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Assessing 30 Years of Land Use Dynamics in Usangu Catchment, Tanzania

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Abstract

This paper assesses land use dynamics in the Usangu catchment from 1986 to 2017. It employs historical data search, which include Landsat 5 Thematic Mapper and Landsat 8 Operational Land Imager collected from the United States Geological Survey. Additional data were generated from field observation in specific GPS points for classification accuracy assessment. Visual analysis of land use was carried out with the aid of Google Earth navigation. In-depth interview with key informants served as a useful means of collecting land use information. Landsat images of 1986, 1996, 2006 and 2017 were classified in ArcMap 10.3 under supervised classification technique to produce land use and land cover maps of the particular years. Land use and land cover changes were assessed based on the classified maps for change detection analysis. The results suggest that land use and land cover had a remarkable transformation during the 30 years of the study period. Open bush land gained 4.34% of land from mixed forest in 2006-2017. Water bodies area decreased by 2.4% between 1986 and 1996 due to an increase in bare land by 1.2% in the catchment. Land for agriculture rose by 2.6% in 1996-2006, but declined by 4.5% in 2006-2017. The revealed negative changes in mixed forests, water bodies and open bush land in Usangu catchment result into serious stress on environmental resources. Therefore, this calls up for more conservation efforts by authorities and stakeholders concerned with environmental management issues in the Usangu catchment.

Keywords: *land use change, land cover change, water catchment, remote sensing, change detection*

1. Introduction

Land use and land cover change (LULCC) is one of the major problems facing the world (Yirsaw et al., 2017). It is emerging as a leading environmental factor for both global and regional change, hence serving as the basis for the development of global and regional models explaining the complex interaction between human-land systems and land ecological systems (Hovious, 1998). Land use and land cover terminologies are often used interchangeably, but they are not synonymous. Literally, land use means the management and modification of natural environment by human beings for socio-economic development like settlements, agriculture and industries, to mention a few

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(Rawat and Kumar, 2015). Land cover means physical characteristics of the earth surface, both natural and manmade, which involves infrastructures, water, vegetation, barren land, among many (Rawat & Kumar, 2015). The way human use land can lead to positive or negative impacts in land covers. In other words, an unwise use of land covers increase the possibility of shifting into negative impacts, hence affecting the biosphere covers; while a wise use of it leads to positive impacts (Butt et al., 2015).

Land use dynamics forces are not universal despite their similarities in the outcomes on land covers (William, 2003). However, various empirical studies have linked the rate and pattern in the dynamics of land use with various socio-economic activities of a particular society, cultural practices, demographic changes, government policies, as well as the political situation of a particular country (Wunder, 2000). Despite natural disasters, anthropogenic activities changing the nature have spatially increased significantly (Lambin et al., 2001; Yirsaw et al., 2017). Such activities include, but are not confined to, daily human activities like the development of settlements, expansion of agriculture, livestock grazing, development of industries, as well as the development of infrastructures. Following human activities and natural process taking place around water catchments, there have been numerous effects on various wetlands, river flow regimes, as well as on the ecology of water catchments (Lambin et al., 2001).

The Tanzania Natural Resource Forum (TNRF) strategy report (2012-2016) pinpointed the challenges facing natural land cover resources in Tanzania, including uncontrolled conversion of valuable tropical forest without replacement (TNRF, 2012). For example, forest loss in the country is claimed to range between 1000 and 4000km^2 annually due to anthropogenic and economic changes (URT, 2014). If the authorities remain silent on this, it is said that in 50 years' time, there will be no forest standing in Tanzania (URT, 2014).

Thicket covers in Itigi, in Singida Region (Tanzania), faces massive clearance following the expansion of anthropogenic activities such as the expansion of agriculture and settlements in the area (Nzunda et al., 2013; Makero & Kashaigili, 2016) reported on the conversion 0.45 km^2 of Miombo forest cover to agriculture and settlements in Kagoma Forest Reserve in Kigoma. The same cover type that is dominant in the Southern Highlands of Tanzania is at great risk (Lupala et al., 2015). These transformations lead to rapid changes in the LULCs of the country.

Knowing the dynamics of LULCs on catchments and their aspects is vital for understanding the expected rate, spatial pattern of LULCC, as well as familiarity with the principal human and biophysical drivers for sustainability of natural covers (Lambin et al., 2001). These complex issues can be addressed through the analysis of LULCC in GIS and remote sensing environment due to its unique capability of spatial analysis. Remote sensing and GIS tools have been—and still are—being widely used in analysing and modelling LULC dynamics, both quantitatively and qualitatively (Kitalika et al., 2018). GIS techniques like normalised difference vegetation index (NDVI), image differencing, classification analysis (supervised and unsupervised), cross-classification, as well as cross-tabulation have been widely used by various researchers (Assefa, 2010; Singh, 2010). Recently, numerous reserchers have used the supervised image classification technique for change detection as it is based on a prio knowledge of a researcher concerning a study area. It has also been employed to easily detect the propotions of change (Wright & Wimberly, 2013). In this paper, supervised classification analysis, cross-classification, as well as cross-tabulation analysis have been used to assess land use and land cover change over time.

The Usangu water catchment has been selected for land use and land cover change detection due to the dramatic conversion of grassland, woodland, and forest into cropland and pasture, which have resulted into the shrinkage of wetlands, forested land, and an increase of bare land (Mtahiko et al., 2006; Mwakalila, 2011). Moreover, the lack of land use plans in most villages accelerates the conversion (Mwakalila, 2011). Despite these conversions in the LULC, the rate and direction of change in Usangu water catchment is not well known. This paper relied on 30 years (1986-2017) of successive years of observatins, in an interval of 10 years, to determine the magnitude and direction of LULCC of the study area. It used remote sensing and GIS techniques to establish the dynamics in the LULCs, and identify particular LULC classes that are highy subjected to changes.

2. Context and Methods

2.1 Description of Study Area

This paper was conducted in the Usangu Catchment, which is part of Rufiji Basin Development Authority (RUBADA), located between latitudes 7° and 9° south of the Equator and longitudes 33° and 35° east of the Greenwich in the Southern Highlands of Tanzania (Figure 1) (Lokina et al., 2010).

The altitude of the Usangu Catchment is between 1000m and 1800m above mean sea level with extensive plains, which make the area to be favourable for various plant growth. It is crossed by rivers like Ruaha, Kimbi, Chimala, Kimani, Ndembera, Muwanga and Mbarali, which is fed by a number of permanent and temporary water streams. The common soil types in the area are loamy, sandy and clay (Mwakalila, 2011). Moreover, the area has extensive wetlands or swampy plains known as Ihefu, which was historically said to be perennially flooded before the 1960s, which is no longer the case.

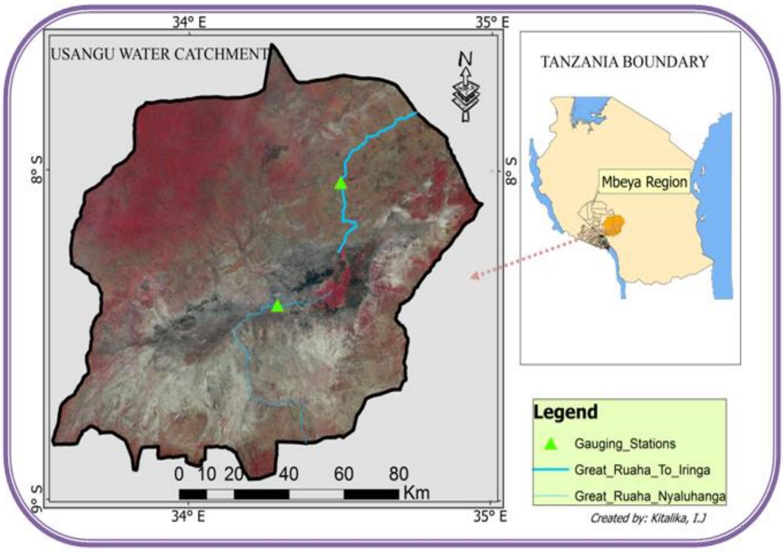

Figure 1: ***Location of Usangu Catchment in Mbarali District***
Source: URT, 2012

The catchment receives seasonal annual rainfall between 450mm to 900mm from December to mid-May, although in some years it stops in early June (Mwakalila, 2011). Its mean annual potential evapotranspiration is almost 1900mm, which is above the annual rainfall range, making the area have a prolonged dry season (Lokina et al., 2010). The average annual temperature in the area fluctuates between 18.5^0 C at high altitude, and 30^0C at low altitudes (Lokina et al., 2010; Mwakalila, 2011). The plains in the Usangu Catchment is characterized by poor tropical and semi-desert natural vegetation, extensive bare land, intensive animal grazing, as well as large- and small-scale paddy production (Lokina et al., 2010).

2.2 Sources of Data and Data Collection Methods

In this paper, both primary and secondary data were used. The primary data used were global positioning satellite (GPS) points of some locations within the water catchment. Apart from that, in-depth interview information were collected from nine (9) key informants. This included five (5) indigenous local people aged above sixty years (60+), and four (4) government official key informants from the Usangu Catchment. The government officials included two (2) Mbarali District land use officials, one (1) official from the Tanzania Forest Service (TFS) based in the Usangu Catchment, as well as one (1) Rufiji Basin Development Authority official in the Usangu Catchment. The information collected from key informants was used to triangulate the observed changes in the LULCC of the study area with the change detection analysis results.

The secondary data were Landsat Thematic Mapper (LTM) images covering the Usangu Catchment downloaded from United States Geological Survey (USGS), website, https//earthexplorer.usgs.gov, for the years 1986, 1996, 2006, and 2017 (Zanter, 2019). All images were of dry season months in 30m resolution to simplify categorization of land cover classes such as permanent water bodies, green vegetation, and paddy farms (Thenya, 2001; Mwita, 2016). The satellite images used were Landsat 5 for 1986, 1996, and 2006. Apart from that, the Landsat 8 Operation Land Imager (OLI) was used for 2017. The main reasons for choosing the 1986 satellite image as a starting year were: first, the availability of free thematic Landsat images as it started its operation in the 1980s; and secondly, the historical background of the study area itself reported better condition in LULCC before the 1980s.

Other secondary data included Google Earth aerial photography in the Google Earth globe covering the study area. This was displayed for visual exploration of the study area because of its high resolution. The Google Earth display was used to compare the existing land cover with the classified land covers for the purpose of assessing accuracy. The collected Landsat images were used to determine the extent and trend of LULCC over the study area within thirty years (1986-2017).

2.3 Data Analysis

2.3.1 Satellite Images

The collected secondary data were pre-processed first before analysing them. The process involved in the Landsat images processing were mosaicking the downloaded scenes to fit the whole study area; projecting the mosaicked scenes to Universal Transverse Mercator (UTM) zone 36 South in accordance with Mbeya Region; then layer stacking of the Red, Green and Blue bands of the particular year to create RGB composites for each step. The bands used in layer stacking for Landsat TM 5 were band 2 (Blue), band 3 (Green) and band 4 (Red); while the Land sat 8 OLI bands used in stacking were band 3 (Blue), band 4 (Green), and band 5 (Red). The study area covered by false colour satellite images was extracted by mask using the Mbarali District polygon map to exclude all areas that were not required in the analysis. This was done to reduce the size of the image, hence saving processing time in the software during analysis. All processes were accomplished in ArcMap 10.3.

2.3.2 Supervised Classification and Change Detection Analysis

Training samples were obtained by digitizing homogenous pixels and drawing the reasonable number of polygons representing the particular land covers so as not to confuse the maximum likelihood algorithm when discriminating the land covers in the study area. The process was done carefully with the help of high-resolution Google Earth data, familiarity with the study area, and ground-truth GPS points. Here, the technical knowledge of the researcher in GIS and remote sensing was central to this. Moreover, each training sample of a particular land cover class was evaluated to ensure that it belongs to a particular class through the examination of the spectral characteristics of signatures they represent. The same signature of each training sample in a particular composite image was stored for supervised image classification. The identified training samples of land covers in the study area were water bodies (WB), open bush land (OB), barren and bare land (BL), agricultural land (AG), and mixed forest (MF), as explained by Rwanga and Ndambuki (2017) (Table 1). Settlements class was aggregated into open bush land because in 1986 they appeared to be very scattered and difficult to identify.

Table 1: Land Use and Land Cover Classification Scheme

Land Cover	Code	Description
Water bodies	WB	Rivers, stream, lakes, reservoirs and swamps
Open bush land	OB	Land with scattered woody vegetation less than 2 meters tall, pasture, settlements, grassland and shrub land
Barren and bare land	BL	Bare ground, Lands with exposed soil, sand or rocks, lands with less than 10% vegetated cover during any time of the year quarries, mines, and gravel pits, temporally pasture.
Mixed forest	MF	Land with mixed woody vegetation more than 2 meters tall
Agricultural land	AG	Lands covered with temporary crops period and Crop fields

The verified signatures stored, which were representing the land cover training samples, were used in image processing hard classifier interface in ArcMap 10.3. The trained Maximum Likelihood algorithm (MaxLike) in supervised classification was used for image classification due to the qualities it possesses such as basing on the probability of posterior and being able to classify all pixels in an image without leaving areas with no data in case they are present (Lin, 2013). Moreover, it considers the homogeneity of selected pixels (ibid.). A map was produced after supervised classification with trained classes, namely water bodies, open bush land with pasture, mixed forest, agricultural land, and barren land. The same procedures were followed in classifying the rest three satellite image composites to produce LULCC maps.

2.3.3 Classification Accuracy Assessment

Assessing the accuracy of a classification activity is a very important step in remote sensing before scientific analysis is carried out. The results from this process validate all analysis that will be carried over a particular classified remote sensing data (Rwanga & Ndambuki, 2017).

Accuracy assessment of the classified land use and land cover maps were accomplished in all images using 110, 100, 105, and 108 ground-truth points for 1986, 1996, 2006, and 2017 Landsat images, respectively. Twelve GPS points collected in the study area were among the ones used in accuracy assessment. The additional points were obtained by digitizing on the original particular Landsat image used to train Land Use Land Cover classes of the study area. This was done with the aid of high-resolution Google Earth data (Parsa & Salehi, 2016); the points collected were overlaid with the classified maps to examine the correctness of classification. Thereafter confusion matrix (error matrix) for each year was created.

Calculations of overall accuracy, kappa coefficient, and producer's and user's accuracy were performed (Lin, 2013). Overall, accuracy means the percentage of the sum of pixels classified accurately in all classes, and was calculated using the following formula.

$$\text{Overall accuracy} = \sum \frac{\text{Correct classified}}{\text{Number of observations}} \times 100$$

$$\text{User's accuracy} = \sum \frac{\text{Correct classified pixels in the row}}{\text{Pixels in the row}} \times 100$$

$$\text{Producer's accuracy} = \sum \frac{\text{Correct classified pixels in the column}}{\text{Pixels in the column}} \times 100$$

The kappa coefficient statistic is a measure of agreement in an output raster after classification, and is calculated by the following formula.

$$KHAT = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} \times x_{+i})}$$

where,

$KHAT$ = kappa coefficient
r = number of rows in the error matrix
x_{ii} = number of observations in row I and column I
x_{i+} = marginal totals of row I
x_{+i} = marginal totals of column I
N = total number of observations

Kappa coefficient values range from -1 to +1, whereby coefficient equal +1 refers to the ideal agreement, and those values closer to '0' means the agreement is poor and probably would be expected by chance. Generally, the coefficient values used to measure the levels of agreement in Kappa are shown in Table 2 (Landis &Koch, 1977).

Table 2: Rating Criteria for Kappa Statistic Agreement

S/N No.	Kappa Statistic	Strength of Agreement
1	<0.00	Poor
2	0.00 – 0.20	Slight
3	0.21 – 0.40	Fair
4	0.41 – 0.60	Moderate
5	0.61 – 0.80	Substantial
6	0.81 – 1.00	Almost perfect

The overall accuracy obtained during the classification ranged between 50% and 75%, although the target required was above 85%. This depends much on a number of factors such as the number of classes involved in a classification, and the quality and quantity of ground-truth points used (Coppin & Bauer, 1996). The 1986, 1996, 2006, and 2017 Landsat images were classified and attained a range of overall classification accuracy of 81.8%, 80%, 83%, and 84.5%, respectively. Their kappa coefficients ranged from 0.80–0.84, and were within the acceptable range of accuracy for the supervised classification process (Kashaigili et al., 2006).

The classified raster maps of 1986, 1996, 2006, and 2017 were used for change detection; cross-classification and cross-tabulation analysis; change detection; analysis of the magnitude of quantities of change in square kilometres; and percentage of the proportion of change of each land cover class were calculated in each year. Also, cross-tabulation and cross-classification analysis of all maps were performed systematically by inputting the earlier and later images of the subsequent years in the module, and were commanded to produce a cross-classification map, cross-tabulation matrix of the proportion of change, and the kappa indices of the agreement. Next, we performed an analysis of the net gain and loss, or relative quantity of change in land use and land cover classes, namely, mixed forest, water bodies, agricultural land, barren land and open bush land. The following formulas were used to calculate the relative quantitative change and the percentage of the proportion of change, respectively.

$$\text{Relative proportion of change} = \text{Later year quantity (km}^2\text{)} - \text{Earlier year quantity (km}^2\text{)}$$

$$\text{The relative percentage of change} = \frac{\text{Observed change of the category}}{\text{Total area of the category}} \times 100$$

4. Results and Discussion

4.1 Land Use and Land Cover Change in Usangu Catchment 1986-2017

Almost all land uses and land covers in the study area showed changes over time as shown by the land use maps presented in Figures 2 through 5, with their subsequent statistics presented in Tables 3 and 4. The results revealed that, in the study area, a large proportion of land (12,277km^2) was covered by open bush land in 1986. However, while this rose by almost 2.8% in the first decade (1986-1996), it started to decline in the next 10 years (1996-2006). About 2.6% of this dominant class was lost on the expense of other land use and land covers classes in the period between 1996 -2006. This loss was compensated in the year 2017 when it rose to 4.34% (Table 3). Despite the slight changes observed in the open bush land, it remained dominant in the whole study period.

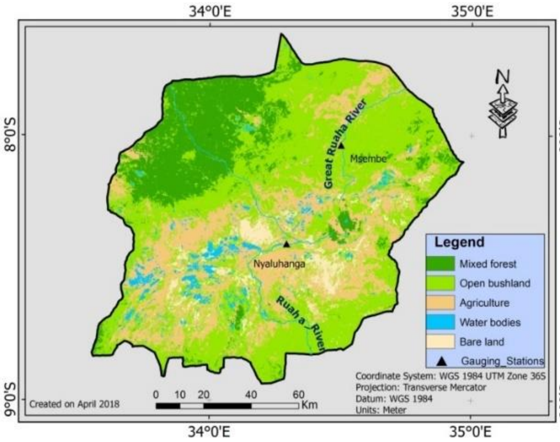

Figure 2: Classified Land Use/ Cover of 1986

Source: Author (2018)

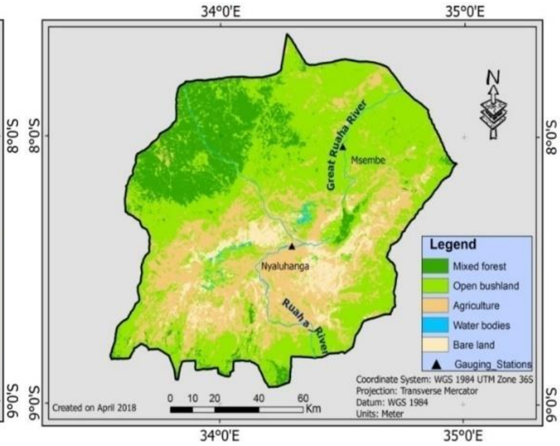

Figure 3: Classified Land Use/Cover of 1996

Source: Author (2018)

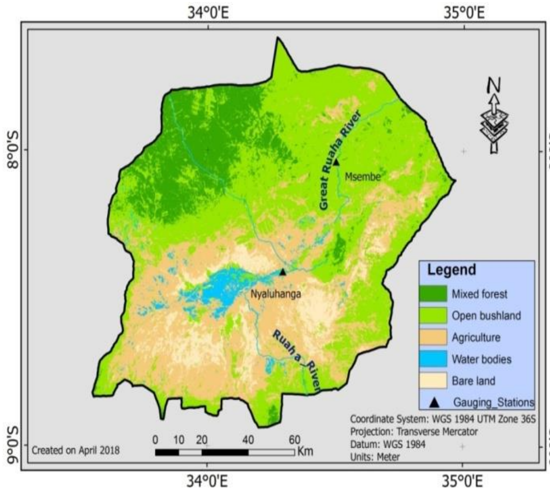

Figure 4: Classified Land Use/ Cover of 2006

Source: Author (2018)

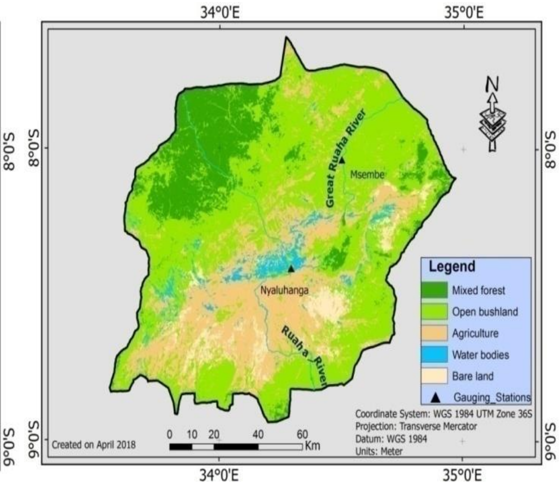

Figure 5: Classified Land Use/ Cover of 2017

Source: Author (2018)

Table 3: Land Use/ Cover Change in the Usangu Catchment In km² and Percentages

Land Use Land Cover	Years							
	1986	*%*	***1996***	*%*	***2006***	*%*	***2017***	*%*
Mixed forest (MF)	4456	19.5	4093	18.0	3553	15.6	4082	17.9
Open bush land (OB)	12277	53.8	12909	56.6	12323	54.1	13311	58.4
Agriculture (AG)	4605	20.2	4606	20.2	5198	22.8	4166	18.3
Water bodies (WB)	616	2.7	75	0.3	597	2.6	579	2.5
Bare land (BL)	845	3.7	1116	4.9	1128	4.9	661	2.9
Total	**22799**	**100.0**	**22799**	**100.0**	**22799**	**100.0**	**22799**	**100.0**

Source: Author (2018)

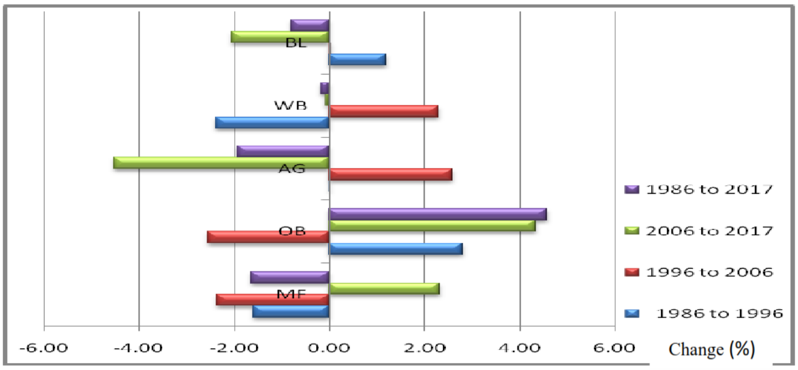

Figure 6: Net Gain and Loss of Each Individual Class in Percentage
Source: Author (2018)

The area covered by mixed forest in 1986 was 19.5%. A total of 1.6% and 2.4% of mixed forest decreased in the period between 1986-1996 and 1996-2006, respectively. The mixed forest appeared to be smaller by 1.6% in 2017, compared to its coverage in 1986 LULCC (see Table 4).

Table 4: Net Gain and Loss of Each Individual Class in Percentage

Land Use class	1986 to 1996	1996 to 2006	2006 to 2017	1986 to 2017
MF	-1.59	-2.36	2.31	-1.64
OB	2.79	-2.55	4.34	4.56
AG	0.00	2.58	-4.52	-1.93
WB	-2.38	2.29	-0.08	-0.17
BL	1.19	0.04	-2.05	-0.81

Source: Author (2018)

On the other hand, agriculture remained stable with almost the same coverage of 20.2% as in the initial land use land cover of 1996. Agriculture gained more land by almost 2.6% in the period 1996-2006. It appeared to lose more than 4.2% in 2006-2017 (see Table 4). One key informant (elder) from Uturo village blamed climate change and increased conflicts on water uses for irrigation as leading to the abandonment of farms by some farmers, particularly in the years between the mid-2000s and 2016.

Open bush land and agriculture showed a negative relationship in the sense that when open bush land gains more land, agriculture lost, and vice versa. This may mean that agricultural land and open bush land substituted each other. The expansion of agriculture relied on open bush land. On the other hand, the abandonment of agricultural land leads to the rising in the open bush land.

The period 2006-2017 witnessed a decline in agriculture. This might have been caused by the abandonment of some farm plots owned by a majority of the local people due to the enforcement of laws and by-laws on the utilization of water for irrigation, following the water management practices by the RUBADA that was introduced in 2001 in the study area. This resulted in a sharp rise of bushland, and a decline in the size covered by bare land in that period. Similarly, when open bush land is uninterrupted it may lead to the development of forest as was the case in the 2006/2017 period. In the in-depth interviews with key informants (elders) on issues concerning their perception on the existing LULC in the study area, one old man from Madibira village said that around the 1960s and 1970s, before the arrival of pastoralist from *Usukuma* with their herds of cattle in Usangu, bushes *(pori)* surrounded their homes almost in all areas; which is no longer the case.

It should be noted that the increase in human population in the study area might have brought mismanagement in LULC. Moreover, the increased demand for traditional sources of energy such as firewood and charcoal contributed in the consumption of mixed forest and open bushland in the study area as has been shown in the Mbarali District Council (MDC) socio-economic profile (Lokina et al., 2010). One of the MDC Land Use officers urgued that, the widespread use of firewood and charcoal, which was the main sources of energy among households in the study area, threatens the forest cover, partly due to poverty and the low price of charcoal compared to other sources of energy. In addition, the lack of villages land use plans in most villages increases threat in the LULC of the study area: 84 out of 107 villages in MDC have no land use plans.

Forest conservation in Tanzania, particularly of natural forest, is managed by the Tanzania Forest Service Agency (TFS). There are several natural forest stands in the Usangu Catchment, among them being, Mwambalizi (46.5 km^2), Ilembo Usafwa (187.78km^2), and Chimala Scarp (175.76km^2). These forests have been invaded by anthropogenic activities such as the construction of settlements, illegal loggings, as well as charcoal burning. This concurs with

Lambin et al. (2003) who reported that activities like logging, expansion of settlements, firewood collection, and charcoal burning in tropical regions has lead to the conversion of tropical forests and bushland to other land uses. Moreover, climate variability and increased conflict on water utilization by various water users—e.g., livestock keepers, domestic users, Mtera hydropower, and farmers—might have contributed to a decline in the area of farmland after 2006. This results are in line with what Kulindwa et al. (2007) reported: the decline of farmland due to the lack of water for irrigation, and water-users' conflicts in Usangu.

Change detection statistics (Table 4) revealed that water bodies lost by 2.4% in the 1986–1996 period, and gained by almost 2.3% in the next 1996–2006 time. It declined by 0.1% and 0.2% in the 2006–2017 and 1986–2017 scenarios, respectively. In the case of bare land, it kept on decreasing for the whole study period. In 1986, the area under bare land was 845km^2, equivalents to 3.7% of the total area (Table 3). This amount increased by 1.2% in the 1986–1996 epoch. The same land cover rose to 0.04% in the next epoch. In the 2006–2017 period bare land decreased by 2.1%, as opposed to its increase in the subsequent epoch (Table 4). The sudden decline in water bodies in the first epoch (1986–1996) was caused by an increased demand in irrigation agriculture and other uses in the study area.

In the same period (1986–1996), especially in the 1990s, there was a threatening situation in the study area when the Great Ruaha River and some important perennial streams had no water flows during the dry seasons for several years (Lankford et al., 2004; McCartney et al., 2008; Walsh, 2012). This was attributed to overgrazing and mismanagement of water in irrigation agriculture as we can see from the rise of bare land and open bushland areas as opposed to the reduction of mixed forest cover. Reminiscing about the past, key informants (elders) from the Madibira village painted a very lucid picture of what had been, but is no longer there. For example one male elder (aged 80 years), who own several cattle, narrated that at his young age, there were very extensive swampy land known as Ihefu, which has now dried. He recalled that it was not easy then to cross over the water of the rivers due to high and fast flows of the waters; and there were no restrictions on the use of natural resources. He ended wondering what has happened as the wetland went on drying, and there were a host of restrictions on the access to natural resources. All studies on the hydrology of Usangu Catchment reveal this state of affairs that existed in the 1950s to 1980s (see, e.g., Coppolillo et al*.,* 2003; Walsh, 2012; Mwita, 2016).

4.2 *Cross-Classification Analysis Results*
Cross-classification results are presented in Figures 6-10 to supplement the information provided in Tables 12-15.

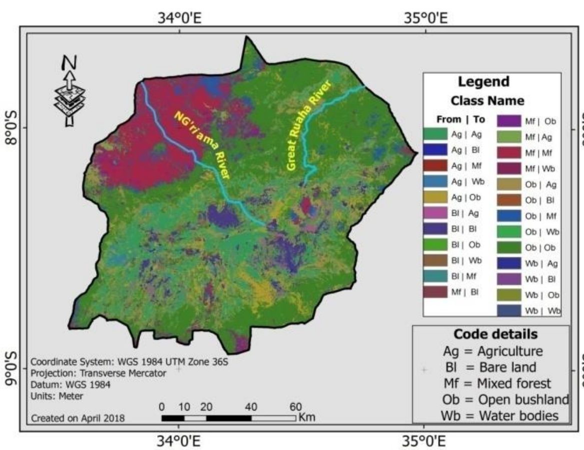

Figure 6: Cross-classification Between 1986 and 1996 LULC

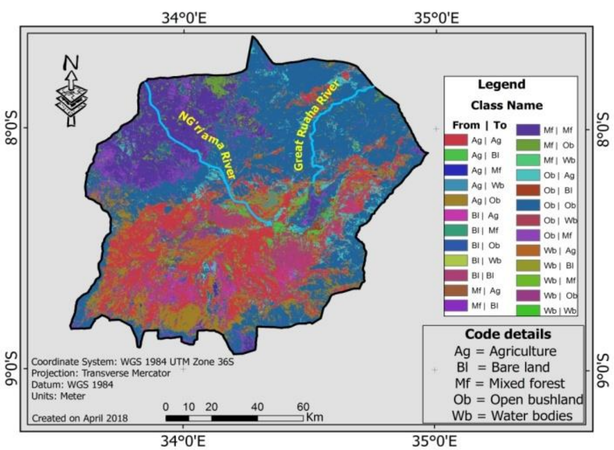

Figure 7: Cross-classification Between 1996-2006 LULC

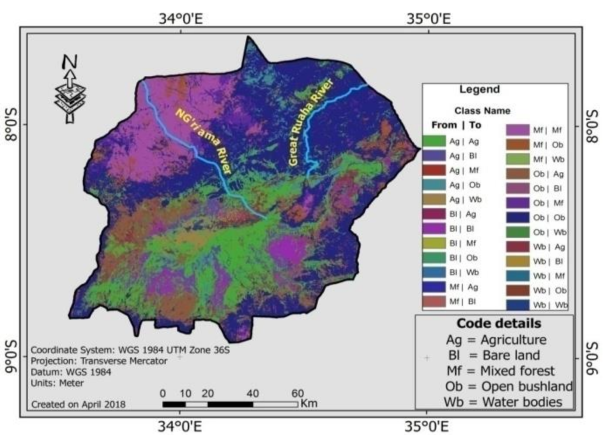

Figure 6: Cross-classification between 2006 and 2017 LULC

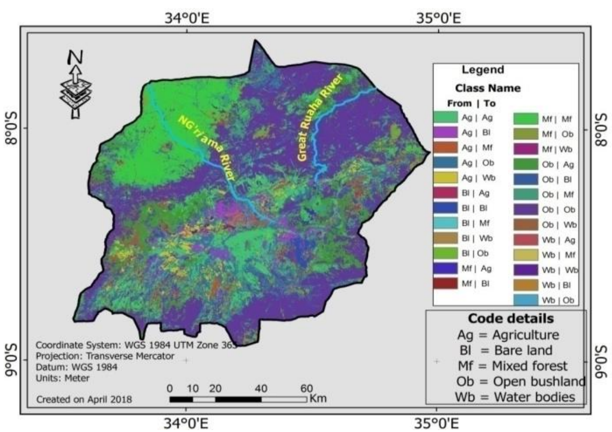

Figure 7: Cross-classification between 1986 and 2017 LULC

Source: Author (2018)

In the cross-classification analysis maps, visual interpretation was the best way of communicating locations with LULC changes. The colours used in the legends of particular maps represent the location of changes of each individual LULC from one cover to another. The results show that, all land covers have their portions transformed from one cover to another in all epochs, i.e., 1986–1996, 1996–2006 as well as 2006–2017. The observed changes have been quantified in the cross-tabulation analysis.

4.3 Cross-tabulation Analysis Results

The cross tabulation analysis were performed to know the fractions of land use and land cover that were transformed from one land use/cover into another, both categorically and quantitatively. Tables 5-8 presents the results.

Table 5: Land use/ Land cover transition matrix for 1986-1996 (km^2)

		1986					
	LULC	MF	OB	AG	WB	BL	**Total**
1996	MF	2958	864	244	25	2	4093
	OB	1363	9028	2047	301	169	12909
	AG	125	2011	2045	226	197	4604
	WB	0	16	27	25	7	75
	BL	9	353	242	41	472	1117
	Total	**4456**	**12273**	**4605**	**618**	**846**	**22799**

Table 6: Land use/ Land cover transition matrix for 1996-2006 (km^2)

		1996					
	LULC	**MF**	**OB**	**AG**	**WB**	**BL**	**Total**
2006	MF	2526	964	62	0	2	3554
	OB	1461	9250	1434	18	160	12323
	AG	55	2232	2533	34	342	5196
	WB	48	258	255	21	16	597
	BL	2	201	324	2	600	1129
	Total	**4092**	**12904**	**4608**	**75**	**1119**	**22799**

Table 7: Land use/ Land cover transition matrix for 2006-2017 (km^2)

		2006					
	LULC	**MF**	**OB**	**AG**	**WB**	**BL**	**Total**
2017	MF	2558	1471	14	39	0	4081
	OB	987	9710	2223	212	180	13312
	AG	7	978	2433	278	470	4165
	WB	2	116	340	66	55	579
	BL	0	48	187	2	424	661
	Total	**3554**	**12323**	**5196**	**597**	**1129**	**22799**

Table 8: Land use/ Land cover transition matrix for 1986-2017 (km^2)

		1986					
	LULC	**MF**	**OB**	**AG**	**WB**	**BL**	**Total**
	MF	2991	828	235	23	7	4083
	OB	1382	9332	2200	187	210	13310
2017	AG	78	1721	1687	317	363	4165
	WB	5	166	267	75	66	579
	BL	2	226	217	16	201	661
	Total	**4457**	**12273**	**4605**	**618**	**846**	**22799**

From Tables 5-8, the total cover of the mixed forest was 3,554km^2 in 2006; and it acquired more land from other land use land covers to increase to 4,081km^2 in 2017. The increase in the area covered by mixed forest was a result of contributions from open bush land (1,471km^2), agriculture (14km^2) and water bodies (39km^2). Contrary to that, in the year 2006 almost 958km^2 of mixed forest were converted to open bush land, where 7km^2 and 2km^2 were converted to agriculture and water bodies, respectively. Only 2558km^2 of mixed forest remained unchanged in 2006.

In the same epoch (2006-2017), the area covered by open bush land was 12,323km^2 and 13,312km^2 in 2006 and 2017, respectively. In the year 2006, out of 12,323km^2 that was open bush land, 9,710km^2 remained open bush land; 1,471km^2 was converted to mixed forest; 978km^2 became agricultural land; and 116km^2 and 48km^2 were converted to water bodies and bare land, respectively. Similarly, the increase in open bush land from 12,323km^2 in 2006 to 13,312km^2 in 2017 was attributed slashing of 2,223km^2 from agriculture, 987km^2 from mixed forest 212km^2; and 180km^2 from water bodies and bare land as well.

Also, in the 1986–1996 epoch, agricultural land covered 4605km^2, however, it lost only 1km^2 in the period of ten years and maintained 4604km^2 in 1996. This may mean that people were not interested in agriculture in this time. Majority of the people concentrated on forest related activities; this fact can be justified by loss of forest cover occurred in this epoch.

The 1996–2006 epoch witnessed a serious decline in the area covered by water bodies that fell to 75km^2 from 618km^2 in 1986, however regained its cover and became 597km^2 in 2006. This was caused by overgrazing and excessive use of water in the catchment in the expansion of agricultural farms, which gained 34km^2 from water bodies in the area. Bare land decreased from 1129km^2 to 661km^2 in the 2006–2017 epoch, which was caused by the increase in open bush land size (48km^2). In addition, 187km^2 of bare land went under agriculture. This might explain the decline in the size of bare land.

5. Conclusion

The study findings reveal that LULCC is inevitable due to the complex relationship existing in the LULC itself. The results also showed that mixed forest and open bush land are the most susceptible to change due to being the only sites for the expansion of settlements and agriculture, the source of energy to the majority poor, as well as a source of illegal logging. The results from this paper provide useful information for stakeholders and authorities concerned with environmental conservation. Moreover, change detection results can save as good reference to policy makers in proper land use management.

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