FOREST CONDITION ASSESMENT IN LIWONDE FOREST RESERVE USING MULTISPECTRAL DATA



FOREST CONDITION ASSESSMENT IN MALAWI

(A STUDY IN LIWONDE FOREST RESERVE)

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July, 2021

DECLARATION

I, Stanley Gusala, declare that the research project is my original work, and that it has never been submitted for academic purposes to this or any other institution.

This paper's sources of data have all been recognized...

Signature:

Date:

DISSERTATION APPROVED BY:

Supervisor's Name: Mr. D Mbeya signature 

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ABSTRACT

Forest deterioration has been a global concern in recent years. The increased pace of deforestation in Malawi is concerning, and thus calls attention to the need to assess the state of the forest in Malawi. The forest in Malawi, especially Liwonde National Park, was employed in this study to examine the current status of the forest stand. The major goal of this research was to use multispectral remote sensing data to assess the state of the forest. In this case, Landsat multispectral data for 2005, 2010, 2015 and 2020 were evaluated using different methods including the vegetation indices NDVI and EVI, as well as Maximum Likelihood classification, using Quantum GIS (QGIS) software with the aim of mapping forest cover and density in Liwonde forest reserve, and mapping changes in forest cover and density in Liwonde forest reserve. However, in both NDVI, EVI and Maximum likelihood supervised classification the forest vegetation cover has been in dynamic state, such that from 2005 to 2015 the forest vegetation has been increasing as recovering from the 2005 Malawi drought that was declared as a national disaster by late president Dr. Bingu Wa Mutharika on 15thOctober 2005. Then from 2015 to 2020 the results show that the forest cover and density has been declining that is from dense forest to moderate and sparse vegetation cover in the Liwonde forest.

While population growth and poverty are important factors in deforestation, Low rainfall should also be taken into account as a factor that affects forest cover and density. Thus a call for the planting of trees that can tolerate drought (low rainfall) and are resistant to parasites and diseases.

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ACRONYMS/ABBREVIATIONS

NDVI	Normalized different vegetation index
EVI	Enhanced vegetation index
TM	Thematic mapper
OLI	Operational land imager
GIS	Geographic information systems
NGO	Non-governmental organization
SCP	Semi-Auto classification plugin
NIR	Near infrared region
RIO	Region of interest
USGS	United states geological survey
NASA	National Aeronautics and Space Administration
VHR	Very high resolution
UAVs	Unmanned aerial vehicles
REDD+	Reducing Emissions from Deforestation and Degradation
GHGs	Greenhouse gases
NDCs	Nationally Determined Contributions

1.0: INTRODUCTION

1.1 BACKGROUND

Forest importance's cannot be underestimated; thus it must be monitored in order to make informed forest management decisions. In rural land management, particularly for sustainable agricultural and forestry management in Sub-Saharan Africa, understanding the dynamics of land use/cover changes has proven critical. Various concerns and human activities are posing a danger to the forest reserves and plantations' original status. One of the most serious issues in Malawi's forest reserves is encroachment for agriculture and habitation. According to (Kainja, 2001), in 571 locations across Malawi, 23,012 hectares of forest reserves were encroached into, accounting for 2.6 percent of the 870,052 hectares of forest reserves. This is due to the fact that the majority of people in rural areas of Central and Southern Africa rely on subsistence agriculture and other natural resources to meet their basic requirements. The integrity of protected areas is being jeopardized by the unlawful manufacturing of charcoal to supply low-cost fuel to metropolitan areas. The majority of the charcoal is produced in forest reserves, with 15,000 hectares removed annually for an estimated 6.08 million standard bags consumed in Malawi's four towns (Kambewa & Chiwaula, 2010). Liwonde forest reserve, one of Malawi's most endangered natural ecological systems, is not immune to the problem, since brick burning, firewood, and charcoal sales have increased in the rural areas surrounding it (Mauambeta et al., 2010). It is commonly accepted that the degradation caused by these human stresses exceeds the forest reserve's regenerating capability. While it is critical to use techniques that aid in the understanding of the causes and implications of land cover dynamics, there is a high demand for reliable, detailed, and current spatial data that can be utilized to influence management decisions in a developing country like Malawi with a growing population and increased pressure on natural resources. Remote sensing (RS) and Geographic Information Systems (GIS) are well-known, powerful, and cost-effective methods for mapping and describing natural

resources and tracking changes in the environment over time (Clapp & Rodriguez, 1998).

1.2 PROBLEM STATEMENT

There has been some uncertainty about the rates of deforestation in Malawi. There is considerably more uncertainty on the additional impacts from degradation. Often reports will combine or overlap deforestation and degradation, even though carbon stocks, emission factors, and drivers may be very different. Increased deforestation has apparently been a major issue in Malawi, as well as on a global scale. As one of the forests, Liwonde forest reserve could be harmed by insects, plant diseases, drought, and human activities as a result of human population development, which promotes greater deforestation for settlement, farming, and fuelwood.

1.3 MAIN AND SPECIFIC OBJECTIVES

The main goal of this research is to assess the condition of the Liwonde forest reserve using multispectral remote sensing data. The following are the study's other particular objectives:

- To map forest cover and density in Liwonde forest reserve.
- To map changes in forest cover and density in Liwonde forest reserve.

1.4 RESEARCH QUESTIONS

Is it necessary to analyze the condition of Malawi's forest reserves? Capabilities of forest monitoring to achieve Malawi Government objectives for forest restoration program are among the areas of special importance that have been explored in this research:

- Is it possible for Malawi to improve the efficiency of forest monitoring by better integrating monitoring programs and technologies?
- Is deforestation a threat to the Liwonde forest reserve?

1.5 SIGNIFICANT OF STUDY

The findings in this research are expected to provide information on the level of vegetation loss and or recover in the Liwonde forest reserve. This also helps to allow decision makers to decide on how best they can maintain and improve forest protection and conservation. It is expected to describe the use of timely update spectral information to get access to the forest in the Liwonde forest reserve to get support to support for forest management planning and monitoring objectives.

The findings are also expected to provide information about the use of spectral features to assess forest reserve, and demonstrate the use of multispectral-multi temporal information and to delineate opportunities for better integrating programs and measurement approaches, drawing on lessons from domestic and national efforts.

2.0 LITERATURE REVIEW

2.1 MALAWI FOREST

Forest services include a wide range of non-consumptive options. Environmental, economic, social, and cultural services are among the services provided (L. C. Zulu, 2010). Because of the wide range of goods and services that forests are expected to provide, forest management solutions are frequently complicated. These services provide a significant contribution to rural livelihood for many rural areas.

Natural and man-made forests both contribute to socio-economic development by providing fundamental human necessities such as fuel, food, fodder, medicine, jobs, income, and foreign exchange (Girdis, 2005). Forests also aid in the preservation of air, water, and soil quality, as well as the management of soil erosion, the reduction of downstream sedimentation, and the incidence of flash flooding. As a result, forests play a critical role in protecting watersheds and boosting water supplies.

Despite the worth of forests, it has been highlighted that Malawi Forests have been subjected to severe and large-scale damage events in recent years, and the impact of forest loss and degradation can be felt at all scales, from global climate change to falling economic worth of forest resources and biodiversity, as well as jeopardized

local livelihoods (Wiyo et al., 2015). Climate change, air pollution, and increasing human activities are the primary causes of this sad development.

2.2 DEFORESTATION IN MALAWI

Uncontrolled tree felling for fuelwood for curing tobacco in the smallholder and estate sectors, opening up new gardens and farming areas, firewood for commercial purposes, infrastructure development, and shifting cultivation are among the top five (5) causes of deforestation and forest degradation, according to the literature on deforestation in Malawi (Timko & Kozak, 2016).

Agriculture remains Malawi's most important economic sector, employing 84 percent of the workforce and covering 59 percent of the country's total land area (Orum et al., 1999). It is frequently noted as a major cause of deforestation (Falcao, 2008). Agriculture grew by 57 percent in Sub-Saharan Africa between 1975 and 2000, according to (Dolean et al., 2020), at the loss of wooded area.
Brick-making also demands a large amount of wood. Because of the requirement to supply burnt bricks to cities, deforestation is rampant in Malawi's major cities and towns. For example, in Lilongwe, the need for wood for burning bricks has put a strain on mango trees in community spaces and indigenous trees in cemeteries (Mauambeta et al., 2010). Brick-burning and the use of wood from non-sustainable sources are commonplace in Malawi, particularly in city and town.

A drought is a prolonged period of abnormally dry weather that disrupts the water supply in an area. The longer droughts lead to longer and hotter fires, which clear more forest, thus speeding up the process (E. Zulu et al., 2012). At the same time, clearing the forest increases the contribution of carbon dioxide (CO_2) into the atmosphere, speeding up climate change and the deforestation-drought-fire feedback loop. Most plants are 80 to 95 percent water (Chirwa & Mahamane, 2017). They use it for transpiration (the release of water vapor through openings in the leaves called stomata), but also to produce energy, in the form of carbohydrates, through photosynthesis.
Another widely claimed direct cause of deforestation in Malawi is the reliance on

fuelwood or charcoal for residential fuel (L. C. Zulu, 2010). This is comparable to the situation in much of Sub-Saharan Africa, where biomass is used to meet 90% of energy demand (Kambewa & Chiwaula, 2010). According to (Timko & Kozak, 2016), 97 percent of Malawi's rural population relies on fuelwood as a source of energy. Long-term and high-intensity fuelwood consumption could lead to land-cover change as a result of successive waves of forest degradation (Miah & Ahmed, 2014). Finally, commercial forest usage has been shown to influence deforestation rates. Malawian timber is cheaper in international trade than that of many other Sub-Saharan African countries, promoting fast deforestation (GoM (Government of Malawi), 2003), and the effects of industries like tobacco curing, which includes massive biomass burning (Mauambeta et al., 2010).

2.3 NATIONAL POLICY CONTEXT FOR FOREST DEGRADATION MONITORING

The main purposes of keeping a protected area are to provide habitat for wildlife and to conserve biological resources. In Malawi, as in most other African countries, a lack of quantitative data on forest degradation rates, location, and biomass is a major impediment to policy formulation linked to greenhouse gas emissions mitigation (Girdis, 2005). National governments are taking steps to include forests in their Nationally Determined Contributions (NDCs) to climate change mitigation and policies and measures for Reducing Emissions from Deforestation and Degradation (REDD+) as a result of the new international climate agreements reached at the 21st Conference of the Parties (COP 21) in Paris in 2015 (Satyal et al., 2020). The REDD+ framework has five agreed-upon scope elements: (1) Carbon Stock Conservation, (2) Reducing Emissions from Deforestation, (3) Reducing Emissions from Forest Degradation, (4) Carbon Stock Enhancement, and (5) Sustainable Forest Management. Yet, many countries are uncertain about the appropriate scope for implementing their REDD+ programs. Much of this uncertainty relates to the lack of available tools and methods for the measurement and monitoring forest degradation as part of these scope elements (Chirwa & Mahamane, 2017). Many countries have important disturbance regimes related to both deforestation and forest degradation (Wiyo et al.,

2015). Excluding forest degradation in the scope of a national REDD+ program limits the actions that would reduce an important greenhouse gas (GHG) emission source. Furthermore, countries that include enhancement actions, such as forest landscape restoration (FLR), would overestimate the positive impact of these mitigation efforts without also accounting for degradation. This could lead to misleading reporting on progress with NDCs. Under the Warsaw Framework, countries developing national REDD+ programs are requested to include five fundamental measurements and reporting streams in their national planning: (1) a national REDD+ strategy, (2) a National Forest Monitoring System (NFMS), (3) forest reference emission levels (REL), (4) safeguards information systems, and (5) a national reporting structure (Girdis, 2005). This REDD+ framework requires countries to develop a national platform for measuring, reporting, and verifying (MRV) GHG emissions and removals on a regular basis. For the most part, this necessitates countries having the technical capability to systematically measure a set of factors related to: (a) changes in the extent and condition of forest cover; (b) carbon stocks in forests of varying stature and condition that change over time; and (c) GHG emissions or removals associated with changes in forest cover and changes in carbon stocks (Falcao, 2008).

The government of Malawi is active in developing capacity for its national REDD+ program. However technical limitations in MRV are obstacles to achieving advanced readiness. For instance, in Malawi's recent publication of a national forest reference emission level (FREL) one method is used for forest cover stratification (medium resolution national cover from remote sensing), another method is used to estimate rates of deforestation (sample-based visual interpretation of Google Earth), and an indirect modeling method is used to estimate forest degradation (a fuelwood demand model using proxy data) (GoM (Government of Malawi), 2003). This can result in incompatible and inaccurate results. For instance, the direct visual sampling method covers all forest areas while the indirect estimation of fuelwood demand from a model that uses external data, such as population, does not accommodate for these areas. As such, this could easily result in double counting when observed and mapped

deforestation was due to fuelwood extraction (Timko & Kozak, 2016). Thus, improvements in MRV are needed to develop a uniform and consistent methodology, which is what this study aims to demonstrate.

2.4 MERITS OF MULTISPECTRAL REMOTE SENSING

Multispectral imaging is a type of imaging in which data is collected from two or more frequency ranges on the spectrum, such as visible light and infrared radiation (GAUTAM et al., 2017). Multispectral imaging has a wide range of applications, and its origins may be traced back to satellite imaging. Remote sensing continues to grow as imaging spectroscopy sensors improve, allowing radiometers and spectrophotometers to be carried more easily in satellites, planes, and other aerial vehicles (Coutts et al., 2019).

We can take use of the various spectral "behavior" of different land surface types by combining multispectral photos. For example, vegetation's chlorophyll provides high reflectivity in the near infrared and strong absorption (low reflectivity) in the red portions of the electromagnetic spectrum. The most extensively used vegetation indices, normalized different vegetation index (NDVI) and enhanced vegetation index (EVI), are derived using the picture bands that correspond to these spectrum segments(Derakhshan et al., 2020). Their values rise as green phytomass increases, however they have an asymptotic relationship with metrics like Leaf Area Index (Luo et al., 2017). They "saturate" and become insensitive to an increase in phytomass as vegetation cover grows dense. The near infrared and red bands are almost always included in image color composites created by assigning distinct image bands to the red, green, and blue guns of the computer screen, with the medium infrared band included when it is available (Gao et al., 2012). The intensity of the color assigned to the near infrared band can then be used to visually assess the presence and concentration of green plants. Satellite images provide data on a greater spatial scale that can be utilized to obtain equivalent variables. Sensors that measure reflected energy within many specific parts (also known as bands) of the electromagnetic spectrum provide multispectral photography. The region's high spectral resolution reflectance spectrum is valuable for identifying a variety of surface cover factors that

are difficult to detect using a wideband, low spectral resolution imaging system(Weng, 2012).

3.0: METHODOLOGY

This covers the study's location, data sources, methodologies, and data analysis.

3.1 STUDY SITE

Liwonde forest reserve, Malawi, comprises 276.83 square kilometers (km2) and is located in the Upper Shire River Valley, 35 kilometers south of Lake Malawi's southernmost extent, mostly inside the Machinga District, at a Latitude: **-15°8'6.18"** Longitude: **35°23'24.26" coordinates**. Riverine wetlands, deciduous forests, open grasslands, mopane and miombo woods, palm savannahs, and countless baobabs are also part of the forest reserve. The reserve is mostly flat and has an elevation of 1045 meters and is southwest of Chaoni Hill. Liwonde forest reserve, Machinga, Malawi is shown in the figure 3.1.1 below.

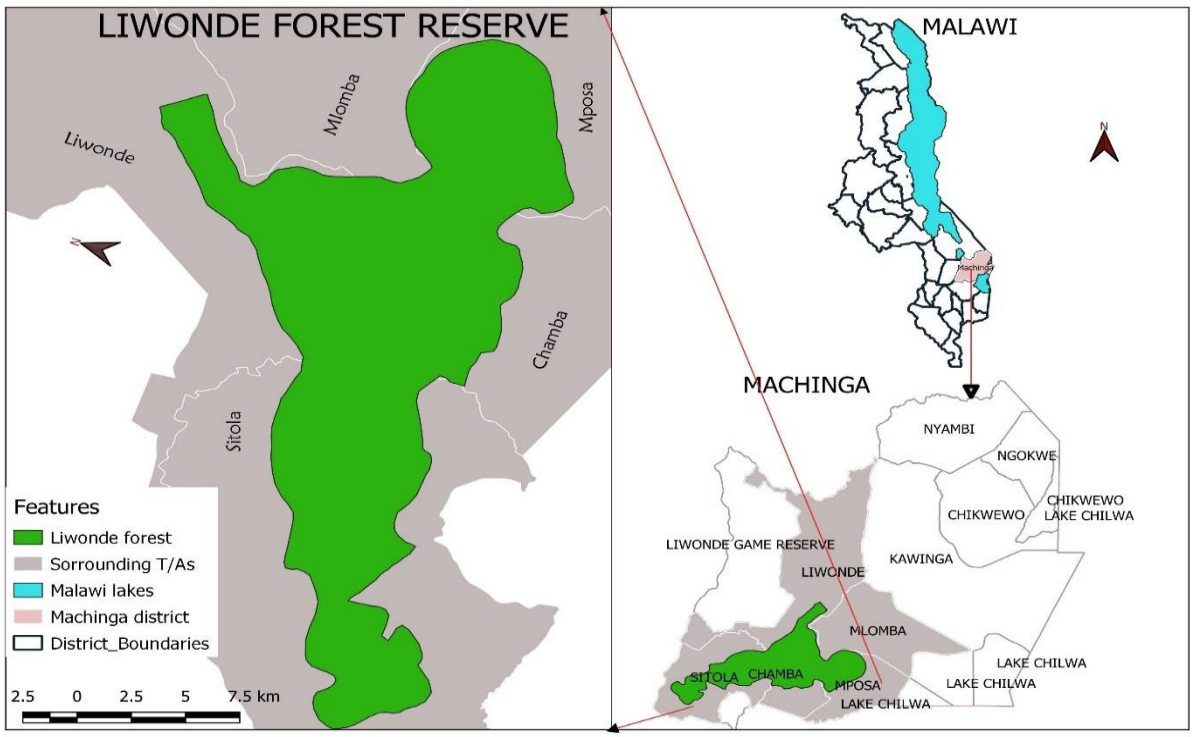


Figure 3.1. 1: showing Liwonde forest reserve (study area).

3.2 DATA SOURCES

I. The assessment for the area was based on remote sensing (RS) data, Landsat 5 Thematic Mapper (TM) pictures, and Landsat 8 OLI images acquired from the USGS website. Data sets were obtained, as shown in table 3.2.1 below.

Year	Day-Month	Path	Row	Satellite imagery	source	Spectral resolution	Spatial resolution (m)
2005	18 November	168	70	Landsat 5 TM	USGS	7	30
2010	11 November	168	70	Landsat 5 TM	USGS	7	30
2015	14 November	251	119	Landsat 8 OLI	USGS	11	30
2020	10 November	251	119	Landsat 8 OLI	USGS	11	30

Table 3.2. 1: showing details of satellite data that has been used in this research.

The satellite images were collected with a 5-year interval in 2005, 2010, 2015, and 2020 as they capture Liwonde forest reserve and were utilized in analysis to detect any deterioration that had occurred in the forest region. These November images were chosen for the investigation and better comparison to minimize errors that could arise as a result of different in data content due to high variability of data capturing months. The images also, had good cloud spatial coverage with cloud cover of below 5 percent with the study area being cloud free.

II. On attempting to comprehend rainfall as a factor that may have influenced the forest's vegetation cover. In comparison to the GIS study, rainfall data from the Malawi metrological department in the Southern area was used to assist comprehend the cause. The table 3.2.2 below shows monthly average rainfall for the Ntaja weather station in Machinga:,

	Annual monthly rainfall for Ntaja, Machinga											
Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sept	Oct	Nov	Dec
2005	227.3	214.8	5.6	5.1	14.2	4.7	11.9	0.0	0.0	0.0	34.8	106.9
2010	54.2	196.7	75.0	91.6	3.6	2.4	0.0	6.2	1.4	0.0	54.8	302.8
2015	350.9	289.1	75.0	21.0	0.0	1.5	0.0	0.0	1.0	31.2	47.6	65.6
2020	389.6	189.2	42.9	4.4	0.0	0.0	0.0	0.0	0.0	17.7	1.6	139.1

Table 3.2. 2: showing rainfall data for ntaja (machinga) that has been used in this research.

The rainfall analysis was performed using the values for monthly rainfall data in table 3.2.2 above to evaluate how different in rainfall could have affected vegetation cover in the Liwonde forest reserve.

3.3 DATA ANALYSIS APPROACHES

Semi-Automatic Classification Plugin (SCP) in Quantum GIS was used to preprocess remote sensing satellite data from both Landsat 5 TM and Landsat 8 OLI.

3.3.1 VEGETATION INDICES

The vegetation of Liwonde forest reserve was analyzed using two vegetation indices: The Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) (EVI). NDVI is a numerical indicator that employs the electromagnetic spectrum's visible and near-infrared bands to examine remote sensing signals and determine whether or not the target being examined includes live green vegetation (Dolean et al., 2020). As a result, it is critical to realize that the NDVI is a measure of vegetative (plant) health, even if it says nothing about the reasons of that health. The vegetation index is more of a hint at what's going on in the field right now. The NDVI value for a given pixel is always between minus one (-1) and plus one (+1); however, no green leaves offer a value near to zero (Xu, 2007).

The NDVI is calculated using a simple mathematical technique (below), which then translates raw satellite data into vegetation indices.

$$NDVI = \frac{\text{NIR} - RED}{\text{NIR} + \text{RED}} \quad \text{...equation 1.}$$

where near-infrared (NIR) band on Landsat 5 TM corresponds to Band 4 and the red band to Band 3, while the near-infrared (NIR) band on Landsat 8 OLI corresponds to Band 5 and the red band to Band 4 accordingly.

The NDVI formula combines the data from the red and near-infrared bands into a single, representative number. It accomplishes this by removing the red spectral band reflectance from the NIR reflectance. Then, depending on the kind of sensor mission, it divides this by the sum of the NIR and red reflectance. With, Landsat 5 TM and Landsat 8 OLI, it divides this by the total of the NIR and red reflectance.

Images were made by converting satellite data into NDVI values to provide a measure of vegetation type, amount, and condition. Different colors were allocated to different ranges of NDVI values since each pixel has a value. In this way, a false-color map of how NDVI fluctuates spatially was made using QGIS and the Semi-Classification Plugin.

Although there is no standard color map for NDVI mapping, one that closely reflects reality—with high NDVI value areas appearing greener—has become popular. Called "stoplight color maps," the scale emulates a stoplight and applies a red-yellow-green palette to NDVI-processed data.

The EVI was utilized to supplement the NDVI analysis; the EVI is an optimized vegetation index developed to increase the vegetation signal with enhanced sensitivity in high biomass regions and enhanced vegetation monitoring by decoupling the canopy background signal and reducing atmospheric impacts (He et al., 2010). EVI calculations always range from minus one (-1) to plus one (+1); nevertheless, no green leaves produce a result close to zero.

EVI was generated mathematically using the generic formula (below), which turns raw satellite data into a vegetation index.

$$EVI = \mathrm{G} \times \frac{(\mathrm{NIR} - RED)}{(\mathrm{NIR} + \mathrm{C1} \times \mathrm{RED} - \mathrm{C2} \times \mathrm{Blue} + \mathrm{L})} \quad \text{...Equation 2.}$$

where C1 and C2 are coefficients used to compensate aerosol scattering in the red band using the blue band, and L is a soil adjustment factor. In general, G=2.5, C1=6.0, C2=7.5, and L=1, such that each sensor mission type, including Landsat 5TM and Landsat 8 OLI bands, were utilized to fill the equation as indicated in the sensor equation below; this is because band location varies depending on sensor mission type:

In Landsat 4-7:

EVI = (Band 4 – Band 3) / (Band 4 +6 × Band 3 – 7.5 × Band 1+1).

In Landsat 8:

EVI = (Band 5 – Band 4) / (Band 5 +6 × Band 4 – 7.5 × Band 2+1).

In most situations, these additions allow for the calculation of background noise, ambient noise, and saturation as a ratio between red and Near-Infrared region (NIR) values.

3.3.2 SUPERVISED CLASSIFICATION

Supervised classification is based on the premise that a user can select sample pixels in an image that represent specific classes, and then instruct image processing software to utilize these training sites as references for the categorization of all other pixels in the picture (Munthali et al., 2019). QuantumGIS software was used to undertake semi-automatic supervised classification of remote sensing pictures using the Semi-Automatic Classification Plugin (SCP), which provides tools to speed up the classification process. It entailed preparing files for input into supervised classification procedures, where most traditional multispectral classifiers are used, by establishing

training areas known as Regions of Interest (ROIs). In the supervised classification, the Maximum Likelihood classification was utilized, in which the class of information (i.e., land cover type) on the image was recognized based on the mean vectors and covariances of the training classes. These are thought to be the best "points of learning that aid in the case of overlapping classes by calculating the likelihood of a pixel belonging to a specific class based on its posterior probability (Gao et al., 2012). If Nc is the number of classes, and the likelihood of a pixel p belonging to a certain class Wi I = 1, 2…, Nc) can be expressed in terms of posterior probability P(Wi/p), then the pixel is allocated to that class."

4. RESULTS AND DISCUSSIONS

The research study's findings are presented in this chapter. The outcomes of this study were based on both field and desk research, and the inferences drawn from them are described below.

4.1 NDVI RESULTS

The findings of the normalized different vegetation indexes have been given in the form of a map and graph to enable for simple comparison of the vegetation distributed across the Liwonde forest reserve. The NDVI map output display for Liwonde forest reserve is shown in figure 4.1.1 below.

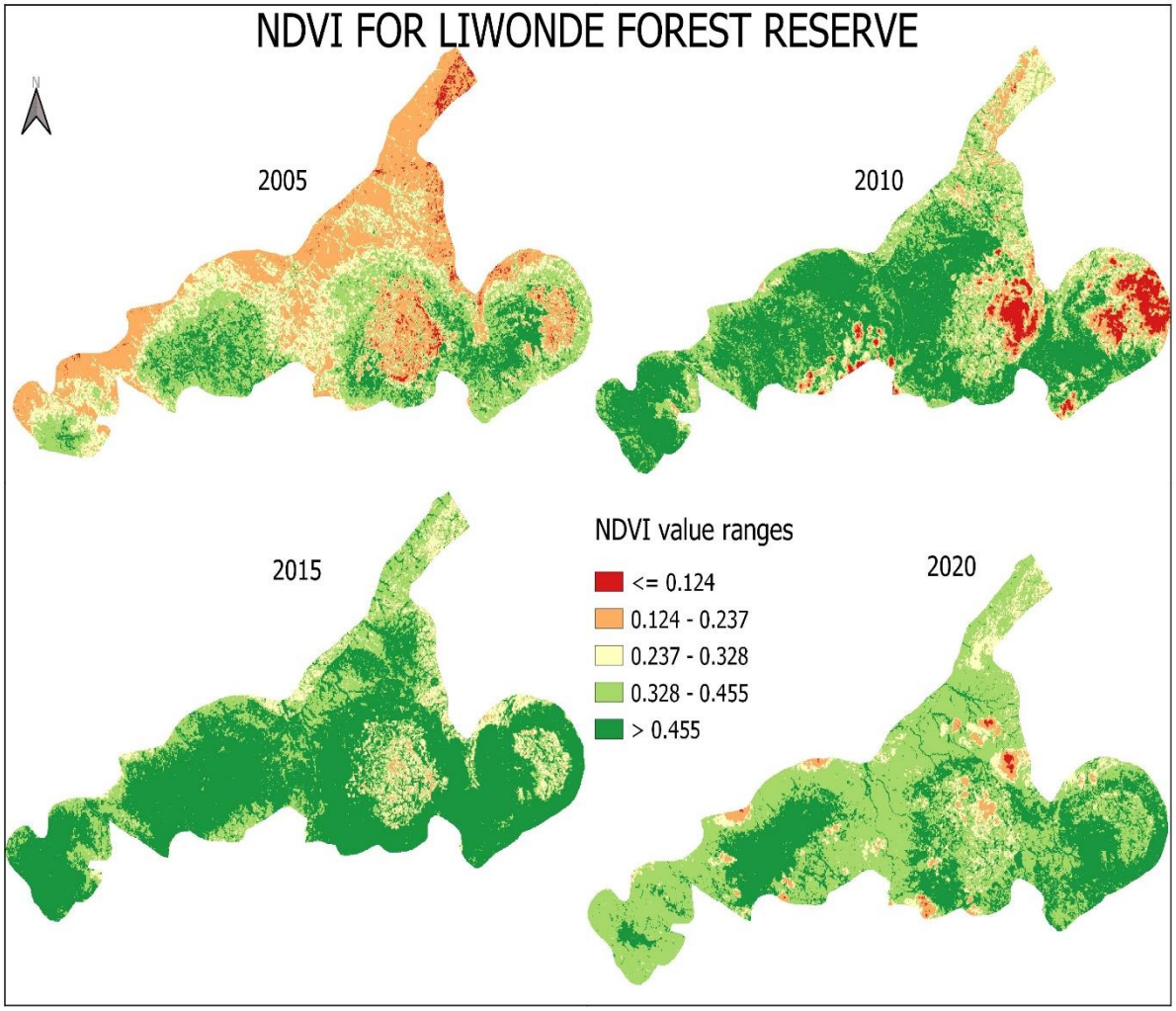


Figure 4.1. 1: showing Normalized Different Vegetation Index maps with respect to the years

Places with healthy vegetation can be seen in the green sections of the image in figure 4.1.1. The color red denotes places where there is no live green biomass. The image's darker green parts have thick, live green vegetation, while the lighter green regions have moderate or scant plant cover. Bare soil or dead vegetation are indicated by orange-red regions.

The NDVI analysis results in the image above for 2005: red to orange colored region (ranging from 0.2 and lower to -1) indicates that the forest had been seriously threatened, leaving significantly (more than half) of the forest area soil exposed (bare soil), either as a result of drought, deforestation, or human-caused forest fire. The

other little area of the forest in the figure, with an NDVI value ranging from 0.25 to 0.45, shows moderate forest vegetation cover, which could be due to valleys that preserve moisture for the surrounding plant's survival.

The forest has been partially disturbed to bare soil or dead plants (sparse vegetation) as shown in the image above, with sections with red to yellow NDVI output value range (varying from 0 to 0.34) covering only a tiny portion of the forest in the north east. The remaining section, which contains bright to dark green areas (range from 0.4 and above), indicates a good abundance of forest regions with little or minimal deforestation.

In the figure 4.1.1 above, the year 2015 reveals strong forest cover, with nearly the entire area having high NDVI values ranging from 0.4 and above, resulting in a dense forest vegetation cover, such that NDVI values below 0.3 cover a relatively little portion of the map, implying that there was little or no deforestation or pest and disease in the forest in that year (s).

Finally, in the figure 4.1.1 above, the NDVI values for 2020 reveal that they are in the range of 0.25 to 0.4, indicating sparse to moderate vegetation on a substantial part(s) of the forest, which could be due to low rainfall or human activities. With NDVI values ranging from 0.24 to -1, the value also indicated the availability of bare ground near the forest's edge in most of the forest's dimension and direction sizes where it could be deforested (negative one).

Random reference points that were preserved in all four photos of the study region (7 points) were selected as a supplement to NDVI analysis, and their NDVI values were determined. With respect to the year, the table below displays the identified NDVI values from the points as shown in figure 4.1.1 above. The map showing fixed sites on which both NDVI and EVI values were taken can be found in the appendix on page below.

	NDVI Values for The Selected Points						
YEAR	A	B	C	D	E	F	G
2005	0.568	0.185	0.155	0.514	0.428	0.139	0.151
2010	0.542	0.351	0.240	0.507	0.455	0.352	0.248
2015	0.891	0.230	0.358	0.723	0.647	0.310	0.243
2020	0.814	0.323	0.315	0.614	0.358	0.187	0.129

Table 4.1. 1: showing the NDVI values from selected areas for the four years

Values from the table 4.1.1 above were used to create annual NDVI mean values, which were then plotted on a graph, providing a comparison of overall plant cover for the years investigated. The graph below summarizes the overall Normalised Different Vegetation Index mean calculated over the years, from the NDVI outputs that aided in the analysis and interpretation of the results:

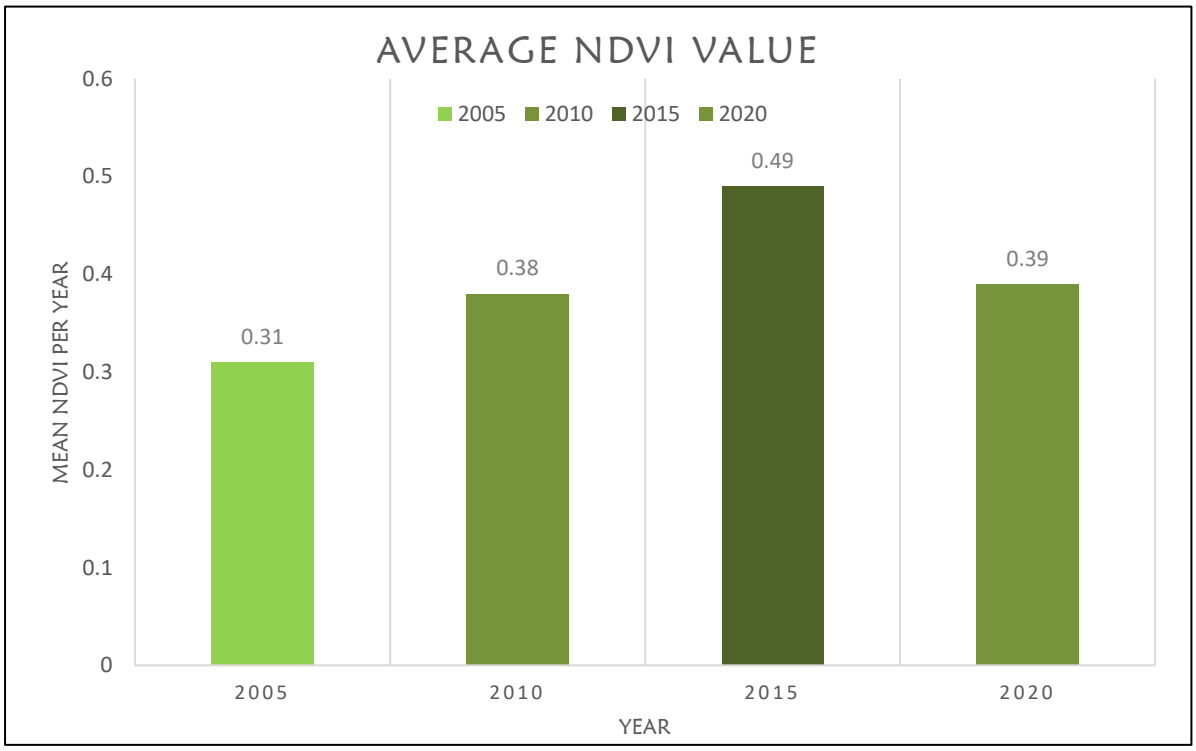


Figure 4.1. 2: showing Normalized different vegetation Index (NDVI) per year for the four years.

Summarizing different NDVI values over time aids in determining the availability of dense or sparse vegetation, which may then be followed up with ground truthing to confirm the major source of the forest hazard. That is the higher dense green bar indicates the availability of large vegetation cover accordingly.

Since NDVI does not correct for changes in solar incidence angle (the angle at which the sun shines on the leaves) NDVI produces vastly different results throughout the day hence in section 4.2 below EVI was used to correct the errors.

4.2 EVI RESULTS

The results of the Enhanced Vegetation Index have also been given in the form of a map and graph, allowing for simple comparison of the vegetation distribution across the Liwonde forest reserve. The Enhanced Vegetation Index (EVI) is calculated similarly to NDVI but uses additional wavelengths of light to correct for the inaccuracies of NDVI. Variations in solar incidence angle, atmospheric conditions like distortions in the reflected light caused by the particles in the air, and signals from the ground cover below the vegetation are corrected for using EVI. The EVI map output depicting Liwonde forest reserve is shown in figure 4.2.1 below.

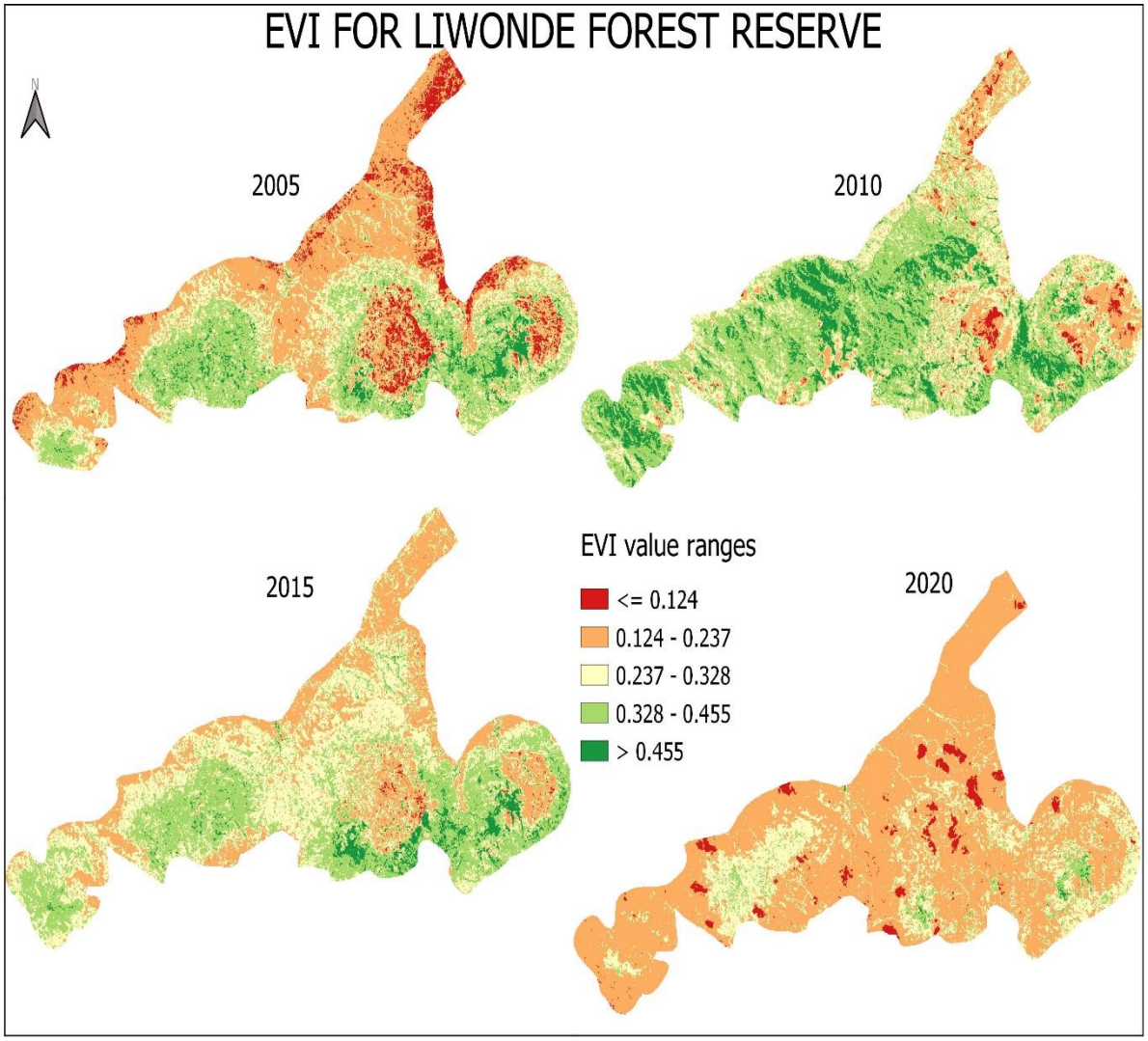


Figure 4.2. 1: showing enhanced vegetation index output map for Liwonde forest reserve

The EVI image has a more constant sensitivity to changes in vegetation and a more even distribution of vegetation greenness values, as seen in (figure 4.2.1).

However, in 2005, the EVI value ranges revealed that much of the northern section of the forest was in poor health, with EVI values of less than 0.15 in most areas, but the southern section was in good condition due to the presence of green cover.

According to figure 4.2.1, EVI output was favorable or good in the year(s) 2010 and 2015, with a wide area covered with healthy green vegetation ranging from moderate to thick forest cover (with values larger than 0.3 up to 1), and the area with less than 0.2 EVI values as bare land was extremely tiny. In 2020, the results show that sparse

to moderate vegetation covers a vast part of the forest, resulting in an orange to yellowish color with EVI values ranging from 0.2 to 0.35, with just a tiny portion having values greater than 0.45, and the remaining region having values less than 0.15. (EVI values).

Following the EVI analysis, seven systematic but fixed reference locations (7 points) were chosen and the EVI values were recorded; the results were then reported in table 4.2.1 below by year (s).

	EVI Values for The Selected Points						
YEAR	A	B	C	D	E	F	G
2005	0.556	0.109	0.121	0.507	0.440	0.126	0.101
2010	0.185	0.386	0.236	0.410	0.530	0.281	0.308
2015	0.564	0.339	0.260	0.469	0.479	0.184	0.195
2020	0.454	0.208	0.222	0.336	0.341	0.197	0.208

table 4.2. 1: showing random Enhanced Vegetation Index values with respect to the given year.

The estimated annual EVI average values in the table above allowed comparison for the years investigated using the graph (figure 4.2.2 below), which summarizes the overall Enhanced Vegetation Index mean for all four years considered. The following is the output graph of results, taken from the EVI output maps:

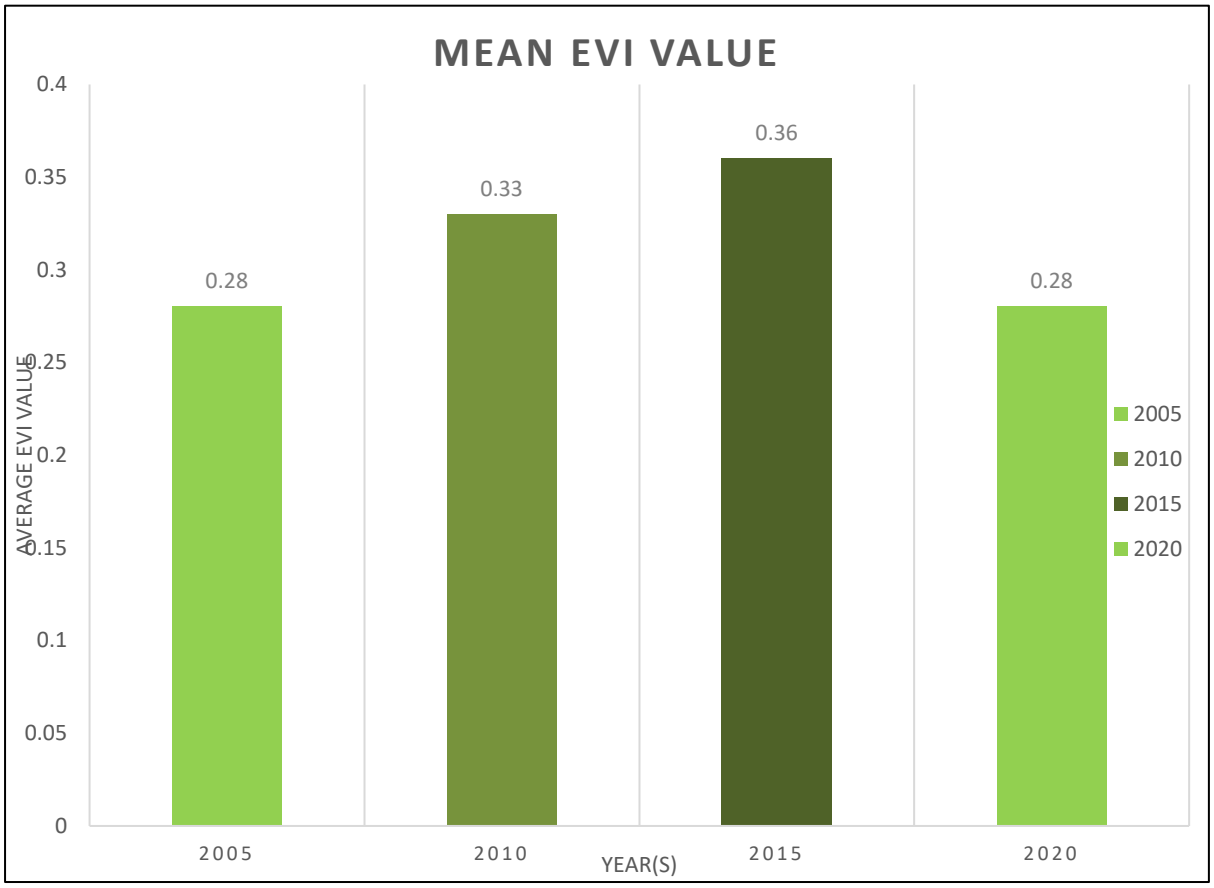


Figure 4.2. 2: showing Enhanced Vegetation Index mean value for the year 2005, 2010, 2015 and 2020.

This aided in the interpretation of the total output for the forest area in that the higher the EVI value from the graph, the better (dense) forest condition as in 2015 dark green bar indicates, followed by 2010, and the lower the EVI value from the graph, the worse (stressed) forest condition as in 2005 and 2020.

The use of both NDVI and EVI helped to reduce some error and also allowed easy comparison of the results to achieve most accurate result interpretation, since NDVI does not correct for the changes in solar incidence angle (the angle at which the sun shines on vegetation) NDVI produces vastly different results throughout the day, the EVI corrects for the difference in solar incidence angle providing data that is more accurate and actionable. However, in both NDVI and EVI the forest vegetation cover has been dynamic state, such that from 2005 to 2015 the forest vegetation has been increasing as recovering from the 2005 Malawi drought that was declared as a

national disaster by late president Dr. Bingu Wa Mutharika on 15thOctober 2005. Then from 2015 to 2020 the results show that the forest cover and density has been declining that is from dense forest to moderate and sparse vegetation cover in the Liwonde forest.

Although the EVI reduces the adverse effects of environmental factors such as atmospheric conditions and soil background, it does not take into consideration the topographic effect, which is defined as the variation in radiance that accompanies a change in orientation from a horizontal to an inclined surface, in response to a change in light source and sensor position, thus a call for supervised classification analysis in section 4.3 below which helped to quantify the vegetation coverage in the forest.

4.3 SUPERVISED CLASSIFICATION

Forest is the most common land cover in 2005, 2010, 2015, and 2020, according to the maximum likelihood classification method of study. A total of 25 training samples were selected for the Maximum Likelihood Classification, of which 15 were for forest vegetation cover and 10 for bare land. In 2005, however, the bare land situation was over half of the Liwonde National Park area (refer to the Figure 4.3.1 below). This is the case because many of the soil patches that constituted the bare land cover type in 2005 have nearly vanished.

For the land use categorization maps of 2005, 2010, 2015, and 2020, the overall classification accuracy was assessed to be 95, 88, 81, and 84 percent, respectively. In 2005, the Kappa coefficient was 0.96, 0.82 in 2010, 0.80 in 2015, and 0.84 in 2016. The fraction of classification errors was substantially higher in 2010, 2015, and 2020, owing in part to differences in imaging observation time.

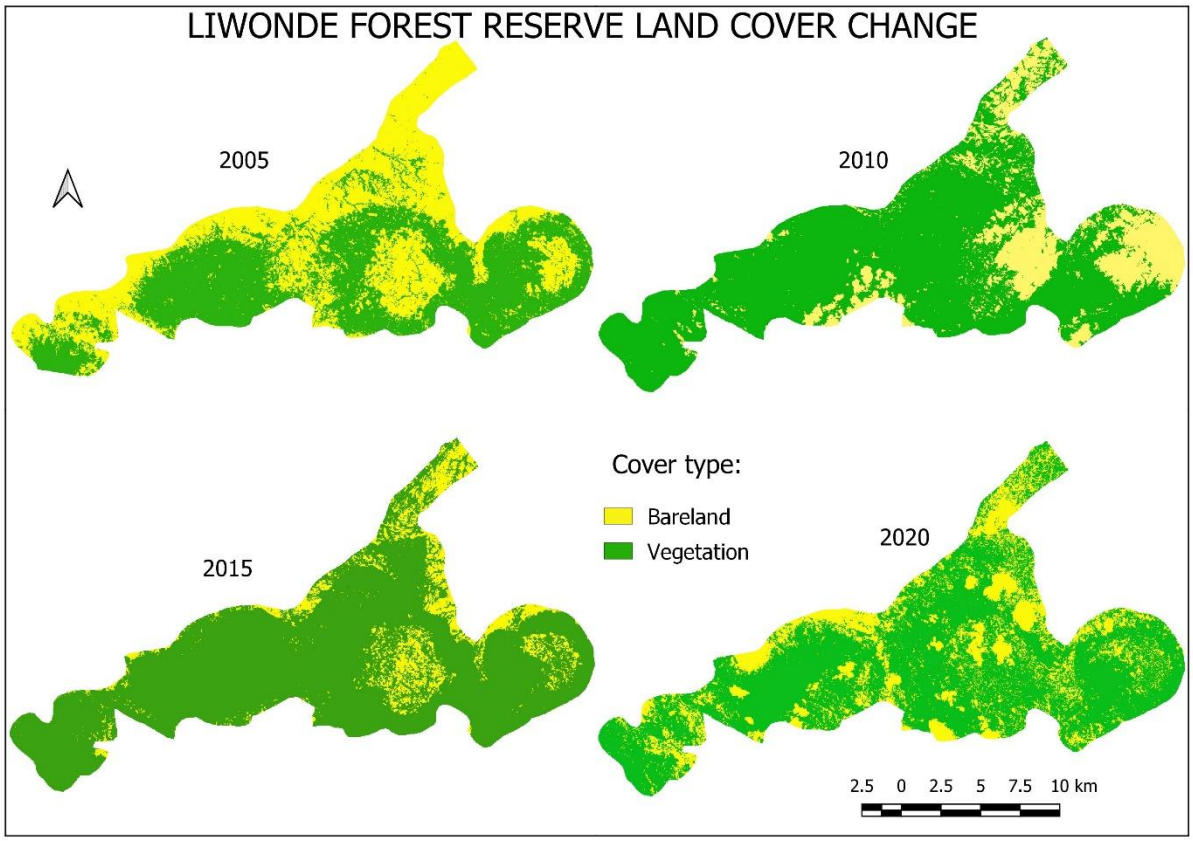


Figure 4.3. 1: land cover classification results for Liwonde forest reserve.

Despite the efforts of the surrounding community to improve environmental management, visual interpretation can also be used to produce statistics directly from sampling point approaches (classification). The statistics figure-chart below indicates that the Liwonde forest reserve lost 48.02 percent of its forest in 2005, with the percentages designated as bare ground (see chart below). While the amount of bare land in 2010 was 23.10 percent, it was 12.37 percent in 2015, and 27.69 percent in 2020. (refer to the figure 4.3.2 below).

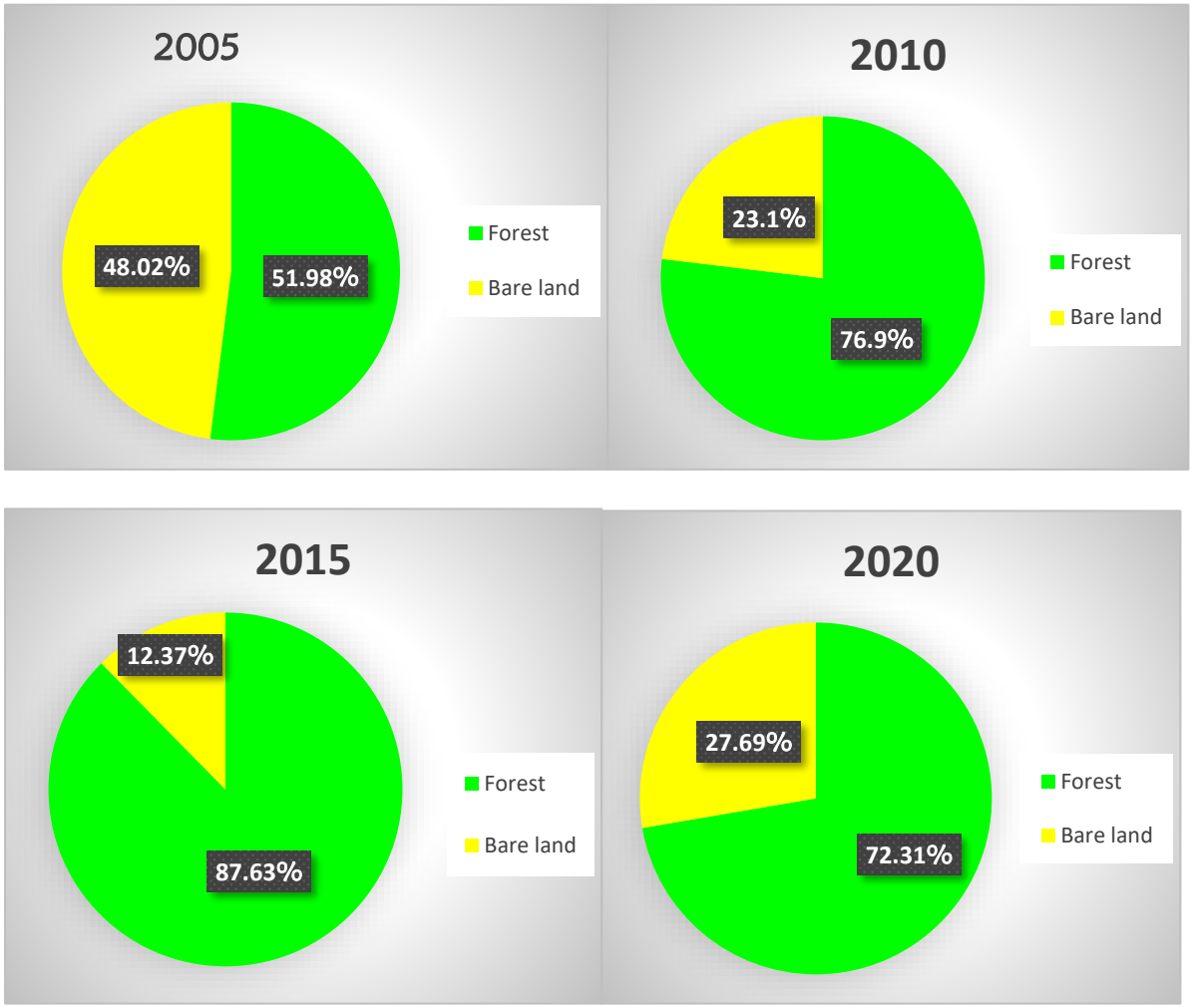


Figure 4.3. 2: Land cover percentages for the Liwonde forest reserve for the indicated years.

According to the above chart (figure 4.3.2), Liwonde forest reserve witnessed a significant loss of forest cover in 2005. After 5 years, the forest had recovered much of the bare land, with vegetation forest cover increasing from 51.98 percent in 2005 to 76.69 percent in 2010, and the vegetation forest cover continued to expand, reaching 87.63 percent in 2015, leaving bare land at 12.37 percent (percent). In 2020, Liwonde forest reserve experienced a sharp drop in vegetative forest cover, from 87.63 percent in 2015 to 72.31 percent in 2020, while bare ground expanded from 12.37 percent to 27.69 percent, nearly doubling the amount of uncovered soil in a five-year period (2015 to 2020 interval).

4.4 CHANGE DETECTION

Change detection in Quantum GIS, in **post-classification change detection**, the images from each time period were **classified** using the same **classification** scheme into a number of discrete categories (land cover types). The method helped in understanding how a given area (Liwonde forest reserve) has changed between two or more time periods. Figure 4.4.1 below shows the changes that have been taking place in Liwonde forest reserve.

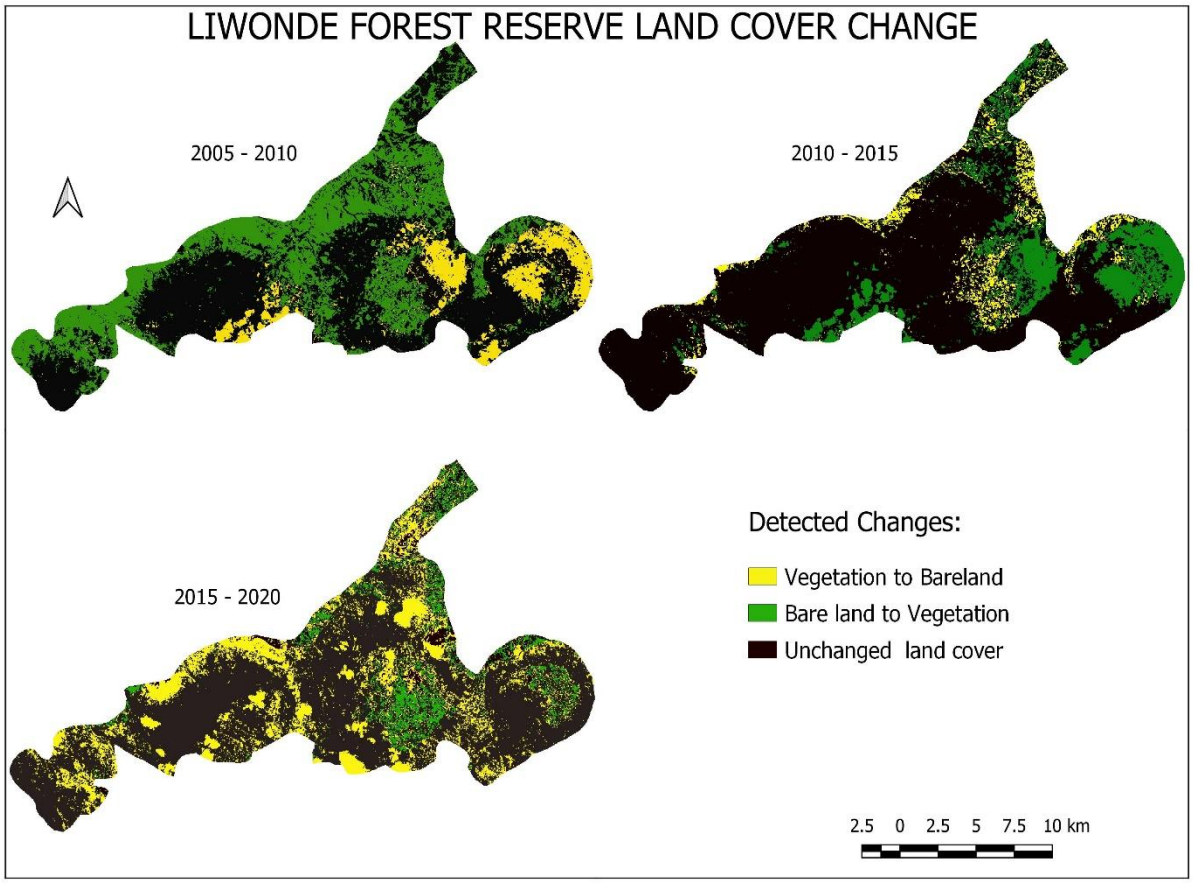


*figure 4.4.1: shows the how the Liwonde forest area has **changed** between two or more time periods*

Change detection as in the figure 4.4.1 above was used to measure different types of change which includes the change in the forest cover in an area (Liwonde forest reserve) over time. As shown in the figure 4.4.1 the changes that were detected are that of from vegetation to bare land (vegetation loss in yellow color), and from bare land to vegetation (vegetation recover in green color) and that of black color indicates areas that have maintained their land cover state (unchanged land cover)

between the years. That is from 2005 to 2010 there has been a very high vegetation recover where almost 69.02 square kilometers (km^2) representing 24.92 percent of the areas that had recovered vegetation, and between 2010 to 2015 the reserve maintained its state of cover, where bare or vegetated cover slightly changed within the respective 5year period as bare land decreased to 34.26 km^2 by 2015, from 63.99 km^2 that of 2010. Where as in between 2015 to 2020 the forest seems to have experienced harm that have accelerated vegetation loss in the 5 years' period with much most parts of the Liwonde forest reserve experiencing vegetation to bare land forest cover change, with almost 76.70 km^2 of the total forest cover (276.82km^2) by 2020 from the 34.26km^2 of 2015. This bring the vegetation cover loss and density decline difference of almost 42.44km^2 representing 15.32 percent bare land increase from 2015 to 2020 respectively.

4.5 RAINFALL VARIATION ANALYSIS

Rainfall as one of the key natural causes of forest condition change was evaluated using the Malawi Metrological Department's information in light of the dynamic forest condition that is taking place in Liwonde forest reserve (figure 4.5.1 below).

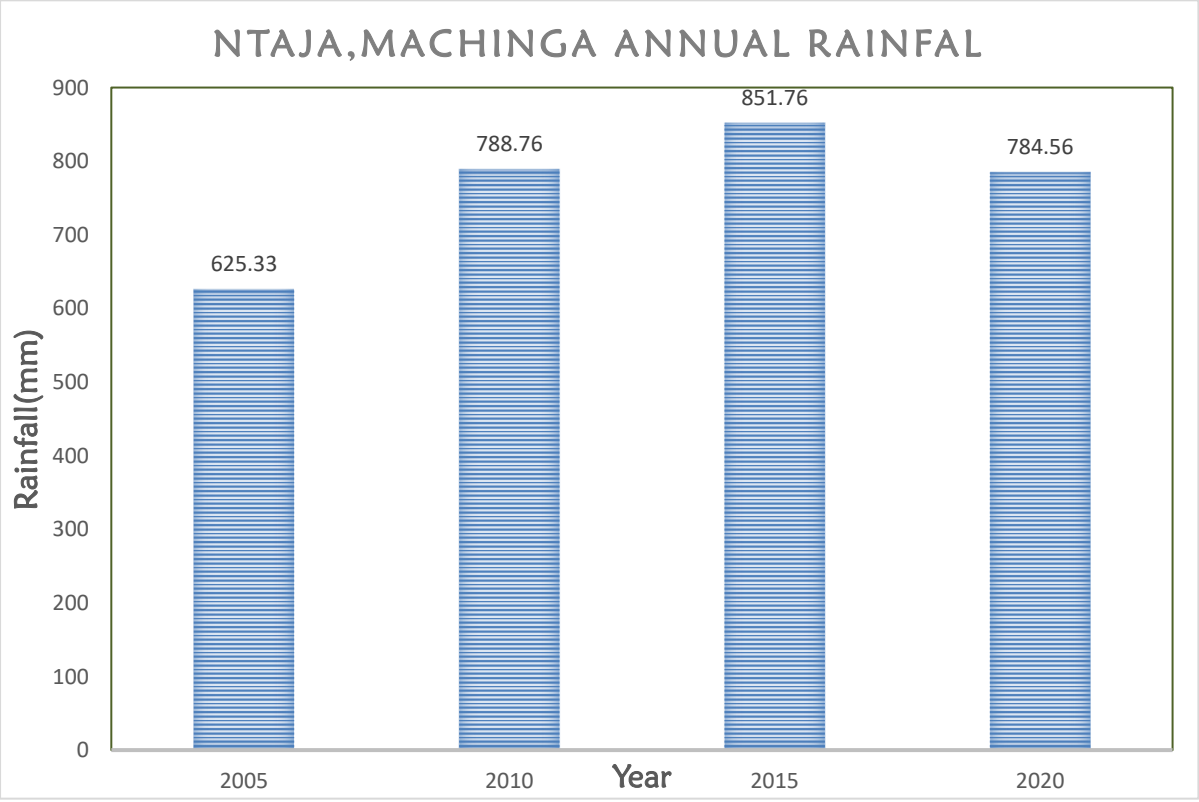


Figure 4.5. 1: annual rainfall for Ntaja in machinga district.

According to E. Zulu et al.,(2012) annual rainfall ranges from 725mm to 2,500mm, with an average of 900mm in Lilongwe, 1,127mm in Blantyre, 1,289mm in Mzuzu, and 1,433mm in Zomba. According to the annual rainfall range (figure 4.5.1), the average annual rainfall in 2005 was extremely low (below the average) which was declared a national disaster to Malawi, thus increasing the sensitivity of the forest to unfavorable conditions, resulting in a high amount of bare land in 2005. As previously stated, the years 2010 and 2020 had almost similar average rainfall of 788.76 and 784.56 millimeters, respectively, resulting in about equal forest cover (figure 4.5.1), while the year 2015 had both high rainfall and forest cover. Soil is also greatly affected by rainfall. If it is too wet or too dry, nutrients in the soil can run off and not make it to the plants' roots, leading to poor growth and overall health.

5.0 RECOMMENDATION(S)

Due to pressures on agriculture productivity and food security, increasing the area of protected forests for wildlife management may be challenging in the future as a result of rising population. Linking Agenda 2063 number 7: Environmentally sustainable and climate resilient economies and communities, and the Sustainable Development Goal (SDG) 15: Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss. The agenda and goal targeted to have fulfilled the promotion of the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally.

So with the SDGs focus, it is also necessary that current forest care should incorporate planting trees that can withstand drought (low rainfall) in the forest, as well as those that are adaptable to a variety of soils and resistant to parasites and diseases such as Baobab, Kentucky Coffeetree, and Bur Oak, as a helpful means to fulfill the SDGs target.

District forestry office should work more closely with the chiefs in mobilizing community forest management participation. Drawing on experiences of other areas where strong tradition leadership has contributed to better management of forest resource, this can take urgent and significant action to reduce the degradation of natural habitats, halt the loss of biodiversity and protect and prevent the extinction of threatened species.

Due to low spatial resolution of the Landsat sensor visibility of some small target features, such as small rivers, could not be recognized on images. The use of high resolution (HR) and or the very high resolution (VHR) sensor imagery has to be incorporated to the monitoring of the forest. This include: commercial high-resolution satellite sensors (for example World View, Quick bird and Spot), and Unmanned Aerial Vehicles (UAVs) including drones to provide very high details of the forest cover change. UAVs also gives cloud effect free data hence increased level of capturing accuracy.

6.0 CONCLUSION

Forests play a critical part in human survival, hence monitoring their state should be done on a regular basis to avoid underestimating their value. Remote sensing plays a critical role in the estimation of forest parameters, and in the monitoring of disturbances and changes in forest cover. With the full availability of satellite multi temporal datasets from many sensors, multi spectral remote sensing (RS) can make it easy and fast to analyze the forest. In this case, Landsat multispectral data were evaluated using different methods including the vegetation indices NDVI and EVI, as well as Maximum Likelihood classification, using Quantum GIS (QGIS) software. The findings illustrate how vegetation cover in Liwonde forest reserve has recovered from 2005 to 2015, and also the density and cover has declined from 2015 to 2020 with consideration to human activities and rainfall variation factor. This study produces new estimates and maps at high spatial resolution of forests in Machinga. The forest map adheres closely to the schema developed by the Malawi government. These new

estimates and the associated maps should be of interest to the national REDD community in Malawi and others for both science and policy use.

Besides a gradual growing deforestation in Liwonde forest reserve, so much as population growth and poverty play important roles, the complex forces of changing economic opportunities have the most significant impacts on deforestation of the forest reserve. It is therefore important that any measures (some of which as recommended) taken to curb this deforestation should build and base on the dynamic social, political and infrastructural changes of the population of the rural community surrounding the reserve.

REFERENCES

Chirwa, P. W., & Mahamane, L. (2017). Overview of restoration and management practices in the degraded landscapes of the Sahelian and dryland forests and woodlands of East and southern Africa§. In *Southern Forests*. https://doi.org/10.2989/20702620.2016.1255419

Clapp, J., & Rodriguez, M. (1998). Using a GIS for Real Estate Market Analysis: The Problem of Spatially Aggregated Data. *Journal of Real Estate Research*. https://doi.org/10.1080/10835547.1998.12090939

Coutts, C., Holmes, T., & Jackson, A. (2019). Forestry policy, conservation activities, and ecosystem services in the remote Misuku Hills of Malawi. Forests. https://doi.org/10.3390/F10121056

Derakhshan, S., Cutter, S. L., & Wang, C. (2020). Remote sensing derived indices for tracking urban land surface change in case of earthquake recovery. *Remote Sensing*, *12*(5). https://doi.org/10.3390/rs12050895

Dolean, B. E., Bilașco, Ștefan, Petrea, D., Moldovan, C., Vescan, I., Roșca, S., & Fodorean, I. (2020). Evaluation of the built-up area dynamics in the first ring of cluj-napoca metropolitan area, romania by semi-automatic gis analysis of landsat satellite images. *Applied Sciences (Switzerland)*, *10*(21), 1–20. https://doi.org/10.3390/app10217722

Falcao, M. P. (2008). Charcoal production and use in Mozambique, Malawi, Tanzania and Zambia: Historical overview, present situation and outlook. *Proceedings of the "Conference on Charcoal and Communities in Africa."*

Gao, F., de Colstoun, E. B., Ma, R., Weng, Q., Masek, J. G., Chen, J., Pan, Y., & Song, C. (2012). Mapping impervious surface expansion using medium-resolution satellite image time series: A case study in the Yangtze River Delta, China. *International Journal of Remote Sensing*. https://doi.org/10.1080/01431161.2012.700424

GAUTAM, V. K., MURUGAN, P., & ANNADURAI, M. (2017). A New Three Band Index for Identifying Urban Areas using Satellite Images. *Mangalore Institute of*

Technology & Engineering, Moodbidri, INDIA, *2017*(January).

Girdis, D. (2005). Malawi: Rural Energy and Institutional Development. *Energy Sector Management ….*

GoM (Government of Malawi). (2003). Forest Act. *Malawi Forest Act*.

He, C., Shi, P., Xie, D., & Zhao, Y. (2010). Improving the normalized difference built-up index to map urban built-up areas using a semiautomatic segmentation approach. *Remote Sensing Letters*, *1*(4), 213–221. https://doi.org/10.1080/01431161.2010.481681

Kainja, S. (2001). Assessment, Conservation and Sustainable Use of Forest Biodiversity. In *Secretariat of the Conservation on Biological Diversity*.

Kambewa, P., & Chiwaula, L. (2010). Biomass energy use in Malawi. *International ESPA Workshop on Biomass Energy, 19-21 October 2010, Parliament House Hotel, Edinburgh. Chancellor College, Zomba, Malawi*.

Luo, X., Peng, Y., & Gao, Y. (2017). An Improved Optimal Segmentation Threshold Algorithm and Its Application in the Built-up Quick Mapping. *Journal of the Indian Society of Remote Sensing*. https://doi.org/10.1007/s12524-016-0656-4

Mauambeta, D., D, C., R, M., & S, G. (2010). Status of forests and tree management in Malawi. *Researchgate*.

Miah, M. D., & Ahmed, F. U. (2014). Conservation of a Tropical Wet Semi-evergreen Forest Ecosystem by an Indigenous Community in the Bandarban Hill District of Bangladesh: The Role of Intervention. *Small-Scale Forestry*. https://doi.org/10.1007/s11842-013-9256-0

Munthali, M. G., Botai, J. O., Davis, N., & Adeola, A. M. (2019). Multi-temporal analysis of land use and land cover change detection for dedza district of Malawi using geospatial techniques. *International Journal of Applied Engineering Research*.

Orum, A. M., Jones, G. W., & Visaria, P. (1999). Urbanization in Large Developing Countries. *Contemporary Sociology*. https://doi.org/10.2307/2655327

Satyal, P., Corbera, E., Dawson, N., Dhungana, H., & Maskey, G. (2020). Justice-

related impacts and social differentiation dynamics in Nepal's REDD+ projects. *Forest Policy and Economics*. https://doi.org/10.1016/j.forpol.2020.102203

Timko, J. A., & Kozak, R. A. (2016). The influence of an improved firewood cookstove, Chitetzo mbaula, on tree species preference in Malawi. *Energy for Sustainable Development*. https://doi.org/10.1016/j.esd.2016.04.002

Weng, Q. (2012). Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends. *Remote Sensing of Environment*. https://doi.org/10.1016/j.rse.2011.02.030

Wiyo, K. A., Fiwa, L., & Mwase, W. (2015). Solving Deforestation, Protecting and Managing Key Water Catchments in Malawi Using Smart Public and Private Partnerships. *Journal of Sustainable Development*. https://doi.org/10.5539/jsd.v8n8p251

Xu, H. (2007). Extraction of urban built-up land features from landsat imagery using a thematic-oriented index combination technique. *Photogrammetric Engineering and Remote Sensing*. https://doi.org/10.14358/PERS.73.12.1381

Zulu, E., Ciera, J., Musila, N., & Wasao, S. (2012). Population Dynamics , Climate Change , and Sustainable Development. *AFIDEP and PAI*.

Zulu, L. C. (2010). The forbidden fuel: Charcoal, urban woodfuel demand and supply dynamics, community forest management and woodfuel policy in Malawi. *Energy Policy*. https://doi.org/10.1016/j.enpol.2010.02.050