GIS-based Landsat Image Classification for Change Detection and Prediction LULC Dynamics: Case Study Kilombero District-Tanzania

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Abstract – Loss of prime agriculture land, forest, bio-diversity, encroachment of protected areas and land degradation are among the emerging impacts of Land Use Land Cover (LULC) dynamics in Kilombero district. Owing to the agricultural and ecological of Kilombero district periodic quantification and prediction of LULC change is vital for sustainable monitoring of natural resources. GIS-based Landsat image classification for change detection and prediction of LULC dynamics, provide basis understand how land have evolved in relation to anthropogenic activities hence guiding in establishing bylaws, policy, regulatory actions and activities for managing the environment. The overall objective was to characterize and predict LULC dynamics using Land sat image classification and GIS based LULC models Cellular Automata-Markov (CA-Markov) model in Kilombero district of Tanzania. The Landsat data were downloaded from the USGS website and classified using ERDAS Imagine software while adopting Maximum Likelihood Classification (MLC) algorithm. LULC composition in year 1985 were 553,217; 136,935; 9,596; 243,763, 346,811 and 70, 466 ha of forest, bush lands, impervious, agriculture,

wetlands, water bodies LULC category. In year 1996 there was about 517492; 279050; 120982; 181243; 217996 and 44025 ha of forest, bush lands, impervious, agriculture, wetlands, water bodies LULC category, correspondingly. In year 2018 the composition of LULC were 303,923; 506,058; 106,296; 365, 954; 70399 and 8158 ha of forest, bush lands, impervious, agriculture, wetlands, water bodies, respectively. Land Change Modeler (LCM) and Cross Tab tool were used for quantifying the LULC changes and its spatial location. Forest land cover decreased from 797438 ha to 517492 ha in year 1985-1996 while contributing about 124548 to agriculture. In 1996-2007 forest increased to 517492 ha while in year 2007-2018 out of 524685 ha of forest only 202260 ha remained forest in year 2018. In year 1985-1996 agriculture land increased from 42856 to 181243 ha with high gains from forest, wetlands and bush lands with area of 124548, 22601, and 25213 ha, correspondingly. In year 2007-2018 out of 349591 ha of agriculture only 280006 ha remained agriculture in year 2018. While out of 1450421 ha of wetlands only 38055 ha remained wetlands in year 2007-2018. CA-Markov model was used for predicting the LULC dynamics for year 2048. The first-order Markov probability was obtained using LULC map of year 1985-1996, 1996-2007 and 2007- 2018. In year 2007-2018 and 1996-2007 agriculture was most stable class remaining unchanged with the probability of 0.31 (31%) and 0.34 (34%), respectively. The chances of forest remaining forest was 0.4 (40%) and 0.4 (40%) in year 1985-1996, 1996-2007 and 2007-2018, respectively. The possibilities of water bodies to remain water bodies was about 0.07 (7%), 0.01 (1%) and 0.07 (7%) for year 1985-1996, 1996-2007 and 2007-2018, correspondingly. In year 2048 a notable decline to about

241001 ha, (17.71%), 347000 ha (25.50%), 68731 ha (5.05%) and 4990 ha (0.37%) were recorded for forest, bush lands, wetlands and water bodies, correspondingly. Agriculture and impervious land cover will increase to 537000 ha (39.46%) and 162066 ha (11.91%), correspondingly. Wetlands and water bodies will be reduced to 68731ha (5.05%), 4990 ha (0.37%), correspondingly. Agro-forestry farming, mitigation options such AFOLU, LULU, GEOGLAM and GEOBIOM highly recommended to reverse the current and future deforestation, wetlands and water bodies' losses in Kilombero district.

Keywords: Image classification; change detection; prediction of LULC dynamic

1.0INTRODUCTION

The advancement in Geographical Information Systems (GIS)-based Landsat image classification, change detection and prediction has aided the assessment and prediction of LULC dynamics globally. Remote sensed imagery presents typical ability for visualization of large areas at a given time and is often regarded as the best sources of up-to-date information and consistent estimates of LULC change with a cost effective manner (Gonzalez & Woods, 2008 & Nouri et al. 2014). Recently, several researchers have demonstrated the capability of remote sensing data as a powerful set of analytical tools to understand how humans interact with the landscape (Reis et al. 2003 & Gong et al. 2015). The commencement 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). Multi-spectral remote sensed data is data which is captured by a multispectral sensor with moderate resolution and several spectral bands at spatial resolution. Hence, multi-spectral Landsat data are captured using 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). All the way through history, the multi-spectral Landsat data has been considered vital for providing information for continuous monitoring of Earth's resources and regarded as the popular and reliable source for documenting changes in land cover and use over time (Reis et al., 2003). The advancement in computer technology, development of geographic information systems (GIS) and in addition to the policy of free accessibility Landsat data are the reasons behind the advancement of Landsat products. Owing to the technical description, the spectral and temporal resolutions of Landsat 5 Thematic Mapper (TM) and 8 were found appropriate for GIS based image classification, change detection and prediction of Land Use Land Cove (LULC) dynamics.

With the Landsat program running for over four decades now different methods for digital image analysis, GIS-based Landsat image classification, post classification, accuracy assessment, change detection and modeling LULC dynamics have been developed. In principle, Landsat image analysis entails digital image processing which involves manipulation and interpretation of the digital image data by specific computer program s to display and extract meaningful information about the surface of the earth (Paul, 2013). Pre-processing and digital image classification which is among the basic image analysis processes governs most of the LULC change detection study (Bruce & Hilbert, 2004 & Canavosio-Zuzelski, 2011). While digital Image classification involves the process of categorizing all pixels in an image or raw remotely sensed satellite data to obtain a given set of labels or land cover themes (Gelsema, 1997). Land cover classification methods using Landsat images originated from early aerial photo interpretation methods which were common in the 1950s and 1960s where land cover was classified based on visible image properties such as texture, color, shape and compactness (Amin & Fazal, 2012)

On the other hand, the term LULC dynamics entails to describe both natural (e.g. weather, flooding, earthquake etc.) and anthropogenic causes of LULC changes (Halmy et al. 2015; Zewdie & Csaplovics, 2015). Research studies on LULC dynamics have called attention in recent times following its impacts to society and environments. Drivers or variables cause changes in the LULC over a period of time at a specific location (Ganasri et al., 2013) while forming a complex system of dependencies, interactions, feedback loops and they affect several temporal and spatial levels of LULC dynamics (Campbell et al., 2005). Research scholars have grouped the driving variables of LULC dynamics as socio-economic, institutional/policy, social/cultural, proximate and biophysical variables (Verburg et al., 2004); Campbell et al. 2005). Other research scholars including Geist,

(2005) & Mahmoud (2016) have described the market forces, economic , trade policy and agreements policy, land use policy, land tenure policy as the causes of LULC dynamics. The economic driving forces include market forces, trade policy and agreements, economic policy, land use policy, land tenure policy (Geist, 2005 & Mahmoud, 2016). Social/cultural driving forces include urbanization, immigration, population dynamics, and cultural change (Geist, 2005 & Mishra et al., 2014). Institutional/policy driving forces include national and international policies to conserve biodiversity and natural climate. While the biophysical drivers are biological and physical factors that drives LULC dynamics including the rainfalls, surface water and topography (Geist, 2005 & Behera et al., 2012). The proximate factors of LULC dynamics are factors that influences LULC dynamics based on the distance from the river, roads, settlements, soil erosion coefficient and soil drainage. While Strapasson et al. (2016) have described the changing trends in food consumption patterns, types of meat production and consumption, crop yields, livestock yields, land degradation, wastes and residues, bio-energy forms and yields as causes of LULC changes. In Kilombero district the causes of LULC dynamics includes socio-economic, institutional/policy, social/cultural, proximate and biophysical variables.

Owing to these ongoing causes of LULC dynamics, change detection basing on GIS Landsat image classification is an important process in monitoring and managing natural resources while providing quantitative analysis of the spatial distribution of the LULC categories (Arsanjani, 2011). Other research scholars have described change detection as a process of identifying differences in the state of an object or phenomenon by observing it at different times (Mashame & Akinyemi, 2016). In principles, change detection procedures involve use data acquired by the same sensor and be recorded using the same spatial resolution, viewing geometry, spectral bands, radiometric resolution and time of day. Opeyemi, (2006) have identified four core importance of land-use change detection which includes: - (i) detecting the changes that have occurred (change / no- change), (ii) identifying the nature of the change, (iii) measuring the areal extent of the change and

(iv) assessing the spatial pattern of the change. Some of applications of change detection include land use changes, habitat fragmentation, and rate of deforestation, coastal change, urban sprawl, and other cumulative changes (Province, 2016). Change detection is useful for monitoring and managing natural resources and urban development because it provides quantitative analysis of the spatial distribution of the activities of interest (Houet et al., 2013). The change detection methods may be classified into two broadly categories which are pre-classification change detection and post-classification comparison (Lu & Weng, 2007). A variety of change detection techniques has been developed for pre-classification change detection, or simultaneous analysis of multi-temporal data, including image differencing (Phiri & Morgenroth, 2017) image regression, image rationing, vegetation index differencing, principal components analysis, change vector analysis, artificial neural networks, and classification tree (Opeyemi, 2006) to name just a few. On the other hand, the post-classification comparison is a comparative analysis of images obtained at different moments after previous independent classification. The most obvious method of change detection is a comparative analysis of spectral classifications for times t1 and t2 produced independently(Lu & Weng, 2007). Although the post-classification comparison method requires the classifications of images acquired from different times, it can not only locate the changes, but also provide “from-to” change information (Jensen, 2004). Post-classification methods are predominantly advantageous for generating from–to maps which can be used to elucidate the extent, rate and location of changes and nature of the changes (Ghosh et al., 2017). Owing these advantages of post-classification methods, the proposed study will use the approach in detecting the LULC changes that have occurred in Kilombero district.

GIS based LULC models are tools to support the analysis of the causes and consequences of land use changes in order to better understand the functioning of the land use system and to support land

use planning and policy (Ganasri et al., 2013). Furthermore, LULC models supports exploration of future land use changes under different scenario conditions (Verburg et al., 2004). Modeling LULC dynamics is one technique for unraveling the complex relationships in land-use change systems and provides insights into the extent and location of land-use change (Houet et al., 2007; Zhigang et al. 2011). Among many LULC GIS models, the Land Change Modeler (LCM) is an integrated software module in IDRISI Selva software environment that performs land change analysis, change prediction, and habitat and biodiversity impact assessment (Province, 2016; Mishra et al., 2014). The LCM is embedded in the IDRISI software where only thematic raster images with the same land cover categories listed in the same sequential order can be input for LULC analysis (Megahed et al., 2015). LCM evaluates land cover changes between two different times, calculates the changes, and displays the results with various graphs and maps (Province, 2016; Mirhosseini et al. 2016) Mirhosseini et al. 2016). In the LCM model, a set of tools is included for the rapid assessment of change, allowing for one-click evaluation of gains and losses, net change, persistence, change (gains, loses and persistence), spatial trend of changes, and specific transitions both in map and graphical form (Hamdy et al. 2017Hamdy et al. 2017; Mirhosseini et al., 2016). On the other hand, the CA- Markov Model operates using the outputs of Markov chain analysis which is accurate estimation and CA model output which adds spatial characteristics. The following are description on the basics and concepts of Markov Chain, CA and CA-Markov model, respectively.Markov Chains: A Markov chain model is described as a set of states, X = {X0, X1, X2……… Xn} in the process which starts from one of the states and moves successively to another (Ma et al.,, 2012). If the system is in current state Xi, then moves to next state Xj at the next step with transition probabilities denoted as (pij). Using the Markov chain, the state of the system Xi+1 is determined using the former state, Xi (Ma et al. 2012). Mathematically, the relationship is described using equation (1 and 2).

$+ \ =$ .... Figure 1

$$P_{ij} = \begin{bmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{bmatrix}$$

$\left(0 \leq P_{ij} < 1 \text{ and } \sum_{j=1}^{N} P_{ij} = 1,\ (i, j = 1, 2, \ldots, n)\right)$. ....Figure 2

Pij is designed in sequence to give the transition probability matrix P, which could be calculated by the equation (2). Where n is the number of wetland type, Pij is the probability that change from type i to type j.

The Markov analysis generates three outputs which are transition probability matrix, a transition areas matrix and a set of conditional probability images (Eastman, 2012 & Hamdy et al., 2017). Transition probability matrix is a text file containing the probability of each LULC category to change to other LULC category (Guan et al., 2011) while transition areas matrix is a text file containing number of pixels which are expected to change from each LULC type to other LULC category (Ahmed et al., 2013). Besides, the conditional probability images report the probability of each LULC type which would be found at each pixel after the specified number of time units (Zhigang et al., 2011). While the CA model in the context of LULC dynamics is used practical tool for urban system simulations (Al-sharif & Pradhan, 2013). In the CA model, the cells of the cellular lattice, can be effectively used to simulate LULC dynamics by using proper neighborhoods of cells on the cellular grid (Putra, 2017). In the hybrid CA -Markov the advantages of Markov chain in accurate estimation are combined to spatial characteristics of CA mode (Behera et al., 2012;

Hyandye & Martz, 2017). The advantages of CA model in CA-Markov are to add spatial characteristics of the accurately estimated and predicted LULC categories using Markov analysis. Previous research work by Megahed et al. (2015); Estes & Loveland (1999) described the role of Markov chain in CA-Markov model which is manages temporal dynamics among the LULC categories based on transition probabilities while spatial dynamics cellu0lar automata spatial filter or transition potential maps (Megahed et al., 2015; Estes & Loveland, 1999).

This research study used the GIS based Landsat image classification for change detection and prediction of LULC dynamics in Kilombero district. Kilombero district have both agricultural and ecological role of national and international values such wetlands, wildlife habitats and forest to mention few. Nevertheless, many research scholars have demonstrated human activities in Kilombero district as source to series of environmental, ecological and social challenges associated with LULC dynamics in Kilombero district (Nindi et al., 2014; Connors, 2015; Johansson & Isgren, 2017). Encroachment of protected area, land conflicts, Loss of prime agriculture land, forest, bio- diversity, encroachment of protected areas and land degradation are among the emerging impacts of LULC dynamics in Kilombero district. Loss of prime agriculture land have resulted to land conflicts (Nindi, Maliti, Bakari, Kija, & Machoke, 2014) and encroachment of protected areas (Johansson & Isgren, 2017) while loss in forests have resulted to deforestation, bio-diversity loss and land degradation in Kilombero district. Policy evidence are also available on the policies and national strategies that have influenced the LULC dynamics including the villagerization policy of 1974; National Forest Reserve Act 1984; the privatization policy of 1996; Kilimo kwanza policy of 2000; National Livestock Development Programme (NLDP) and Agro-industry policy of 2002. Among of the globally reported mitigation options for impacts of LULC dynamics are Agriculture, Forestry and Other Land Use (AFOLU), Group on Earth Observations (GEO), Land Use, Land-Use Change and Forestry (LULUCF), Global Biosphere Management Model (GLOBIOM), Geo Global Agricultural Monitoring (GEOGLAM) which both require spatial information of LULC dynamics. GEO is working to improve the availability, access and use of Earth observations for the benefit of society through promoting broad, open data sharing while GLOBIOM is used to analyze the competition for land use (Deshayes, 2014). Adoption of these mitigation options in Kilombero district with ongoing forest clearing for farm establishment, timber and charcoal harvesting bush fire, uncontrolled and excessive grazing, and expansion of agriculture and infrastructure development (Sophia & Emmanuel, 2017) is deemed immediate strategy to manage the impacts of LULC dynamics. Impacts LULC dynamics have resulted into decrease in vegetation cover, biodiversity loss, climate change, carbon dynamics, environmental pollution and changes in hydrological regimes in Kilombero district(Balama ,et al., 2013; Sophia & Emmanuel, 2017). These impacts are threatening the ecological and agriculture role of Kilombero district. To attain all- encompassing growth and development in various sectors while prioritizing land for food and nutritional security for the ever growing population in Kilombero district, implementation of mitigation options for the impacts of LULC dynamics is vital. However, information on the past, current and future LULC dynamics are required to generating better insights on selecting appropriate mitigation options of the impacts of LULC dynamics in Kilombero district. In relation to country development strategy, research studies on LULC dynamics are vital for implementation of the Climate Smart Agriculture (CSA) action plan in Tanzania, Tanzania's National Development Vision (TNDV) - 2025 and Sustainable Development Goals (SDGs). The TNDV-2025 and SDGs in seeking the balance of current land use with future land demand for socioeconomic transformation in Kilombero district, then information on current and future LULC categories were deemed important. Moreover, these research findings are vital for increasing level of awareness to all communities, developing strategies to create bylaws and local regulations to reverse the current deforestation, water bodies and wetland losses in Kilombero district.

METHODOLOGY

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 3 represents the geographical location of the study area.

Data collection

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, 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. Table (1) presents the Landsat dataset collected for this study.

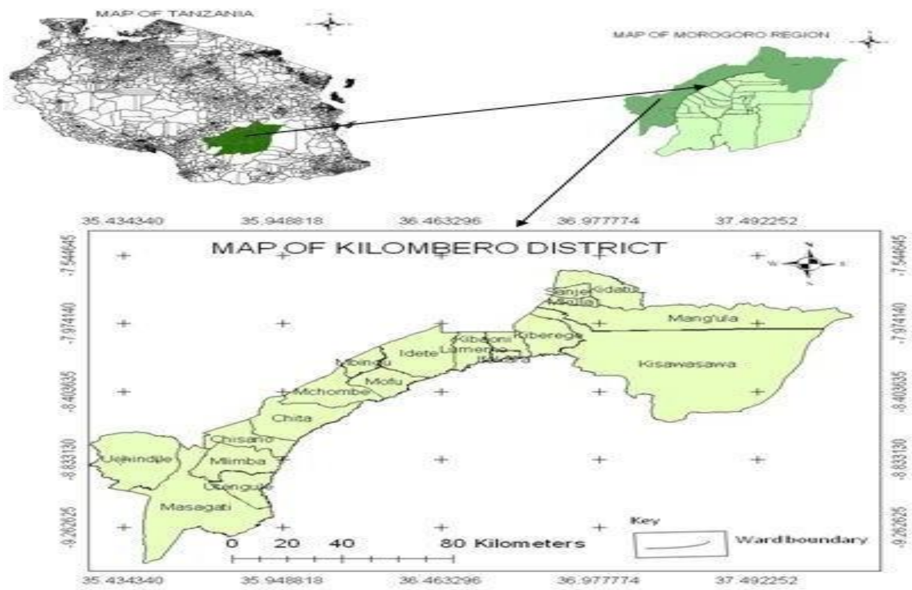


Figure 3: Geographical location of the study area

Table 1:Landsat dataset collected for this study

Dataset	Path and row	Date acquired
Landsat 5 TM	P167r65	1985-04-17
	P167r68	
	P168r66	1985-06-14
		1985-04-17
	P167r65	1996-12-27
Landsat 5 TM	P167r67	
	P168r66	1996-12-27
		1996-10-15
Landsat 5 TM	P167r65	2007-01-24
	P167r68	
	P168r66	2007-01-24
		2007-04-05
Landsat 8	P167r65	2018-05-30
	P167r68	
	P168r66	2018-05-30
		2018-05-30

(Source: USGS website)

Data processing and analysis

Data 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. Equation (1 and 2) was used for concerting the DN into radiance and radiance into reflectance, respectively.

$$= (\quad - \quad) \; 255* \quad + \qquad \text{Equation (3).}$$

Where L is the spectral radiance; LMAX and LMIN represent the highest and lowest possible values of radiance, which vary with gain state. This value is saved for each band in the MTL file saved with your Landsat scene.

$$= \; . \quad . \; 2 \; . \qquad \text{Equation (4).}$$

Where Lλ is the spectral radiance at the sensor's aperture, d is the distance from the earth to the sun in astronomical units (AU), ESUNλ is the mean solar exo-atmospheric irradiance and θs is the solar zenith angle.

Layer stacking and image Mosaicking: Band 1, 2, 3, 4, 5 and 7 of Landsat 5 TM images of year

1985, 1996 and 2007 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: 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

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

Data analysis

Image classification, post classification and accuracy assessment: 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.

Change detections using Cross Tabulation Tool and LCM: Cross tabulation tool of ERDAS Imagine were used for quantification of LULC category that have changed to other LULC category. Pair wise comparison of classified image of 1985 – 1996; 1996 – 2007; 2007-2018; 1985 – 2018 were developed in ERDAS Imagine software. Cross tabulation matrix tables were created for each pair wise comparison of classified image of year 1985 – 1996; 1996 – 2007; 2007-2018 and 1985 – 2018. Besides, the LCM of Idris Selva software was used to the graph of gain and loss as well as the graph of net change of each LULC categories for period between years of 33 years. In LCM analysis of LULC change was achieved by one-click evaluation of the change analysis panel of LCM through pair wise comparison of classified images of year 1985 – 1996; 1996 – 2007; 2007-2018 and 1985 – 2018. While the graph of net change by LULC was constructed by taking the earlier LULC areas, adding the gains and then subtracting the losses was also constructed using IDRISI Selva.

Prediction of LULC dynamics: In this research Markov analysis was used for creating transition probability matrix, a transition areas matrix, and a set of conditional probability images. The LULC map of 1985-1996 and 1996-2007 was used to generate the transition probability matrix, a transition areas matrix, and a set of conditional probability images. Transition probability matrix is a text file that records the probability that each land cover category will change to every other category while transition areas matrix is a text file that records the number of pixels that are expected to change from each LULC category over the specified number of time units. While conditional probability images report the probability that each LULC category would be found at each pixel after the specified number of time units. The conditional probability images were calculated as projections from the later of the two input LULC images of year 1996-2007.

The CA-Markov module of IDRISI Selva the CA-Markov combines the CA, Markov Chain, Multi- Criteria/Multi Objective Land Allocation (MOLA) and land cover prediction procedure. This research used such combination to add an element of spatial contiguity as well as knowledge of the likely spatial distribution of transitions to Markov chain analysis. In this research study, the a transition areas matrix, and a set of conditional probability images created using LULC map 1996- 2007 was used to simulated the LULC map of year 2018 and 2048 in CA-Markov model. The simulated LULC map of year 2018 was validated by comparing with actual LULC map of 2018 using validate module of IDRISI Selva. While the same LULC map 1996 -2007 was simulated to 22 years and used for predicting the LULC map in year 2048.

RESULTS AND DISCUSSION

LULC classification results

The classification results of four different study periods have depicted the quantity land use land cover status in year 1985, 1996, 2007 and 2018. Six LULC classes classified were agriculture, forest, wetlands, impervious, water bodies, wetlands and bush lands. Using Table 2 in year 1985 forest, wetlands and bush lands were major LULC category with 58.60, 20.05 and 15.45 % composition, respectively. In the year 1985 a small % composition estimated to be 0.88, 1.87 and 3.15% for impervious, water bodies and agriculture constituted was recorded. However in year 1996 the LULC category with high % composition were forest, bush lands, wetlands and agriculture with recoded % composition of 38.03, 20.51, 20.51, 16.02 and 13.32%, correspondingly. Notably agriculture and agriculture were found to increase from year 1985 to 1996 this occurred following expansion of agriculture and over population. Impervious land cover increased to 8.89 while water bodies increased to 3.24 ha in 1996. Impervious land cover has increased subsequently to the expansion of anthropogenic activities such as agriculture, bare lands and settlements. In year 2007 agricultural lands becomes the second largest land use with 25.69 % composition while forest remained the largest land cover with 38.56% composition. The % composition of wetlands and forests declined to 10.66 and 0.8038.56% composition while bush lands declined to 18.82 in 2007. In year 2018 bush lands becomes the largest land cover category with 37.19 followed by agriculture with 26.89 while forest decline to 22.33% composition. Similarly, water bodies declined to 0.60 while impervious land cover increased to 7.81. In general, forest has declined from 797438 ha (58.60%) in year 1985 to 303923 ha (22.33%) in year 2018 with loss of 493515 ha (36.27%). Wetlands decreased from 272881 ha in year 1985 to 70399 ha in year 2018 with loss of about 202481 ha (14.88%). Water bodies beg off from 25443 ha to 8153 ha in year 2018 with loss of 17285 ha (1.27%). However agriculture has increased from 42854 ha in year 1985 to 365954 ha in year 2018 while bush lands increased from 210199 ha in 1985 to 365954 ha in year 2018 with

increase of 295859 ha. Similarly area under impervious land cover has increased from 11973 ha in year 1985 to 106296 ha in year 2018.

Table 2:The area and (%) composition of LULC categories for year 1985, 1996, 2007 and 2018

LULC Class	Year 1985		Year 1996		Year 2007		Year 2018	
	Area (Ha)	%Composition	Area (Ha)	%Composition	Area (Ha)	% Composition	Area (Ha)	% Composition
Forest	797438	58.60	517492	38.03	524685	38.56	303923	22.33
Bush lands	210199	15.45	279050	20.51	256125	18.82	506058	37.19
Impervious	11973	0.88	120982	8.89	74494	5.47	106296	7.81
Agriculture	42854	3.15	181243	13.32	349591	25.69	365954	26.89
Wetlands	272881	20.05	217996	16.02	145042	10.66	70399	5.17
Water bodies	25443	1.87	44025	3.24	10851	0.80	8158	0.60
TOTAL	1360788	100	1360788	100	1360788	100	1360788	100
Overall accuracy (%)		86	86			88		88

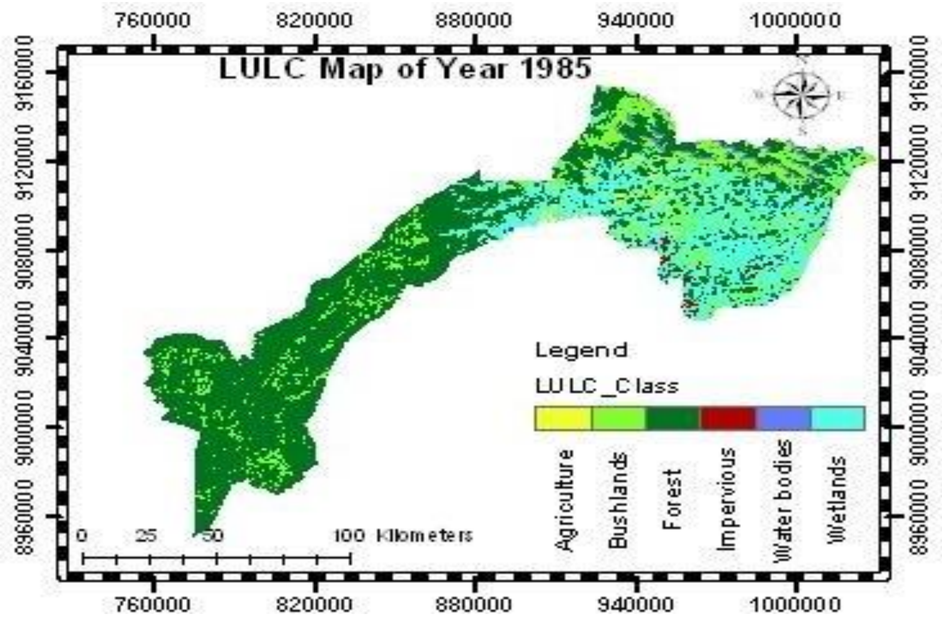


Figure 4:Spatial distribution of LULC categories in year 1985

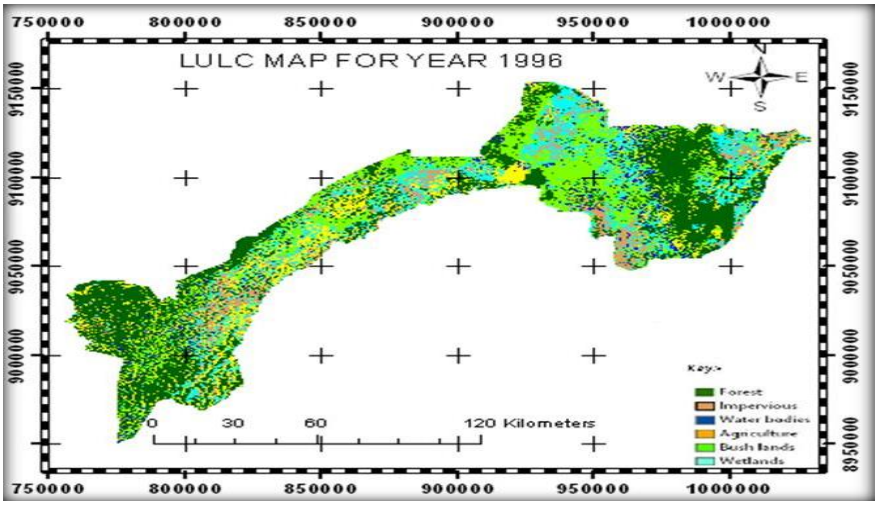
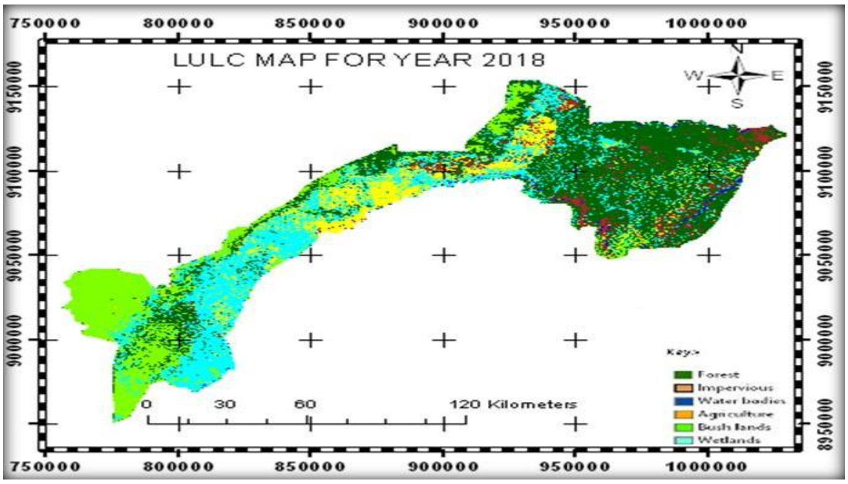


Figure 5:Spatial distribution of LULC categories in year 1996

Figur 6:Spatial distribution of LULC categories in year 2007



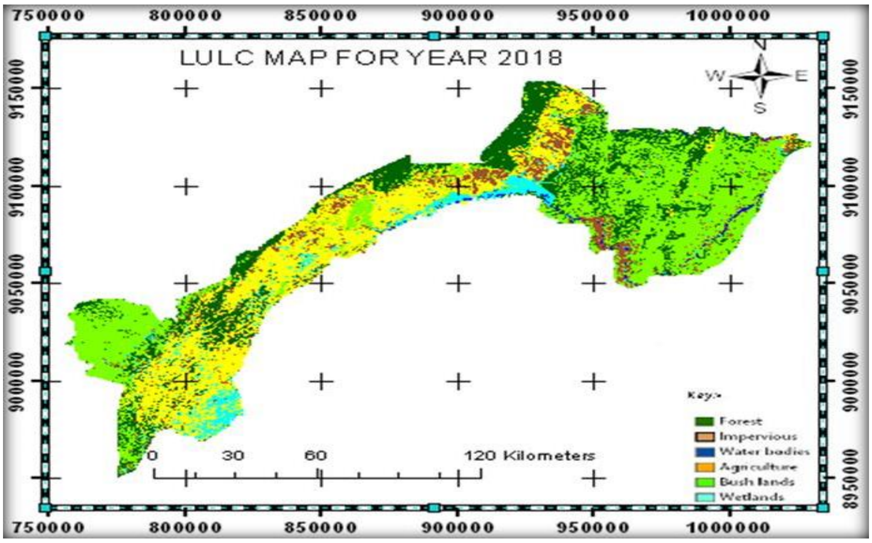


Figure 7:Spatial distribution of LULC categories in year 2018

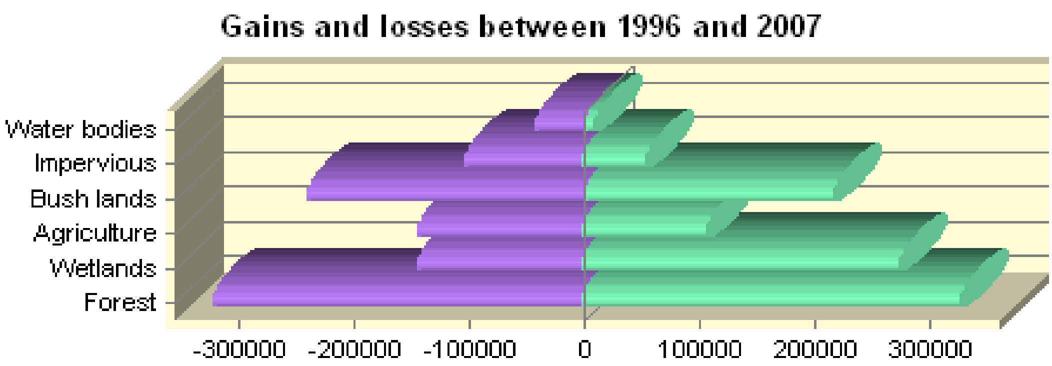


Figure 10:Gain and loss of LULC categories from year 1996 – 2007

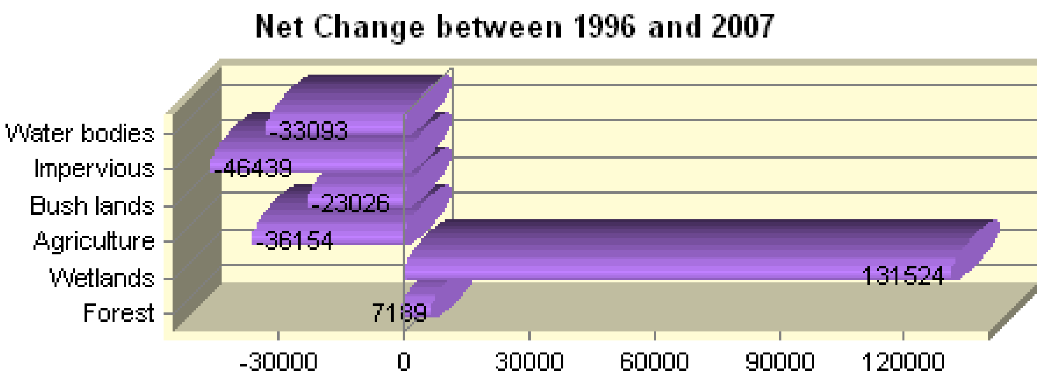


Figure 11:Net change of LULC categories from year 1996- 2007

Using Figure 12 and **Figure 13**; in the year 2007-2018 water bodies lost about 23,386 hectares and gained about 6078 hectares with net loss of about 17,308 hectares. The loss in water bodies is supported by previous research by (Nindi, 2009 & Connors, 2015) who demonstrated the ever increasing human and livestock population, expansion of the anthropogenic activities and expansion of commercial agricultural farms as major cause of water losses in Kilombero district. A net loss of about 493301 hectares of area under forest is supported by abundance of illegal harvesting of trees for charcoal, timber and fire wood due to the increased population that demands construction materials and cooking energy (Sophia & Emmanuel, 2017). Similarly Hall et al., (2009) reported the loss of about 25% forest area of Kilombero district since 1955. While area under agriculture land use has experienced a net gain of 93101 hectares in year 2007 to 2018. Agriculture has gained following the availability of national strategies for increasing agriculture production including Kilimo Kwanza (Sophia & Emmanuel, 2017) and Agro-industrial policy. While impervious class lost about 8149 hectares and gained about 102374 hectares with net gain of 94,225 hectares. The increase in area under the impervious land use category resulted from increased anthropogenic activities in Kilombero district (Connors, 2015). Also, the substantially increase of area under bush lands with net gain of about 295826 ha imply the ever increasing anthropogenic activities resulting to deforestation in Kilombero district.

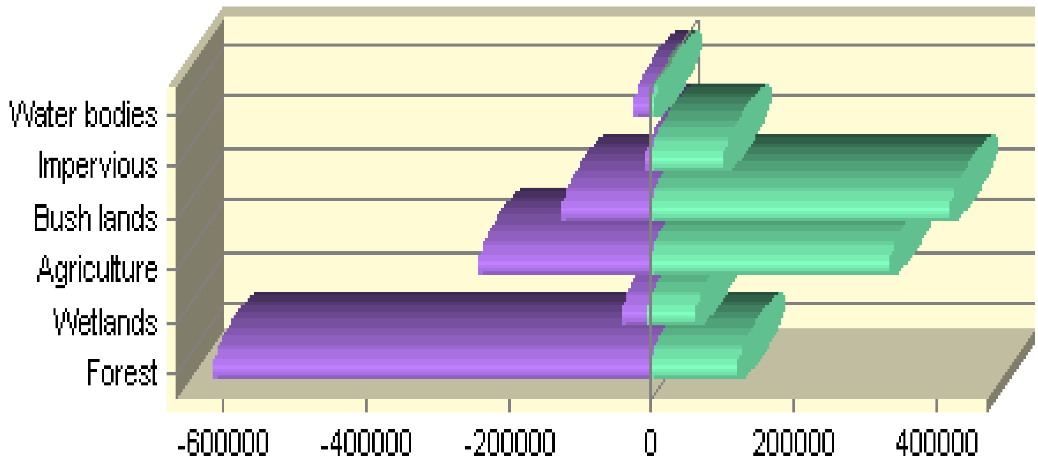


Figure 12:Gain and loss of LULC categories from year 2007 -2018

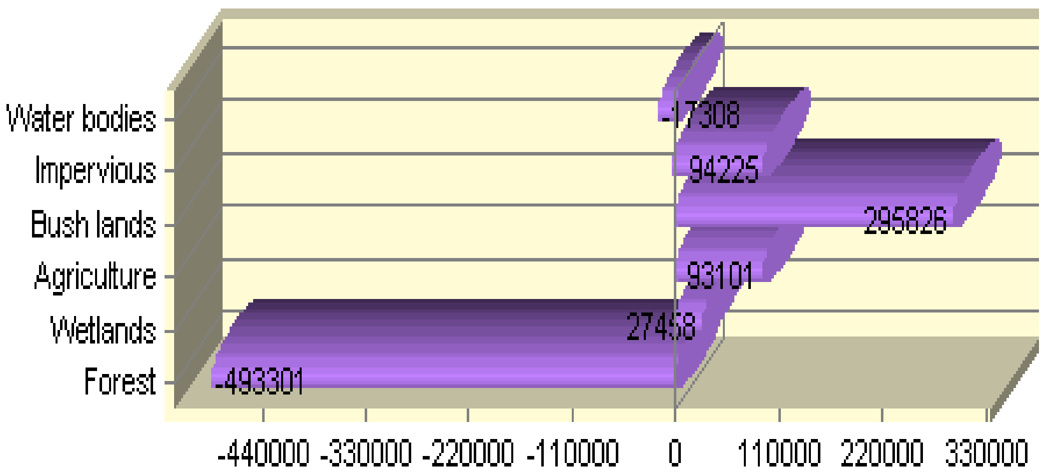


Figure 13:Net change of LULC categories from year 2007 -2018

4.3.2 Cross tabulation results

Cross tabulation determines the amounts of LULC conversions from a given LULC category to the other LULC categories at later date. Hence, the cross-tabulation results of the classified image of year 1985-1996, 1996-2007; 2007-2018; and 1985-2018 were used to characterize the historical development based on quantity of change. Table (3-7) are the cross tabulation results for year 1985-1996, 1996-2007; 2007-2018; and 1985-2018, respectively.

Forest: In year 1985 to 1996 forest land cover decreased from 797438 ha in 1985 to 517492 ha in year 1996 while portraying its highest contribution to agriculture and bush land with estimated area of about 124548 and 214829 ha, correspondingly (Table 3). While about 320199 ha remained forest land cover in 1985 to 1996, about 63392; 47301 and 27167 ha of forest were converted to wetlands, impervious and water bodies, respectively. The huge expansion of bush lands and agricultural lands signify the presence of illegal harvesting of forest products, shifting cultivation inform of tree clearing and burnt. Hall et al. (2009) assessed and reported the 50% decline of natural forests of Kilombero district due to anthropogenic activities from 1955. The rapid deforestation witnessed in 1980s-1990s occurred following expansion of public plantation farms for rubber, cotton, sugar cane and rice crops. Besides, a notable change of forest to impervious which also indicate the expansion of settlements and bare lands amounting to 47301 ha. The expansion of impervious land cover suggested the presence of human and livestock immigrants have entered Kilombero district following the abundance of fertile soil and favorable climate which supports production of diverse crops including cereals, legumes, and horticultural crops since 1980s. On the other hand, wetlands and bush lands were the main contributor to forest land use cover estimated to 96060 and 75750 ha, respectively. The regeneration of forest cover of timber marketable at Magombera Forest Reserve which were harvested during the construction of

Tanzania and Zambia Rail way (TAZARA) in 1976 contributed to observed pattern of LULC change. Besides, agriculture, impervious and water bodies remained the least contributor to area cover by forest only donating 12868; 4999 and 7617 ha, respectively.

In year 1996 to 2007 forest increased to 517492 ha although the area under forest remained considerable small estimated to 195568 ha. Thus, in this period deforestation have continues as usually though plantation of teak trees in 2000S have contributed to the increase in areas under forest cover. Besides, the acceptance and implementation of Ramsar Convention in Tanzania in year 2002 have also contributed to strictly conservation and protection of forested area in the wetlands of Kilombero district. The inception and implementation of Ramsar Convention in Tanzania have resulted to re-allocation of farmers and protection of forest in wetlands of Kilombero district. However, forest cover remained the main contributor to bush lands and agriculture with an estimated area of 163484 and 97104 ha, correspondingly. While area under wetlands, impervious and water bodies received about 31563, 24987 and 4786 ha, respectively. On the other hand, in the period of 1996 to 2007 bush lands and wetlands becomes the largest contributor to the land area under forest cover with estimated area of 16233 and 79135 ha, respectively. While area contribution from agriculture, impervious and water bodies increased to 36074; 30945 and 20625 ha the period of 1996 to 2007. In Kilombero district, the promotions of teak tree farming have encouraged replacement of formerly cultivated crops into teak farms which in turn have portrayed effects on area under the forest cover in year 2007.

Using Error! Reference source not found. in year 2007 to 2018 out of 524685 ha of forest available in 2007 only 202260 ha remained forest in year 2018 while an estimated area of 5148, 16748, 28348, 17000 and 45 ha were singled out to wetlands, agriculture, bush lands, impervious and water bodies respectively. However about 23856, 6072, 69762, 177 and 195 ha of wetlands, agriculture, bush lands, impervious and water bodies respectively were gained by forest land cover in year 2018. The expansions of agriculture in year 2007 to 2018 occurred following the implementation of Kilimo Kwanza policies have resulted to expansion of agricultural lands (Nangware, 2019). Ongoing deforestation resulting from illegal and legal timber harvesting, charcoal and fire wood are the main agent for increased area under bush lands. Area under wetlands, impervious and water bodies received about 38886, 24987 and 1149 ha, respectively from forest land cover. Agricultural expansion in lowland has resulted to deforestation of swampy forest hence leading to the marked increase in areas under wetlands while ever increased anthropogenic activities have resulted to an increase in areas under impervious land cover.

Table 3: Cross tabulation matrix for year 1985 - 1996

LULC category	Forest	Wetlands	Agriculture	Bush lands	Impervious	Water bodies	Total of Year 1996
Forest	320199	96060	12868	75750	4999	7617	517492
Wetlands	63392	100990	7139	38518	1593	6363	217996
Agriculture	124548	22601	6151	25213	813	1917	181243
Bush lands	214829	8180	6306	47919	944	872	279050
Impervious	47301	39374	9818	16197	3294	4998	120982
Water bodies	27167	5675	575	6600	331	3677	44025
Total of Year 1985	797438	272880	42856	210198	11974	25443	1360788

Table 4: Cross tabulation matrix for year 1996 - 2007

LULC category	Forest	Wetlands	Agriculture	Bush lands	Impervious	Water bodies	Total of Year 2007
Forest	195568	79135	36074	*162338*	30945	20625	524685
Wetlands	31563	37757	37247	15176	20900	2399	145042
Agriculture	97104	73837	71089	55747	42000	9814	349591
Bush lands	163484	10512	27192	39485	8259	7193	256125
Impervious	24987	16104	8123	5458	18223	1599	74494
Water bodies	4786	651	1518	846	655	2395	10851
Total of Year 1996	517492	217996	181243	279050	120982	44025	1360788

Table 5: Cross tabulation matrix for year 2007 - 2018

	Forest	Wetlands	Agriculture	Bush lands	Impervious	Water bodies	Total of Year 2018
Forest	202260	23856	6072	69762	177	195	303923
Wetlands	5148	38055	16209	8278	2197	511	70399
Agriculture	16748	15046	280006	50541	2779	831	365954
Bush lands	283481	47690	26019	116670	31686	510	506058
Impervious	17000	20000	21147	10871	35821	1455	106296
Water bodies	45	395	137	1.226	230	7348	8158
Total of year 2007	524685	145042	349591	256125	74494	10851	1360788

Agriculture: In year 1985 to 1996 agriculture land increased from 42856 ha in 1985 to 1812ha in 1996. In the period agricultural land uses represent its highest contribution to forest and impervious land cover with estimated as 12868 and 9818 ha, respectively. On the other hand, agricultural land use gained about 124548, 22601, and 25213 ha from forest, wetlands and bush lands, respectively. Similarly, impervious and water bodies contributed to the agricultural land uses with least estimated area of about 813 and 1917 ha, respectively. . Besides, an estimated area of about 7139, 6306, and 575 ha of wetlands, bush lads and water bodies, correspondingly gained from agricultural land use in period of year 1985 to 1996. Owing to the fact that, only 6151 ha of agricultural land remained unchanged which imply the presence of shift cultivation as main cause of deforestation in Kilombero district during 1980s-1990s. Most of agricultural farms were government owned and located in Mang'ula, Kidatu, Sanje and Kiberege wards with thousands of workers from different parts of the country. Besides, the privatization policy of year 1990s also encouraged the sugar industry to develop sugar cane out grower farmers who extended the production through clearing more lands. Using Error! Reference source not found. in 1996 to 2007 out of 181243 ha of agriculture only 71089 ha remained agriculture while about 36074, 37247, 27192, 8123, 1518 ha went to forest, wetlands, bush lands, impervious and water bodies, respectively. On the other hand, agricultural land use gained about 97104, 73837, 55747, 42000, 9814 ha from forest, wetlands, bush lands, impervious and water bodies, respectively. These signify the persistence of deforestation and shifting cultivation in Kilombero district till year 2007. The expansion of agricultural in the period is in line to the impacts of Kilomo Kwanza policy in 200 which encouraged large acquisition of land for agricultural use, accessibility to production inputs and agricultural technologies. Other policies such as the agro-industrial policy of year 2005 also have contributed to forest clearing for agricultural purpose. Using Error! Reference source not found. in year 2007 to 2018 out of 349591 ha of agriculture of year 2007 only 280006 ha remained agriculture in year 2018 while about 6072, 16209, 26019, 21147 and 137ha were singled out to forest, wetlands, bush lands, impervious and water bodies respectively. On contrary, agricultural land use received about 16748, 15046, 50541, 2779 and 831 ha from forest, wetlands, bush lands, impervious and water bodies, respectively. These signify the ongoing tendency of converting forest to agricultural lands, though about 59477 ha of agricultural land have been converted to forest in year 2007 to 2018.

Wetlands: Using

Table 3:Cross tabulation matrix for year 1985 – 1996

LULC category	Forest	Wetlands	Agriculture	Bush lands	Impervious	Water bodies	T
Forest	320199	96060	12868	75750	4999	7617	5
Wetlands	63392	100990	7139	38518	1593	6363	2
Agriculture	124548	22601	6151	25213	813	1917	1
Bush lands	214829	8180	6306	47919	944	872	2
Impervious	47301	39374	9818	16197	3294	4998	1
Water bodies	27167	5675	575	6600	331	3677	4
Total of Year 1985	**797438**	**272880**	**42856**	**210198**	**11974**	**25443**	**1**

Table 4: Cross tabulation matrix for year 1996 – 2007

LULC category	Forest	Wetlands	Agriculture	Bush lands	Impervious	Water bodies
Forest	195568	79135	36074	*162338*	30945	20625
Wetlands	31563	37757	37247	15176	20900	2399
Agriculture	97104	73837	71089	55747	42000	9814
Bush lands	163484	10512	27192	39485	8259	7193
Impervious	24987	16104	8123	5458	18223	1599
Water bodies	4786	651	1518	846	655	2395
Total of Year 1996	**517492**	**217996**	**181243**	**279050**	**120982**	**44025**

Table 5: Cross tabulation matrix for year 2007 – 2018

	Forest	Wetlands	Agriculture	Bush lands	Impervious	Water bodies
Forest	202260	23856	6072	69762	177	195
Wetlands	5148	38055	16209	8278	2197	511
Agriculture	16748	15046	280006	50541	2779	831
Bush lands	283481	47690	26019	116670	31686	510
Impervious	17000	20000	21147	10871	35821	1455
Water bodies	45	395	137	1.226	230	7348
Total of year 2007	**524685**	**145042**	**349591**	**256125**	**74494**	**10851**

ever increasing anthropogenic activities.

Using Error! Reference source not found. out of 217996 ha wetlands available in 1996, about 79135, 73837, 10512, 16104 and 651 ha went to forest, agriculture, bush lands, impervious and water bodies, respectively. While only 37757 ha remained unchanged wetlands also it received about 31563, 37247, 15176, 20900 and 2399 ha from forest, agriculture, bush lands, impervious and water bodies, respectively. Thus, from 1996 to 2007 wetlands contributed highly to agriculture and forest respectively.

Using Error! Reference source not found. out of 1450421 ha of area under wetlands only 38055 ha remained wetlands in year 2007 while receiving about 5148, 16209, 8278, 8278, 2197 and 511 ha from forest, agriculture, bush lands, impervious and water bodies, respectively. Besides, wetlands singled out about 23856, 15046, 47690, 20000 and 395 ha to forest, agriculture, bush lands, impervious and water bodies, correspondingly. In year 2007 to 2018 out of 145042 ha of wetlands only 38055 ha remained unchanged while giving to forest, agriculture, bush lands, impervious and water bodies an estimated area of 23856, 15046, 47690, 20000 and 395 ha, respectively. Thus, resulting from natural and anthropogenic activities have resulted to drying of wetlands which also have encourage sprouting of trees in form of shrubs.

Impervious land cover: Using Table 3 out of 11974 ha of impervious land cover only 3294 ha remained impervious from year 1987 to 2007. The impervious received 47301, 39374, 9818, 16197 and 4998 ha from forest, wetlands, agriculture, bush land and water bodies. However, the impervious land cover of 4999, 1593, 813, 944 and 331 ha were converted to forest, wetlands, agriculture, and bush land and water bodies. Using Error! Reference source not found. out of 120982 ha of impervious land cover of year 1996, only 18223 ha remained unchanged in year 2007. While about 24987, 16104, 8123, 5458, 18223 and 1599 ha were received from forest, wetlands, agriculture, bush land and water bodies, respectively. In the period the impervious land cover singled out to forest, wetlands, agriculture, bush land and water bodies with estimated area of 30945 , 20900, 42000, 8259, 18223 and 655, respectively.

Using Error! Reference source not found. Out of 74494 ha of impervious land cover only 35821 ha remained impervious while about 177, 2197, 2779, 31686, 35821 and 230 ha were converted to forest, wetlands, agriculture, bush land and water bodies, respectively. Besides, impervious land cover gained about 17000, 20000, 21147, 10871 and 1455 ha from forest, wetlands, agriculture, bush land and water bodies, respectively.

Bush lands: Out of 210198 ha under bush land cover only remained 47919 ha remained unchanged from year 1985 to 1996. However, about 75750, 38518, 25213, 16197 and 6600 ha of impervious land cover were converted to forest, wetlands, agriculture, bush land and water bodies, respectively. In the same period, bush lands cover received about 214829, 8180, 6306, 47919, 944 and 872 ha from forest, wetlands, agriculture, bush land and water bodies, respectively. In 1996 to 2007 out of 279050 ha covered by bush land only 39485 ha remained bush lands though about 162338, 15176, 55747, 39485, 5458 and 846 ha went to forest, wetlands, agriculture, bush land and water bodies, correspondingly. While in year 2007 to 2018 out of 256125 ha of bush lands only 116670 remained unchanged from year 2007 to 2018 while about 69762, 8278, 50541, 10871 and

1.226 ha. In the same period, bush land cover received about 283481, 47690, 26019, 31686 and 510 ha from forest, wetlands, agriculture, bush land and water bodies, respectively.

Water bodies: Out of 25443 ha only 3677 ha remained unchanged from 1985 to 1996, but also water bodies gave out about 7617, 6363, 1917, 872, 4998 and 3677 ha to forest, wetlands, agriculture, bush land and water bodies, respectively. Besides, it received 27167, 5675, 5675, 575, 6600, 331 ha from forest, wetlands, agriculture, bush land and water bodies, respectively. The expansion of irrigation schemes, hydro-power and deforestation are among of major drivers of water losses in Kilombero district.

Prediction Results

Results of Markov model

The first-order Markov probability was obtained using LULC map of year 1985-1996, 1996-2007 and 2007- 2018 (Table 3, Table 4 & Table 5). Transition probability matrix generated was used to portray the likelihood of each LULC category to change into other LULC category from 1985-1996, 1996-2007 and 2007- 2018 (Table 3, Table 4 & Table 5). In both periods the transition probability of LULC category did not remain unchanged, however the dynamism of agriculture, forest, water bodies and wetlands to other LULC categories were considered important for this research study.

In year 2007 to 2018 and 1996 to 2007 agriculture land use portrayed to be among the most stable class remaining unchanged with the probability of 0.31 and 0.34, respectively. While the probability of agriculture remained unchanged in year 1985 to 1996 was very low and estimated to be 0.1. In year 1985 to 1996 the shifting cultivation resulted to the low probability of agriculture remained unchanged. The mass abandoning of shift cultivation among small scale farmers have resulted to the observed stability of agriculture in 1996-2007 and 2007-2018(Table 3, Table 4 & Table 5).

Whilst for year 1985-1996 and 1996-2007 forest remained stable with probability of 0.4 and 0.4, respectively. However from year 2007 to 2018 the probability of forest remaining forest has been reduced to 0.24 which imply the ever increased anthropogenic activities in Kilombero district (Table 3, Table 4 & Table 5).

Water bodies has portrayed dynamism in year 1985-1996, 1996-2007 and 2007-2018 with estimated transition probability of 0.0662, 0.0102 and 0.0662, correspondingly (Table 3, Table 4 & Table 5). While wetlands have expressed dynamism in both period of research study 1985-1996, 1996-2007 and 2007-2018. In 1985-1996 the probability of wetlands remaining wetlands was 0.16,

while in 1996-2007 and 2007-2018 was0.14 and 0.07, respectively.

Table 3:Transition probability matrix 1985 -1996

LULC category	Forest	Wetlands	Agriculture	Bush lands	Impervious	Water bodies
Forest	0.4015	0.1447	0.1538	0.1807	0.0908	0.0286
Wetlands	0.3005	0.1666	0.0745	0.3745	0.0405	0.0434
Agriculture	0.3521	0.1008	0.1008	0.1008	0.0894	0.0393
Bush lands	0.3604	0.1833	0.1199	0.2280	0.0768	0.0316
Impervious	0.4177	0.1335	0.0665	0.9788	0.2760	0.0274
Water bodies	0.2994	0.2507	0.0754	0.1906	0.1177	0.0662

Table 4:Transition probability matrix 1996-2007

LULC category	Forest	Wetlands	Agriculture	Bush lands	Impervious	Water bodies
Forest	0.4029	0.0981	0.2471	0.2000	0.0449	0.0069
Wetlands	0.3158	0.1372	0.2957	0.3083	0.1573	0.0074
Agriculture	0.3305	0.1447	0.3083	0.1573	0.0523	0.0069
Bush lands	0.3681	0.0971	0.2417	0.2384	0.0468	0.0079
Impervious	0.3091	0.1469	0.3100	0.1621	0.0649	0.0070
Water bodies	0.3708	0.1020	0.2513	0.2184	0.0473	0.0102

Table 5:Transition probability matrix 2007-2018

LULC category	Forest	Wetlands	Agriculture	Bush lands	Impervious	Water bodies
Forest	0.2444	0.0394	0.2382	0.4080	0.0678	0.0022
Wetlands	0.1834	0.0662	0.3158	0.3313	0.0991	0.0043
Agriculture	0.1977	0.0623	0.3055	0.3428	0.0886	0.0393
Bush lands	0.2345	0.0447	0.2533	0.3929	0.0715	0.0316
Impervious	0.1977	0.0478	0.2600	0.3820	0.1078	0.0274
Water bodies	0.0896	0.0956	0.2302	0.2183	0.1445	0.0662

CA-Markov results Predicted LULC in 2048

In year 2048 a notable decline to about 241001 ha, (17.71%), 347000 ha (25.50%), 68731 ha (5.05%) and 4990 ha (0.37%) were recorded for forest, bush lands, wetlands and water bodies, correspondingly. Thus, the ongoing cultivation in the wetlands, harvesting and clearing of trees if will persist for 30 years, the recorded decline trends will be evident in Kilombero district.

Table 6:Matrix of LULC classes for year 2018 to 2048

LULC Classes in 2018			**LULC Classes in Year 2048**	
LULU Class	**Area (Ha)**	**%Composition**	**Area (Ha)**	**% Composition**
Forest	303923	22.33	241001	17.71
Bush lands	506058	37.19	347000	25.50
Impervious	106296	7.81	162066	11.91
Agriculture	365954	26.89	537000	39.46
Wetlands	70399	5.17	68731	5.05
Water bodies	8158	0.60	4990	0.37
Total	**1360788**	**100**	**1308180.10**	**100.00**

In year 2048 agriculture and impervious land cover will increase to 537000 ha (39.46%) and 162066 ha (11.91%), correspondingly. The expected increase in agriculture is obvious following the conception of as the main economic activities of about 80% of the human population living in

Kilombero district (Nindi et al., 2014)(Nindi et al., 2014). Effort to manage the future situation will include development and promotion of agricultural technology that encourage yield increase per unit existing agricultural land.

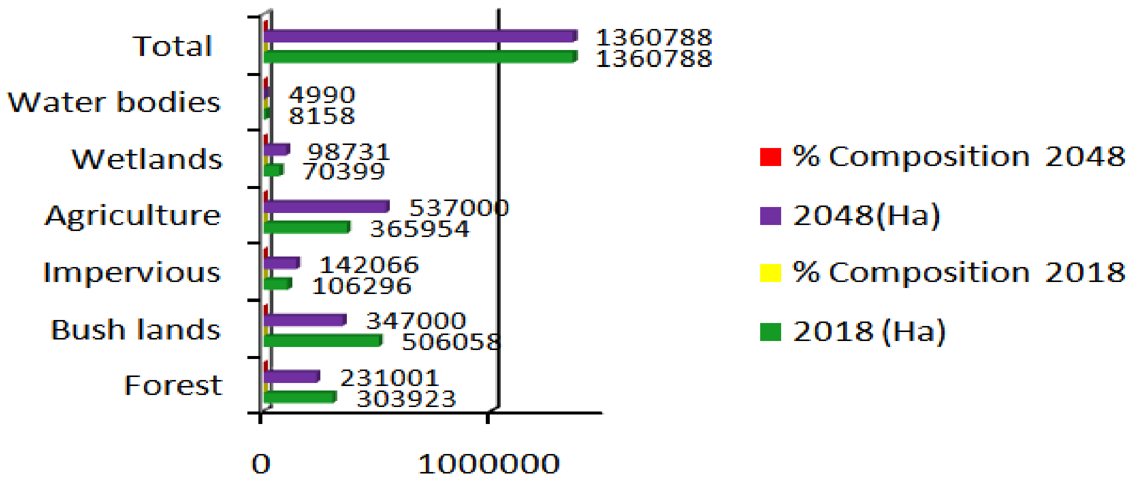


Figure 14:Area (Ha) and % Composition of LULC categories for year 2018 & 2048

Besides the future spatial configuration of LULC categories are portrayed using **Figure 3.** Agriculture and impervious land cover will continue to expand along the central part from North- East towards the South-West of Kilombero district. The central and south-west zone wards comprising of Idete, Mbingu, Mofu, Masati, Mchonde and Mlimba will experience the continued expansion of agriculture and impervious land cover. Owing to this agricultural expansion research strategies focusing at maximizing agricultural production without increasing production are deemed necessary in Kilombero district.

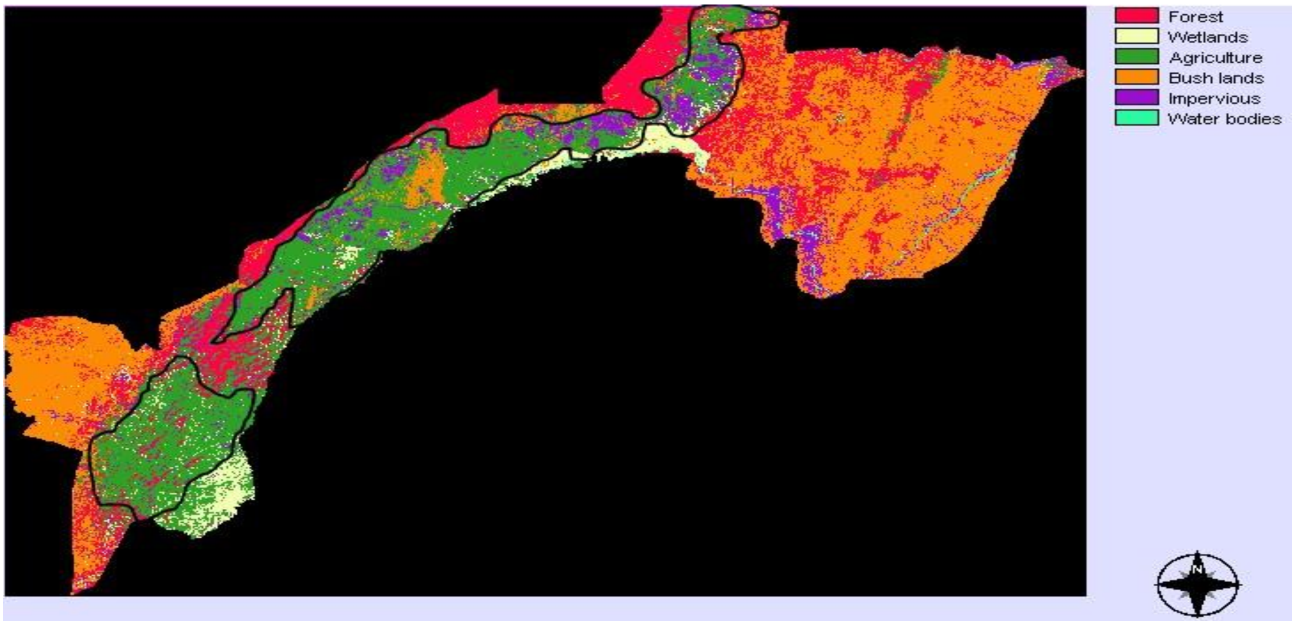


Figure 15:Future spatial distribution of agriculture and impervious land cover for year 2048 While forest in year 2048 will be highly distributed on north particularly in the mountain of Udzungwa Forest Reserve and in parts of Magombera Forest Reserve which inter joins with Selous Game Reserve. Besides, bush lands/shrubs will also remain in the west part of Masagati wards and south of Mang'ula and Kisawasawa wards particularly in Magombera Forest Reserve. In year 2048 wetlands will remain along the Kilombero River though on the south-west part of Kilombero

district agriculture will expands in wetlands. Figure 16 portray the spatial distribution of wetland cover in year 2048.

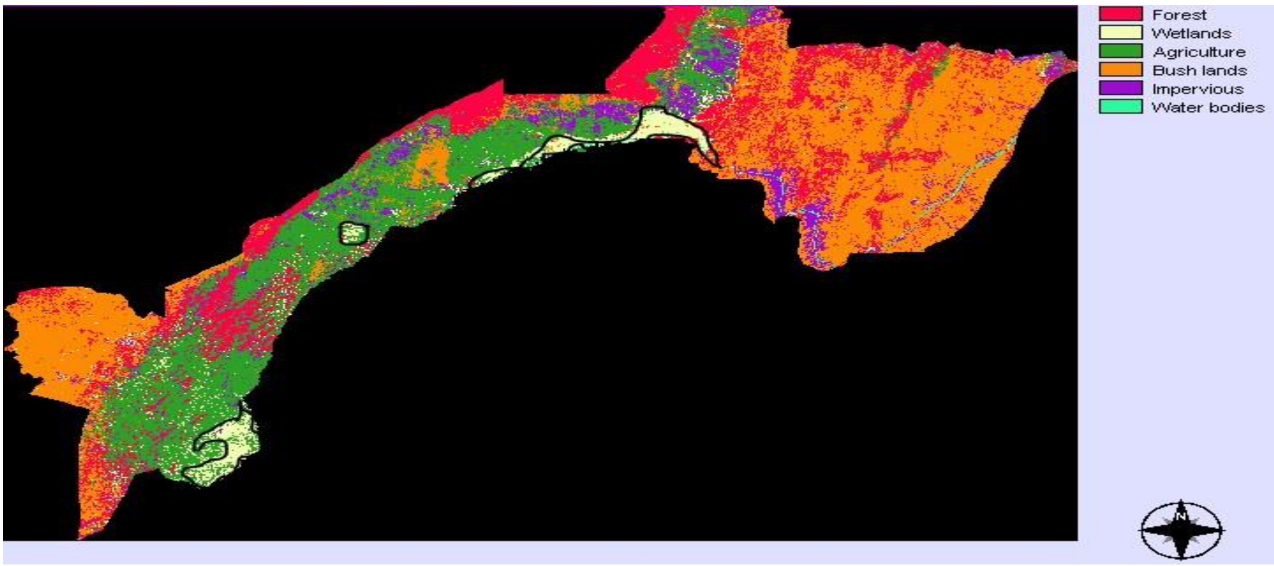


Figure 16:Spatial distribution of wetlands in year 2048

CONCLUSION AND RECOMMENDATIONS

Conclusions

This research carried GIS-based Landsat image classification for change detection and prediction of LULC dynamics in Kilombero district Tanzania. Owing to the emerging impacts of LULC change in Kilombero district which includes prime agriculture land, forest, bio-diversity, encroachment of protected areas and land degradation. It was sought vital to generate the past, current and future information on LULC dynamics, such LULC information provide basis for establishing bylaws, policy, regulatory actions and activities for managing the environment. The research has demonstrated the applicability of GIS based image classification and LULC models for characterization, change detection and prediction of LULC dynamics. Owing to free cost and accessibility of Landsat data and open sources GIS based software for executing image classification, change detection and prediction it's concluded that, GIS-based Landsat Classification is vital for monitoring and management of natural resources.

Recommendations

The data collected, results, discussion and conclusion of this research study have opened room for other research and operational use of these research findings. Even so, the following recommendations are highly proposed in Kilombero district to attain ecological and agriculture well-being for future generations.

1. The observed trends in deforestation, water bodies and wetlands losses from year 1985 to 2018 require multi-sector intervention while involving community. Agro-forestry farming is highly recommended to manage the emerging impacts of LULC dynamics in Kilombero district.

2. The observed increase in areas covered by agriculture from year 1985 to 2018 imply that, the current agriculture production have resulted from increasing production area. Hence, agricultural technologies that increase production yield per unit area and without confronting other LULC categories are highly recommended in Kilombero district.

3. 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.

4. 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.

5. Biological and chemical environmental effects of rapid expansion of agricultural lands and its associated heavy application of herbicides and pesticides is still unclear, hence further research is required to investigate environmental effects associated with agricultural expansion in Kilombero district. Besides, research on agricultural pollution on the surface and underground water is deemed necessary for sustainable land management while protecting ecosystems.

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

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

8. There is need to develop, implement and practices appropriate urban management strategies to inhibit further pollution, deforestation and urban sprawl while monitoring agricultural expansion.

9. 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.

10. Finally, the Landsat datasets and Ca-Markov model used in this research study are highly recommended as prototype for further research and application in other study areas with similar environmental settings.

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