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Remote sensing analysis of land cover/use conditions of community-based wildlife conservation areas in Tanzania

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All maps are the work of the thesis author.

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Abstract
Community based approaches to conservation in the developing world have generally been criticized for not meeting their goals of sustainable conservation and local development. Inadequate local participation and inequitable benefits sharing among others are some of the major concerns. In Tanzania wildlife management areas (WMAs) are one of the forms of community-based wildlife conservation initiatives established since 2003 around country's extensive network of protected areas bordering villages. Success stories and challenges about WMAs have already been written about but not land cover/use conditions of such areas under the current debate about their role to local communities. It is therefore expected that land cover/use conditions of the WMAs would be deteriorating. By using Remote Sensing data and Geographical Information System (GIS) analysis tools this study intends to fill in that gap by analyzing normalized difference vegetation index (NDVI), land cover/use characteristics and change and human-wildlife conflicts datasets over the last twenty-eight years to understand the trend, current conditions and predict its future for informing decision makers and other involved stakeholders. NDVI trend analysis and land cover/use change detection have been carried out to assess land cover/use conditions of an area. Human-wildlife conflicts data have also been summarized as total number of incidents to gain some insights about the extent of wildlife species presence as conditioned by conservation or/and degradation activities. Conflicts data are also useful for understanding the trend. The results show that ecosystem of the WMA is degrading as predicted by the criticisms leveled against the establishment processes and management of WMAs in the country. Tree greenness trend is slightly positive but human land use activities (farming and grazing) within the study area have been increasing after its establishment while other land cover types have been transitioning from one type to another. Different land cover/use types like agriculture especially have been growing on deciduous forest which is the largest land cover category in the area. Because the area size of deciduous forest has slightly increased it has therefore been growing on all other land cover/use types. Furthermore, problem animal incidents have also been increasing with an increase of human population size in the area. Therefore, the results show that there is no positive correlation between WMA and conditions of its ecosystem. However, for a complete analysis of the ecosystem other ecological and non-ecological variables such as wildlife population trend and rainfall should also be analyzed.

Key words: Geography, Geographical Information Systems GIS, remote sensing, wildlife management area and Tanzania

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Dhahania/Ufupisho-Abstract (Swahili)

Uhifadhi shirikishi katika nchi zinazoendelea umekosolewa kwa kushindwa kutimiza madhumuni yake makuu ya uhifadhi na maendeleo endelevu kwa jamii. Ushirikishwaji finyu na faida zisizo sawia ni miongoni mwa sababu kadhaa zinazoleta utata. Jumuiya za hifadhi za wanyamapori Tanzania ni moja ya jitihada zinazoshirikisha jamii katika uhifadhi zilizoanzishwa tangu mwaka 2003 pembezoni mwa maeneo yaliyohifadhiwa nchini (mfano hifadhi za taifa). Mafanikio na changamoto za jumuiya hizi zimekwishajadiliwa kwa kina tayari isipokuwa hali ya uoto wa asili na matumizi ya maeneo haya hususani wakati huu wa mjadala juu ya faida za jumuiya hizi kwa jamii. Kwasababu ya kuwepo kwa kutoridhika na faida za jumuiya hizi inategemewa kwamba hali ya uoto wa asili na matumizi ya maeneo haya si nzuri. Kwa kutumia vyanzo vya data za Kijiografia na technolojia ya Mfumo wa Taarifa za Kijiografia kwa ajili ya kufanya tathmini kazi hii inanuwia kuziba pengo hilo kuweza kujua rasmi hali ya uoto wa asili na matumizi ya maeneo haya yakoje kwa sasa. Katika kufanya tathimini hiyo kazi hii imetumia picha maalum za satelaiti zioneshazo ukijani wa miti, sura ya nchi ili kuweza kujua hali na mabadiliko na takwimu za mwingiliano kati ya binadamu na wanyamapori katika kipindi cha miaka 28 iliyopita. Tathmini hii inawezesha kujua mwenendo wa uoto wa asili na hali yake ya sasa kwa ajili ya kuwajuza watoa maamuzi na wadau wengine. Kufanikisha hili picha za satelaiti zinazoonesha mwenendo wa ukijani wa miti na sura ya nchi ili kuwezajua kama kuna mabadiliko zimetathminiwa. Kwa upande mwingine, jumla ya matukio ya mwingiliano kati ya bindamu na wanyamapori imetathminiwa pia ili kuwezakujua uwepo fulani wa wanyamapori na mwenendo wa matukio hayo. Matokeo ya tathmini yanaonesha kwamba uoto wa asili katika jumuiya unaharibika kama ilivyotegemewa kwasababu ya mapungufu yatokanayo na uanzishwaji na uendeshwaji wa jumuiya hizi. Mwenendo wa uoto wa asili ni chanya kidogo lakini shughuli za kibinadamu zimekuwa zikiongezeka mara baada ya kuanzishwa kwake. Aidha aina mbali mbali za uoto huo wa asili umekuwa ukibadilika pia kutoka aina moja kwenda nyingine. Misitu ya miombo ambayo ndiyo inayochukua eneo kubwa zaidi katika eneo hili imeathiriwa zaidi na mashamba na nyasi japo navyo vimekuwa vikiongezeka pia katika aina zingine za uoto wa asili. Zaidi ni kwamba matukio ya wanyama waharibifu karibu na jumuiya hii yameongezeka sambamba na ongezeko la watu. Hivyo basi, hakuna uhusiano chanya kati ya uwepo wa jumuiya hii na hali yake ya kimazingira. Hata hivyo tathimini zingine za kiikolojia na zisizo za kiikolojia kama vile mwenendo wa idadi ya wanyamapori na mvua ziangaliwe ili kuweza kujua vyanzo vingine zaidi zinavyochangia uharibifu.

Maneno muhimu: Jiografia, Mfumo wa Taarifa za Kijiografia, jumuiya ya hifadhi ya wanyamapori na Tanzania

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LIST OF ABBREVIATIONS

CBA	Community Based Approach
GEE	Google Earth Engine
GIS	Geographical Information System
GTZ	Geselleschaft fur Technische Zusammenarbeit
NDVI	Normalized Difference Vegetation Index
WMA	Wildlife Management Area

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CHAPTER 1

1. Introduction

Biodiversity loss is one of the major global environmental problems. Despite its importance to human survival on provision of goods and services it is approximated that 100 birds, mammals and amphibians of the assessed species have gone extinct globally during the twentieth century (Pereira et al 2012). Moreover, more than 30,000 species globally are currently threatened with extinction (https://www.iucn.org/resources/conservation-tools/iucn-red-list-threatened-species#RL_categories). Habitat loss, over exploitation of resources and climate change have been named as some of the leading direct drivers for the loss or local extinction (Davies et al 2012; CBD 2014; Wiens, 2016; IPCC, 2018). It is reported that more than 35–40% of the world's terrestrial habitats have been converted to cropland and pasture hence making habitat change as the number one cause (Pereira et al 2012). The lack of awareness of biodiversity and its values; the incorporation of biodiversity values into accounting systems, and decisions on economic development and planning have also been identified as some of the major underlying causes of biodiversity loss across the globe especially in the developing world (CBD, 2014). Tanzania's wildlife policy (2007) has identified loss of wildlife habitats and biodiversity and deforestation as some of the several environmental problems conservation industry is facing. For instance, wildlife lands are actively converted into farms and wildlife corridors have increasingly being blocked by agriculture activities and settlements development in some parts of the country. As a result, there have been a decline in wildlife population of megafauna species like East African Oryx (*Oryx beisa*) and Puku (*Kobus vardonii*) in some of these areas (Jones et al, 2009; Sachedina and Nelson 2009; URT 2019).

Tanzania's wildlife policy proposal for the development or protection of buffer zones, wildlife migration corridors and dispersal areas around core protected areas namely National Parks and Game Reserves by establishing community-based wildlife conservancies locally known as wildlife management areas (WMAs) aims at protecting wildlife and its habitats as a primary goal. To achieve that goal local participation and benefits sharing between the State and local communities for sustainable conservation and local development are promoted. WMAs are community wildlife land adjacent to the core PA where tourism activities are taking place for revenues generation. The revenues are shared in a defined arrangement between the communities and the government (URT 2009). WMA programs have their origin from community-based conservation approaches (CBAs) which started from 1970s designed to promote benefit sharing for local development around PAs as an incentive for local people to conserve natural resources sustainably (Adam and Hulme 2001; WWF 2012)

1.1 Aim of the study and justification

This study aims at assessing landcover/use trend and change in the study area to understand the interplay and impacts of different factors shaping the ecosystem. Such an understanding is useful for predicting the current and near future of wildlife conservation and rural development success. To understand the statuses reliably the assessment is done for the period of last twenty-eight (28) years. That means, for a balanced analysis, the assessment covers both periods before and after the establishment of WMA.

Across Tanzania there are several reports about status, the origin, local community participation, establishment process and management, costs and benefits, local attitudes, challenges etc. (IRA 2007; Sulle, et al., 2011; Kaswamila, 2012; WWF, 2012) but not land cover/use status of these areas. Land cover/use condition is important because it defines the quality and quantity of wildlife habitat and food resources for their survival. The assessment of landcover/use conditions by using remote sensing especially is lacking. Hence this proposed study seeks to address just that by looking at tree greenness trend, land cover/use characteristics and change, and human-wildlife conflicts. It is important to look at the conditions of WMAs because if the general conclusion is that the performance of WMAs in the country is minimal due to incomplete devolution and inequitable benefit sharing compared to the costs incurred (IRA, 2007; Igoe and Croucher 2007; Kaswamila, 2012; WWF, 2012) then land-use/cover conditions of these areas may not be the same as they were before. Lack of complete devolution to promote active participation for example echoes the third principle of Elinor Ostrom's 8 rules for managing the commons (2015). The third principle explains that local people are likely to follow the rules if they are fully involved in decision making.

CHAPTER 2

1. Background

Following a substantial decline of big game population in 1970's and 1980's, cost incurred by villagers living nearby wildlife, high administration costs of PAs, and continuous poverty in rural areas under the *fences and fines* or fortress conservation approach in developing world, community-based approaches (CBAs) were proposed by international conservation community and donor countries (Adams and Hulme, 2001; Nelson, 2007; Kaswamila, 2012; Kothari et al. 2013). Fences and fines involve isolating the core PA from local people because they are believed to use the available resources unsustainably hence degradation of the environment (Brockington, 2002; Adams and Huttons, 2007). Since the PA are managed exclusively without local people participation the violators such as hunters and gatherers entering these areas without permission are subject to arrests and fines. Global growth of environmentalism and concerns for human development especially among donor countries and environmentalists, and the growth of democracy in developing countries also contributed to the emergence of CBAs (Nelson, 2007). The central belief of CBAs is that people feel the sense of ownership of wildlife when there is participation and benefits from conservation (WWF, 2012). The core aim of these approaches is sustainable wildlife conservation which is made possible by empowerment, local participation, awareness, and education that they promote (Meguro, 2009).

Generally, the international debate about CBAs to conservation namely integrated conservation with development projects, community-based conservation, community conservation and community based natural resources management approaches has substantially been centered around their differences and similarities between them, and their performance (Adams and Hulme 2001; Mehta and Heinen, 2001; Chapin 2004; Meguro 2009; Ngurumwe and Muchemwa, 2011; Kaswamila, 2012; Kothari et al., 2013). These approaches are in a continuum (Meguro, 2009) and WMAs are one of the several forms of CBAs (Kaswamila, 2012). Biodiversity conservation is the goal of each of these approaches as they embark on promoting local participation and benefits sharing, local empowerment, and fulfillment of human needs/market economy for sustainability (Meguro, 2009).

Although WMAs have increased an area size for wildlife conservation the current consensus revolving around community approaches is that so far, they have attained minimal success in the developing world especially Tanzania (Croucher and Igoe 2007; Schmitt 2010; Sulle et al., 2011; Kaswamila 2012; WWF, 2012). For instance, because of the little benefits extended to communities, compared to costs incurred, Tanzania National Parks Authority community programs designed to improve relationship with local people living nearby PAs have poorly been approved by the locals in improving conservation (Sachedina and Nelson, 2009; Davis, 2011). Decline of wildlife species and their habitats, natural resources conflicts and persistence of rural poverty around PAs have been linked to a poor performance of CBAs projects. Minimal success of

CBAs is characterized especially by inequitable benefits sharing, lack of monetary benefits to individual households and centralization of power by the governments. Other reasons for poor success include insufficient knowledge about what WMA is exactly, weak WMA management capacity, insufficient monitoring and evaluation, failure to link social benefits and objectives of conservation and illegal and unsustainable utilization of resources within WMAs. (Chapin 2004; IRA, 2007; Schmitt 2010; Ngurumwe and Muchemwa, 2011; Kaswamila, 2012; WWF 2012; Kothari et al., 2013; Qorro, 2016).

Moreover, not everyone sees CBAs suitable model for conservation. There are claims that local and indigenous people do not possess the necessary knowledge and skills, and resources to manage wildlife resources sustainably (Adams and Hulme, 2001; Goldman, 2003; Chapin, 2004; Adams and Hutton, 2007; Igoe and Croucher, 2007). In forestry conservation for example, the approaches have been criticized for being more efficient in income generation for small groups than for big conservation activities which the State is believed to excel (Larson and Soto, 2008). However, Adams and Hulme (2001) and Kothari et al. (2013) have both argued that CBAs as a concept is a long-term process which keeps on evolving hence it should not be judged as a failure or a concept to be dismissed partly because it takes time for the State and local communities to develop trust on each other for its tangible success to start showing up.

1.1 Development and management of WMAs in Tanzania

Establishment of WMAs in Tanzania is a result of lack of tangible or direct benefits from some programs under CBAs (Kaswamila, 2012). Local benefits derived from WMAs are proposed as a mechanism to offset the costs of living next to the PA (Kideghesho, 2008; Davis, 2011) and stimulate positive attitudes towards conservation (WWF, 2012). One of the major aims of wildlife policy in protecting wildlife habitats and wetlands is to encourage villagers living adjacent to PAs, wetlands, or wildlife corridors to establish WMAs (URT, 2007). Technically, lots of different wildlife land categories such as wildlife corridors, wetlands, dispersal areas, migratory routes, game-controlled areas, and buffer zones where WMAs are developed are Indigenous People and Local Community Conserved Territories and Areas (ICCAs) (Kothari et al., 2013). They have been owned and managed by the surrounding communities for generations before they were officially declared to be part of conserved areas by the States.

Each participating village is supposed to contribute some land for development of WMA. WMAs were first legally established through the WMA Regulations of 2012 and are now established in the Wildlife Conservation Act of 2009 (URT, 2009; 2012a). Hence, Tanzania started implementing WMAs on a pilot phase in 2003 through 2007 when the country started creating WMAs countrywide beyond the previous 16 sites that were created in 2003 (IRA 2007; WWF, 2012). Currently, there are at least 33 WMAs spread all over the country under different stages of development including those which have completed their establishment process and therefore for some time now tourism

activities have been carried out within them. They cover an area of more than 30,000 sq.km (WWF, 2012).
In partnership with the government the development of WMAs in the country has been facilitated by different international conservation organizations and development agencies such as African Wildlife Foundation, World Wide Fund for Nature, Frankfurt Zoological Society, Gesselleschaft fur Technische Zusammenarbeit (GTZ) and United States Agency for International Development (IRA, 2007; Nelson, 2007). All WMAs, as it is required by the 2012 WMA regulations are managed a Community Based Organization which later, after being granted user rights to wildlife by the Minister, becomes an Authorized Association. Community Based Organization is formed by some members of the community itself usually nominated by the villagers at the general village assembly meeting once they have accepted WMA.

Forty five percent (45%) of the total revenues from a WMA that comes from tourism activities like safari hunting and photographic tourism is retained by the Authorized Association (WWF, 2012). Of this, half goes to the member villages and the other half is for WMA administration and conservation. Additionally, 35% goes to Tanzania Wildlife Management Authority (Sulle, et al., 2011). Generally, the income from many WMAs has not been significant in part due to underdeveloped environments (e.g., poor or insufficient lodging and transport facilities) and a presence of big number of participating villages in the WMA which must share revenues. For example, it is reported that from 2007 to 2012, 13 WMAs which conduct safari hunting business in their areas earned annual average income of $20,000 from hunting fees (WWF, 2012). Specifically, between 2012/13-2017/18 Mbarang'andu WMA in southern Tanzania earned about $172,000 as revenues from tourism (Personal communication with WMA management, December 2018).

Provision of some community development projects is seen a suitable alternative to direct payment method to communities because of smaller amount of monetary resources usually obtained from tourism revenues relative to high number of available households (IRA 2007; Kaswamila 2012). Community development projects mainly schools, bursaries, health centers, insurance, water facilities, micro-lending programs and conservation education have therefore become important benefits accrued from WMAs to offset the costs from conservation (IRA 2007; WWF 2012). Another challenge facing these areas is that employment and business opportunities offered by WMAs are highly limited by location, type of tourism conducted, presence of valuable huntable species etc. factors (WWF 2012). Due to the issues of inequitable benefits sharing, costs incurred from wildlife caused damage which supersedes the benefits, participation, poverty etc. local people around PAs in some parts of the country have been carrying out activities mainly agriculture and grazing which are incompatible with conservation (Kideghesho 2008; Davis 2011; WWF 2012). Poor success of CBCs is therefore demonstrated by the failure to achieve its conservation goals of promoting environmental conservation and reducing poverty in rural landscapes around PAs (Adams and Hulme 2001; Croucher and Igoe 2007; Schmitt 2010; Sulle et al., 2011;

WWF 2012). It is for such reasons that this study hypothesizes that it is more likely than not that environmental degradation in different forms could be happening in the study area as well.

Therefore, to investigate the aim of the study the following research questions about tree canopy greenness trend and land cover/use conditions in the study area from 1990 to 2019 will be answered. Human wildlife conflicts question is also part of the analysis because it contributes to some understanding about the extent of wildlife species presence within WMA. It also reveals the extent of megafauna problem animals around the area which in turn negatively affect local livelihoods. Lack of or low number of problem animals in a relatively populated surrounding may sometimes signify absence or low wildlife species population hence possible degraded ecosystem.

1.2 Research questions

i. What has the tree greenness trend in the study area been before and after establishment of a WMA?

ii. What have the characteristics and change of landcover/use types in the study area been before and after the establishment of a WMA?

iii. What has human-wildlife conflict trend in the study area been before and after establishment of a WMA?

CHAPTER 3

3. Methods

3.1 Study area description

3.1.1. Location

Mbarang'andu WMA is one of many WMAs in Tanzania. The WMA is located between 9°53' - 11°8'S and 35°42' - 36°41'E in Namtumbo District in Southern Tanzania within the Selous-Niassa Wildlife Corridor which facilitates wild animals' movements between Selous Game Reserve in the North and Niassa Game Reserve in the South, Mozambique (WWF, 2012) (Figure 1).

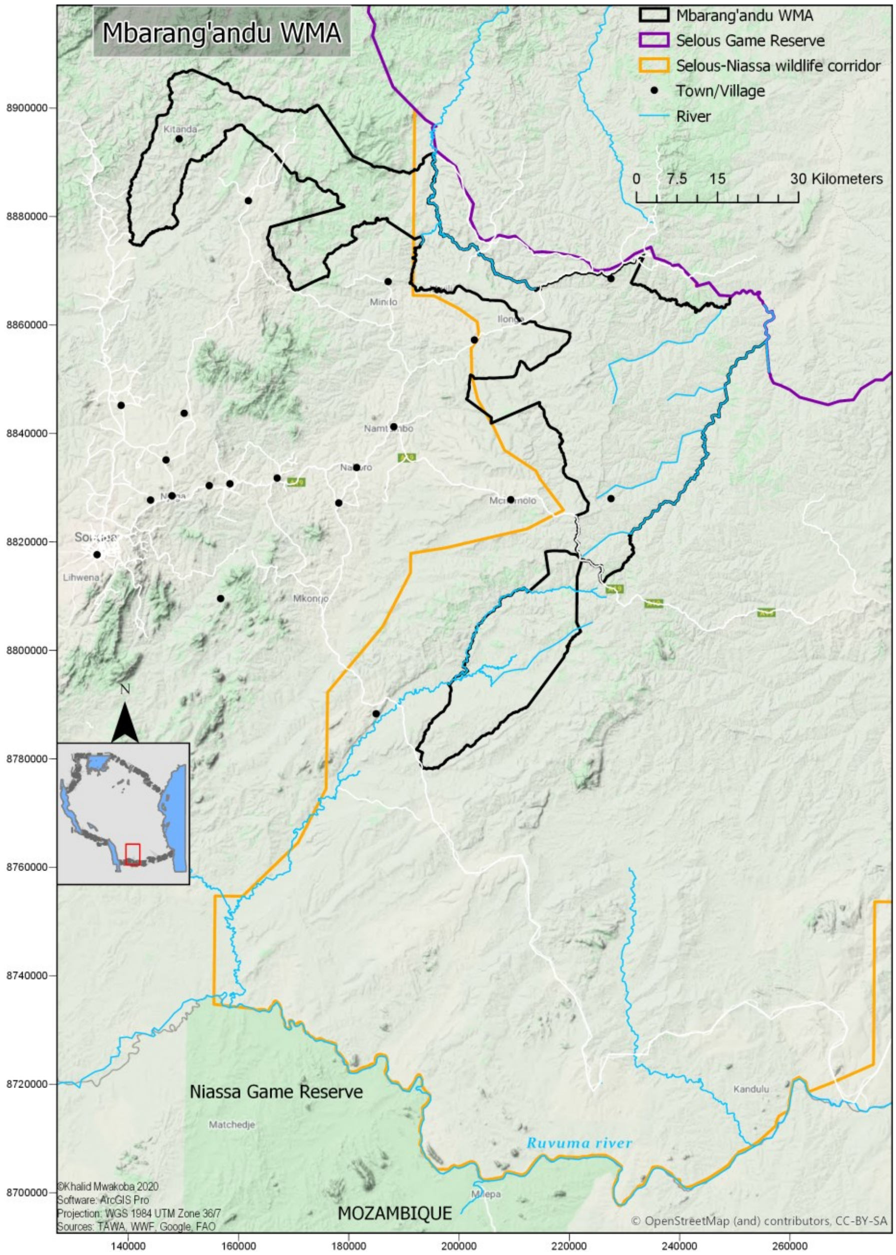

Figure 1: Mbarang'andu WMA in Southern Tanzanian: Location and surroundings

Mbarang'andu WMA has an area of about 3018 Km². It is made up of at least seven (7) village members which have contributed their lands for its formation (WWF 2012). To date the WMA has more than 75,170 people within and around it (WWF, 2012). German International Cooperation Agency/Organization, The Deutsche Gesellschaft für Internationale Zusammenarbeit GmbH (GTZ) facilitated its establishment in 1989 when these community projects started to be established in the country. It then became official in 2006 (IRA, 2007).

The WMA is chosen for the study because of its location in Selous Niassa wildlife corridor facilitating wildlife movements between the two major PAs (Figure 1). Also, it is one of the biggest WMAs in the country.

3.1.2. Climate

The climate of the District where the WMA is, is tropical savannah with the total average annual rainfall between 800 mm – 1200mm (URT, 2014). Temperature ranges between 20 °C to 25 °C during dry or hot season which is from June to November (URT, 2014).

3.1.3. Physical characteristics

Namtumbo District where the study area is located lies around 500 and 1600 meters above mean sea level (URT, 2014). The western parts of the District are dominated by undulating hills. The central and northern parts of the District where most the WMA is located are hilly. There are a few seasonal rivers within and around the WMA but further South within the Selous-Niassa corridor there is a permanent river, Ruvuma River which is a boundary between Tanzania and Mozambique.

3.1.4. Wildlife biodiversity

Elephants (*Loxodonta africana)* and wild dogs (*Lycaon pictus*) are some of the major wildlife species found in this Brachystegia species dominated ecosystem. (Mpanduji et al 2002; WWF 2012). Other medium to large animals found in the ecosystem includes hippopotamus (*Hippopotamus amphibious*), leopard (*Panthera pardus*), buffalo (*Syncerus caffer)*, hyena (*Crocuta crocuta*), zebra (*Equus quagga*), bush pig (*Potamochoerus larvatus*), warthog (*Phacochoerus africanus),* hartebeest (*Alcelaphus buselaphus*), wildebeest (*Connochaetes*) , sable antelope *(Hippotragus niger*), and reedbuck (*Redunca redunca*). Small animals such as aardvark *(Orycteropus afer*), rabbits (Lepus victoriae), hyrax (*Hyracoidea*), and varieties of amphibians, reptile and bird species etc. are also common.

3.1.5. Tourism and benefits

Mbarang'andu WMA has not many tourism activities going on within its boundaries. Until 2018 it had only one trophy hunting company operating (Personal communication with WMA management, December 2018). Despite several challenges facing WMAs in the country, income from revenues generated from tourism activities and socio-economic development projects (e.g., clinics, schools, scholarships, health insurance and water points) are some of the benefits communities have been receiving from such conservancies (WWF 2012; Personal communication with WMA management, December 2018)

3.1.6. Socio-economic activities

As it is for most Tanzanians, the residents around the WMA are subsistence farmers (URT, 2014). Food and cash crops such as maize, beans, cassava, paddy, tobacco, leguminous plants, tomatoes etc. are some of the major crops grown by the communities around the WMA.

3.2. Data sources

3.2.1. Normalized Difference Vegetation Index (NDVI) from Landsat 5 and 8

NDVI derived datasets from Landsat 5 and 8 and surface reflectance image bands (2, 3, 4 and 5) which are radiometrically calibrated and atmospheric corrected have been used for assessing tree greenness trend, and land cover/use change before and after WMA was established. Landsat data have a moderate resolution of 30 m which has the major advantage of being the only moderate resolution data available from 1970s. NDVI datasets have been used for trend analysis from 1990 to the present. Cloud free images for all years do not exist in this part of the country. Therefore, 90 images with cloud cover of less than 15% have been used for analysis. The higher the threshold the more the images one gets from GEE. Images for year 2002 and 2012 either do not meet the minimum cloud threshold/limit criteria or are unavailable thus they have missing data for analysis to be included in trend analysis. Image scenes from neighboring or adjacent WMAs have been used to fill in missing data of four years which would otherwise also had missing data. Depending on the availability in a specific year, images could either cover an entire study area or just part of it and therefore such image scene(s) is/are used for analysis to represent the conditions of the whole area.

3.2.2. Satellite Images from Landsat 5 and 8

On the other hand, fifty-eight (58) images used for land cover/use change detection have the cloud cover of not more than 5% throughout the study period. To get images for the whole study area with such small cloud cover threshold all images spanning between 1990 and 2002, and 2013 to 2019 are searched and combined/mosaicked from respective image collections. Land cover/use type classification and change detection have been analyzed for 1990-2002 period before a WMA was established and after in the period of 2013-2019. Analyses of the first and second periods of 1990-2002 and 2013-2019 are for understanding the baseline and current conditions before and after the WMA was established, respectively. Mid period of 2003-2012 is not analyzed for change detection because between 2003 and 2005 WMAs were being piloted and 2006 to 2012 is not the most recent time.

Median NDVI and image values during Peak dry season data (July, August, and September) have been used for both trend analysis and land cover classification. Dry season values are more suitable for analysis because they provide an unambiguous opportunity to measure conservation efforts or degradation in an area. Dry season values make identification of different land cover types possible because so often different tree types have different greenness. Furthermore, dry season values make detection of any an unusual high vegetation or tree greenness in the area easier.

3.2.3 Human-wildlife conflicts data

Limited human-wildlife conflicts data were obtained from local WMA office records for analysis and comparison. The data are recorded based on incidents reported by the locals. The analyzed megafauna wildlife data cover only year 2017, 2018 and 2019. For that reason, the data were used as they are just to get a glimpse of what is going on after WMA. Due to the lack of availability information and data on the subject matter before WMA were obtained through literature review. Data and information such as crop raiding and livestock attacks by wild animals, and wildlife caused human injuries or deaths were accessed. An increase or decrease of the incidents in relationship to other data and information such as tree growth trend and land cover/use serves as an indicator for an improvement or stability or degradation of the ecosystem.

3.2.4. Focus group discussions

Two focus groups discussions with the heads of households who have been living in the study area long enough before the establishment of WMAs were carried out. Information from focus groups for this study have been used for making comparison and verifying results from remote sensing analysis. Focus groups are useful for gaining insight into participants' understanding of an issue and understand how their views relate to each other (Conradson, 2005). Heads of the households were obtained by snowball sampling. Snowball sampling involves targeting recommended people who are also knowledgeable about the subject matter in question for interviews (Valentine, 2005). It is fast and the level of trust to a researcher is high because someone the respondents know referred a researcher to them. The groups were asked different questions in relation to history of local ecological status, conservation, benefits and costs, challenges of a WMA area before and after its establishment etc. (Appendix I). Qualitative data and information supplement quantitative analysis performed and literature review to answer various questions pertaining to the past and status of the ecosystem.

3.2.5. Key informants' interviews

Likewise, key people who worked for the establishment of WMA and those who are currently involved with its management were asked almost similar questions pertaining to history, local participation, ecology, costs and benefits, challenges facing WMA area before and after its establishment etc. (Appendix II). Interviews complimented remote sensing analysis by verifying it. Semi structured questionnaire questions were used for questioning. This method is quick and easy to complete once the respondents have been identified (Valentine, 2005).

3.2.6. Onsite observations and Google Earth

Some areas were visited for understanding costs and benefits of the WMA (e.g., crop damage and schools), verification of land cover/use present in that area and familiarization. Google Earth played a key role of verifying land cover/use in different parts of WMA.

3.2.7. Literature review

Different literature and internet sources on research questions of the study were consulted for analysis and making conclusion.

3.3. Methods of data analysis

3.3.1 Introduction

Google Earth Engine (GEE) has been used to acquire Landsat data and analyze NDVI trend. GEE is a is a computing platform that allows users to run geospatial analysis on Google's infrastructure whereby the client/user interact with the platform through the code editor. The code editor is a web-based integrated development environment for writing and running scripts on either JavaScript or Python programming languages (https://earthengine.google.com/platform/). Moreover, ArcGIS Pro has been used for data structuring, processing, and analyses e.g., land cover/use classification, change detection, etc. To address the objectives of the study the following steps are performed.

3.3.2. Defining geographical boundaries for the study area and projecting the data

All the data such as satellite imageries and vector data e.g., geographic boundaries, rivers and settlements have been clipped to the study area by masking and projected to WGS 1984 UTM Zone 37S.

3.3.3. NDVI theoretical background, datasets processing and trend calculations

NDVI is used for biomass productivity trend analysis, biomass change, and for identification and classification of different land cover/use categories (Herrmann et al., 2014). But the fact biomass/vegetation productivity is limited during dry season NDVI analysis for this study has essentially investigated tree canopy greenness. NDVI is a reflectance difference between the red wavelengths and the near infrared wavelengths. It ranges from -1 to 1+ value. Positive number represent varying levels of tree growth. Negative values very likely stand for water and very low values from 0.1 and below represent urban areas, bare land including rocks and sand, and snow. Positive values range such as 0.2 – 0.5 represent moderate growth (e.g. grassland and shrubland) and 0.6 - 0.9 values as maximum (e.g. tropical forests) (https://www.usgs.gov/land-resources/eros/phenology/science/ndvi-foundation-remote-sensing-phenology?qt-science_center_objects=0#qt-science_center_objects/)

Mathematically it is given as $$NDVI = \frac{NIR-RED}{NIR+RED} \quad \text{(Equation 1)}$$

Function code formula for median NDVI values (Appendix III) is applied to relevant Landsat 5 and 8 image bands that is band 5, 4 and 3 to plot graphs showing the trend between the two time periods. Landsat 5 is used to produce time series graph from 1990 to 2011. On the other hand, Landsat 8 is employed to produce graph from 2013 to the present. Median values from available image scenes are chosen to represent general conditions during dry season because median values exclude clouds and shadows as high and low values, respectively (https://developers.google.com/earth-engine/tutorial_api_05). Moreover, median is not affected as much as mean values by outliers (Weisberg, 1992) which in is this case is some evergreen trees and the degree of or differences in dryness during dry season especially between the month of July and September.

Median annual NDVI cell values for dry season are then averaged for trend analysis. For quantitative assessment of the trend or changes slope/trend line and R^2 (coefficient of determination) are calculated as.

$$y = \alpha + \beta x \qquad \text{(Equation 2)}$$

Where:

α is the offset, where the regression lines intercepts y-axis at $x = 0$ β is the slope or gain coefficient of a straight line, showing how much the y value is changing for each change in x value (Schroeder et al., 2017). Hence slope shows how tree greenness has changed in each period.

And $R^2 = R^2 \{(1 / N) * \sum [(x_i - \dot{x}) * (y_i - \bar{y})] / (\sigma x * \sigma y)\}^2$ (Equation 3)

It is a statistical measure which indicates the degree to which the data fits regression line (the goodness of fit). It shows how changes in independent variable influence changes in a dependent variable (Schroeder et al., 2017). In this case it shows to what degree influencing factors/predictors affect tree greenness.

Where:

N: number of obrsevation used to fit the model

$\sum$: summation

x_i: x value for observation i

$\dot{x}$: mean x value

y_i: y value for observation i

$\bar{y}$: mean y value

σx: standard deviation of x

σy: standard deviation of y

3.3.4. Land cover/use classification and change detection

For classification of Landsat images, the following processes to derive land cover/use types and detect changes in the study area the following steps have been performed.

- **Image bands acquisition**

A median code for extracting relevant bands from respective Landsat 5 and 8 sensors has been used to get infrared images for the period of 1990 to 2002 and 2013 to 2019 (Appendix IV). The extracted bands which have been combined to make a resultant false color composite images displayed as red, green, and blue are green, red and near infrared.

- **Identification and marking of land cover/use categories**

The National Land Cover Dataset for North America 2011 is customized for categorization. Different land cover/use categories (e.g., forests, agriculture etc.) for each of the three composite layers in the study area were identified and mapped/marked by using Global Positioning System device. Apart from expert judgement historical vegetation and topographical maps were used for mapping old images of 1990 to 2002. Land cover/use categories identified are barren, deciduous forest (open woodland), evergreen/riverine forest (closed woodland), grassland and cultivated/farmland. Evergreen/Riverine forests are treated as one category due to similarities in their spectral signatures. Four (4) Global Positioning System points were marked on each land cover/use type available in the study area as representative samples for classification.

- **Image Enhancement**

Image visibility was enhanced by maximum and minimum stretching levels whereby contrast and brightness levels were adjusted before segmentation so that features are more visible and can differentiated for grouping.

- **Image segmentation**

Classification has been done by object-based method by using support vector machine classifier. Object-based classification uses image segmentation approach. Segmentation groups together nearby pixels with similar spectral characteristics into a segment by mean shift approach. In turn the segments sharing similar objects, spectral and spatial characteristics are grouped together into objects. These objects are finally grouped as feature classes (settlements, roads etc.) on a real world. (https://pro.arcgis.com/en/pro-app/tool-reference/spatial-analyst/understanding-segmentation-and-classification.htm).To achieve this segmentation parameters namely spectral detail, spatial detail and minimum segment size in pixels are set to low values as 5, 6 and 5 respectively. This is due to various factors such as low level of details required, few land cover/use categories, and medium cell resolution of the raster used (https://learn.arcgis.com/en/projects/calculate-impervious-surfaces-from-spectral-imagery/).

- **Creating training samples**

Different training areas/polygons representing different land cover/use categories identified before are digitized under training sample manager on segmented composite bands for 1990-2002 and 2013-2019 images. Additional samples for each land cover/use category are identified and mapped on each image on training sample manager. At least six (6) more samples for each category are created making it a total of at least ten (10) samples combined per category.

- **Training support vector machine classifier**

The classifier is trained, and the results are evaluated. Where need be the segmentation parameters and training samples are adjusted. Support vector machine is an 'advanced machine learning classification method that is able to process a segmented raster input or a standard image'. It is less affected by noises and useful when there are few training samples (https://pro.arcgis.com/en/pro-app/help/analysis/image-analyst/the-image-classification-wizard.htm).

3.3.5. Classification and Reclassification

Supervised classification by using object-based method is used for this study. Object based is a modern method for generalization of similar neighboring features hence it does not have a significant 'salt and pepper effect' as pixel-based classification (https://pro.arcgis.com/en/pro-app/help/analysis/image-analyst/the-image-classification-wizard.htm). Moreover, object-based classification has been used because of the dominance of one land cover category hence useful for generalization. Also, supervised classification is chosen because of the researcher's prior knowledge of the area and therefore a guided classification by using the created training samples is useful in this case because it yields more accurate results. The results are five land cover/use categories made from classification for 1990-2002 and 203-2019 periods. Where there was a misclassification that category was reclassified by a re-classifier.

3.3.6. Land cover/use change detection and cross tabulation

The land cover/use change detection between 1990-2002 period and 2013-2019 period follows. This is done by subtracting the current image from the former image (2019-2013 minus 1990-2002) to establish the changes that might have taken places in the ecosystem between the two time periods. This is done by using *difference* function on image processing window whereby the most current raster is placed at the top and the old one underneath it for subtraction operation. The subtraction is done on pixel-by-pixel basis. For that reason, *first* option for overlapping cells between two rasters is chosen under processing function. That means because the purpose is to understand the current changes that might have happened cell values of the most recent dataset are used for subtraction. The temporary output layer is made permanent for mapping by exporting. Similar object-based classification process as described before is applied to this layer for mapping process.

Then, it is also useful to understand direction of the changes (i.e., transition among land cover/use types). This is done by using tabulate area under zonal functionality. It calculates cross-tabulated areas between two datasets. The old raster defines the zones into which areas of transition are calculated/summarized while the current dataset becomes an input to summarize the changes or transition between the two periods.

3.3.7. Calculating map accuracy

Map accuracy assessment is done for both periods. To assess the accuracy of classification map accuracy assessment is done by comparing the classified value of the image at the location of each point with actual land cover/use type-ground truth on the field/with reference data. For this *create accuracy assessment points* tool is used whereby 1990-2002 and 2013-2019 maps as inputs. Since onsite verification was not done due to resource constraints classified target field is chosen instead. Classified field contains classified values of the raster for the points to be generated. The area size of the study area is not small/big and has several landcover/use categories hence medium number of random points to be generated is chosen. For this, ninety-seven (97) points are created, and default sampling strategy-stratified random sampling is accepted. Each land cover/use category has number of points in proportional to its relative area size. The resulting tables of accuracy points contain classified values of the raster datasets (e.g., 1. 2, 3 etc. for different landcover/use categories). Each point shows the type of land use/cover it stands on.

To validate whether point values stand on actual specified category type on the original historical and current image/ground the ground truth field which is the second field on attribute table of the accuracy points is edited and filled in with correct data values as it is on the original image (e.g. all point values corresponding to ground truthing values are assigned value 1 and those which do not as 0). This is done by zooming in to each point on respective georeferenced historical, recent and current maps, satellite images and Google Earth satellite images used for assessment/verification. All 97 assessment points for each period independently, that is, past and present (historical and current maps) are therefore verified.

3.3.8. Confusion matrix computation

Comparison table for classified and ground truth values above must be made to determine the percentage of accuracy of the map. This done by using *compute confusion matrix* tool whereby accuracy point data produced above becomes an input. Confusion matrix/table is produced. The columns contain ground truth point values of landcover/use types and the rows represent classified point values of land cover/use types. Matching or comparing correct and incorrect mapped land cover/use classes on the maps and what is on the ground is done. Consequently, the following map accuracy measurements/estimates are calculated and described.

User accuracy: number of correctly classified assessment points / total number of assessment/map data points. It compares the map with the field data. For a randomly selected point on the map, the user accuracy indicates the probability that this point is correctly mapped (i.e., has the same value as the ground truth). That is to say, water body sample point for example, picked off from the map the probability for that point being is water body on the ground is reflected by the amount of percentage calculated

Producer accuracy: number of correctly classified sample points / total number of ground truth points. It compares field data with the map, indicating the probability that a randomly selected point from ground truth (e.g., a point in field) is correctly mapped. It measures work accuracy of the mapper. For instance, if urban area land cover type is picked off from the ground truth data the probability that it falls on the same land cover category on a map is reflected by that percentage calculated.

Overall accuracy: total number of correctly classified sample points (from all classes)/ total number of points. It reflects the probability that a randomly selected point, regardless of the class, on the map is correctly classified. This is a generalized estimation for it considers all land cover categories at once.

Kappa coefficient: (total number of points * number of correct mapped points) - sum of correctly mapped points

/total number of points^2 - sum of the products between ground truth and map data for each class

It incorporates the influence of chance and therefore it is used to measure the goodness of the map.

3.3.9. Ground Truthing

The study area was visited to understand its general ecological (e.g., vegetation/tree types) and climatic characteristics (e.g. rain patterns). Also, where possible few selected land cover/use types which for some reasons could barely be recognized on the image (e.g., barren, burnt area etc.) were visited for verification.

3.4. Human-wildlife conflicts analysis

Because of lack of or incomplete data only available major human-wildlife conflicts recorded data especially crop raiding, livestock attacks by wild animals, wildlife caused human injuries or deaths are analyzed to understand where conflicts occur and why. The data cover only three years; 2017, 2018 and 2019. Historical data are therefore analyzed through literature review. It was reported that due to absence of enough working gears for follow up, lack of timely and clear evidence on the damage caused etc. human-wildlife incidents except for human death or injury are not always recorded (Personal communication with WMA management, December 2018). Conflicts' trend is a good indicator of the status of the ecosystem. Big number of conflicts could indicate either an increase of wild animal species population or people or both. An increase in human-wildlife conflicts pose a threat to the sustainability of the ecosystem. Retaliatory killings of the carnivores (Kideghesho, 2008) and the invasion of WMAs for farmland or charcoal making for example (Kaswamila 2012) affect the population size of wildlife species negatively and deprives them of their habitats and food resources, respectively.

CHAPTER 4

4. Results

The results of the analyses from both two time periods of NDVI raster datasets show that tree greenness is slightly decreasing and increasing before and after establishment of a WMA, respectively. The R^2 value is not significant but is positive and negative respectively as shown on figure 2 and 3. That means the influence of human activities on the observed marginal negative and positive trends is very low.

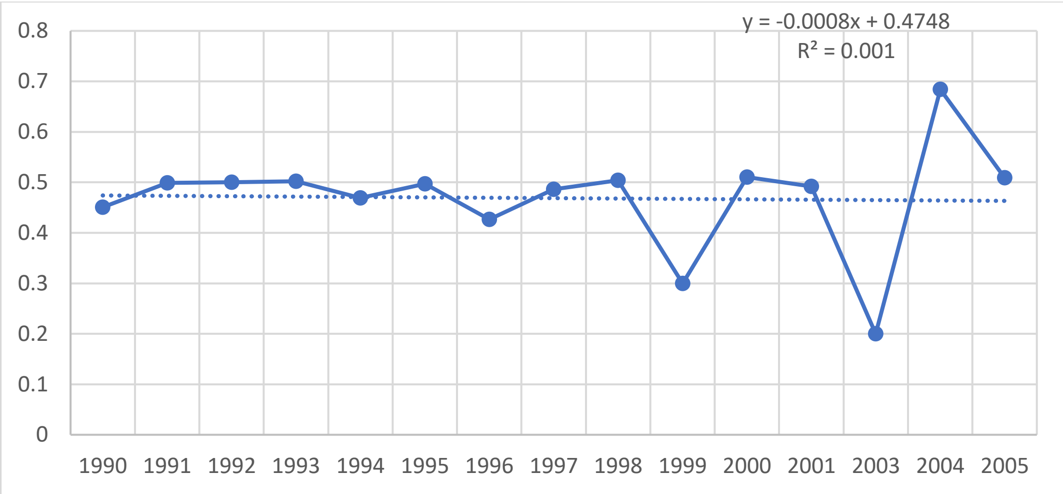

Figure 2: Decreasing NDVI trend before establishment of Mbarang'andu WMA in 2006

Throughout this period annual individual NDVI value of around 0.5 was common. Moderate growth persisted even in 2003 which was a drought year (Paavola 2008). Apart from shrubs and grasses, deciduous forests are also likely to have moderate growth during dry season when they shed leaves.

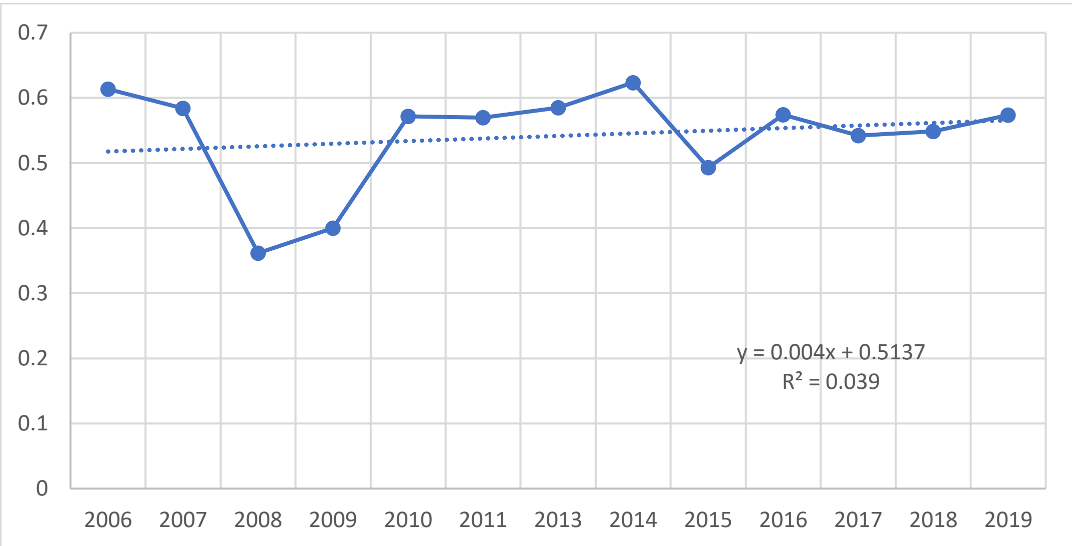

Figure 3: Increasing NDVI trend after establishment of Mbarang'andu WMA in 2006

This period has higher annual individual NDVI values compared to the period of a decreasing trend. Few years had maximum growth.

NDVI trend alone is not enough to understand the conditions of the ecosystem. Understanding characteristics of land cover/use types, changes over time, and visualizing where that happens add more value to the analyses. Figure 4, 5 and 6 below show land cover/use types in the study area in the period of 1990-2002, 2013-2019 and the change between the two time periods.

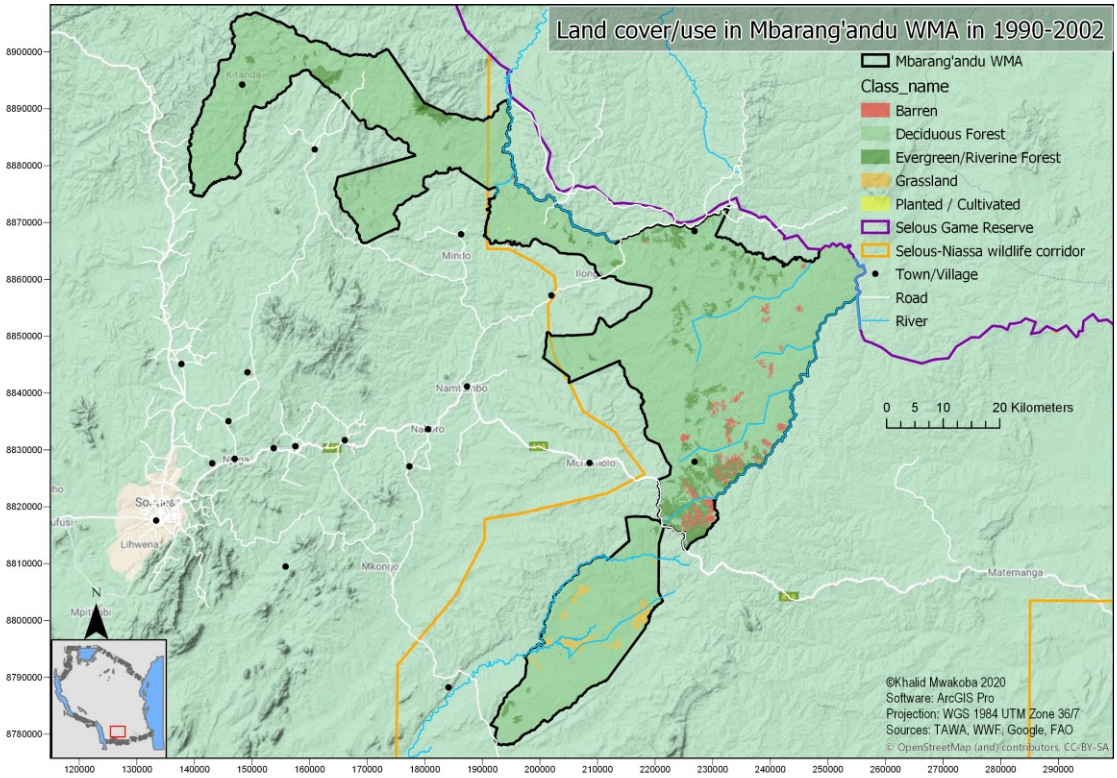

Figure 4: Land cover/use types in Mbarang'andu WMA in 1990-2002

Most of the area is dominated by deciduous forests locally known as open woodland (Mpanduji et al 2002). Evergreen/Riverine forests are distributed on the highlands or along the rivers. There are some few grasslands and barren lands in the south. Limited presence of human activities in the area especially farming and dominance of open woodland support the observed slightly decreasing trend of tree greenness. Farming during this period accounts for only 1 km sq. (less than 1%) which is equivalent to 100 hectares out of 3018 km. sq. of the total WMA area. (Table 1).

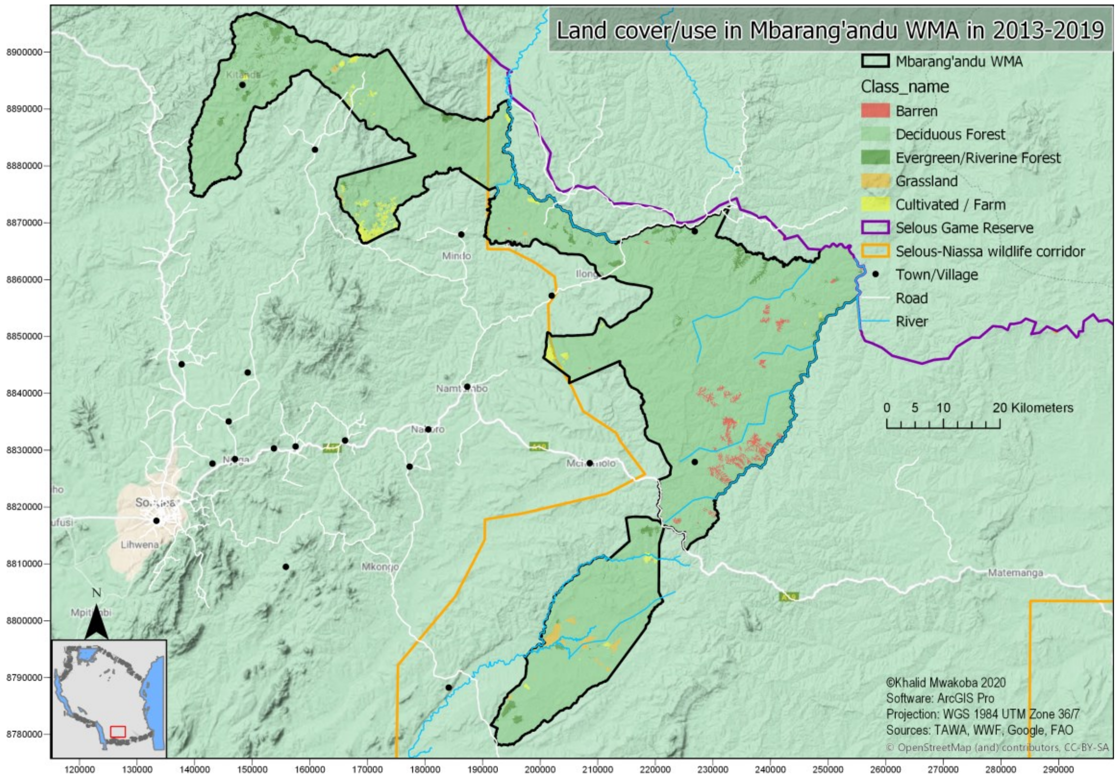

Figure 5: Land cover/use types in Mbarang'andu WMA in 2013-2019

Deciduous forest is still the leading category during this period. Evergreen/Riverine forests have decreased. Cultivated land or farms have increased significantly especially around the boundaries of the WMA. These are also areas which are close to the roads which facilitate accessibility to the area as it was also confirmed by interviewees. Here too the presence of human activities in the area concur with observed marginal increasing trend of tree greenness after WMA was established. Farming is only 1% of the total area of a conservancy (Table 1). Small percentage of presence of human activities in the area has marginally reduced the growth hence the observed insignificant positive trend which would otherwise become better or significant.

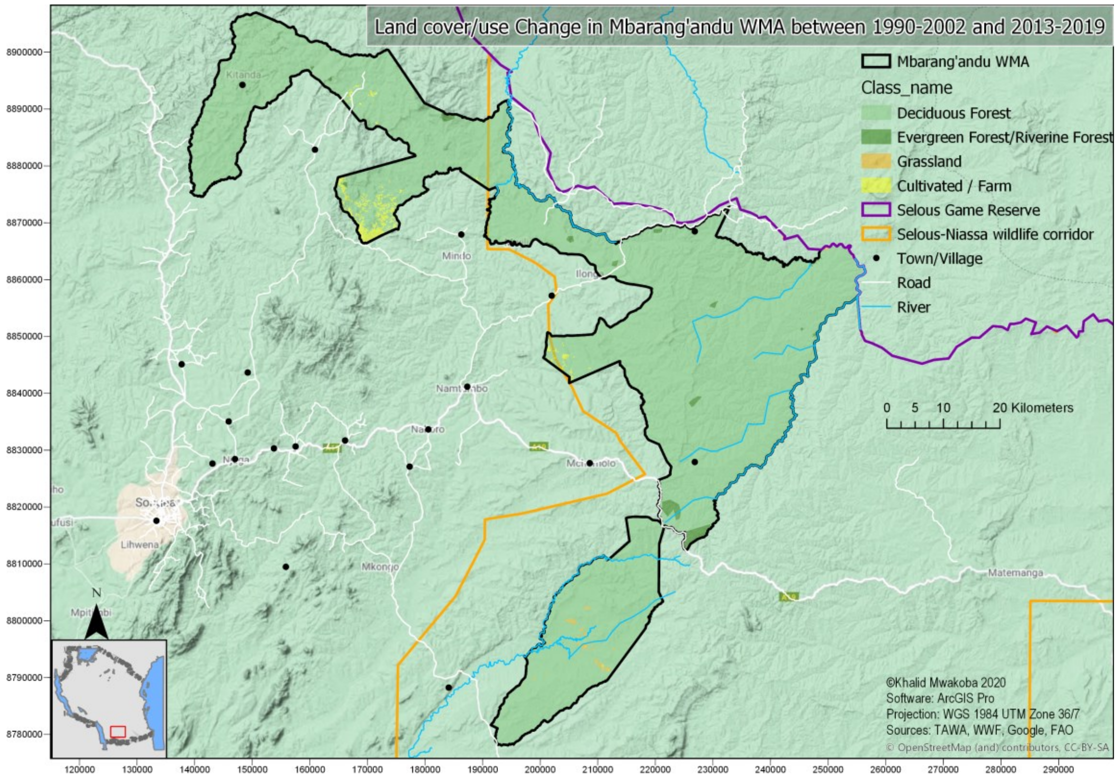

Figure 6: Land cover/use change in Mbarang'andu WMA between 1990-2002 and 2013-2019

Generally, the only major change has been the appearance of cultivated land/farms close to the boundaries in the northwestern parts of the WMA. Also, evergreen/riverine forests have decreased.

Table 1 below shows the quantity of each land cover/use type and the change between the two time periods.

Table 1. Landcover/use statistics in Mbarang'andu WMA in 1990-2002 and 2013-2019

ObjectID	Landcover/use	AREA (Km.sq) in 1990-2002	AREA (Km.sq) in 2013-2019	Change (Km.sq)
1	Barren	44	35	-9
2	Deciduous Forest	2754	2861	107
3	Evergreen Forest	183	60	-123
4	Grassland	36	21	-15
5	Cultivated/Farms	1	41	40
	TOTAL	**3018**	**3018**	

The area size of deciduous forests and cultivated land categories have increased while the rest of the categories have decreased. That means, these two categories have expanded on the areas where other three categories used to be.

Interviews with focus groups also revealed ever-growing presence of human activities especially farming in the WMA along the edges. Immigration into the areas around a WMA was mentioned as one of the contributing factors.

Table 2 below show land cover/use types which have been replaced by farms and deciduous forests especially which have been having a major growth. This is important to understanding the most affected or vulnerable land cover/use.

Table 2. Tabulated area table

	PERIOD	2013-2019					TOTAL AREA (SQ.KM) in 1990-2002
ObjectID	**1990-2002**	Barren	Deciduous Forest	Evergreen /Riverine	Grassland	Cultivated/ Farm	
1	Barren	15.3	29.1	0.0	0.0	0.4	44.8
2	Deciduous Forest	17.1	2643.1	40.9	13.5	39.4	2754.0
3	Evergreen/Riverine Forest	2.2	161.2	19.1	0.0	0.4	182.9
4	Grassland	0.0	27.3	0.1	7.8	0.8	36.1
5	Cultivated/Farm	0.1	0.2	0.0	0.0	0.2	0.5
	TOTAL AREA (SQ.KM) in 2013-2019	34.8	2860.9	60.2	21.4	41.1	**3018.0**

Cultivated land/farming has been done on deciduous forests while deciduous forests have been replacing evergreen/riverine forests and some growing on barren land and grassland areas. Likewise, some evergreen forests and grassland have been growing on deciduous forests. The green boxes represent quantities where there have not been changes while white boxes are the quantities of transitioning land cover/use. When compared to other land cover/use types the area size of deciduous forests has largely remained unchanged. Thus, while the first table (Table 1) shows absolute changes of different land cover/use types the second table (Table 2) shows how these changes have been taking place or transitioning.

Finally, error/confusion matrix is calculated to understand level of accuracy of classification whereby user accuracy, producer accuracy, overall accuracy and kappa coefficient estimates are calculated from the 97 accuracy assessment points (Table 3 and 4)

Table 3. Error/Confusion matrix for 1990-2002 classification

(C_0 = misclassified, C_1 = correctly classified)

ObjectID	Landcover/use	C_0	C_1	Water	Barren	Deciduous Forest	Evergreen Forest	Grassland	Planted/Cultivated	Total	U_Accuracy 100%	O_Accuracy	Kappa
	C_0	0	0	0	0	0	0	0	0	0	0	88%	0.84
	C_1	0	0	0	0	0	0	0	0	0	0		
1	Water	0	10	10	0	0	0	0	0	10	100		
2	Barren	0	10	0	10	0	0	0	0	10	100		
3	Deciduous Forest	4	43	0	1	43	1	1	1	47	91		
4	Evergreen Forest	0	10	0	0	0	10	0	0	10	100		
5	Grassland	0	10	0	0	0	0	10	0	10	100		
6	Planted/Cultivated	7	3	0	6	1	0	0	3	10	30		
	Total	**11**	**86**	**10**	**17**	**44**	**11**	**11**	**4**	**97**	0		
	P_Accuracy	0	0	100	59	98	91	91	75	0	0		

Planted/cultivated has largely been misclassified as barren. Consequently, both user and producer accuracy estimate for all categories except user accuracy for planted/cultivated are high. Overall accuracy and Kappa coefficient are also high.

Table 4. Error/Confusion matrix for 2013-2019 classification

ObjectID	Landcover/use	C_0	C_1	Water	Barren	Deciduous Forest	Evergreen Forest	Grassland	Planted/Cultivated	Total	U_Accuracy	O_Accuracy	Kappa
	C_0	0	0	0	0	0	0	0	0	0	0	93%	0.90
	C_1	0	0	0	0	0	0	0	0	0	0		
1	Water	0	10	10	0	0	0	0	0	10	100		
2	Barren	0	10	0	10	0	0	0	0	10	100		
3	Deciduous Forest	0	47	0	0	47	0	0	0	47	100		
4	Evergreen Forest	2	8	0	0	1	8	0	1	10	80		
5	Grassland	0	10	0	0	0	0	10	0	10	100		
6	Planted/Cultivated	5	5	0	4	0	1	0	5	10	50		
	Total	**7**	**90**	**10**	**14**	**48**	**9**	**10**	**6**	**97**			
	P_Accuracy	0	0	100	71	98	89	100	83	0			

Here too only one category has slightly been misclassified. Again, some cultivated/farms have been misclassified as barren land but overall, all estimates are very high.

Generally, all estimates during both time periods are high. That means the accuracy of the maps is high enough, they represent what was/is there on the ground.

The analyzed human-wildlife conflicts data not only show an increase in farming activities in and around WMA after its establishment but also presence of grazing, charcoal making and poaching activities in Selous-Niassa wildlife corridor where this WMA is located. Mpanduji et al (2002), WWF (2012) and URT (2019) have all discussed the presence of such unsustainable utilization of resources in the WMAs and corridor before and after WMAs came into being.

The other aspect of human-wildlife conflicts for three-year period indicates that both and herbivore and carnivore animal problem incidents by megafauna around WMA have been increasing after it came into being. These are minimum number of incidents for many incidents unless it is wildlife caused human death or injury go unreported or unrecorded as explained before. Table 5-10 below show the trends in three years since 2017.

Table 5. Herbivore problem animal incidents in 2017

2017	Village	Harbivore problem animal	Incident	Number of incidents	Quantity (acre)	Number of people affected
1	Mtonya	Elephant	Crop raiding	No records	22	13
2	Kilimasela	Elephant and Hipopotamus	Crop raiding	No records	27	24
3	Likusanguse	Elephant	Crop raiding	No records	3	3
4	Mandela	Elephant	Crop raiding	No records	82	35
5	Nambecha	Elephant and Hipopotamus	Crop raiding	No records	39	17
6	Likuyuseka	Elephant and bush pig	Crop raiding	No records	33	28
TOTAL					**206**	**120**

Table 6. Carnivore problem animal incidents in 2017

2017	Village	Carnivore problem animal	Incident	Number of incidents
1	Luegu	Crocodile	Human injury	1
2	Mtonya	Crocodile	Human death	1
3	Masuguru	Leopard	Human injury	1
4	Mandela	Crocodile	Human injury	1
TOTAL				**4**

Crop raiding by elephants (*Loxodonta Africana*) especially was leading in 2017 in the recorded incidents destroying two hundred and six (206) acres affecting one twenty (120) different farmers. Crocodile (*Crocodylus niloticus*) attacks on human along the rivers and permanent ponds among carnivore problem animals were the major incidents in the same year attacking two (2) people and killing one (1).

Table 7. Herbivore problem animal incidents in 2018

2018	Village	Harbivore problem animal	Incident	Number of incidents	Quantity (acre)	Number of people affected
1	Mtonya	Hipopotamus	Crop raiding	1	4	4
2	Kilimasela	Elephant	Crop raiding	2	21	14
3	Mgombasi	Elephant and Hipopotamus	Crop raiding	3	16	9
4	Mandela	Elephant	Crop raiding	4	5	18
5	Nambecha	Elephant and Hipopotamus	Crop raiding	7	40	26
6	Likuyuseka	Elephant, Eland and bush pig	Crop raiding	4	22	18
7	Mchomoro	Hipopotamus	Crop raiding	3	**5**	**5**
8	Libango	Hipopotamus	Crop raiding	3	14	14
9	Nahoro	Hipopotamus	Crop raiding	1	8	6
10	Ulamboni	Hipopotamus	Crop raiding	1	7	6
11	Sasawala	Bush pig	Crop raiding	2	5	6
12	Limamu	Buffalo	Crop raiding	2	0.25	2
13	Kitanda	Buffalo and bush pig	Crop raiding	2	1	3
14	Mtelawamwahi	Eland and bush pig	Crop raiding	1	0.75	2
TOTAL				**36**	**149**	**133**

Table 8. Carnivore problem animal incidents in 2018

2018	Village	Carnivore problem animal	Incident	Number of incidents
1	Mwinuko	Hyena	Goat and pig death	2
2	Libango	Crocodile	Cow death	1
3	Hanga	Leopard	Goat death	1
TOTAL				**4**

In 2018 crop raiding incidents probably increased from the previous year with hippopotamus caused raids topping the list followed by elephants. One hundred and forty-nine (149) acres and one hundred and thirty-three (133) individuals were impacted by thirty-six (36) raiding incidents. Other animals like bush pigs (*Potamochoerus larvatus*), elands (*Taurotragus oryx*), and buffalos (*Syncerus caffer*) were also implicated.

Crocodile (*Crocodylus niloticus*) and leopard (*Panthera pardus*) attacks continued. Each killed one domesticated animal. Two (2) animal deaths caused by hyena (*Crocuta crocuta*) were also recorded.

Table 9. Herbivore problem animal incidents in 2019

2019	Village	Harbivore problem animal	Incident	Number of incidents	Quantity (acre)	Number of people affected
1	Mtonya	Hipopotamus	Crop raiding	3	10	10
2	Kilimasela	Elephant	Crop raiding	1	31	36
3	Mgombasi	Hipopotamus	Crop raiding	4	6	6
4	Mandela	Elephant	Crop raiding	3	112	106
5	Nambecha	Elephant	Crop raiding	9	125	69
6	Likuyuseka	Elephant	Crop raiding	2	37	36
7	Minazini	Hipopotamus	Crop raiding	4	**22**	**18**
8	Luegu	Hipopotamus	Crop raiding	1	3	9
9	Lisimonji	Hipopotamus	Crop raiding	1	0.5	2
10	Lusewa	Reedbuck	Crop raiding	1	0.25	1
11	Sasawala	Bush pig	Crop raiding	2	0.5	3
12	Njomulole	Hipopotamus	Crop raiding	1	0.5	1
13	Likusanguse	Elephant	Crop raiding	2	4	7
14	Kitanda	Elephant	Crop raiding	2	6	9
15	Ligunga	Elephant	Crop raiding	2	3	6
TOTAL				**38**	**361**	**319**

Table 10. Carnivore (and herbivore) problem animal incidents in 2019

2019	Village	Carnivore problem animal	Incident	Number of incidents
1	Luegu	Crocodile	Human injury	1
2	Mandela	Crocodile and Elephant	Human injury	2
3	Sasawala	Crocodile	Human injury	1
TOTAL				**4**

Crop raiding incidents by elephants were dominant again in this year followed by hippopotamus (*Hippopotamus amphibious*). Thirty-eight (38) incidents in total were recorded causing crop damage on three hundred and sixty-one (361) acres affecting three hundred and nineteen (319) at minimum. Crop raiding by reedbuck (*Redunca redunca*) was also reported. Crocodile (*Crocodylus niloticus*) caused human injuries were the major carnivore animal problem in this year again whereby three (3) attacks were reported.

Mpanduji et al (2002) reveals that from 1990 to 2000 the district where this WMA is located recorded 75 incidences of predator attacks on livestock in different villages within the Selous-Niassa corridor. This demonstrate that as human population increases human-wildlife conflicts in this area have also been rising.

CHAPTER 5

5. Discussion

Generally, the results show that there is an inverse correlation between establishment of WMA and the conditions of its ecosystem. Tree greenness trend is not noticeable during both periods. Land cover/use change detection reveals an increase of cultivation within WMA. Human-wildlife conflict is increasing but alongside an increasing vegetation cover degradation and population growth around the study area.

Degradation of WMA ecosystem in the study area paint a different picture from some studies in the forestry management in Tanzania which have found out that village participatory land use plans in the context of Reduced Emission from Deforestation and Forest Degradation plus (REDD+) improves forests management (Amani et al 2019). They argued that it can therefore be a useful tool for forest management and conservation. Depending on the level though that leads to success, participation creates sense of ownership of natural resources and justifies further benefit sharing concept. Instead, degradation of the ecosystem echoes the third rule for managing the commons (Ostrom 2015). When people are not involved fully in decision making process, they are not likely going to follow the imposed rules. Because of limited level of participation and other factors local people in this area have not restrained themselves from unsustainable uses of resources inside the ecosystem.

An increase of human-wildlife conflicts in the area is compounded by previous mentioned challenges facing management of WMA. For example, benefit sharing from WMA revenues in the ratio of around 45% to 55% between local people and government is perceived as inequitable because it is local people who bear the costs of conservation mainly contribution of local land for conservation and wildlife attacks on people and property with little or no compensation (Igoe and Croucher 2007; Kideghesho, 2008). This was also reported as a cause for most of local people to be resentful (Personal communication with WMA management, December 2018).

The R^2 is very low both before and after WMA. This is due to very low/small strength of the predictors/influencing factors (e.g., conservation efforts, human invasion, rainfall etc.) to bring about significant changes/impacts. Just only 1% of the total WMA area has been cultivated. There is a very limited causality between the predictors and the observed conditions especially after WMA for R^2 to be high.

Trend analysis has used image data from available scenes which many not necessary cover the whole study area. That means other areas of a WMA have not been represented for analysis. But change detection analysis has offset that by including the whole study area. For that reason, the results between trend analysis and change detection analysis are largely on agreement.

An increase of human-wildlife conflicts involving man and megafauna species in the study area is supported by several different authors. Kideghesho (2016) reported that elephants' population in the larger Selous-Mikumi ecosystem which shares the southern boundary with Selous-Niassa wildlife corridor went down to 13,084 in 2013 from 38,975 in 2009 and from 70,406 in 2006. Furthermore, Kideghesho (2008) mentioned an increase of crop damage, wildlife caused human deaths and injuries and livestock depredation in Selous ecosystem. Elephants (*Loxodonta Africana)*, hippopotamuses (*Hippopotamus amphibious*), bush pigs (*Potamochoerus larvatus*)*,* buffalos (*Syncerus caffer)*, reedbucks (*Redunca redunca*), elands (*Taurotragus oryx)*, lions (*Panthera leo*), leopards (*Panthera pardus*), crocodiles (*Crocodylus niloticus*) andhyenas (*Crocuta crocuta*) have all been reported as the major leading problem animals in the ecosystem. Likewise, the Citizen newspaper (https://www.thecitizen.co.tz/magazine/INSIGHT--Mbarang-andu-area-key-in-wildlife-conservation/1840564-2420880-gyrwj3/index.html) using official data from WMA itself reported an increase of crop damage by elephants in the study area after the establishment of WMA. Elephant's (*Loxodonta Africana)* population has not stabilized yet after a poaching wave in Selous ecosystem in late 2000's and early 2010's but more elephants are seen now than during that period it was reported (Personal communication with WMA management, December 2018). The fact that human population was low in the past and now it has increased the likelihood of an increase of conflicts is very high even though many incidents in the past might have gone unrecorded.

However, there are some natural issues at play and technical issues that might have influenced the results but without diverting them far from reality.

Since some crops like maize/corn, tobacco and cassava might have NDVI values like shrubs and grassland human encroachment in form of farming in a PA might not be differentiated or identified hence not counted as degradation. From field visits it was observed and/or reported that some villagers sneak into the PA for paddy and tobacco cultivation. These crops are cultivated on the lowlands and/or nearby water sources during dry season in the study area. Nevertheless, it was reported that these are usually small farms of less than an acre in size (Personal communication with WMA management, December 2018).

When it comes to classification due to different reasons which affect spectral signatures of various land cover/use types such as cultivated land and barren lands especially have slightly been misclassified in some areas. However, the fact that cultivated land due to its spectral signature similarities with barren land has in few areas been misclassified as such it has not caused significant impact on its area size. For example, before WMA especially cultivated land was not even above 1 sq. km. For the same reason cultivated land after WMA might be less than 41 sq.km but several barren land areas close to the farms or WMA's boundaries might as well be abandoned/barren farms.

As a result of misclassification user accuracy before WMA is low (Table 3). This is because farms during dry seasons are barren hence share the similar spectral signatures or characteristics with barren land. Even though additional area has been misclassified as barren still area of the farms before WMA is/would otherwise still be small (Table 1). Other sources of error for misclassification might include mistakes in collecting and/or creating training samples.

Object-based classification method smoothen the resultant classified map image. In the process of doing so local landcover/use details/types (e.g., water) especially if medium resolution dataset like Landsat have been used for analysis are omitted by being generalized into major neighboring category.

Furthermore, sensor shifts between platforms and orbit shift such as Landsat 5 through 8 in this case are known to cause errors in NDVI trends due to discontinuities or breaks in NDVI time series data (Tian et al., 2015). Abrupt changes in NDVI values (i.e., low to high and vice versa) have been observed in some places of the world especially where there is sparse vegetation (de Jong et al., 2011). But since the end point of Landsat 5 NDVI data for this study is 2011 and there is a missing data for 2012 the effects platform or sensor shift may not applicable. Also, because this study used a medium resolution NDVI data and the study area is mostly open woodland the effects of platform and/or sensor shift may not be significant.

Moreover, impacts of climate change in Tanzania have been reported before (Pavoola, 2008; URT 2012b). The observed significant changes in the mean values of some climatic variables like rainfall across the country (Chang'a et al., 2017) might have influenced NDVI trend analysis results especially. More extreme rain or drought spells in either of the two periods, before and after WMA, means positive or negative growth trend and vice versa.

Finally, the boundaries of the study area are contentious, they are not 100% correct everywhere especially in the north. That means except for cultivated areas which are within the correct boundaries, area size of some land cover/types might have been under or over reported.

The results of the study support the hypothesis of the study that long-standing problems with devolution and benefit sharing may trigger unsustainable utilization of the WMA by local people. The growth of human population around the study area especially poses another danger to sustainability of a WMA. It is therefore highly recommended that such shortcomings related to the management of WMA are addressed. But for a complete understanding of the past and present statuses of WMA ecosystem an analysis of additional ecological and non-ecological variables in the area should be done.

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Personal communication with WMA management, December 2018

Appendix I

Focus group discussion with one group of the heads of households of seven people who have been living in the WMA area before its establishment of was conducted in the study area. The following semi-structured questions were asked for anyone to answer or contribute.

What are the current ecological conditions of the WMA area compared to the past before it was established?

What do you think about the presence of a WMA in your area?

What is your opinion about wildlife conservation?

How did you participate in its establishment and to what extent?

What are the socio-economic benefits of the WMA to the surrounding communities?

What is your opinion about the benefits?

What are the challenges of a WMA?

What do you propose to deal with such challenges?

What do you think is the reason for the success or failure of a WMA?

Appendix II

Several key ppeople from the government and different conservation organizations who were involved in the establishment of WMA and the management team were asked the following semi structured questions. (Appendix II)

When did the WMA start and why was it established?

How did the local people participate in its establishment and to which extent?

What are the current ecological conditions of the WMA area compared to the past before it was established?

What the socio-economic benefits of a WMA to the communities?

What is your general opinion about the benefits?

What are the challenges faced by the WMA area?

Appendix III

CODE FOR LANDSAT 5 DATA: From 1990 to 2011

```
//Metadata function
var addDATE_YEAR_MONTH = function(img){
  var oneimg = ee.Image(img);
  var dateAcquired = ee.String(oneimg.get('SENSING_TIME'));
  var shortDate = dateAcquired.slice(0, 10);
  var yr = ee.Number.parse(shortDate.slice(0, 4)); // get the year
  var mo = ee.Number.parse(shortDate.slice(5, 7)); // get the month
  return img.set({'DATE_ACQUIRED': shortDate})
          .set({'Year': yr})
          .set({'Month': mo});
};
// Filtering
var WMA = ee.ImageCollection("LANDSAT/LT05/C01/T1_SR")
.filterBounds(table)
.filter(ee.Filter.lt('CLOUD_COVER',15))
.map(addDATE_YEAR_MONTH)
.filterDate('1990-07-01' , '2011-09-30')
.filter(ee.Filter.inList('Month', [7, 8, 9]))
.select(['B4', 'B3', 'B2']);
print('WMA', WMA);

// Clipping function
var clipper = function(image){
  return image.clip(table);
}

// Call the clipper
var clipped = WMA.map(clipper);

// Function to add an NDVI band
var addNDVI = function(img) {
  // Calculate NDVI using the normalizedDifference EE function
  var ndvi = img.normalizedDifference(['B4', 'B3'])

  // Let's add the band to the original image and name the band "NDVI"
  return img.addBands(ndvi.rename('NDVI'))
};

// Now, map the NDVI function across the collection
var collectionNDVI = clipped.map(addNDVI)
print("collectionNDVI", collectionNDVI)

// Look at the first image and check that the NDVI band has been added
var ndviFirst = collectionNDVI.first().select('NDVI')
//Map.addLayer(ndvi_first)
print(collectionNDVI.first().bandNames())

// Printing median graph
print(ui.Chart.image.series(collectionNDVI
.select(['NDVI']), table, ee.Reducer.median(), 300)
.setOptions({title: 'Selous NDVI1990-2011', vAxis: {title: 'NDVI'}, hAxis: {title: 'Date'}}));
```

CODE FOR LANDSAT 8 DATA: From 2013 to 2019

```
 // Metadata function
var addDATE_YEAR_MONTH = function(img){
  var oneimg = ee.Image(img);
  var dateAcquired = ee.String(oneimg.get('SENSING_TIME'));
  var shortDate = dateAcquired.slice(0, 10);
  var yr = ee.Number.parse(shortDate.slice(0, 4)); // get the year
  var mo = ee.Number.parse(shortDate.slice(5, 7)); // get the month
  return img.set({'DATE_ACQUIRED': shortDate})
           .set({'Year': yr})
           .set({'Month': mo});
};
// Filtering
var WMA = ee.ImageCollection('LANDSAT/LC08/C01/T1_SR')
.filterBounds(table)
.filter(ee.Filter.lt('CLOUD_COVER',15))
.map(addDATE_YEAR_MONTH)
.filterDate('2013-07-01' , '2019-09-30')
.filter(ee.Filter.inList('Month', [7, 8, 9]))
.select(['B5', 'B4', 'B3']);
print('WMA', WMA);

// Clipping function
var clipper = function(image){
  return image.clip(table);
}
// Call the clipper
var clipped = WMA.map(clipper);


// Function to add an NDVI band
var addNDVI = function(img) {
  // Calculate NDVI using the normalizedDifference EE function
  var ndvi = img.normalizedDifference(['B5', 'B4'])// I didn't initially trust this. It can be written
manually as well.

  // Let's add the band to the original image and name the band "NDVI"
  return img.addBands(ndvi.rename('NDVI'))
};

// Now, map the NDVI function across the collection
var collectionNDVI = clipped.map(addNDVI)
print("collectionNDVI", collectionNDVI)

// Look at the first image and check that the NDVI band has been added
var ndviFirst = collectionNDVI.first().select('NDVI')
//Map.addLayer(ndvi_first)
print(collectionNDVI.first().bandNames())

// Printing median (reducer .mean)  NDVI values from the collection
print(ui.Chart.image.series(collectionNDVI
. select(['NDVI']), table, ee.Reducer.median(), 300)
.setOptions({title: 'WMA NDVI2013_2019', vAxis: {title: 'NDVI'}, hAxis: {title: 'Date'}}));
```

Appendix IV

CODE FOR LANDSAT 5 DATA: From 1990 to 2002

```
var addDATE_YEAR_MONTH = function(img){
  var oneimg = ee.Image(img);
  var dateAcquired = ee.String(oneimg.get('SENSING_TIME'));
  var shortDate = dateAcquired.slice(0, 10);
  var yr = ee.Number.parse(shortDate.slice(0, 4)); // get the year
  var mo = ee.Number.parse(shortDate.slice(5, 7)); // get the month
  return img.set({'DATE_ACQUIRED': shortDate})
         .set({'Year': yr})
         .set({'Month': mo});
};

var WMA = ee.ImageCollection("LANDSAT/LT05/C01/T1_SR")
.filterBounds(table)
.filter(ee.Filter.lt('CLOUD_COVER',5))
.map(addDATE_YEAR_MONTH)
.filterDate('1990-07-01' , '2002-09-30')
.filter(ee.Filter.inList('Month', [7, 8, 9]))
.select(['B4', 'B3', 'B2']);
print('WMA', WMA);

var clipper = function(image){
  return image.clip(table);
}
var clipped = WMA.map(clipper);
print('clipped', clipped);

var median = clipped.median();

// Visualize it
var visParams = {bands: ['B4', 'B3', 'B2'], min:0, max: 4000, gamma: 1};
Map.centerObject(median, 3);
Map.addLayer(median, visParams, 'Median Image');

// Exporting the data
Export.image.toDrive({
  image: median,
  description: '1990_2002_median_Image',
  scale: 30,
  region: table,
});
```

CODE FOR LANDSAT 8 DATA: From 2013 to 2019

```
var addDATE_YEAR_MONTH = function(img){
  var oneimg = ee.Image(img);
  var dateAcquired = ee.String(oneimg.get('SENSING_TIME'));
  var shortDate = dateAcquired.slice(0, 10);
  var yr = ee.Number.parse(shortDate.slice(0, 4)); // get the year
  var mo = ee.Number.parse(shortDate.slice(5, 7)); // get the month
```

```
  return img.set({'DATE_ACQUIRED': shortDate})
         .set({'Year': yr})
         .set({'Month': mo});
};

var WMA = ee.ImageCollection('LANDSAT/LC08/C01/T1_SR')
.filterBounds(table)
.filter(ee.Filter.lt('CLOUD_COVER',5))
.map(addDATE_YEAR_MONTH)
.filterDate('2013-07-01' , '2019-09-30')
.filter(ee.Filter.inList('Month', [7, 8, 9]))
.select(['B5', 'B4', 'B3']);
print('WMA', WMA);

var clipper = function(image){
  return image.clip(table);
}
var clipped = WMA.map(clipper);
print('clipped', clipped);

var median = clipped.median();

// Visualize it
var visParams = {bands: ['B5', 'B4', 'B3'], min:0, max: 4000, gamma: 1};
Map.centerObject(median, 3);
Map.addLayer(median, visParams, 'Median Image');

// Exporting the data
Export.image.toDrive({
  image: median,
  description: '2013_2019_median_Image',
  scale: 30,
  region: table,
});
```

Series from Lund University

Department of Physical Geography and Ecosystem Science

Master Thesis in Geographical Information Science

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