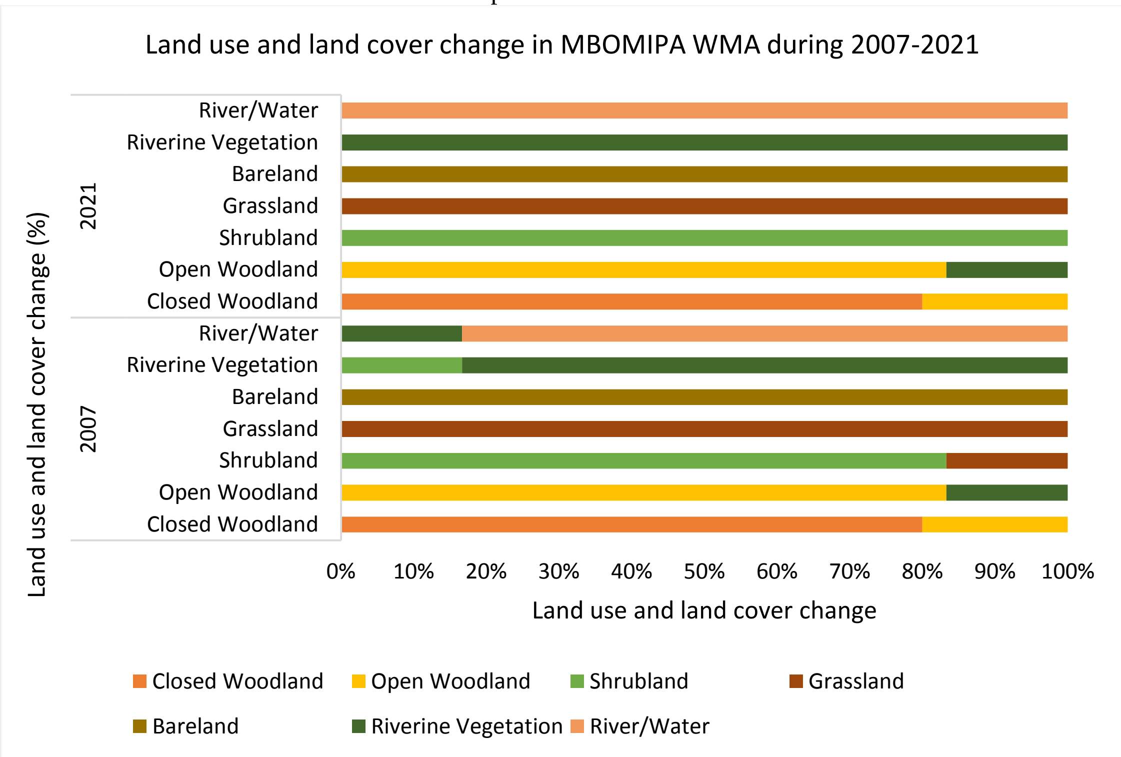

Fig. 9. LULC change (%) of the protected area from 2007 to 2021.

Discussion

LULC Cover Types

Throughout the 24 years of assessment from 1997 to 2021, Closed woodland and open woodlands had the highest proportions across the entire Wildlife Management Area. The high coverages of these land cover types in the WMA are attributed mainly to the nature of the land attributed with gneiss and granite as well as human activities which were practiced in the area before the gazettement of the area. Apart from other vegetation types mainly *Acacia* woodland/bushland, *Acacia* – *Commiphora*-bushland, *Brachystegia*-woodland, *Commiphora-Combretum*-bushland, *Acacia tortilis* thorn scrub, and Acacia-induced woodland modified by human activities, Hyphaene plus *Acaciatortilisriparian* vegetation, and Combretum woodland can be observed across the entire ecosystem (Sosovele and Ngwale, 2002).

LULC Cover Change

Throughout the entire WMA environment, Shrubland, grassland, and bareland increased from 1997-2021 at the expense of both closed and open woodland cover. Bare-land areas were low during 1997 but increased from

2002, 2007 to 2021. During the 1997 to 2021 period, grassland amplified especially in the northern part of the WMA, unlike shrubland which increased mostly in the southern part of the WMA across the entire study period (1997-2021) and while shrubland contracted in the northern part of the WMA. The expansion of grassland and shrubland cover in the WMA is likely the outcome of conversions from other cover types, mainly open and/or closed woodlands as a result of herbivory (grazing and browsing) and fire, as discussed by "Mammo et al. (2018), mostly of the threats to Land cover, is the result of the human being. These circumstances have been identified and mentioned by "Kaja et al, (2020) in the Serengeti ecosystem in Northern Tanzania as well. According to "Mdete (2016), wildfire has been an issue in the WMA, and the rise in bare land covering is related to fire events and encroachment. Apart from that the increase in bare land and grassland is associated with heavy rainfall resulting in flooding from Great Ruaha in the 2020 river which bounds the WMA on the western side.

The decline in woodland cover from 1997 to 2021 in the WMA area was due to the conversion of woodlands to other cover types. Woodland vegetation is also cleared for timber and fuel, often resulting in shrubland and other cover types. This has been proved by the study by "Mdete (2016), the community members around the WMA identified some of the threats to the biodiversity in the WMA including deforestation, bushfire, fuel wood gathering, and illegal grazing as a result of former forest areas have become bare, and inhospitable to animals. The study has further described the presence of deforestation in the WMA as a result of fuel wood collection since most of the community around the WMA does not have trees in their general lands according to "Monela, (2007), "Felix and Gheewala, (2011), and "Preston (2012), whom all corroborate this argument, fuel wood is the favored energy source since it is easily accessible, relatively priced, and simple to use. Typically, users obtain it from the wild. The reduction of forests is usually linked, among other environmental effects, to land degradation, soil erosion, shifting, and a loss of biodiversity because of habitat destruction.

On the other side MBOMIPA, WMA is among the critical areas for the large Elephant population of the Ruaha Rungwa ecosystem in the southern highlands of Tanzania. Given that, the woodland decrease is concurrent with the presence of elephants and their increase in the WMA. African elephants destroy woody vegetation, particularly during the dry season when food is scarce. These claims have been reported in neighboring protected areas in the southern highlands of Tanzania and these include Ruaha National Park "Barnes, (1985) and Rungwa Game Reserve which shares the boundary with the WMA (Barnes, 1883). Similarly, the Northern parts of Tanzania including the Tarangire Manyara ecosystem and Serengeti ecosystem have been reported by "Prins, and Van der Jeugd, (1993) and "Kija et al. (2020). In addition to elephant browsing, fire occurrences brought on by bushmeat and honey poaching have also been linked to woodland reductions in the WMA. (Mdete, 2016). Apart from that, there has been a slight decrease in rivers/water and riverine vegetation between 1997 and 2021 in the WMA. This decline is associated with rapid land cover transformations in the WMA. Generally, the declines in land cover near the protected areas threaten conservation initiatives run in the WMA as they promote community involvement in conservation through benefit-sharing systems while reducing activities that destroy biodiversity. WMAs are central to enlisting the support of local people for the management of natural resources and enforcing land use plans in line with protected ranges.

LULC Cover Trajectories

Changes in land use and land cover trajectories bring more attention to dynamic changes in various cover types. The major conversion in the WMA during the 1997-2021 period involved the conversion of Closed and open woodlands mainly to shrubland and grassland. These conversions varied across the entire WMA, partially reflecting differences in the level of human-caused impacts across the WMA. "Mdete, (2016), suggested the villages near the WMA boundary are mostly associated with encroachment and poaching". In addition, the conversions in the WMA area are partly due to fire. Fire moderately drives woodland and other vegetation to bushland and grassland as well as bushland to grassland. These conversions as a result of fire have been mentioned in different ecosystems in Tanzania and beyond (Van Langevelde et al 2003, Holdo et al. 2009). According to "Kija et al. (2020) woodland can also change into grassland and other forms of cover due to herbivory and its interaction with climatic factors. Moreover, animals such as elephants also tend to influence a particular area's vegetation or land cover. An example of this has been documented by "Van de Koppel and Prins (1998) in South Africa where elephants were part of the conversion of woodland to grassland in Kruger National Park. Browsers have been said to influence the conversion of woodland in Tanzania (Kija et al. 2020) and in Botswana (Barnes, 2001).

Conclusion

This study employs remote sensing data and GIS technologies to examine changes in land use and land cover in a community-owned Wildlife Management Area in the Iringa region of southern Tanzania. The findings demonstrate that major changes in land use and/or land cover occurred between 1997 and 2021. Results indicate the detection of a significant increase in shrubland, grassland, and barren land. Closed and open woods, riverine vegetation, and rivers or bodies of water are decreasing on the opposing side. The study presents some warnings for the benefit of the species and shows clearly how the land cover has changed significantly. This work serves as another evidence of how well GIS and remote sensing technologies may be used together to manage and assess changes in land use or cover. For the entire management, as well as policymakers and the general public, the quantification of land use and land cover in the MBOMIPA WMA area is particularly valuable for improving understanding of the surrounding environment.

Acknowledgments

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