Discovering the Deforestation Hotspots with Landsat and GIS: Case study Kilombero district Tanzania

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ABSTRACT

Deforestation is among of environmental challenge in most of the districts in Tanzania including the Kilombero district. However, in Kilombero districts there are inadequate tools for rapid and economical assessment, quantification and mapping the spatial configuration of deforestation. Alternatively, the advent in remote sensing data, image classification and the free accessibility of remote sensing data with acceptable spatial and temporal resolution grant ability to carry out rapid and economical assessment, quantification and mapping the spatial configuration of deforestation. The overall objective of this research were to carry out Landsat image classification and Normalized Difference Vegetation Index (NDVI) using Landsat of 1996, 2007 and 2018 in Kilombero district of Tanzania. Landsat image were downloaded from United State Geological survey website and processing using ERDAS Imagine 2014 and ArcGIS 10.3 software. Landsat data were pre-processed and post-classified using ArcGIS 10.3 software while Maximum Likelihood Classification (MLC) algorithm in ERDAS Image 2014 software was used for Landsat image classification. The research were as follows, in year 1996 the forest, bush lands, wetlands and agriculture with recoded with 517492 ha (38.03% composition), 279050 ha (20.51% composition), 217996 ha (16.02% composition), and 181243 ha (13.32% composition), respectively. Impervious land cover increased to 120982 ha (8.89% composition) while water bodies increased to 44025 ha (3.24% composition) in 1996. In year 2007 agricultural lands becomes the second largest land use with 349591 ha (25.69% composition) while forest remained the largest land cover with 524685 ha (38.56% composition).While water bodies and wetlands declined to 10851 ha (0.80% composition) and 145042 ha (10.66% composition), respectively. Impervious and bush land were increased to 74494 ha (5.47% composition) and 256125 ha (18.82% composition), correspondingly. In year 2018 bush lands becomes the largest land cover category with 506058 ha (37.19% composition) and followed by agriculture with 365954 ha (26.89% composition) while forest declined to 303923 ha (22.33% composition).Water bodies and wetlands declined to 8158 ha (0.60% composition) and 70399 ha (5.17% composition), respectively while impervious land cover increased to 106296 ha (7.81% composition). While the NDVI results have revealed an increase in NDVI values from 1996 to 2007 imply increase in vegetation density which occurred following the interception and implementation of the national and international environmental conventions. Notable decrease of NDVI values is observed from 2007 to 2018 whereby the high NDVI value of 1 in year 2007 to has reduced from NDVI value 0.1812 in year 2018. Build capacity of local personnel for successful utilization of RS and GIS data, establishment of nursery for agro-forestry seedlings/propagating material and other research using concepts of AFOLU, GLOBIOM and LULUCF are highly recommended in Kilombero district.

Key words: Deforestation and image classification; NDVI and deforestation

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1.0 INTRODUCTION

1.1 Background information

Deforestation and land degradation is among of the impacts following climate and Land Use Land Cover (LULC) change. In Tanzania deforestation and land degradation have impacted the society and environments while threatening the agricultural sustainability in many parts of the country (National Audit Office, 2018). Kilombero district is not exempted from these impacts of climate and LULC change including deforestation and land degradation. According to Wikipedia, (2019) deforestation consists of clearing and cutting a forest or stand of trees while convert forest land cover/use to non-forest use such as farms, ranches, or urban use. In many parts of Tanzania including Kilombero district, deforestation have remained issue of great concerning owing to the fact that about 80% of human population in Kilombero district depends on forest as source of energy (Sophia & Emmanuel, 2017).

The on going removal of trees without sufficient reforestation in Kilombero district has resulted to habitat damage, biodiversity loss, and decline in water bodies as highlighted by (Nindi, 2009); (Connors, 2015) and (Sophia & Emmanuel, 2017). Forests sequester and store more carbon than any other terrestrial ecosystem hence considered as an important natural control on the impacts of LULC and climate change (Gibbs et al., 2007). The unending forest clearing for timber, charcoal and firewood results to the release of carbon dioxide (CO2) from cleared or degraded to the atmosphere (Gibbs et al., 2007). In attempt to reverse the unending deforestation, the need of spatially-explicit information on deforestation is of great concern in Kilombero district.

On the other hand, land degradation is the reduction in the capability of the land to produce benefits from a particular land use under a specified form of land management (Metternicht, 2006). Land degradation is among the major environmental and anthropogenic problems driven by land use-land cover (LULC) and climate change worldwide (Mashame & Akinyemi, 2016). Major causes of land degradation includes presence of anthropogenic activities and climatic variations which results to relentless risk on livelihoods and sustainable development (Metternicht, 2006 & Ahmad & Pandey, 2018). Additionally, Mashame & Akinyemi (2016) reported the soil erosion, tillage erosion, soil salinization, water stress and forest fires (Connors, 2015), encroachment into forest and wetlands (Sophia & Emmanuel, 2017).

In Kilombero district, both deforestation and land degradation have been previously mentioned by research scholars as the emerging impacts of climate change and LULC dynamics. Despite of the previous research work, inadequate information is in place to facilitate decision making to reverse the current situations. Spatial information on where deforestation and land degradation are occurring is missing; this has delayed the implementation of site specific efforts for reversing the deforestation and land degradation in Kilombero district. Understanding where deforestation and land degradation are occurring is a priority information required when planning for creating awareness and campaigning against deforestation, site specific management of forest and land resources, establishing bylaws and regulation at ward level to sustainably manage the forest and land resources of Kilombero district. While Asner et al., (2009) emphasized on monitoring deforestation and land degradation is central to assessing changes in carbon storage, biodiversity, and many other ecological processes in tropical regions. Several methods for assessing the deforestation and land degradation have been developed by previous research scholars including the expert opinions, field observations and remote sensing (Metternicht, 2006). The expert opinions and field observations are expensive, cumbersome, tiresome and neither cover the large geographic area nor repetitive. Alternatively, Landsat data with long history in capturing the earth data with spatial resolution of 30 meters, temporal resolution of 16 days and freely accessible in the United state geological survey website, serves as alternative to aerial photographs and field surveys.

The launch of the Earth Resource Technology Satellite (ERTS) 1, latterly called Landsat 1 in July 1972, has contributed significantly to the development of remote sensing applications such as land cover classification (Phiri & Morgenroth, 2017). The main aim of the Landsat satellite program was to provide a tool for continuous monitoring of Earth's resources. Landsat is a multispectral sensor with moderate resolution acquiring images in several spectral bands at spatial resolution of 30 meters and temporal resolution of 16 days (Bruce & Hilbert, 2004). Landsat data have long history and reliability hence regarded as the popular source for documenting changes in land cover and use over time (Reis et al., 2003). For the purpose of this research study, Landsat 5 Thematic Mapper (TM) and Landsat 8 were considered useful. The technical description of Landsat 5 Thematic Mapper (TM) and Landsat 8 are presented in Table 1 and

Table 1: The bands of Landsat 5 TM

Bands	Region in EMS	Temporal resolution	Spatial Resolution

Band 1	Visible (0.45 - 0.52 μm)	16 days	30 m
Band 2	Visible (0.52 - 0.60 μm)	16 days	30 m
Band 3	Visible (0.63 - 0.69 μm)	16 days	30 m
Band 4	Near-Infrared (0.76 - 0.90 μm)	16 days	30 m
Band 5	Near-Infrared (1.55 - 1.75 μm)	16 days	30 m
Band 6	Thermal (10.40 - 12.50 μm)	16 days	120 m
Band 7	Mid-Infrared (2.08 - 2.35 μm)	16 days	30 m

Source: Global Land Cover Facility (2004

Table 2: The bands of Landsat 8 Bands

Bands	Region in EMS	Temporal resolution	Spatial Resolution
Band 1	Coastal (0.433 - 0.453μm)	16 days	30 m
Band 2	Blue (0.450 – 0.515 μm)	16 days	30 m
Band 3	Green (0.525 - 0.600 μm)	16 days	30 m
Band 4	Red (0.630 - 0.68 μm)	16 days	30 m
Band 5	NIR (0.845 – 0.885 μm)	16 days	30 m
Band 6	SWIR(1.560-1.660 μm)	16 days	60 m
Band 7	SWIR (2.100- 2.300 μm)	16 days	30 m
Band 8	PAN (0.5 – 0.680 μm)	16 days	30 m
Band 9	Cirrus (1.360- 1.390 μm)	16 days	30 m
Band 10	Thermal (10.6-11.2 μm)	16 days	100 m
Band 11	Thermal (11.5-12.5 μm)	16 days	100 m

Source: Global Land Cover Facility (2004)

On the other hand GIS, the capability of GIS in storing, processing, analyzing and disseminating vast categories of information also dole out as substitute to conventional approaches for data storage, processing and dissemination. Thus, this research study used Landsat and Geographical

Information Systems (GIS) for identification of hotspots for deforestation and land degradation in Kilombero district.

2.0 METHODOLOGY

2.1 Description and geographical locations and of study area

Kilombero district is one of five districts in Morogoro region; other districts are Morogoro, Ulanga, Mvomero, Morogoro urban and Kilosa district. The district is located between 08° 00′ – 16° South and 36° 04′ - 36° 41′ East with elevation ranging from 262 to about 2111 m (Augustino et al., 2013)(Augustino et al., 2013) and covering an area of about 1,424,000 hectares (Ha).The district is situated in a floodplain of Kilombero river been in the South-East and the Udzungwa-Mountains been in the North-West. Most of the areas of Kilombero district are still predominantly rural with the semi-urban district headquarters Ifakara as major settlement. In the Eastern side it is bordered with Kilosa district while North-East it's bordered with Morogoro rural. In the North and West side the district borders to Mufindi and Njombe districts of Iringa and Njombe region, respectively. While in the South and South-East it shares the border with Songea district of Ruvuma region and Ulanga district, respectively.

In Kilombero district, the rainfall pattern is bi-model rains (usually occur in two seasons) which supports production of several crops including rice, maize, bananas, vegetables and cassava and average annual rainfall is in the region of 1200-1400 mm (Connors, 2015).While the topography is characterized by flat in lowlands clay, loam, sand and some cotton black soil in flooded areas while in uplands topography is undulating hills with red soil (Laswai, 2011). More than 80% of the population is involved in agriculture and agriculture sector considered as major source of income and food in Kilombero district (Sophia & Emmanuel, 2017). Besides, in Kilombero district about 80% of the population depends on forest for several products including timber for construction purpose, charcoal and firewood harvesting for domestic and commercial cooking purpose (Valley, 2019). Other economic activities include bee keeping and fishing which also rely on the availability of health forest and wetlands of Kilombero district (Wilson et al., 2017).

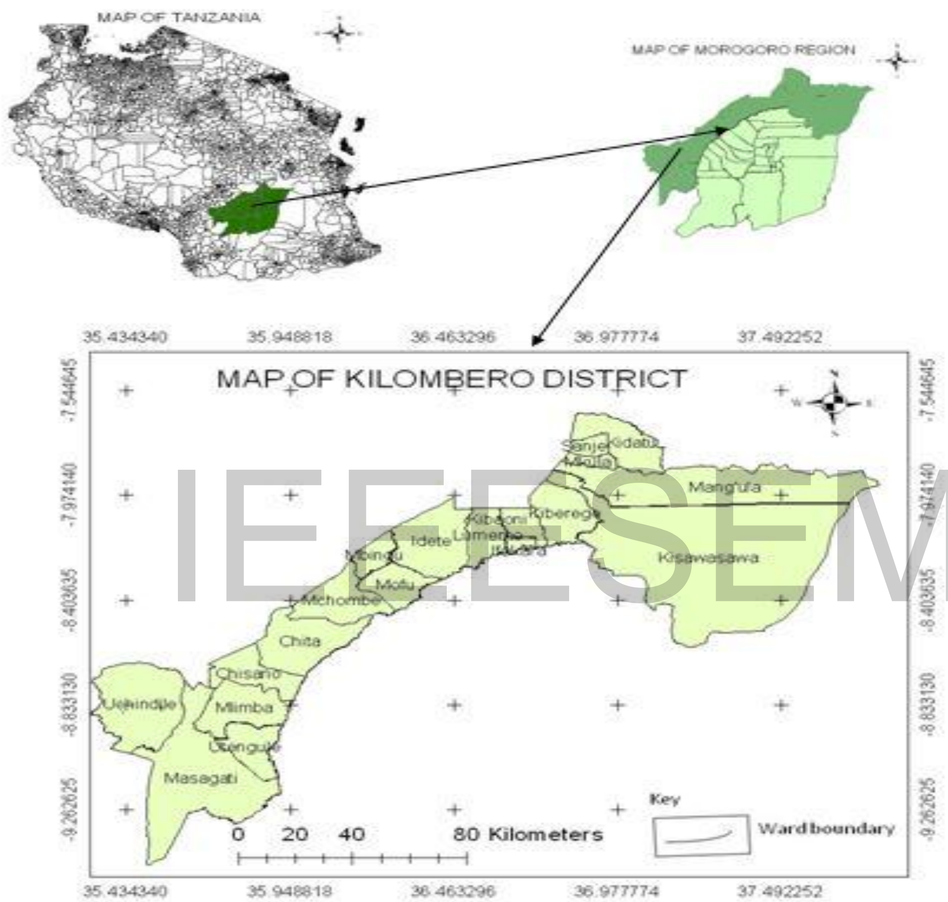

Figure 1: Geographical location of the study

2.2 Data collection and analysis

Landsat is a multispectral sensor with moderate resolution acquiring images in several spectral bands at spatial resolution of 30 meters and temporal resolution of 16 days (Bruce & Hilbert, 2004). Landsat data have long history and reliability hence regarded as the popular source for

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documenting changes in land cover and use over time (Reis, 2008). Hence study Landsat 5 Thematic Mapper (TM) of 1985 and Landsat 8 of year 2018 was in this research.

Landsat data collection: The Level 1 Terrain (Corrected) Product (L1TP) of Landsat 5 TM of year 1985, 1996, 2007 and 2018 was downloaded from United State Geological Survey (USGS) official web site (http://www.earthexplore.usgs.gov.com). To accommodate the study area three images captured at path and row of 167065, 167066 and 168066, were downloaded. The Landsat data sets were subjected to visual assessment of the percentage cloud cover d and images of cloud cover of less or equal to 20% were found appropriate and were downloaded for the purpose of this research study. **Error! Reference source not found.** presents the Landsat dataset collected for this study.

Table 3: Landsat dataset collected for this study

Dataset	Path and row	Date acquired
	P167r65	1996-12-27
Landsat 5 TM	P167r67	1996-12-27
	P168r66	1996-10-15
Landsat 5 TM	P167r65	2007-01-24
	P167r68	2007-01-24
	P168r66	
		2007-04-05
Landsat 8	P167r65	2018-05-30
	P167r68	2018-05-30
	P168r66	2018-05-30

Source : (United State Geological Survey Website).

2.2.1 Image processing

Conversion of digital numbers (DN) into reflectance: The conversion of digital numbers (DN) into reflectance was carried to normalize the Landsat datasets for better comparisons between images of different years of research study. The conversion involved two different steps that were carried out using ArcGIS 10.3 software. In the first step the digital number (DN) values of each pixel was converted into the radiance while the second step involved conversion of radiance into reflectance.

Layer stacking and image Mosaicking: Band 1, 2, 3, 4, 5 and 7 of Landsat 5 TM images of year 1996, 2007 and 2018 from path and row (167068, 167066 and 167065) were layer stacked using ERDAS Imagine software. While the band 1, 2, 3,4,5,6, 7 and 9 of Landsat 8 of year 2018 from path and row (167068, 167066 and 167065) were layer stacked using ERDAS Imagine software. Following completion of layer stacking procedure, the layers stacked bands from path and row 167068, 167066 and 167065 for Landsat 5 TM of year 1985, 1996, 2007 and Landsat 8 of year 2018 were then subjected to Mosaicking procedure using ERDAS Imagine software. The Mosaicking procedure was carried using MosaicPro from 2D view tool accessed via the Raster tool in the tool main bar of ERDAS Imagine. In Landsat 5 TM, the band 6 were excluded due to its spatial resolution of 120 M while in Landsat 8 the band 6,8,10 and 11 were excluded as it possess the spatial resolution of 60, 15 and 100 M , respectively.

Image sub-setting: This was done to extract the Area of Interest (AOI) using ERDAS Imagine software. The shape file of Kilombero district developed by National Bureau of Statistics (NBS)-Tanzania was used to extract the AOI. The mosaicked band of Landsat 5 TM of year 1985, 1996, 2007 and 2018 was used for extract the AOI for the study year 1985, 1996, 2007 and 2018, respectively.

Delineation of training sites in Landsat 5 TM and Landsat 8: The sub-set image of Landsat 5 TM of year 1985, 1996, 2007 and 2018 each were separately subjected to visual assessment using three bands that were displayed as Red, Blue and Green (RGB) color composite using ERDAS Imagine software. The RGB color composites images were developed to facilitate visualization, interpretation and delineation of training sites. Band 4, 3 and 2 were used in displaying in RGB color composites images for Landsat 5 TM of year 1985, 1996 and 2007. While the band 5, 4 and 3 were used in displaying in RGB color composites images for of Landsat 8 of year 2018. The training sites were delineated following the classification scheme level II by Anderson et al., (1976) with some modification. Thus in this research study only six classes which are forest, wetlands, crop lands, water bodies, bush lands/shrubs and impervious LULC class were considered during image classification. Table (2) narrates the classification scheme for this research study. Delineation of training sites comprised of selecting the training sites based on visual interpretation on the image, knowledge of LULC types identified and information visualized in Google earth images. At least 20 samples of training site were developed for each identified LULC class based on the LULC type been numerous, representative, relatively homogeneous and as large as possible while maintaining homogeneity and avoiding mixed pixels at the edges of objects. Finally, the 20 samples selected for each LULC class were merged using signature editor of ERDAS Imagine to form one class.

Table 2: Classification scheme proposed for the research study.

S/N	LULC CLASS	DESCRIPTIONS

1	Crop lands	These comprised of cropland, confined feeding operation area, pasture, orchards, nurseries and horticultural area.
2	Forest	Forest class was formed by trees at least 5m high and canopy cover more than 50%, it comprise of deciduous, evergreen land and mixed forest.
3	Impervious	This comprised of residential places, commercial and services, industrial, transportation, communication and utilities, industrial and commercial complexes. Impervious land use also comprised of sandy areas, bare exposed rock, strip mines, quarries, and gravel pit, mixed barren land.
4	Bush lands /shrubs	This comprised of non-cultivated and cultivated land with young growing crops/nurseries and shrubs.
5	Wetlands	This consisted areas which are covered by water at near the surface of the soil all year or for varying periods of time.
6	Water bodies	This comprised of water bodies comprised of rivers, streams, flooded lands and ponds

Source: (Modified from Anderson et al., 2001)

Classification, post classification and accuracy assessment of Landsat dataset: The ERDAS Imagine software was used for classification of Landsat dataset for year 1985, 1996, 2007 and 2018 covering the Kilombero district. Maximum Likelihood Classification (MLC) algorithm was used to develop classified images of year 1985, 1996, 2007 and 2018 using the signature files of Landsat image of year 1985, 1996, 2007 and 2018, respectively. The classified images of year 1985, 1996, 2007 and 2018 were subjected to accuracy assessment using ERDAS Imagine software. The overall accuracy, producer's accuracy, user's accuracy and kappa coefficient were computed using equations (2-5).

$$\text{Procuder's accuracy} = \frac{\text{Total correctly classified pixel in row i (in the diognal cell)}}{\text{Total number of pixel in the row i}}$$ …….Equation 1

$$\text{User's accuracy} = \frac{\text{Total correctly classified pixel in column j (the diognal cell)}}{\text{Total number of pixel in the column j}}$$ ………..Equation 2

$$\text{Overall accuracy} = \frac{\text{Total number of correctly classified pixels}}{\text{Total number of pixels in the error matrix}}$$ ……………………….Equation 3

$$\hat{K} = \frac{N\sum_{\substack{i=1\\j=1}}^{m} Dij - \sum_{\substack{i=1\\j=1}}^{m} R_i \cdot C_j}{N^2 - \sum_{\substack{i=1\\j=1}}^{m} R_i \cdot C_j}$$ ………………………………………………….Equation 4

Where

K= Kappa-coefficient,; N – Total number of pixels; m – Number of classes; ΣDij – Total diagonal elements of an error matrix (sum of correctly classified pixels in images); Ri – Total number of pixels in row i and Cj – Total number of pixels in column j.

2.2.2 Developing the NDVI for mapping deforestation

Arcmap 10.3 software was use for the calculation of the NDVI from multi-date satellite images of Landsat data of year 1996, 2007 and 2018 covering the area of Kilombero district. Mathematical formula expressed in equation () was used for generating NDVI maps which facilitated the assessment of the "greenness" or relative biomass.

NDVI = (IR – R)/(IR + R)…………………………………………………………………………Equation 5

The normalized difference vegetation index or NDVI button is used to perform image algebra on the red (band 3 for Landsat TM) and near infrared (band 4 for Landsat TM) bands. While in the Landsat 8 the red and near infrared is band are represented by in band 4 and 5, respectively. In the NDVI map the brighter (higher) value indicates a higher percentage of vegetation, healthier vegetation, or plant species differences. Thus, the generated map of spatial-temporal variability of NDVI was assessed to study deforestation and land degradation in Kilombero district.

3. RESULTS AND DISCUSION

3.1 LULC classification results

The classification results of four different study periods have depicted the quantity land use land cover status in year 1996, 2007 and 2018. Six LULC classes classified were agriculture, forest, wetlands, impervious, water bodies and bush lands. In year 1996 the forest, bush lands, wetlands and agriculture with recoded with 517492 ha (38.03% composition), 279050 ha (20.51% composition), 217996 ha (16.02% composition), and 181243 ha (13.32% composition), respectively. Notably agriculture and agriculture were found to increase from year 1996 to 2007 this occurred following expansion of agriculture and over population (Kato, 2007). Impervious land cover increased to 120982 ha (8.89% composition) while water bodies increased to 44025 ha (3.24% composition) in 1996. Impervious land cover has increased subsequently to the expansion of anthropogenic activities such as agriculture, bare lands and settlements (Connors, 2015). In year 2007 agricultural lands becomes the second largest land use with 349591 ha (25.69% composition) while forest remained the largest land cover with 524685 ha (38.56% composition).While water bodies and wetlands declined to 10851 ha (0.80% composition) and 145042 ha (10.66% composition), respectively. Impervious and bush land were increased to 74494 ha (5.47% composition) and 256125 ha (18.82% composition), correspondingly. These decrease in wetlands, water bodies and forest land cover have occurred due ever expansion of anthropogenic activities in Kilombero district (Connors, 2015 & Nindi, 2009).While the over dependence of about 80% of population on forest resources as source of construction and cooking energy in Kilombero district have resulted to decline in forest (Sophia & Emmanuel, 2017). In year 2018 bush lands becomes the largest land cover category with 506058 ha (37.19% composition) and followed by agriculture with 365954 ha (26.89% composition) while forest declined to 303923 ha (22.33% composition).Water bodies and wetlands declined to 8158 ha (0.60% composition) and 70399 ha (5.17% composition), respectively while impervious land cover increased to 106296 ha (7.81% composition). The expansion of agricultural lands is supported by ever-increasing population with 80% depending on agriculture as main economic activities (Sophia & Emmanuel, 2017), the previous agro-industry policy which has resulted to expansion of commercial farms (Johansson & Isgren, 2017) and previous abundance of fertile soils and favourable climate for agricultural activities (Kato, 2007). While area under bush lands increased from 210,199 ha (15.45% composition) in 1985 to 506058 ha (37.19% composition) ha in year 2018 with increase of 295859 ha (58% composition). Similarly, area under impervious land cover has increased from 11,973 ha (0.88% composition) in year 1985 to 106,296 ha (7.81% composition) in year 2018. The overall accuracy for classified image of year 2018 was 93.58% while producer accuracy was 97.92, 95.45, 97.56, 92.65, 84.21 and 91.43% for forest, wetlands, agriculture, bush lands, impervious and water bodies, correspondingly. At the same time, the user accuracy for year 2018 were 95.92, 86.30, 90.91, 100 and 96.97% for forest, wetlands, agriculture, bush lands, impervious and water bodies, correspondingly. The overall accuracy for classified image of year 2007 was 92.86% while producer accuracy was 96.96, 92.31, 87.88, 93.33, 94.29 and 93.33% for forest, wetlands, agriculture, bush lands, impervious and water bodies, correspondingly. At the same time, the user accuracy for year 2018 were 90.57, 87.80, 90.63, 96.55, 94.29 and 97.67% for forest, wetlands, agriculture, bush lands, impervious and water bodies, correspondingly. The overall accuracy for classified image of year 1996 was 96.26% while producer accuracy was 98.09, 86.27%, 100, 100, 88 and 100% for forest, wetlands, agriculture, bush lands, impervious and water bodies, correspondingly. At the same time, the user accuracy for year 2018 were 98.09, 95.65, 83.33, 97.30, 100 and 95.45% for forest, wetlands, agriculture, bush lands, impervious and water bodies, correspondingly.

Table 4: Area (ha) and % composition of LULC categories in year 1996, 2007 and 2018

LULC Class	**Year 1996**		**Year 2007**		**Year 2018**	
	Area (ha)	% Composition	Area (ha)	% Composition	Area (ha)	% Composition
Forest	517492	38.03	524685	38.56	303923	22.33
Bush lands	279050	20.51	256125	18.82	506058	37.19
Impervious	120982	8.89	74494	5.47	106296	7.81
Agriculture	181243	13.32	349591	25.69	365954	26.89
Wetlands	217996	16.02	145042	10.66	70399	5.17
Water bodies	44025	3.24	10851	0.80	8158	0.60
TOTAL	**1360788**	**100**	**1360788**	**100**	**1360788**	**100**
Overall accuracy	**93.58**		**92.86**		**96.26**	

3.2 NDVI for mapping the deforestation

According to NDVI is interpreted on the scale of -1, 0, 1 whereby 0.3 to 0.8 reveals a dense vegetation canopy , 0.1 to 0.2 means soils and very low positive or even slightly negative for

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clear water. Then using Figure () the spatial distribution of NDVI in year 1996 was about -1 to 0.7326 where by area with NDVI value of -1 are covered by water bodies and has been scattered in the south parts of wards in Kilombero district. This implies that in 1996 there Kilombero district was dominated by wetlands and water bodies along the Kilombero River. On the other hand, the NDVI value of 0.7326 reveals that, the land is dominated by dense vegetation. The slight vegetation were concentrated on the north part each ward of Kilombero district. In 2007 the NDVI values between -1 and 1 were recorded Figure (X). The NDVI value of -1 implies presence of water bodies and wetlands in Uchindile wards and the south part of other wards along the Kilombero River. While the NDVI value of 1 imply health and dense vegetation in most of the wards. The increase in NDVI values from 1996 to 2007 imply increase in vegetation density which occurred following the interception and implementation of the national and international environmental conventions. The agro-industry policy of Tanzania and the created awareness on the environmental impacts of shift cultivation, LULC and climate change in Kilombero district also have resulted to this increase in vegetation cover in most of Kilombero wards.

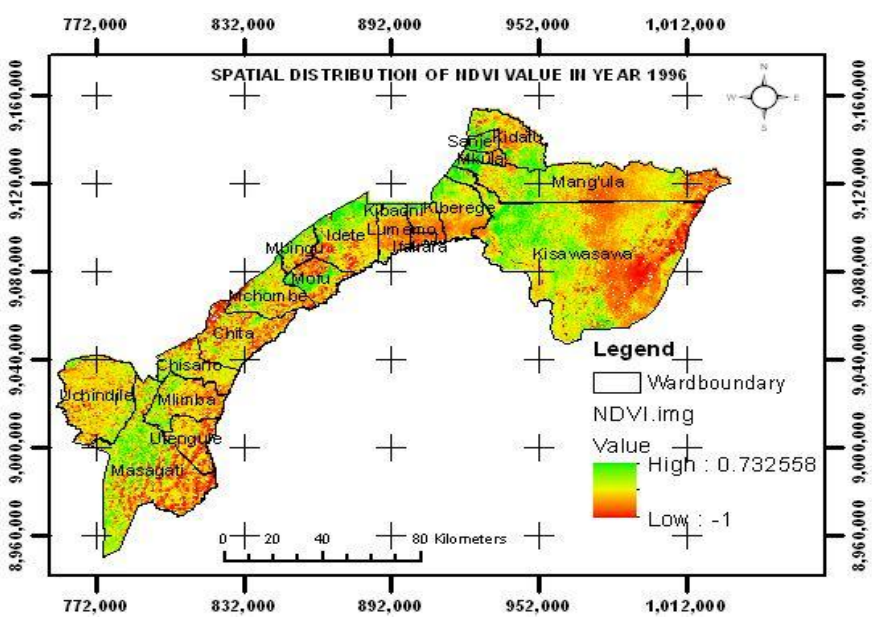

Figure 2: Spatial Distribution of NDVI in Kilombero district in 1996

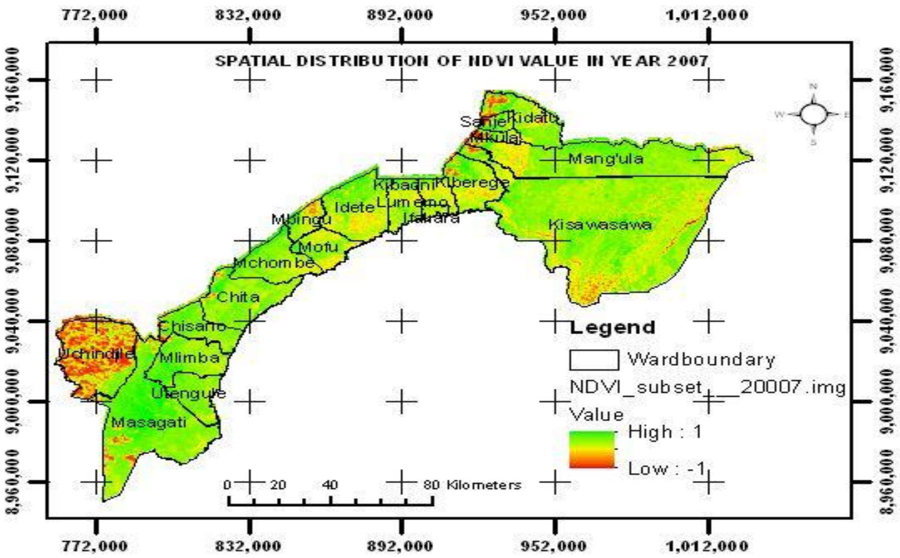

Figure 3: Spatial Distribution of NDVI in Kilombero district in 2007

In 2018 the NDVI values between -0.1346 and 0.1812 were recorded Figure (X). The NDVI value of -0.1346 implies presence of water bodies and wetlands in Kidatu to Idete wards via Ifakara road.In the South-West only Uchindile and Masagati were covered with NDVI values of -0.1346. While Uchindiles, Mlimba, Chita, Mofu and Mbingu ward were recorded with the NDVI value of 0.1812. While the NDVI value of 0.1812 soils and NDVI value of -0.1346 implies presence of water bodies and wetlands. Notable decrease of NDVI values is observed from 2007 to 2018 whereby the high NDVI value of 1 in year 2007 to has reduced from NDVI value 0.1812 in year 2018. This supported by other previous research study which have demonstrated the decline in forest resources following expansion of agriculture in Kilombero district. Similarly, high NDVI values have decreased from 0.7326 in year 1996 to 0.1812 in year 2018.

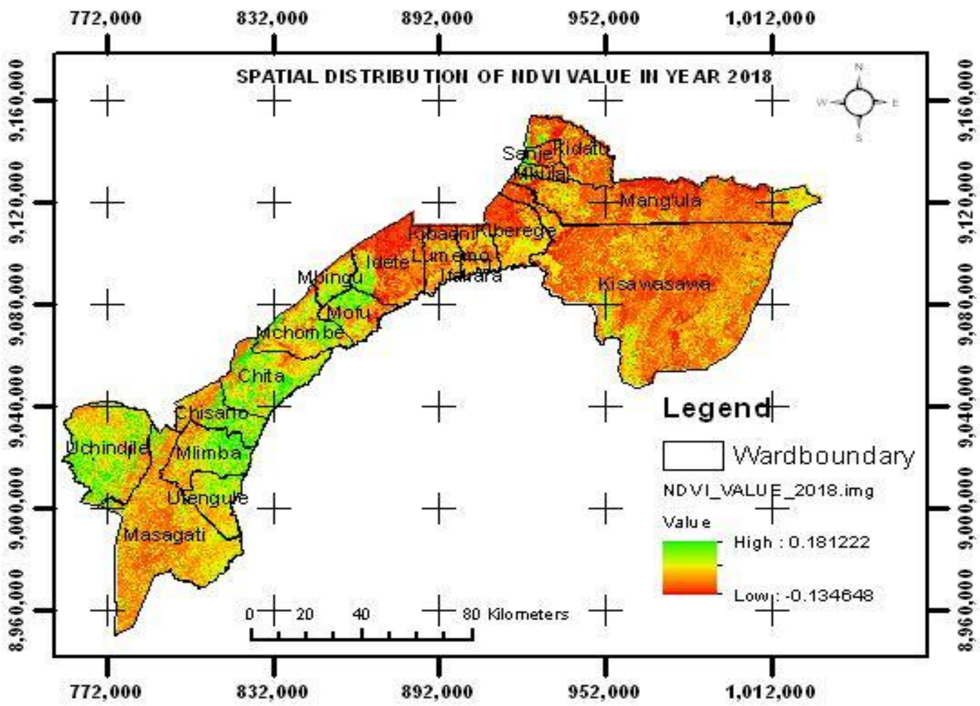

Figure 4: Spatial Distribution of NDVI in Kilombero district in 2018

4. CONCLUSION AND RECOMMENDATIONS

4.1 Conclusion

Landsat image classification and NDVI have revealed the composition and spatial configuration of forest resources in Kiombero district. In year 1996 forest have 517492 ha (38.03% composition), in 2007 there was about 524685 ha (38.56% composition) while declining to 303923 ha (22.33% composition) in 2018. While the NDVI results have revealed an increase in NDVI values from 1996 to 2007 imply increase in vegetation density which occurred following the interception and implementation of the national and international environmental conventions. Notable decrease of NDVI values is observed from 2007 to 2018 whereby the high NDVI value of 1 in year 2007 to has reduced from NDVI value 0.1812 in year 2018. Basing on the data and methodology used in this research study, Landsat image classification and NDVI have the potential as economical and rapid tools for monitoring the forest resources in Tanzania

4.2 Recommendations

i. Local Government Authority (LGA) and other stakeholders should build capacity of local personnel for successful utilization of RS and GIS data in forest and deforestation monitoring and management.

ii. Local Government Authority (LGA), research organization and other stakeholders should develop and promote nursery of trees for evaluation, multiplication and dissemination of agro-forestry seeds, seedlings/propagating material among community members is highly recommended to research and agricultural extension services of Kilombero district.

iii. Safe and affordable energy sources as alternatives to fire wood and charcoal sources need to developed, tested, evaluated by research organization and disseminated to community members of Kilombero district.

iv. Mitigation option of the LULC impacts such as AFOLU, GLOBIOM and LULUCF are highly recommended in Kilombero district

v. GIS based Agro Zonation Systems (GIS-EAS) also required to aided agriculturalist, pastoralists and other land stakeholders to operate efficiently are in Kilombero district.

vi. There is need to develop, implement and practices appropriate urban management strategies to inhibit further deforestation and urban sprawl.

vii. Kilombero district council must establish bylaws to protect forest and water sources, create awareness, company for agro forestry farming, create and encourage the nursery tress business and entrepreneurship in Kilombero district.

viii. Finally, the Landsat data image classification and NDVI used in this research study are highly recommended as prototype for further research and application in other study areas with similar environmental setting.

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