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Multi-Temporal land use change detection analysis using landsat data: The case of Lilongwe City

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Abstract Land use land cover (LULC) studies have played a significant role in sustainable urban planning and development. In this study, Remote Sensing and GIS was used to detect and analyse LULC change for the years 1998, 2008 and 2018 in Lilongwe city. The maximum-likelihood algorithm was adopted for supervised classification Landsat TM and Landsat OLI images. Classification results showed that built-up area increased substantially whereas bare land and vegetation declined, while water remained constant throughout the study period. Post-classification comparison of the classified images based on the transition matrix revealed that for the period of 1998 to 2008, vegetation had the highest transition with 47.35 km² (47.20%) of its total area in 1998, the majority being converted to bare land (40.24 km²), built-up area (7.05 km²) and water (0.056 km²). The results further showed that built-up area increased at an annual rate of 7.8%, 14.5% &, and 16.81% for the period of 1998 to 2008, 2008 to 2018, and 1998 to 2018 respectively. The overall accuracies for 1998, 2008 and 2018 images, were 95.46%, 94.23%, and 89.73% respectively. The study unveiled LULC change dynamics for Lilongwe city and the rate at which changes were taking place. With an ever-increasing urbanization in this City, these findings present a call for the City to strengthen measures for restoring the deteriorated environment in order to ensure a sustainable environment for all city dwellers.

Keywords: *Geographic Information System; Remote Sensing; Supervised classification; Accuracy assessment; Transition matrices.*

1. Introduction

Globally, Land Use Land Cover (LULC) Change has become a popular subject in recent decades because the change in landscape is always linked to various substantial environmental processes (Dadhich et al., 2017; Mohajane et al., 2018; Marondedze & Schütt, 2019; Mawenda & Watanabe, 2020). Asselen et al. (2013) highlighted that advancement in urban, agricultural, infrastructural, and industrial development activities have contributed to land use change. This unveils a complexity of challenges that are emanating from the simultaneous pursuit of development and ecological sustainability. For example, anthropogenic hazards such as floods and soil erosion have manifested in most of the cities due to land use change (Douglas et al., 2008). This has made researchers across the globe to monitor and detect changes in LULC using remote sensing (RS) and Geographical Information Systems (GIS) and provide recommendations to policy developers on how subsequent policies should be framed and implemented (Asaad et al., 2019; Baynard, 2013; Munthali et al., 2019; Taloor et al., 2020). LULC studies have also played a pivotal role in providing valuable information that can be used to inform more sustainable natural resource management strategies (Munthali et al., 2019).

Unaccustomed global population has exerted pressure on existing land resources (Ramankutty et al., 2014; Rawat et al., 2013). In 2018, about 55 per cent of the world's population lived in urban areas, a proportion that is projected to reach 68 per cent by 2050 (United Nations, 2015). Almost 90 per cent of this projected growth will occur in Asia and Africa, especially in medium and small-sized cities (United Nations, 2019). In most of the developing countries, poverty compels people to move from rural to urban areas for employment opportunities (United Nations, 2019). As of 2018, the urban population in Africa was 42.9 % and is expected to reach 56 % by 2050 (United Nations, 2019). The nature of spatial expansion and growth of smaller settlements will significantly influence Africa's urban landscape (United Nations, 2016). This has been proved by Maina et al. (2020) through a study which detected LULC change using RS and GIS from 1987 to 2017 in Kieni, the central part of Kenya (Maina et al., 2020). The results showed an expansion in built-up and bare lands by 314.9%, signifying an increase in urban population and escalation of environmental devastating activities such as deforestation (Maina et al., 2020).

Similarly, Sub-Saharan Africa (SSA) has the annual urbanization rate of 4.5% whereby a majority of people in urban areas live in informal settlements (Akinyemi et al., 2016). The reported rate of urbanization account for the observed urban expansion in order to accommodate the growing population (Güneralp et al., 2017). Urban expansion in SSA is characterized by unplanned and unregulated urban growth (Cirolia & Berrisford, 2017). It is being exacerbated by weak urban planning institutions (Güneralp et al., 2017), complicated settlement-governance arrangements with weak local authorities and poor land-use management capacity (Cirolia & Berrisford, 2017). This points out to the need for conducting more LULC studies to help in designing responsive land management policies (Mawenda & Watanabe, 2020).

Several LULC Studies have been conducted in SSA aimed at detecting and assessing land use change (Marondedze & Schütt, 2019; Matlhodi et al., 2019). For example, Marondedze & Schütt (2019) detected LULC change using RS and GIS from 1984 to 2018 in Harare, Zimbabwe. Results showed that built-up areas extended from 279.5 km² (1984) to 445 km² (2018) with high-density residential areas growing dramatically from 51.2 km² (1984) to 218.4 km² (2018). However, more updated LULC information is needed with the alarming rate of urbanization (Mohajane et al., 2018).

Malawi is one of the most rapidly urbanizing countries in the world, with an annual rate of 5% (Malawi Government, 2015). Malawi's urban population has been on the increase from about 850,000 in 1987 to 2.8 million in 2018 (National Statistical Office, 2019). The Malawi National Urban Policy, has highlighted that the major drivers of urbanization are high natural increase of population, rural-urban migration, and immigration (Malawi Goverment, 2019). The growing urban population has been noted in its four major cities of Blantyre, Lilongwe, Mzuzu and Zomba, and other towns and districts such as Kasungu, Salima and Mangochi, and Gazetted town planning areas (Manda, 2015). However, the four major cities are the main urbanizing centres in Malawi (Malawi Goverment, 2019). Among the four cities, Lilongwe, the capital city, has experienced the fastest growth (Malawi Government, 2015). This is the case as poverty compels people to flock from rural areas to cities in the search for employment and other business opportunities (Malawi Goverment, 2019). As of 2018, Lilongwe city constituted 5.6 % of the total population, which is higher compared to other cities (National Statistical Office, 2019). In 2018, the Lilongwe City had a total population of 989, 318 people with a growth rate of 3.8% with respect to 2008 statistics (National Statistical Office, 2019). An increase in population has exerted pressure on existing land resources which has resulted into LULC (UN Habitat, 2011). This land use change has been evidenced through the creation of informal settlements, poor drainage systems, encroachment of reserved areas, and socio-economic activities such as sand mining and brick moulding (Malawi Goverment, 2019).

LULC changes have induced anthropogenic disasters such as urban flooding and stormy winds in cities including Lilongwe (Douglas et al., 2008; Malawi Government, 2015). For example, Lilongwe city has been hit by devastating flooding events (UN Habitat, 2011).

RS and GIS technologies are well-known, powerful, and cost-effective tools that are effective at mapping and characterizing natural resources as well as tracking alterations in the landscape over time (Rubinato et al., 2019). These technologies have proved their efficiency and applicability in exploring the relationship between people and the environment hence necessary for detecting LULC change (Maina et al., 2020; Malik & Bhat, 2014). Furthermore, recent developments in these technologies and methods have aided researchers to model and predict LULC change effectively for inaccessible regions (Murayama et al., 2015). However, the tools only identify the nature, extent, and rate of LULC changes on the landscape without explaining the underlying causes of LULC dynamics (Munthali et al., 2019).

In Malawi, LULC changes have been observed through previous studies (Gondwe et al., 2018; Mawenda & Watanabe, 2020; Munthali & Murayama, 2011; Munthali et al., 2019). For example, results from LULC study conducted in Blantyre city, southern Malawi revealed an increase in built-up area, and a decrease in bare soils and vegetation throughout the 24 years period (1994 to 2018) (Mawenda & Watanabe, 2020). A similar trend was observed in studies conducted in Dedza district and Lilongwe city (Munthali et al., 2019; Gondwe et al., 2018). However, the LULC study in Lilongwe was conducted with respect to surface temperature changes (Gondwe et al., 2018), leaving aside LULC class transitions which signifies dominant human activities that are environmentally threatening within the city. Furthermore, the rate at which previous LULC change took place within the City remains uncovered. Annual rate for LULC change signifies how fast human activities are threatening the natural environment. According to Elagouz et al. (2020) and Maina et al. (2020), it is essential to have frequently updated LULC information for various socio-economic and environmental applications. Therefore, this study using RS and

GIS aims at detecting and quantifying LULC change from 1998 to 2018 while at the same time evaluating the rate at which these changes were taking place over space.

The essentiality of studying historical LULC changes is for better planning and to understand the trend of urban expansion (Gadrani et al., 2018; Marondedze & Schütt, 2019; Mawenda & Watanabe, 2020; Owoeye & Ibitoye, 2016). Knowing the annual rate change of various LULC categories will also help in expediting responsive policy development and implementation. Furthermore, results from this study will guide in decision making process for urban planners, researchers, environmentalists and development stakeholders hence ensuring that there is a balance between development and ecological sustainability.

2. Materials and methods

2.1 Study area

Lilongwe city is located in the north-central of the Lilongwe district (Figure 1) and has an area of 403 km^2, 60 percent being public land, 30 percent being private land and 10 percent being customary land (UN Habitat, 2011). The city's population was 989,318 in 2018, thus reflecting a 3.8% growth rate (National Statistical Office, 2019). Approximately 76 percent of the city's population lives in informal settlements (UN Habitat, 2011). The city has several rivers such as Lingadzi, Likuni, Msamba, Namathanga, and Lilongwe, which run throughout the year. The city has also been affected by 2012, 2015, 2017, and 2018 flooding events that claimed the lives of people and caused property damage (Goverment of Malawi, 2019; Malawi Goverment, 2019).

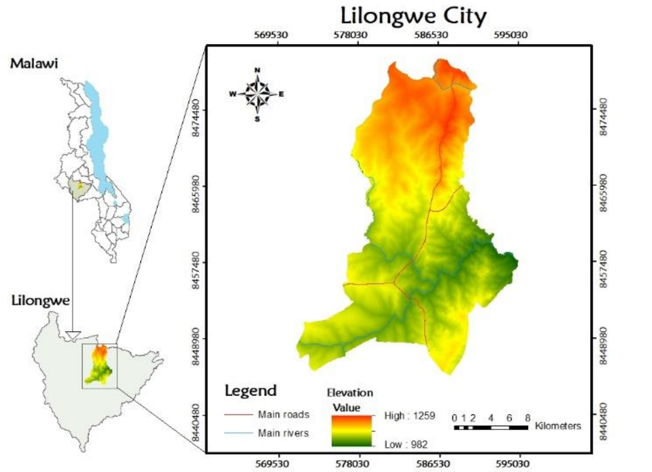


Figure 1: Location of Lilongwe City in Central Malawi

Malawi has a sub-tropical climate with two distinct seasons: a wet, warm season and a dryer, cooler season. The wet, warm season runs from October to April, while the dry cold season runs from May to September (National Statistical Office, 2020).

2.2 Data collection

The study used two separate Landsat Missions, Landsat 5, and Landsat 8. Different sensors from different missions were used despite having a different spectral resolution in providing data that covers the timeframe of the study (1998 to 2018). Particularly, cloud-free Landsat Thematic Mapper, and Landsat Operational Land Imager data obtained in the years of 1998, 2008, and 2018 respectively, was downloaded from the United States Geological Survey (https://www.usgs.gov) Besides having free access, Landsat imagery was used because of its optimal ground resolution and spectral bands to efficiently track land use change. Landsat 5 was used for 2008 instead of Landsat 7 because Landsat 7 has scan line error resulting in some scene not being scanned thus affecting the classification output and subsequent analysis. Table 1 summarises the Landsat data used in this study.

Table 1: Landsat data used for LULC change detection Analysis

Satellite data	Path/Row	Spatial Resolution (m)	Temporal Resolution (Days)	Acquisition Date	Source
Landsat TM 1998	168/070	30	16	21 October, 1998	https://www.usgs.gov
Landsat TM 2008	168/070	30	16	30 September, 2008	https://www.usgs.gov
Landsat OLI 2018	168/070	30	16	28 October, 2018	https://www.usgs.gov

2.3 Image pre-processing and classification

The study used Quantum GIS 3.4.3 Madeira for data analysis. Before classification, datasets were subjected to pre-processing in Semi-Automatic Classification Plugin (SCP). This involved the application of radiometric and geometric corrections to the 1998, 2008 and 2018 satellite images. Radiometric correction was applied to calibrate the pixel values and correct for errors in values hence improving the quality and how the images should be interpreted (Congalton, 2001). Geometric correction was applied to compensate for the distortions and produce a collected image with a high level of geometric integrity (Haque & Basak, 2017). The pre-processed datasets were then clipped to the extent of the study area. Composite images were then created from a selection of visible bands from the clipped data sets to aid the process of classification. Particularly, the false colour composites were created using spectral bands 4, 3, and 2 for Landsat 5 TM and 5, 4, 3 for Landsat 8 OLI. LULC Classes of Built-up area, vegetation, bare land, and water were then generated for all the 1998, 2008, and 2018 datasets. The Four LULC classes with their associated descriptions were adopted from (Kumar, Babu, Rajasekhar, & Ramachandra, 2019; Marondedze & Schütt, 2019; Mawenda & Watanabe, 2020) and modified to suit the study area as shown in Table 2.

Table 2: LULC Classification scheme used in the study area

LULC Class	Description
Built-up Area	Residential, commercial and services, industrial, socio-economic infrastructure, transport and airport.
Vegetation	Protected forests, deciduous forest, mixed forest lands and forest on customary lands.
Bare Land	Areas with no or little vegetation cover including exposed soils, rocks, landfill sites and stock quarry.
Water	Rivers, dams and sewages

For each optical imagery used in the study period, representative spectral signatures were purposively taken from each identified spectral grouping. These ranged from five to twenty training sites per LULC category that were used to train a classification algorithm. Besides having prior knowledge about the study area, reference was also made to the Google Earth archived images when collecting the training samples. The study used supervised classification method using the maximum likelihood algorithm. The algorithm was adopted as it is considered the most widely accepted procedure used for supervised classification of multispectral image data (Haque & Basak, 2017; Nath, Wang, Ge, Islam, & Singh, 2020; Rawat et al., 2013). Sieving of classified images was conducted in SCP to remove isolated pixels in the final classification output.

2.4 Accuracy assessment

Accuracy assessment is a substantial step in the LULC classification process. It aims at quantitatively evaluating how effectively pixels are grouped into the correct feature classes in the study area (Batar, Watanabe, & Kumar, 2017). The assessment process uses error matrices to compare the classified results with geographically referenced data that are assumed to be true. For this study, the reference data for 1998, 2008, and 2018 maps were obtained from historical google earth images for the respective years. A set of 116, 72 and 76 reference points were generated using stratified random sampling in SCP, based on the sizes of the LULC classes for 1998, 2008, and 2018 classified maps respectively. The total number of samples (reference points) per each classified image was calculated after (Olofsson et al., 2014) equation (refer to equation 1). The total number of reference points were then multiplied by the proportion of each LULC class. Table 3 shows details of reference points for each LULC class.

$$N = \sum i = 1 \left(\frac{W_i * S_i}{S_O}\right)^2 \quad \text{………..} \quad \textbf{(1)}$$

Where:

W_i = mapped area proportion of class i;

S_i = standard deviation of stratum i;

S_o = expected standard deviation of overall accuracy;

C = total number of classes.

Table 3: Details of reference points for each LULC class

	1998	**2008**	**2018**
LULC Class	**Number of Reference Points**	**Number of Reference Points**	**Number of Reference Points**
Built-up Area	20	19	26
Vegetation	29	21	12
Bare land	52	40	28
Water	15	12	10

The user's, producer's, and overall accuracies as well as kappa coefficient were all calculated using the SCP.

2.5 Post classification comparison technique

The Post-classification comparison technique is a statistical technique used to compile a detailed tabulation of changes between two classification images (Haque & Basak, 2017). The technique was incorporated for LULC change detection analysis using multi-date classified images for all the classes used in the study. The approach is widely used and has proven to produce reliable results by many studies (Haque & Basak, 2017; Malik & Bhat, 2014; Marondedze & Schütt, 2019; Mawenda & Watanabe, 2020). In this study, LULC transition-matrices were tabulated using Land Cover Change functionality in SCP. It involved pixel-by-pixel change analysis highlighting spatio-temporal LULC changes and distribution (Marondedze & Schütt, 2019). The generated transition matrices revealed areas that were converted from one class to another, and those which were persistent between the period of 1998 to 2008, 2008 to 2018, and 1998 to 2018 respectively.

2.6 Calculation of annual rate of change

The study adopted a method by (Malik & Bhat, 2014) to calculate annual rate at which land use change is taking place as depicted in equation 2. However, the equation only gives a standard for comparing Land use changes that are not susceptible to different periods between study periods.

$$r = \left(\frac{L_b - L_a}{L_a}\right) X \left(\frac{1}{T}\right) X\ 100 \ldots\ldots\ldots\ldots\ldots\ldots \quad \textbf{(2)}$$

Where;

r = The annual rate of change

L_a = Amount of the LULC category in the year a.

L_b = Amount of the LULC category in the year b.

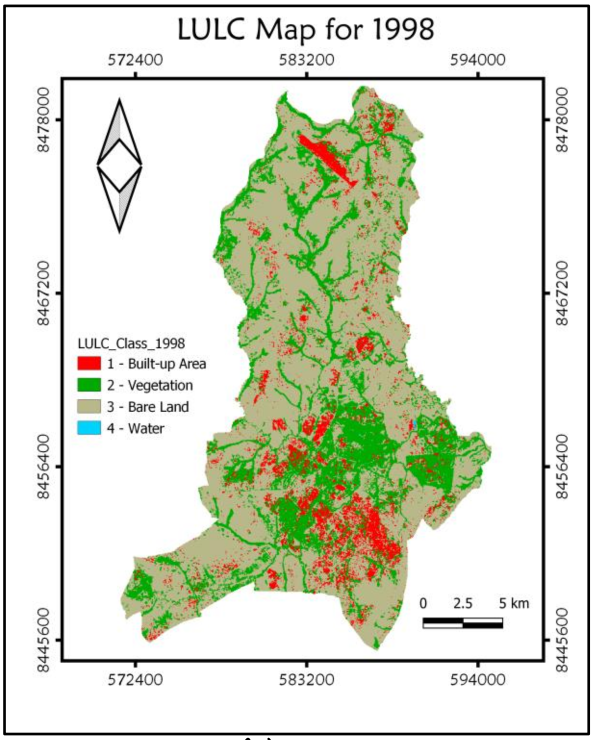
T = Length of time between year a and b.

Based on the calculations, a positive value signifies that a particular LULC class area has increased at a particular annual rate of change for a given period. Whereas negative value denotes that a given LULC class has declined at a particular annual rate of change in a given period of time. Annual rate of change of a particular LULC class for a given period, remained constant.

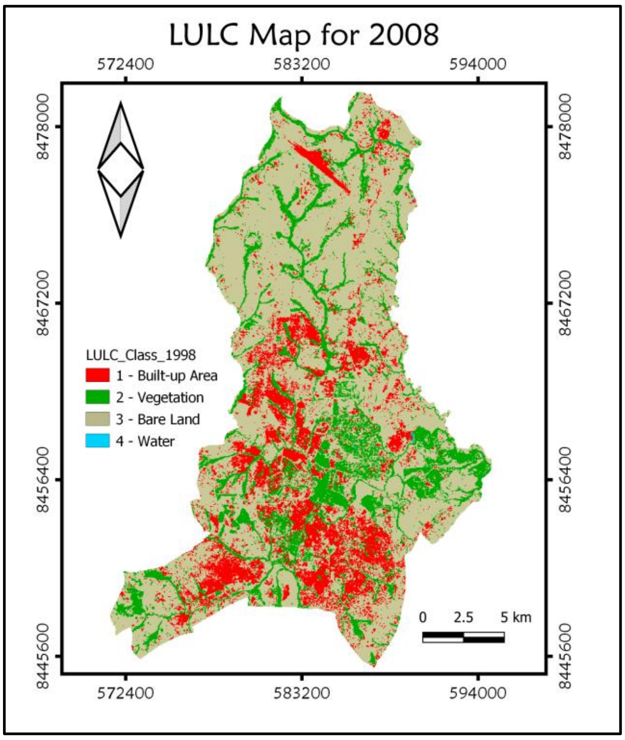
3. Results

3.1 Land Use Land Cover Classification

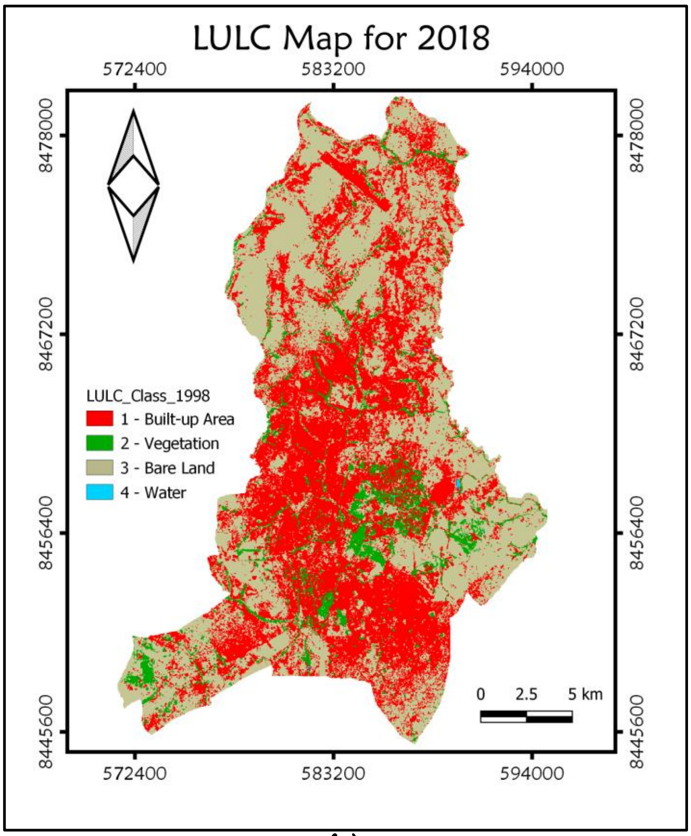
Prominent changes in LULC classes investigated in this study for 1998, 2008, and 2018 based on the supervised classification process of Landsat images are shown in Figure 2.



(a)



(b)



(c)

Figure 2: Classified LULC Maps for Lilongwe City in (a) 1998, (b) 2008 and (c) 2018.

Table 4 illustrates the temporal changes in the LULC from 1998 to 2018. The results indicate that there have been substantial LULC changes within Lilongwe City from 1996 to 2018. This has been evidenced through the observed general increase in built-up area and a decrease in vegetation and bare land. In 1998, bare land represented 62.4 % of the total area followed by vegetation with a proportion of 24% and built-up area with 19% respectively. In 2008 bare land, vegetation and built-up area covered 62.76%, 19.20%, and 18.00% respectively. Whereas in 2018 bare land, vegetation and built-up area covered 48.49%, 7.30%, and 44.12% respectively.

Table 4: LULC Distribution for Lilongwe City (1998-2018)

		1998		2008		2018	
No.	**LULC Classes**	**Area (km²)**	**%**	**Area (km²)**	**%**	**Area (km²)**	**%**
1	Built-up Area	40.80	10.12	72.62	18.00	177.96	44.12
2	Vegetation	100.31	24.87	77.43	19.20	29.43	7.30
3	Bare Land	261.97	64.95	253.12	62.76	195.57	48.49
4	Water	0.28	0.07	0.17	0.041	0.38	0.09

Figure 3 presents the statistics of the LULC changes for 1998, 2008, and 2018.

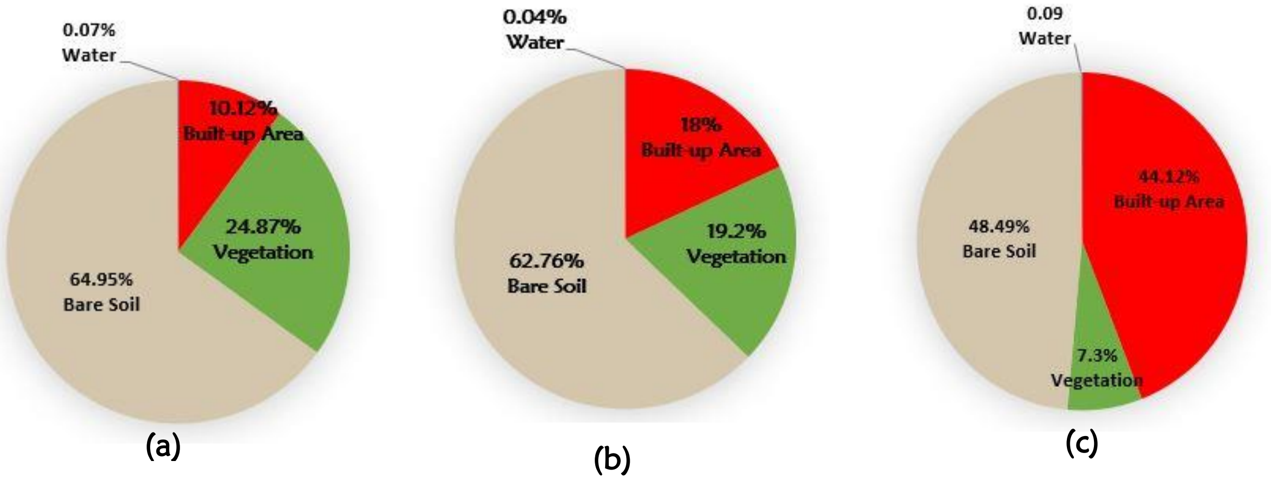


Figure 3: LULC changes statistics for (a) 1998, (b) 2008 and (c) 2018 respectively.

Based on the results, it is evident that water remains almost constant throughout the study period and that bare land was the main LULC class in the study area. Water remained almost constant because only man-made water bodies were captured during classification owing to image resolution. Spatial resolution of the images made some of the existing rivers to be captured as vegetation

3.1 Post-Classification Change Detection Analysis

Tables 6, 7, and 8 show the LULC transition matrix generated from the classified maps of the periods 1998 to 2008, 2008 to 2018, and 1998 to 2018 respectively.

Figure 4 (a, b and c) shows statistics of transition matrices for 1998 to 2008, 2008 to 2018, and 1998 to 2018 respectively. Whereby the first, second, third and fourth ring from the hole shows LULC class of built-up area, vegetation, bare land and water respectively. For Tables 5a, 5b and 5c, diagonal entries of each matrix show the amount of the LULC classes that were persistent throughout the period. Overall, 65.78% (265.44 km²), 57.68% (232.68 km²) and 44.45% (197.3 km²) of the study area were persistent between 1998 to 2008, 2008 to 2018, and 1998 to 2018 period respectively.

Table 5a: Transition matrix between 1998 and 2008 (km²)

Reference class	**Built-up Area**	**Vegetation**	**Bare Land**	**Water**	**Total 1998**
Built-up Area	**19.34**	4.7	16.74	0.015	40.80
Vegetation	7.05	**52.96**	40.24	0.056	100.31
Bare Land	46.17	19.69	**196.08**	0.039	261.97
Water	0.073	0.068	0.066	**0.056**	0.26
Total 2008	72.62	77.43	253.12	0.17	**403.34**

Table 5b: Transition matrix between 2008 and 2018 (km²)

Reference class	Built-up Area	Vegetation	Bare Land	Water	**Total 2008**
Built-up Area	**56.91**	0.44	15.23	0.03	72.62
Vegetation	26.00	**23.30**	27.89	0.23	77.43
Bare Land	94.98	5.66	**152.41**	0.07	253.12
Water	0.06	0.02	0.02	**0.06**	0.17
Total 2018	177.96	29.43	195.57	0.38	**403.34**

Table 5c: Transition matrix between 1998 and 2018 (km²)

Reference class	Built-up Area	Vegetation	Bare Land	Water	**Total 1998**
Built-up Area	**28.53**	1.49	10.77	0.02	40.80
Vegetation	38.58	**22.72**	38.79	0.2	100.31
Bare Land	110.70	5.19	**145.99**	0.09	261.97
Water	0.15	0.03	0.02	**0.06**	0.26
Total 2018	177.96	29.43	195.57	0.38	**403.34**

During the 1998 to 2008 period, 47% (19.34 km²), 53% (52.96 km²), 75% (196.06 km²) and 21% (0.056 km²) of built-up area, vegetation, bare land and water respectively were persistent (**Figure 4(a)**). For the 2008 to 2018 period, 78% (56.91 km²), 30% (23.3 km²), 60% (152.41 km²) and 38% (0.06 km²) of built-up area, vegetation, bare land, and water respectively were persistent (**Figure 4(b)**). Whereas for the 1998 to 2018 period, 70% (28.53 km²), 23% (22.72 km²), 56% (145.99 km²) and 23% (0.06 km²) of built-up area, vegetation, bare land and water respectively were persistent (**Figure 4(c)**).

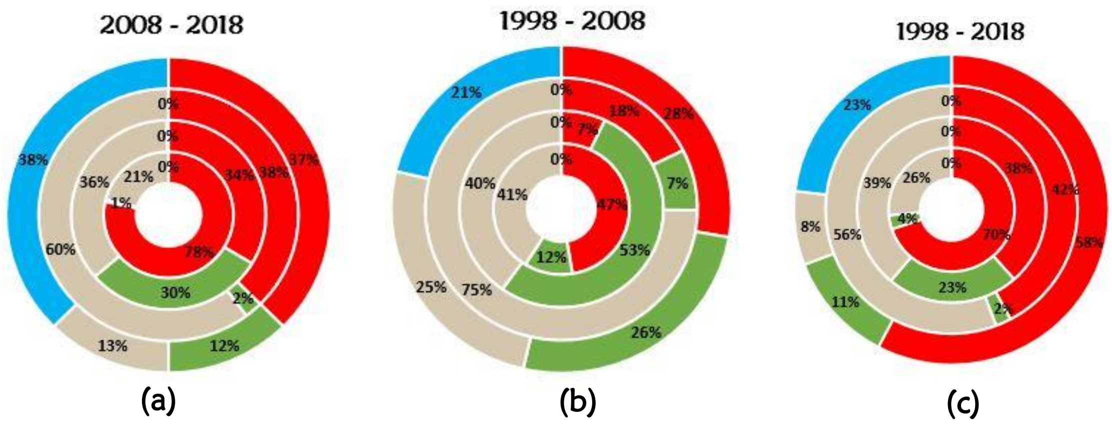


Figure 4: Statistics of transition matrices for (a) 1998 to 2008, (b) 2008 to 2018, and (b) 1998 to 2018

Overall, the results revealed that persistent areas for vegetation and bare land decreased with the subsequent periods. This affirms the fact that changes were more rapid in the later period than the former, which signifies that anthropogenic activities were prevalent throughout the study period. On the other hand, persistent area for built-up area increased with the subsequent period denoting the expansion of urban areas within the city.

The study also uncovered that there were substantive changes and transitions in LULC classes of vegetation, bare land and vegetation and not water. During 1998 to 2008 period (Table 5a and Figure 5(a), the vegetation experienced the highest transition with 47.35 km² (47.20%) of its total area in 1998, the majority being converted to bare land (40.24 km²), built-up area (7.05 km²) and water (0.056 km²). Vegetation was seconded by bare land which experienced a transition of 65.90 km² (25.16%) of its total area in 1998. In the same period, built-up area gained area from 7.05 km² (7%), 46.17 km² (18%) and 0.073 km² (28%) of vegetation, bare land and water respectively. Water bodies such as dams and sewage were converted to built-up area, vegetation and water because many of these man-made water bodies such as sewage system in Kauma, Area 58 (Lumbadzi) and Dam in area 10 have pavements and vegetation within their vicinity. In the circumstance that water level has declined especially during September to October season, sensors could have recorded the spectral reflectance of either pavements or vegetation instead of water. Similarly, during this period like other periods (2008 -2018, & 1998 – 2018), results have shown that 4.7 km² (12%) and 16. 74 km² (41%) of built-up area has been converted to vegetation and built-up area respectively. This could be attributed to the reflectance of the roofs of the houses such as iron sheets that appeared to be rocks and low vegetation area.

In addition, results have revealed that bare land concerning study area, has experienced dominant proportions of the transaction of 65.90 km² (25%), 100.71 km² (40%), and 115. 98 km² (44%) for the period of 1998 to 2008, 2008 to 2018, and 1998 to 2018 respectively. Apart from water which almost remained constant, built-up area registered the least transaction 21.46 km², 15.97 km², 12.28 km² of its total built-up area in the period of 1998 to 2008, 2008 to 2018, and 1998 to 2018 respectively.

During the 2008 to 2018 period, a proportion of 94.98 km² and 26.00 km² for bare land and vegetation respectively, were translated into built-up area. This accounts for the drastic growth of urban areas compared to the 1998 to 2008 period, since a large proportion of land was converted from other LULC classes into built-up area

3.2 Annual Rate of Change (%) Calculation

The rate at which annual change has been happening for all the respective LULC classes is shown in Table 6. The results show that built -up area increased at an annual rate of 7.8%, 14.5, and 16.81% for the period of 1998 to 2008, 2008 to 2018, and 1998 to 2018 respectively. Vegetation has decreased at an annual rate of 2.28%, 6.2%, and 3.53% for the period of 1998 to 2008, 2008 to 2018, and 1998 to 2018 respectively. Similarly, bare land has decreased at an annual rate of 0.34%, 2.27% and 1.27% for the period of 1998 to 2008, 2008 to 2018, and 1998 to 2018 respectively. Whereas water decreased at an annual rate of change of 4.14 for the first period (1998 to 2008) and later on increased with an annual rate of 13.15% and 1.78. As already highlighted, this could be attributed to the fact that the main water bodies captured in the study are sewages and dams which are surrounded by pavements and sometimes vegetation. Hence a decrease in water level could be seen as a shift from one class to another i.e. from water to built-up area or bare land in case of low vegetation

Table 6: Annual Change rate (%) for Different Periods

LULC CLASS	**1998 to 2008**	**2008 to 2018**	**1998 to 2018**
Built-up Area	7.8	14.5	16.81
Vegetation	-2.28	-6.2	-3.53
Bare Land	-0.34	-2.27	-1.27
Water	-4.14	13.15	1.78

3.3 Accuracy Assessment

The results of the accuracy assessment for the 1998, 2008, and 2018 classified LULC maps are shown in Table 7. The overall accuracies for 1998, 2008 and 2018 images, were 95.46%, 94.23%, and 89.73 respectively. The kappa coefficient of 0.91, 0.88 and 0.82 for the respective maps showed a strong agreement between the classified map and the reference (Congalton, 2001). Hence, the classified results can be used for post-classification comparisons analysis

Table 7: Accuracy Assessment for the generated thematic Maps of 1998, 2008, 2018.

	1998		**2008**		**2018**	
LULC Class	**User's Accuracy (%)**	**Producer's Accuracy (%)**	**User's Accuracy (%)**	**Producer's Accuracy (%)**	**User's Accuracy (%)**	**Producer's Accuracy (%)**
Built-up Area	80	76.41	77.78	100	84.61	100
Vegetation	100	99.96	90.91	99.92	100	67.69
Bare Land	96	96.85	100	91.6	92.86	86.9
Water	71.43	100	66.67	100	80	100
Overall Accuracy (%)		95.46		94.23		89.73
Kappa hat classification		0.91		0.88		0.82

4. Discussion

There is continuous increase in built-up area because of population pressure and economic development (UN Habitat, 2011). The city had a population of 440 471, 669 532 and 989, 318 by 1998, 2008 and 2018 respectively (National Statistical Office, 2019; UN Habitat, 2011). The increase in population correlates with the increase in built-up area.

This signifies that due to population growth more land was converted from LULC classes of bare land and vegetation into built-up areas in the name of settlements and infrastructural development. Overall, the general increase in the built-up area is comparable to other studies conducted in the sub-Saharan African cities, including the Lusaka city in Zambia, Dar es salaam in Tanzania, and Harare city in Zimbabwe (Marondedze & Schütt, 2019; Mzava et al., 2019; Nguvulu, 2017). For example, Lusaka city experienced an increase in build-up areas which included industrial, commercial and residential areas by 21.41% between 1995 and 2015 (Nguvulu, 2017). Similarly, in Dar es salaam an increase of 17.55 % for built-up areas was observed with an annual growth rate of 7.51% from 1998 to 2014 (Mzava et al., 2019).

Results show that during the 2008 to 2018 period, a great deal of land was converted from bare land and vegetation into built -up area. This indicates that there has been a radical growth of built-up environment within the city hence a possibility of creating potential environmental shocks such as urban flooding. According to (Douglas et al., 2008), flooding in urban areas is not just related to heavy rainfall and extreme climatic events but also changes in built-up areas. An increase in urban or built-up areas denotes a possible land cover change which involves the alteration of urban land surface and diversion of natural flows.

These changes produce increased surface run-offs with a low rate and level of infiltration and consequently resulting in higher flood frequency, magnitude, and duration (World Meteorological organisation, 2012). This is often attributed to increase in impervious surfaces and blockage of natural drainage systems. In this regard, the dynamics in LULC with a remarkable increase in built-up area from the years over the study period may probably also account for the increased frequency of urban flooding events this city (Goverment of Malawi, 2019).

The results also revealed that both bare land and vegetation decreased throughout the study period. Vegetation decreased with 70.88% compared to bare land which decreased by 3.8%. This entails that restoration of the vegetative cover has been quite problematic despite having instruments that preach of conserving and protecting the environment. For example, (Government of Malawi, 2004), articulated in section 5.2 on the need to promote and support the conservation and protection of forest, ecosystem and by the growth of trees by individual companies and communities. As of 2008, Lilongwe city council indicated to have had a major tree planting exercise, in a project which encouraged the participation of primary schools and communities in planting and taking care of trees (UN Habitat, 2011). However, from the results, vegetation has been decreasing without being replaced implying that the stipulated tree planting exercise and environmental policies did not produce expected results.

The annual rate of change rate for LULC signifies that during the period, changes have been happening at a faster rate. This calls for urgency in the implementation and enforcement of policies that aim at restoring and conserving the environment.

5. Conclusion

The study has proven the substantiality of using RS and GIS to detect and analyse LULC change and also evaluating an annual rate of change for LULC changes. Therefore, it is imperative to conclude that Lilongwe city has undergone serious LULC changes between 1998 and 2018. The study reveals that built-up area has increased while bare land and vegetation has decreased throughout the study period. On the other hand, water has remained constant since only dams and sewages were classified because of the spatial resolution of the used images.

The continued decrease of vegetation signifies loopholes that are inherent in existing policy implementation and enforcement mechanisms. For example, despite the Malawi environment policy stipulating the need to conduct extensive tree planting exercises. It is worthy to note that the planting of trees did not match the rate at which deforestation was taking place. Hence findings from this study will help the city to plan on how to restore the deteriorated environment with a higher pace of project implementation to meet up with the pressure exerted from the growing population. Results can also be used in planning for sustainable development of the city such as the use of drainage systems to mitigate impacts of urban flooding. The study recommends that another study should be conducted to investigate anthropogenic activities that are contributing to the noted LULC changes.

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Author Contributions

B.K., V.K., F.C., and S.G., designed the study, analysed the datasets, drafted and edited the manuscript.

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Declaration of conflict of interest

The authors declare no conflict of interest.

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