Change Detection Analysis for Urbanization of Blantyre City, Southern Malawi

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ABSTRACT

Changes in land use and land cover have occurred in Blantyre City, Southern Malawi, as a result of high urbanization and population growth. Understanding and quantifying the spatial-temporal dynamics of urban land use and land cover shifts, as well as the factors that drive them, is critical for developing appropriate policies and tracking processes for decision-making on urban development. By combining GIS and remote sensing techniques with land-use change modeling tools, urbanization patterns related to land use and land cover changes in Blantyre City were analyzed. ENVI software was used to preprocess satellite data from Landsat 4-5 TM for 1990, 2000, 2010, and Landsat 8 OLI for 2020. Land use and land cover maps were generated using the Maximum Likelihood Algorithm of Supervised Classification. To map the dynamics of Built-Up area and vegetation for the past decades, Normalized Difference Built-up Index (NDBI) and Normalized Difference Vegetation Index (NDVI) analyses were performed. A confusion matrix was used to determine the overall accuracy of classified land use and land cover maps, with results exceeding the minimum and appropriate threshold standard. The developed land cover maps were used with the Change Detection Analysis tool to measure land use and land cover changes, analyze land-use transitions between land cover classes, and identify built-up area gains and losses with other land cover classes, as well as assess the spatial pattern of built-up areas.

Finally, data interpolation was conducted in MS Excel to model and forecast potential urban land-use changes in Blantyre City. In general, the findings of this study indicate that built-up areas have expanded at the cost of vegetation and bare land over the last 30 years, rising from 12.87% in 1990 to 16.36% in 2000, then 20.67% in 2010 and 31.77% in 2020. In comparison to other directions, the spatial trend of built-up areas revealed a rising trend in the central west and eastern parts of Blantyre City, water bodies have shown a decreasing trend over the study period. Therefore, the findings of this study could provide decision-making for urban planning and other stakeholders interested in environmental studies related to land-use change analysis.

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CHANGE DETECTION ANALYSIS FOR URBANIZATION OF BLANTYRE CITY, SOUTHERN

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ACRONYMS/ABBREVIATIONS

ENVI	Environment for Visualization of Images
GIS	Geographic Information System
GPS	Global Positioning System
MASDAP	Malawi Spatial Data Application Portal
NIR	Near Infrared
NSO	National Statistical Office
NDBI	Normalized Difference Built-Up Index
NDVI	Normalized Difference Vegetation Index
OLI	Operational Land Imager
RS	Remote Sensing
TM	Thematic Mapper
SWIR	Shortwave - Infrared
USGS	United States Geological Survey
UTM	Universal Transverse Mercator

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1. CHAPTER 1: GENERAL INTRODUCTION

1.1. Background

Human activities such as urbanization, deforestation, agriculture, and a variety of other factors have altered the earth's surface significantly in recent decades. Even though rates of land conversion to agriculture and deforestation vary across the world, the number of people living in cities has been steadily growing. There have been no recorded cases of declining urbanization anywhere on the planet earth, according to current records. This study aimed to examine urbanization trends concerning land use and land cover changes in Blantyre city.

Cities are incubators for economic growth and social change, resulting from the accumulation of citizens and economic activities; however, unhealthy urban conditions have appeared all over the world. Economic prospects in towns, according to (Cui et al., 2019), catalyze rapid urbanization around the world. The rate of urbanization varies by country and is much higher in developing countries (Drakakis-Smith, 2017). For decades, the key trend of natural resource and socioeconomic climate studies in developing countries has been rapid population growth in most cities. Land cover and land-use changes, like other anthropogenic-environmental interactions, react to socioeconomic, political, cultural, demographic, and environmental factors, which are primarily characterized by a concentration of humans (Masek et al., 2000). As a result, combining and analyzing remote sensing and spatially explicit data aids our understanding of land use/land cover transition. To understand the causes of land-use change and forecast possible evolutions using models, it is essential to incorporate Geospatial techniques to aid comprehension of the complexity for the study.

Several studies have used Remote Sensing data and GIS techniques to effectively communicate knowledge about land-use change and degradation around the world. To enhance our understanding of changes in cities and their effect on natural resources and environmental processes, it is essential to track urban evolution at both spatial and

temporal scales. Various aspects of remote sensing are routinely used to detect and map features and changes on land, sea, and atmospheric surfaces that influence urban sustainability (Kadhim et al., 2016). Airborne and satellite remote sensing are very accurate and useful Geospatial tools since they can be used to monitor deforestation, changes in agriculture, the ecosystem, and land use transition trends in environmental sciences. (Dinda et al., 2019) and (Gharbia et al., 2016) used GIS and Remote Sensing techniques to analyze the trends, patterns, and directions of urban growth for sustainable land use management. The effective management of urban forests for the steady and sustainable provision of a broad spectrum of environmental services; needs timely and reliable information on the status, patterns, and interactions between socio-economic and ecological processes related to urban growth occurring at multiple temporal and spatial scales.

Urbanization is one of the most significant environmental consequences of population agglomeration in urban areas (Shao et al., 2020). Recent issues related to urban growth have attracted growing attention in the literature, ranging from spatial and temporal land cover trends, factors influencing urban growth, and urban growth scenarios using Land Cover maps, Geographic Information Systems (GIS), and various modeling techniques, to gain a better understanding of the urban growth process. The ability to examine urbanization trends in a specific area using remote sensing satellite imagery data combined with GIS techniques allows for the identification of spatial-temporal patterns over time. The findings provide insight into the spatial and temporal trends of urbanization, based on inferences drawn from socioeconomic practices and population growth in a given area.

Malawi is one of the world's fastest urbanizing nations, with an annual urban growth rate of more than 5% and a nearly 20% urban population. In 1992, the cities of Blantyre, Lilongwe, Mzuzu, and the Municipality of Zomba were given responsibility for urban planning in Malawi. All assemblies were required by the Local Government Act of 1998 to establish plans for their areas' social, economic, and environmental growth. In Malawi, urban planning has historically been focused on the structure planning principle, which divides the city into land use zones. Malawi is one of the world's least developed countries and one of Africa's most heavily populated. After its independence on July 6, 1964,

Malawi, like other developing countries in Sub-Saharan Africa, has experienced progressive urbanization (Malawi National Statistical Office, 2018). From 1994 to the present, Malawi's government transitioned from a one-party dictatorship to a multiparty democratic regime. During the democratic era, the population of the country's four major cities grew by more than 90%, from 1,095,419 in 1998 to 2,115,867 in 2018. (National Statistics Office, 2019).

1.2. Problem Statement

Diversity of inhabitants and intensive use of the resources through the increasing of population coupled with economic activities drive coherent land use and land cover changes (Peter & Bakari, 2019). These changes lead to transformations in the hydrological, ecological, geomorphologic, and socio-economic systems and which are often neglected by both rural and urban administrations. Cities throughout the world, however, suffer from a host of problems, including congestion, pollution of air and water, inadequate water supplies, wasteful use of energy, problems of waste disposal, inadequate housing, the spread of communicable diseases, and the deterioration of social support systems. Due to rapid urbanization, many cities have expanded into areas prone to earthquakes, floods, and other natural disasters (Rimal et al., 2015). Even those cities which are no longer growing in population continue to expand in the territory, dwelling space, transportation density, resource consumption, and production of wastes. Thus, special attention and continuous assessment are required for monitoring and planning urban development and decision making (Y. Chen et al., 2020).

The population of Malawi in 2018 was 4 times the population of 1966, the first census after independence. The period 2008-2018 recorded a 2.9 percent average annual growth rate. The highest increase between censuses since 1966 was a 3.7 percent average annual growth rate between 1977 and 1987. The lowest average annual intercensal growth rate observed was 2.0 percent which was experienced between 1987 and 1998. Table 1 below summarizes the total population and intercensal growth rates in Malawi.

Table 1. 1966-2018 Malawi Population and Housing Census

Census Year	Population Size	Average Annual Growth Rate (Intercensal) %
1966	4,039,583	---
1977	5,547,460	2.9
1987	7,988,507	3.7
1998	9,933,868	2.0
2008	13,077,160	2.8
2018	17,563,749	2.9

The urban population size of Malawi has increased from 2.0 million people in 2008 to 2.8 million people in 2018. Correspondingly, the rural population of the country has risen from about 11.0 million to 14.8 million. The percentage of urban population which is one of the measures of urbanization had increased from 14.4 percent in 1998 to 16.0 percent in 2018. Blantyre district particularly in urban areas is densely populated due to some pull factors. This would have a significant impact on the surrounding ecosystem including loss of agricultural land, destruction of forest cover, depletion of water resources, and the benefits generated from the land. Because of this rapid growth on the urban-rural fringe, planners and policymakers lack accurate, timely, and cost-effective land use data which is most essential to decide on land resource management. Analyzing and modeling changes in land use and land cover for the future time, therefore, is important in the Blantyre district for monitoring and resolving the negative consequences. This could be useful for better land use management and environmental development in the study area.

1.3. Research Objective

The main objective of this research was to detect and analyze urbanization trends concerning land use and land cover changes in Blantyre city.

1.3.1. Specific Objectives

The specific objectives for this research were;

1. To produce land use and land cover maps of the study area for selected times.

2. To analyze the dynamics/variations of urban land-use changes over the past years.
3. To conduct NDBI and NDVI analysis for all images from the study period to assess the built-up area and vegetation pattern respectively.
4. To predict future urbanization patterns of Blantyre City based on population trends as well as classification maps prepared over the past decades.

1.4. Research Questions

As this study mainly focused on urbanization drive and studies using remote sensing, the following research questions were set:

- Were there any major changes in land use and land within the study periods?
- How was the spatial trend of changes (growth) of land cover classes during the study periods?
- How was the contribution of other land cover classes for the growth of built-up areas?
- Had the models been satisfactory in detecting, analyzing, and predicting urban trends?

1.5. Significance of Study

Land use and land cover change detection with the help of satellite imagery is important for monitoring environmental changes. Successful examination of environmental changes depends on the repetitive collection of data at varying temporal and spatial scales. Detecting change on the face of the globe using GIS (Geographic Information System) aided by remotely sensed imagery is now becoming a requisite tool in managing the environmental resources of planet earth (Khan et al., 2016). The spatially explicit nature of the analysis allows the identification of significant patterns of land cover change, urban growth inclusive, as well as indicating the regions with differing long-term patterns of change in the phenomenon under investigation.

Understanding the spatial distribution and growth of urban areas is essential for urban planning and resource management (Bertrand-Krajewski et al., 2000), and one of the basic activities required for this purpose is mapping the built-up areas. Analyzing and modeling urban land-use changes provide great importance to the research community, urban planners, stakeholders as well as decision-making groups in terms of understanding the impacts of land use and land cover changes in Blantyre city. The results of this study could provide better information about the changes in land use quantified through the integrated application of GIS and remote sensing. In addition, it also provides the opportunity to understand the trends of changes in built-up areas as a result of driving variables. Furthermore, the results of this study will be an initial recent input for future research direction for interested groups within the discipline.

2. CHAPTER 2: LITERATURE REVIEW

2.1. Land Use and Land Cover Changes

The definition of land use and land cover has been used interchangeably in the land use research community because of the availability of many existing information systems. However, these two terms explain two different issues and meanings. Land cover refers to the observed biophysical cover on the earth's surface including vegetation, bare soil, hard surfaces, and water bodies. Whereas land use is the utilization of land cover type by human activities for agriculture, forestry, settlement, and pasture by altering land surface processes including biogeochemistry, hydrology, and biodiversity (Sugawara & Nikaido, 2014).

Land use and land cover changes currently is a prominent research topic on the global environmental change in as far as different disciplines in earth sciences are concerned. For instance, in meteorology issues to do with climate change are explained coherently with earth surface dynamics thus land use and land cover changes are of great precedence. Land use and land cover changes are caused by direct and indirect consequences of human activities on the environment to have a better life. One of the direct impacts of humans is population growth where its increase has effects on land use, especially in the developing world at longer time scales. According to (Lambin et al., 2003) it can also be caused by the mutual interactions between environmental and social factors at different spatial and temporal scales as land use and land cover change is a complex process.

Furthermore, land use and land cover changes have significant consequences on hydrology, air pollution, biodiversity, and global warming. On the same note about climate change, much less attention has been paid by policymakers to monitor, model, and manage the impacts of climate change on the dynamics of earth surface systems (Knight & Harrison, 2013). However, identifying the causes and impacts of land use and land cover change requires understanding both how people make land-use decisions and how specific environmental and social factors interact to influence these decisions. To understand the impacts of dynamic land use and land cover changes, the use of land-use change models

becomes an advantage since they provide information of land-use trajectories projecting for the future. Therefore, the ability of these models is important for better environmental management and land use planning.

2.2. Trends of Urban Growth

Economic development and population growth have triggered rapid changes to earth land use/land cover as a result of urbanization & industrialization in the last two centuries and there is every indication that the pace of these changes will accelerate in the future (Jat et al., 2017). Urban growth is the expansion of city areas concerning the increase in number and size of the settlement. Urban expansion heavily depends upon human desires for their betterment, need for better livelihood, facilities, and employment. The world is currently undergoing the largest wave of urban growth in history. The (UN Population Fund, 2020) recently reported that rapid population growth has been concentrated in towns and cities of the world. The report also projected that in just a few decades to come the vast majority of this growth will be observed in the developing world of Africa and Asia where urban growth is highly concentrated. This has been the case because cities offer a lot of opportunities such as jobs and sources of income unlike the case in rural areas, thus, they attracted a lot of people.

Land in Malawi is governed by the Land Act of 1965 and the Registered Land Act of 1967. The most significant urban sector challenges facing Malawi today are rapid urbanization and growing urban poverty. The rapid urbanization has led to a pressing housing demand that far exceeds the rate of new housing delivery. As a result, over 80% of the demand is met through informal housing, resulting in insecure tenure, poor quality of housing, and overcrowding. In terms of population sizes of urban centers in Malawi, the 2018 Population and Housing Census showed that the four cities: Lilongwe (989,318); Blantyre (800,264) Mzuzu (221,272); and Zomba (105,013) accounted for 76.7 percent of the total urban population in Malawi. Table 2 below summarizes the distribution of the urban population in Malawi.

Table 2. Urban population distribution, 2018 Malawi Population and Housing Census

Urban Area	Urban Population Size	Percentage of Total Urban Population
Zomba	105,013	3.8
Mzuzu	221,272	8.0
Blantyre	800,264	29.0
Lilongwe	989,318	35.9
Districts and other urban centers	700,625	23.3

In 1966, Blantyre was the prime city in Malawi with 109,461 people, seconded by Zomba, the then capital city, with only 19,666 inhabitants. With the transfer of the capital city from Zomba to Lilongwe, as part of a deliberate government policy to redistribute the urban population and implement spatially balanced development across the country, Lilongwe started to grow rapidly. The population grew from a mere 19,425 in 1966 to nearly 100,000 in a decade. By the year 2008, Lilongwe had overtaken Blantyre by about 7700 people. Lilongwe city continued to grow ahead of Blantyre city in 2018, registering a population of 989,318 against 800,264 in Blantyre. Blantyre city currently hosts almost 5 percent of the national population and has the highest population density in the country with 3328 people/km^2. Over 91 percent of the city residents are below the age of 45 years, and over 65 percent reside in informal settlements. Furthermore, in the past 10 years, a lot of urbanization has happened in Blantyre City.

2.3. Land use and land cover Changes in Malawi

In Malawi, urban areas refer to the four major cities of Blantyre, Lilongwe, Mzuzu, and Zomba and other towns and Bomas, and gazetted town planning areas. About 84 percent of the population in Malawi resided in the rural areas of the country in 2018 (National Statistics Office, 2019) Currently about 85% of Malawi's economy is dependent on agriculture with traditional farming. The growth of urban population from time to time, with an increase of migration of rural population to cities for a better life and the

encouraging land lease policy to investors, become important to study land use and land cover changes and their impacts in Malawi to design management and monitoring policies. There have been publications on land use and land cover changes in Malawi involving different regions and disciplines depending on the availability of data and tools to perform analysis. Most of the studies have focused on deforestation, the expansion of cultivated land to land degradation, river catchments and watersheds, natural ecosystems and forests as well as the associated consequences.

(K. G. Munthali & Murayama, 2011) reported an expansion of bare land at the expense of natural forest cover between 1990 and 2008 in Dzalanyama forest reserve, Lilongwe, the central region of Malawi. The study also investigated a series trend of land degradation activities such as deforestation triggered by underlying factors including population growth and poverty hence dwindling of natural forests coverage. From most of the recent studies related to this research topic, it is evident that population pressure is one of the major drivers of land use and land cover changes through destruction of forest and vegetation cover for agricultural and urban expansion as discussed by (M. Munthali et al., 2019) and (Pielke et al., 2007). Population growth coupled with migration from rural to cities leads to further expansion of urban areas at the expense of vegetation cover which is commonly practiced in most of the major cities in Malawi.

However, temporal aspects of remote sensing require that analysis on detection change should be performed using data that has been acquired at regular time intervals to track the changes in the phenomenon. While three map models of land cover and land use classification were used for (K. G. Munthali & Murayama, 2011) study in 18 years, this could not clearly indicate the underlying changes in the land cover classes as they were just a few. Temporal resolution is how often data is collected to detect changes in a phenomenon or an object over some time. To achieve high temporal analysis data this study generated four map models for the land cover/land use classes from the year 1990 to 2020 a study

period of 30 years at 10-year intervals from the study area hence generating more accurate and precise analysis about the changes.

2.4. Application of Remote Sensing and Geographic Information System (GIS) on Land Cover and Land Use Changes

Traditional data collection methods such as demographic data, census, and sample maps are not satisfactory for urban land use and land cover management (Maktav et al., 2005). Accurate information on land use and land cover changes, therefore, are of great importance to many groups. To achieve this information remotely sensed data integrated with geographic information systems can be used since it provides land cover information. Remote sensing refers to the science or art of acquiring information about an object or phenomena on the earth's surface without any physical contact with it (Chinkaka, 2020). Whereas, Geographic Information System (GIS) refers to a computer system for capture, input, analysis, storage, and output of digital spatial data. Remote sensing can be done through sensing and recording of either reflected or emitted energy and the information being processed, analyzed, and applied to a given problem. The data generated by remote sensing can be further digitized with GIS for planning, monitoring, and administering natural resources and social-economic environments.

Furthermore, Remote sensing is important for estimating levels and rates of deforestation, habitat fragmentation, urbanization, wetland degradation, and many other landscape-level phenomena. Such useful information can be then integrated into many regional to global-scale models, including those that are used to develop parameters for carbon fluxes and hydrological cycles. Following this, several applications of remote sensing for land use and land cover studies have shown the potential to map, monitor, analyze, and predict urban land use and infrastructure in the study area. Land use information in high thematic, temporal, and spatially accurate, derived from remotely sensed data, is an important condition for decision support of city planners, economists, ecologists, and resource managers. Generally, land use and land cover changes have a wide range of impacts on

environmental and landscape attributes including the quality of water, land and air resources, ecosystem processes, and functions. Therefore, the use of remote sensing data and analysis techniques integrated with GIS provides accurate, timely, and detailed information for detecting and monitoring changes in land use and land cover.

2.5. Image Classification

Image classification refers to the extraction of differentiated classes or themes, usually, land cover and land use categories, from raw remotely sensed digital satellite data (Weng, 2012). The resulting raster from image classification can be used to create thematic maps. Image classification using remote sensing techniques has attracted the attention of the research community as the results of classification are the backbone of environmental, social, and economic applications. Underlying factors such as; the characteristics of a study area, availability of high resolution remotely sensed data, ancillary as well as ground reference data, suitable classification algorithms, analyst's experience, and time constraint determines the quality of image classification. Generally, image classification approaches can be categorized into two, namely; supervised and unsupervised image classification techniques.

Unsupervised image classification algorithms are based on categorizing each pixel to unknown cluster centers and then moving from one cluster center to another. Whereas in the case of supervised image classification the analyst has previous knowledge about pixels to generate representative parameters for each land cover class of interest (Haq et al., 2020). For instance, the Maximum Likelihood classification, under the category of supervised classification, which is the most widely used method by taking into account spectral information of land cover classes. The maximum Likelihood supervised classification algorithm assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class (Mustapha et al., 2010). Each pixel is assigned to the class that has the highest probability.

The method of image classification used heavily affects the quality of information extracted from remote sensing data (C. H. Chen, 2007). This research topic used supervised image classification technique using Maximum Likelihood Algorithm since it provides more accurate and precise information from land cover classes as compared to Unsupervised Image Classification techniques. The Supervised Classification technique is a user-guided type of classification which requires the analyst to have prior knowledge of the spatial and spectral characteristics of the land cover classes. The main activities involved the classification of satellite datasets into a defined number and specified types of land cover classes and apply smoothing algorithms to refine the classification output.

2.6. Band Rationing

Band rationing means dividing the pixels in one band by the corresponding pixels in a second band. Sometimes differences in brightness values from identical surface materials are caused by topographic slope and aspect, shadows, or seasonal changes in sunlight illumination angle and intensity. Band rationing is one of the most common transforms applied to image data. Image rationing serves to highlight subtle variations in the spectral responses of various surface covers (F. Wang & Huang, 2009). By rationing the data from two different spectral bands, the resultant image enhances variations in the slopes of the spectral reflectance curves between the two different spectral ranges that may otherwise be masked by the pixel brightness variations in each of the bands.

The concept of spectral rationing used in this study was Normalized Difference Built-up Index (NDBI) as well as Normalized Difference Vegetation Index (NDVI).

3. CHAPTER 3: METHODOLOGY

3.1. Study Area

Blantyre district is located in the southern region of Malawi with a total area of about 2100km^2. Blantyre City is the oldest and second-largest city in Malawi. It was established by the Scottish missionaries in the 1870s and declared a planning area in 1897. It is the main commercial city hosting most of the private sector headquarters in the country. Particularly, Blantyre city is situated in the southeast of Blantyre district with a surface area of about 240km^2. Blantyre city comprises townships such as Ndirande, Machinjiri, Mbayani, Limbe, Chirimba, and others. Blantyre city comprises of two urban centers (satellite towns) namely; Limbe and Blantyre Town. Below is a map showing the location of Blantyre City.

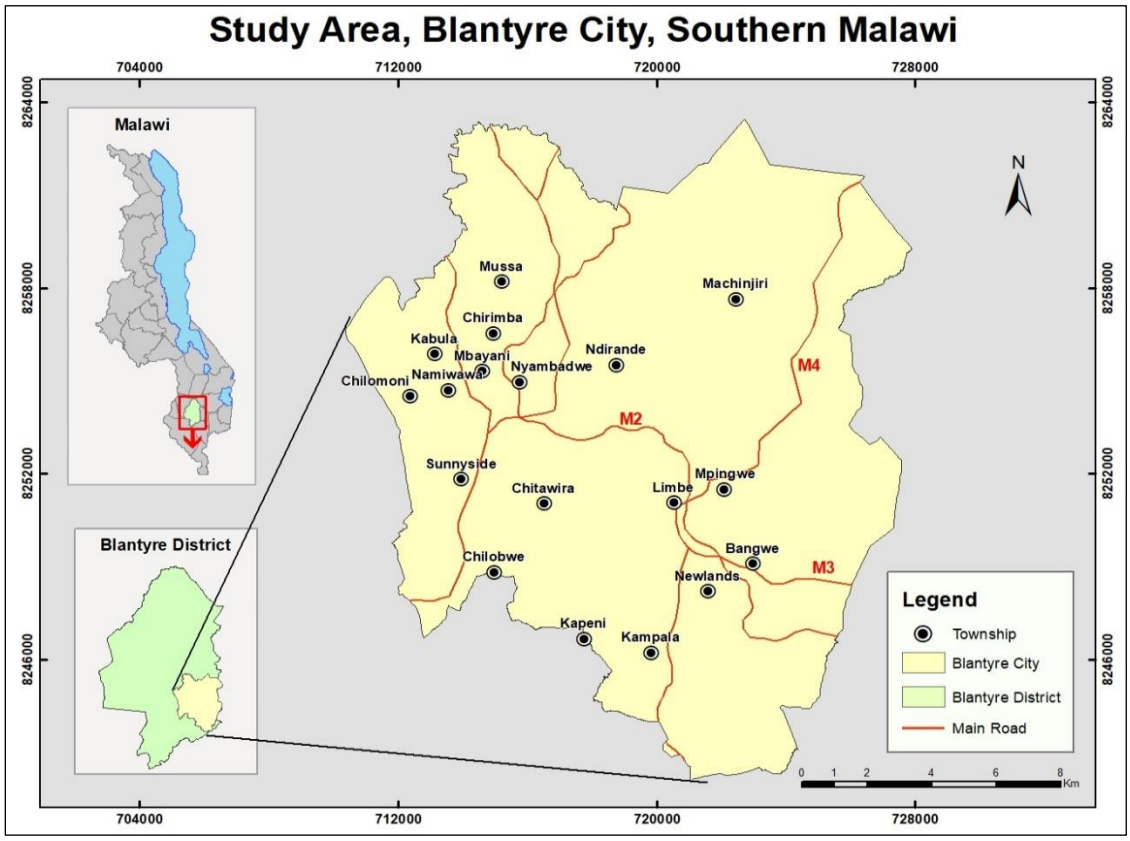


Figure 1. Study area map

The last three population censuses conducted by National Statistical Office (NSO) were in 1998, 2008, and 2018 respectively. Malawi Population and Housing Census report in 1998 said the population of Blantyre city was 502,053. After 10 years in 2008, the second census has also been conducted and the total population was 648,852 with an increase of about 29% from 1998. In 2018, the total population has become 800,264. The value increased by about 23% of the population of 2008 according to the Malawi Population and Housing Census (PHC) report by NSO. Table 3 below shows urban population trend for Blantyre City from 1998 to 2018.

Table 3. Urban Population trend, Blantyre City.

Year	Total Population
1998	502,053
2008	648,852
2018	800,264

Blantyre city stretches over a relatively gentle land with some noticeable slope change. The elevation variation in the area ranges from 780 meters in lowlands to 1,600 meters in hilly areas.

Blantyre city has been selected for this study not haphazardly or randomly but rather judgmental due to anticipated urban growth for the past decade. This has been the case to make meaningful conclusions from the research thus the study area. Blantyre City is an appropriate study area as it will facilitate the detection of significant changes in land use and land cover changes due to reported urbanization in the city.

3.2. Research Design

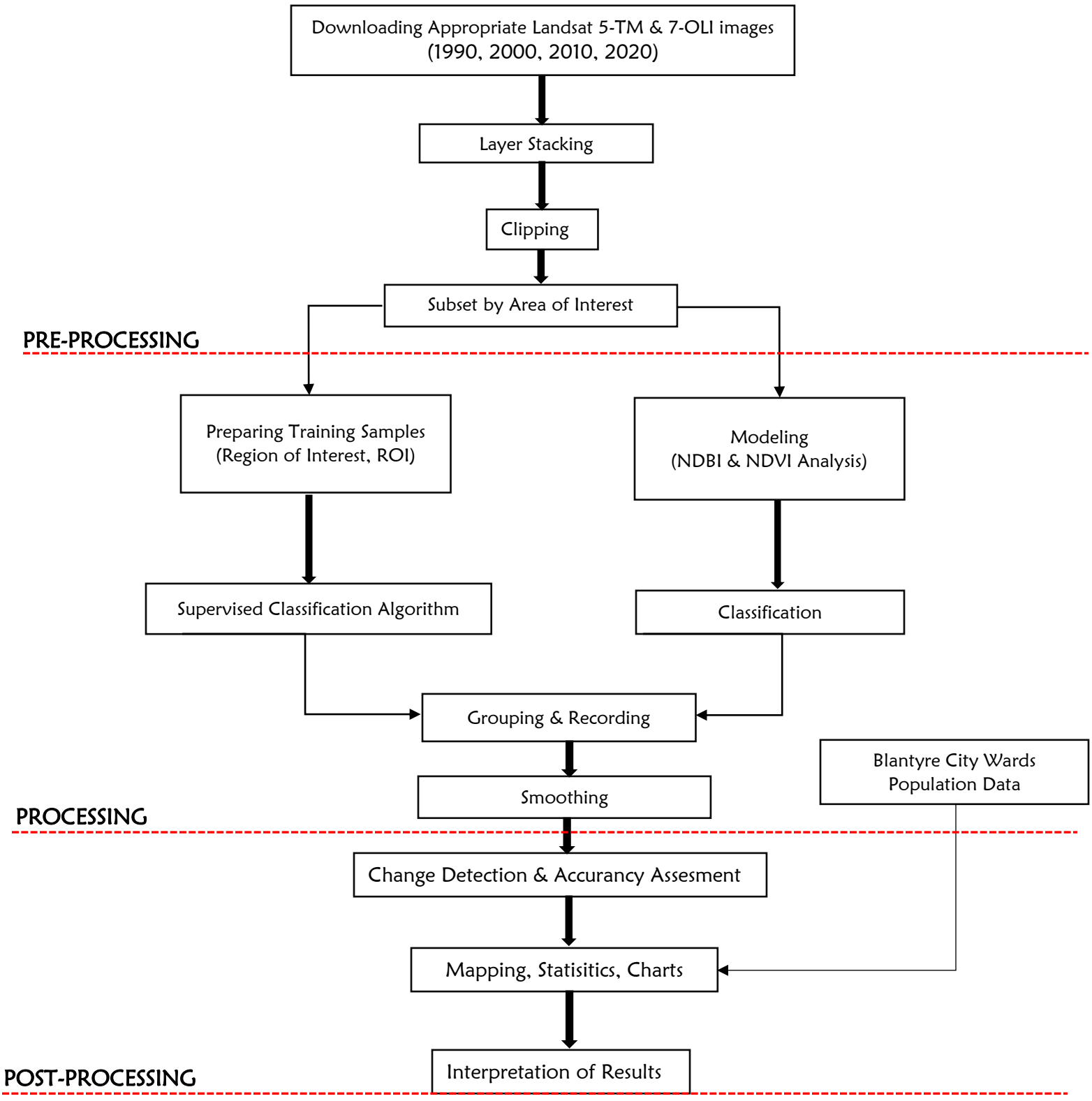


Figure 2. Methodology Flow Chart

3.3. Data and Processing

The datasets used in this study were; Landsat images, administrative boundaries for Malawi, and other shapefiles, in particular, roads. 30m spatial resolution satellite images of the study were obtained from USGS Earth Explorer under Landsat Collection 1 Level 1 dataset. The USGS provides some satellite image archives free of charge ranging from 1970s to present (Wulder et al., 2016). The vector shapefiles of the study area were downloaded from Malawi Spatial Data Application Portal (MASDAP) and www.diva-gis.org open-source website respectively. In this study, the satellite images downloaded were from the same season of the year and with the same spatial resolution for the study periods of 1990, 2000, 2010, and 2020. Thus, summer was the most conducive season for comparison of changes and patterns that occurred in the study time under discussion since other images collected in winter or spring, a couple of the images exceeds the acceptable 10% cloud cover percentage. The images were extracted to Tiff formats for processing and the details of image properties acquired are summarized in table 4 below.

Table 4. Metadata of the Satellite images used

Year	Satellite	Acquisition Date (yyyy, mm, dd)	Level of Processing	Path/Row	Spatial Resolution	Projection
1990	Landsat 5 TM	1990-10-08	Level 1	167/71	30m	WGS-1984 Zone 36S
2000	Landsat 5 TM	2000-09-01	Level 1	167/71	30m	WGS-1984 Zone 36S
2010	Landsat 5 TM	2010-12-18	Level 1	167/71	30m	WGS-1984 Zone 36S
2020	Landsat 8 OLI	2020-10-10	Level 1	167/71	30m	WGS-1984 Zone 36S

As illustrated in table 4 above this research used four satellite imagery data for a study period between 1990-2020, at 10-year intervals. The data were pre-processed, in this case, since all Landsat images downloaded were cloud-free, the atmospheric correction was not

necessary, in particular, cloud masking. Rather Radiometric Correction was run upon every image to convert Digital Number Values to Reflectance. The phrase "Digital Number" or "DN" refers to pixel values that have not yet been calibrated into physically meaningful units, whereas "reflectance" refers to the ratio of the radiation striking a surface to the radiation reflected off of it (De Keukelaere et al., 2018). Radiometric correction is done to calibrate the pixel values and correct for errors in the values. The process improves the interpretability and quality of remotely sensed data. Radiometric calibration and corrections are particularly important when comparing multiple data sets over some time (Humboldt State University, 2019). Sensor-specific information was used to carry out this calibration process. In the case of Landsat data, the metadata file archived with the image bundle downloaded contained the necessary information to perform Radiometric Calibration. ENVI 5.3 image processing software package has a radiometric calibration tool. Thus, Landsat data were converted directly to reflectance, without needing to first calculate radiance. Layer stacking was used to build a new multi-band file from georeferenced images of various pixel sizes, extents, and projections. The input bands were systematically resampled and reprojected to a common spatial grid. The process explained was conducted on each and every image dataset separately.

Landsat images cover large areas, for example, one Landsat 8 scene covers 185 km by 180 km. The raster file sizes were very large in terms of disk space (about 1GB) and processing can be time-consuming. Often the actual area of interest was much smaller. Therefore, the Blantyre City vector shapefile was used to subset Landsat images that only include the area of interest, that is, Blantyre City. This saved disk space and processing time. In ENVI Software Package, a tool referred to as Subset Data by ROI was used. This process created a new dataset that only contained Landsat image data subset.

Satellite bands were composed in different ways to identify surface features in the study area. For instance, True color composite is usually known as RGB 321 combination where band 3 reflects red color, band 2 reflects green and band 1 reflects blue color for Landsat 5 TM except for Landsat 8 OLI where true color composite corresponds to RGB 432. This was the case since different satellite sensors have different spectral properties. Another

composite called "false-color composite" which uses an RGB combination of 432 and 543 for Landsat 5TM and Landsat 8 OLI respectively were employed. In this band combination band 4 represents the NIR, band 3 belongs to red, and band 2 to green for Landsat 5 TM. Whereas, in Landsat 8 OLI, band 5 represents the NIR, band 4 belongs to red, and band 3 for green. False-color image band combination gives better visualization in identifying vegetation which looks red given Near Infrared (NIR), Red and Green bands RGB combination. Figure 3 below illustrates images of the study area generated using the false-color 432 (Landsat 5 TM) and 543 (Landsat 8 OLI) combination, where vegetation is seen as red and dark red, water correspond to shades of blue, while the built-up area is seen as cyan (light blue).

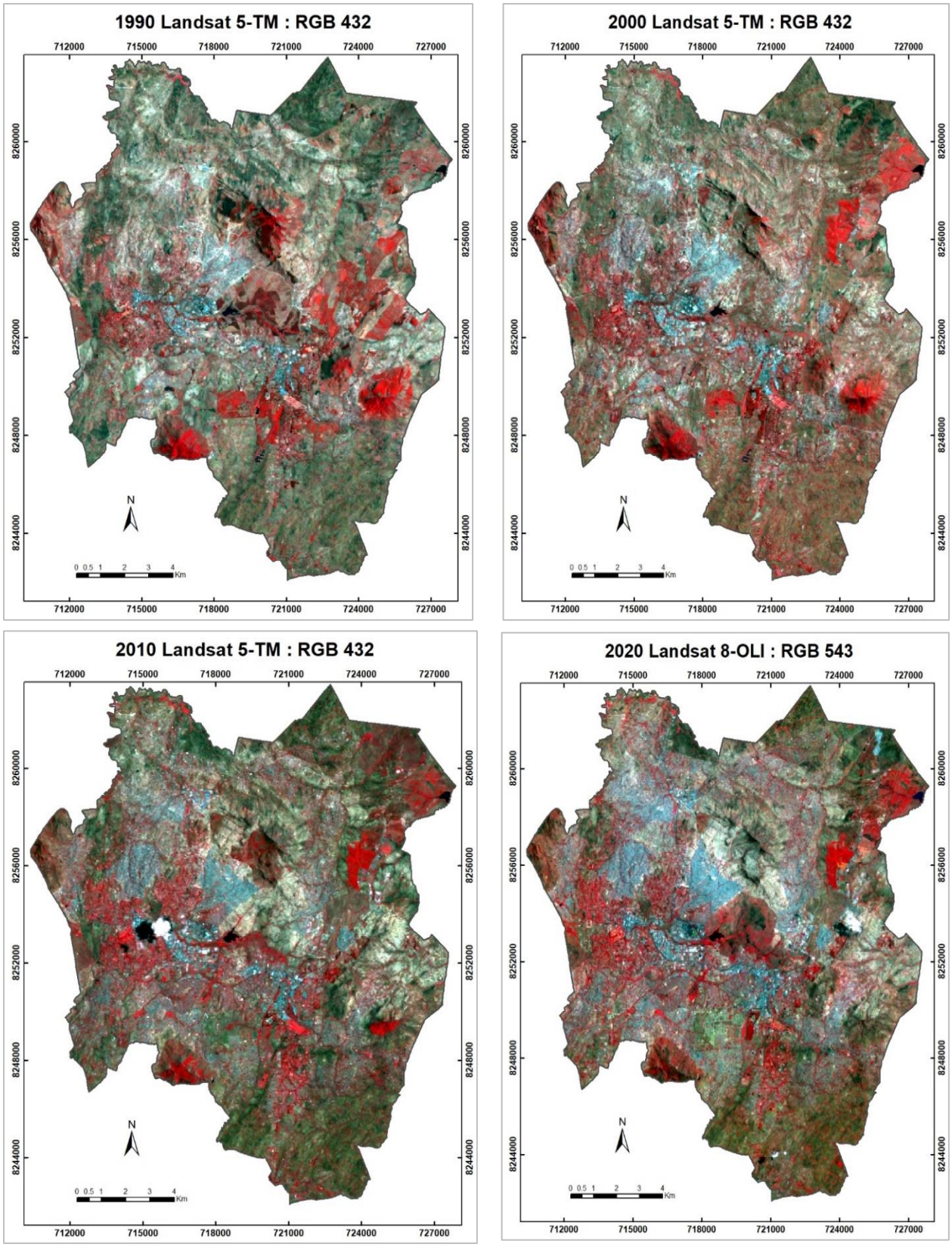


Figure 3. False Color Composites of the Landsat Images

3.3.1. Cover Classes Terminology

Before collecting training samples, the land cover classes were known to make the classification easier. Training samples also referred to as regions of interest (ROIs) were collected for each image for supervised image classification followed by post-classification smoothing algorithms to generate accurate and precise land cover maps for the study periods. Table 5 below summarizes the land cover classes that were used for supervised classification.

Table 5. Land cover classes nomenclature

Land Cover Class	Description
Built-Up Area	Consists of Urban, Industrial, commercial, and transport units, dump, and construction sites.
Bare Land	Open spaces with little or no vegetation, beaches, dunes sands, bare rocks, sparsely vegetated areas
Vegetation	Forests, Shrub and herbaceous vegetation association, Arable land, Permanent crops, Pastures, and Heterogeneous agricultural areas.
Water Bodies	Watercourses, dam areas,

Upon being clear that for each training area was defined as a class, polygons were drawn (that has to be closed, that is to say, no open ends) and ROI name was assigned (this is very similar to an onscreen digitizing procedure in a GIS). A sufficient number of points for each ROI were collected, so that it should be accepted by the classifier. Thus, this method, aimed for as many points as possible for each training area as long as the sample remains representative. Generally speaking, the more training pixels, the more accurate the results for a statistical classifier. However, this did not mean that ROI was constructed of an entire feature as this defeats the purpose of a representative area.

3.3.2. Image Classification

For this study, land cover maps were generated based on the pixel-based supervised classification through several processes. The first step was done using a collection of training samples for each land cover class which typically were representative of land cover classes explained earlier. These samples were collected based on the researcher's personal

experience and physiographical knowledge of the study area. Furthermore, image enhancement and false-color band composition were applied for better determination of land cover classes. Using these approaches about 80 training samples were collected for each Landsat imagery. The next step was performing the supervised image classification using the Maximum Likelihood Classifier through ENVI 5.3 image processing software. In this stage, post-classification smoothing procedures were used to improve the classification and neglect misclassified cells.

Finally, the accuracy assessment of the classified images was assessed by using the original Landsat images against the classification output image with aid of Confusion Matrix Tool in ENVI 5.3. For performing this analysis, randomly selected points were taken as references for each land cover map of 1990, 2000, 2010, and 2020.

3.3.2.1 Accuracy Assessment

Accuracy assessment is a general term for comparing classification results to geographical data that are assumed to be true, to determine the accuracy of the classification process. It is conducted by comparing a map created by using remote sensing analysis to a reference map based on different information sources such as original mosaic images and Google Earth Landsat image archives. Using the approach, an interpretation was then made of how close the newly produced map from the remotely sensed data matched the reference (source) map. (Rwanga & Ndambuki, 2017) reported that a variety of errors are encountered when evaluating an image classification and capturing remotely sensed data. Thus, evaluation of the accuracy of a classified image was done using an error matrix also referred to as a confusion matrix with aid of ENVI 5.3 Image processing Software.

Error Matrix is a square array of numbers laid out in rows and columns that expresses the number of sample units assigned to a particular category relative to the actual category as verified in the field. The columns normally represent the reference data, while the rows indicate the classification generated from the classified image. It also provides an excellent summary of the two types of thematic error that can occur, namely, omission and

commission. The error of omission refers to pixels in the reference map that were identified as something other than their "accepted" value. Whereas error of commission, on the other hand, refers to pixels that were incorrectly classified as a class in a row (Olofsson et al., 2014). Most of the classification accuracy measurements are derived from an error matrix.

In this study, a total of 60 test pixels for all land cover classes were collected for each separate image from the study period. In this case, the researcher has examined the test sample plots and assigned a class value to each. The accuracy assessment was conducted for each classification result. Thus, agreement and disagreement of the analysis was evaluated by using an error matrix and simple descriptive statistics.

3.3.3. Band Rationing

Band Ratios are used to enhance the spectral differences between bands and to reduce the effects of topography. This is done by Dividing one spectral band by another thus producing an image that provides relative band intensities. The image enhances the spectral differences between bands. ENVI Software Package can output band ratio images in either floating-point (decimal) format or byte data format. The floating-point format is the default. This study used the principle of band math/rationing to derive thematic models depicting built-up and vegetation patterns using NDBI and NDVI respectively

3.3.3.1. Normalized Difference Built-Up Index (NDBI)

The normalized difference built-up index (NDBI) has been useful for mapping urban built-up areas using Landsat Satellite data. The applicability of this index to the Landsat 5-TM and Landsat 8-OLI data was used during this study and as a method for built-up area extraction. This index highlights urban areas where there is typically a higher reflectance in the Shortwave-Infrared (SWIR) region, compared to the near-infrared (NIR) region. Formally, NDBI is given by the formula

$$NDBI = \frac{(\mathrm{SWIR} - \mathrm{NIR})}{(\mathrm{SWIR} + \mathrm{NIR})}$$

The NDBI was originally developed for use with Landsat TM bands 5 and 4. However, it will work with any multispectral sensor with a SWIR band between 1.55-1.75 μm and a NIR band between 0.76-0.9 μm thus the index was applied for all images downloaded in this study. Bands 5 and 6 of Landsat 8-OLI were used in the index as they fall within the required Near-Infrared and Shortwave-Infrared regions respectively for the given index.

3.3.3.2. Normalized Difference Vegetation Index (NDVI)

NDVI is a common and widely used remote sensing index. NDVI is calculated as the ratio between TOA reflectance of a red band around 0.66µm and a near-infrared (NIR) band around 0.86µm. The NDVI of a densely vegetated area returned positive pixel values, whereas water and built-up areas were represented by near-zero or negative values. Formally, NDVI is given by the formula;

$$NDVI = \frac{(\text{NIR} - \text{Red})}{(\text{NIR} + \text{Red})}$$

The NDVI tool was used to transform multispectral data into a single image band representing vegetation distribution. The NDVI (Normalized Difference Vegetation Index) values indicate the amount of green vegetation present in the pixel. Higher NDVI values indicate more green vegetation. Valid results fall between -1 and +1. In this case, bands 4 and 3 for Landsat 5-TM as well as bands 5 and 4 for Landsat 8-OLI were used in the index since they correspond to NIR and Red regions respectively.

3.3.4. Change Detection Analysis

The change detection analysis panel provides a rapid quantitative assessment of changes, allowing the researcher to generate evaluations of gains and losses, net change, persistence, and specific transitions both in the map and graphical form. It also provides a means of generalizing the pattern of trend between two land cover map transitions. In this study, land use and land cover maps of the study area obtained from image classification for the periods of 1990 and 2020 were used for the analysis. Based on the principle of land change analysis, maps of gains and losses, contributions to net change, transitions of land cover

classes between different categories, and spatial trend analysis were examined both in the map and graphical form.

Change Detection Statistics was used to compile a detailed tabulation of changes between two classification images, 1990 and 2020 classification outputs. The statistics report generated includes a class-for-class image difference, the analysis focused primarily on the initial state classification changes; that is, for each initial state class, the analysis identified the classes into which those pixels changed in the final state image. ENVI 5.3 Software reported changes as pixel counts, percentages, and areas. In addition, a special type of mask image (classification masks) that provides a spatial context for the tabular report was produced. The class masks are ENVI classification images with class colors matching the final state image, making it easy to identify not only where changes occurred but also the class into which the pixels changed.

3.3.5. Mapping deriving factors for Urbanization

People who live in cities are increasingly becoming the majority of the population. The majority of them live in developing countries, with an ever-increasing proportion in major cities. The majority of the world's largest cities are now located in developing countries, and they are expanding to unprecedented proportions. The urban population is increasing at a rate many times that of rural areas, either due to natural growth or a combination of factors. Since a city is the political, economic, social, and cultural hub of a given area, its degree of urbanization is linked to the quality of life and the long-term growth of local people. Urbanization is primarily influenced by anthropogenic factors such as human migration and socioeconomic practices.

In the maps below we see the distribution of population size and density that gives a clue as deriving factor urbanization of over Blantyre City as per wards.

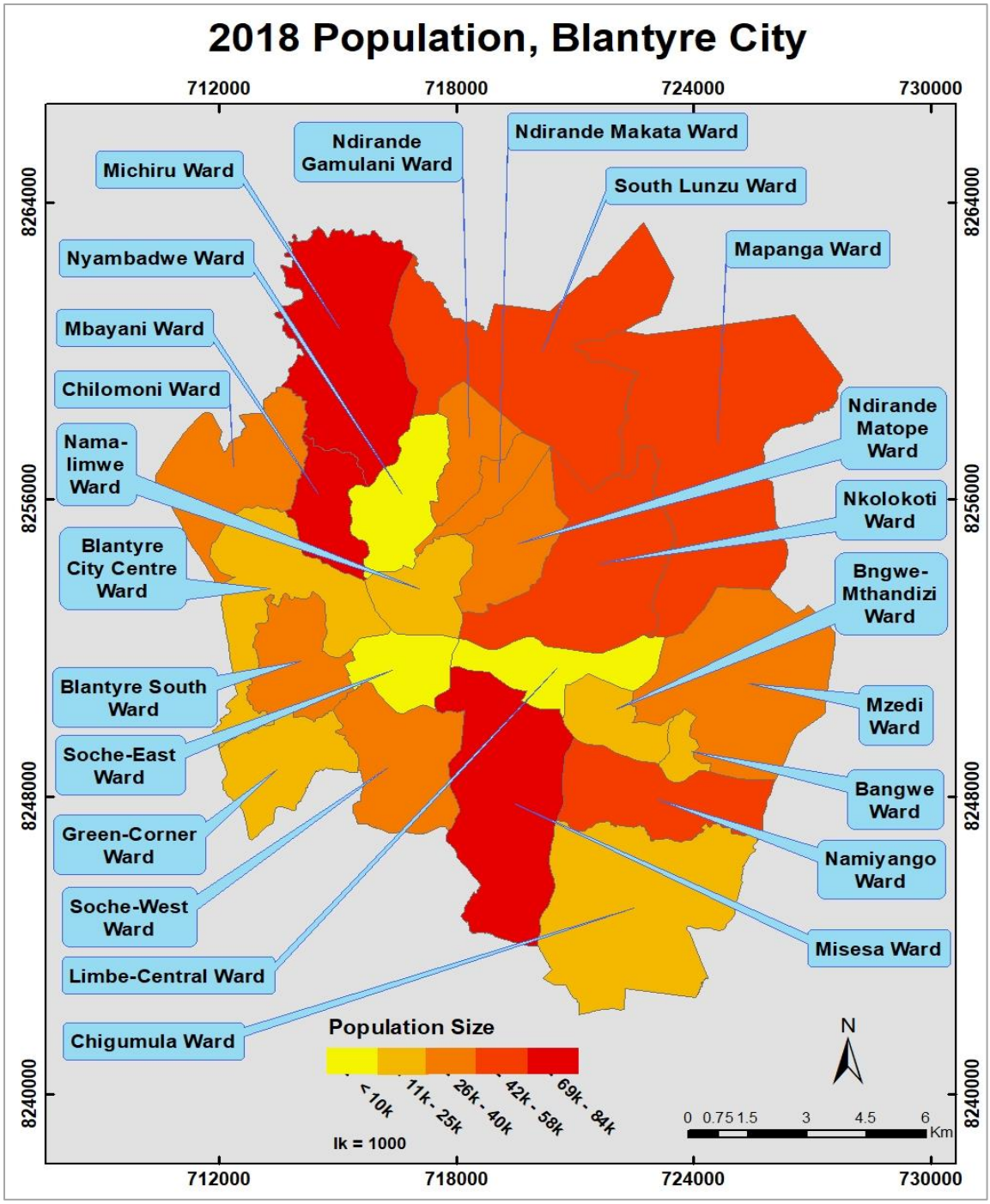


Figure 4. 2018 Population Distribution in Blantyre City Wards

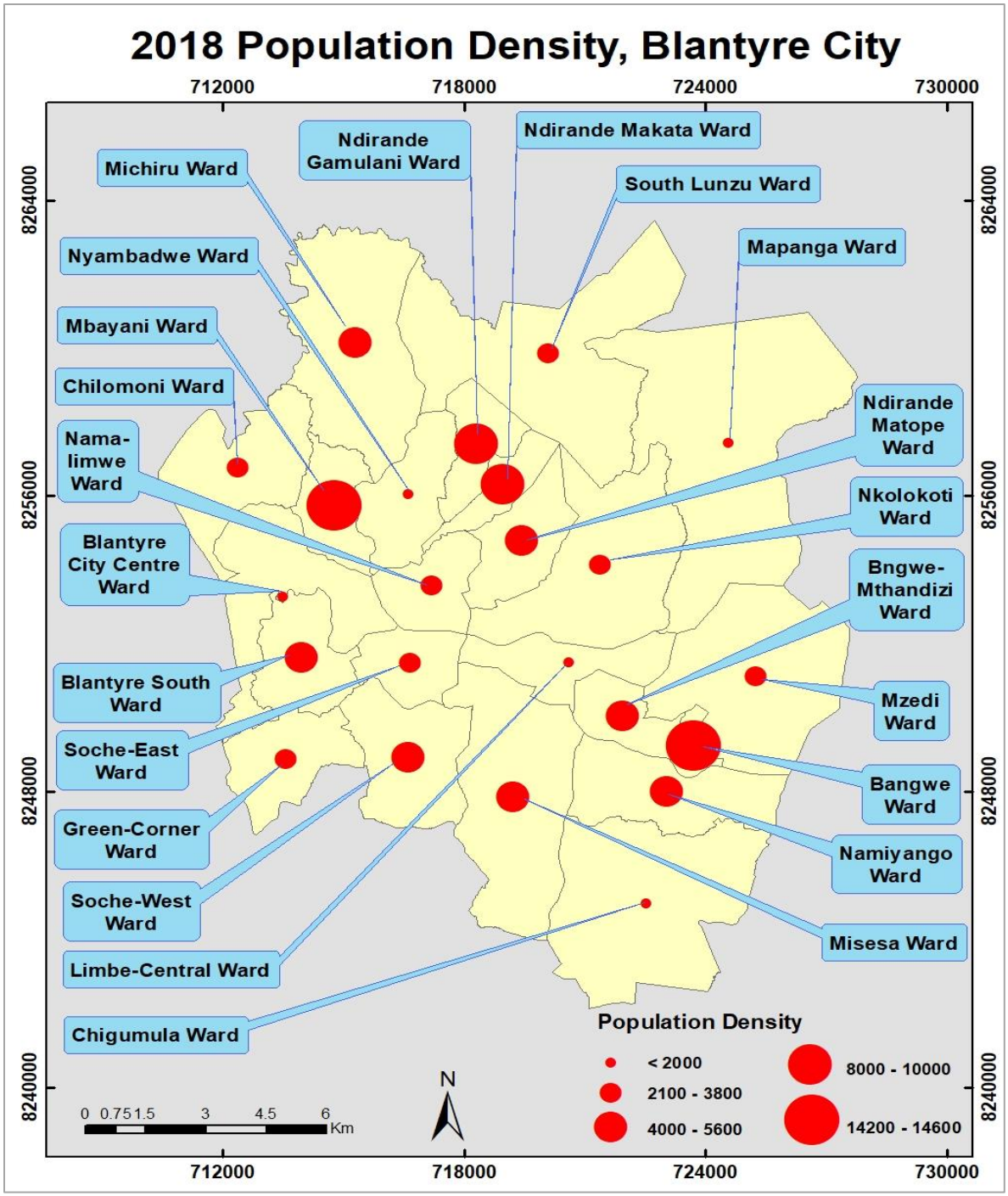


Figure 5. 2018 Population Density distribution in Blantyre City Wards

Based on these maps, the assumption is that the population dynamics are directly correlated to urbanization taking place in the study area.

4. CHAPTER 4: RESULTS

4.1. Land Cover Classification Outputs

The land cover maps generated after running a maximum likelihood supervised classification, as well as a post classification algorithm, are presented in figure 6 below.

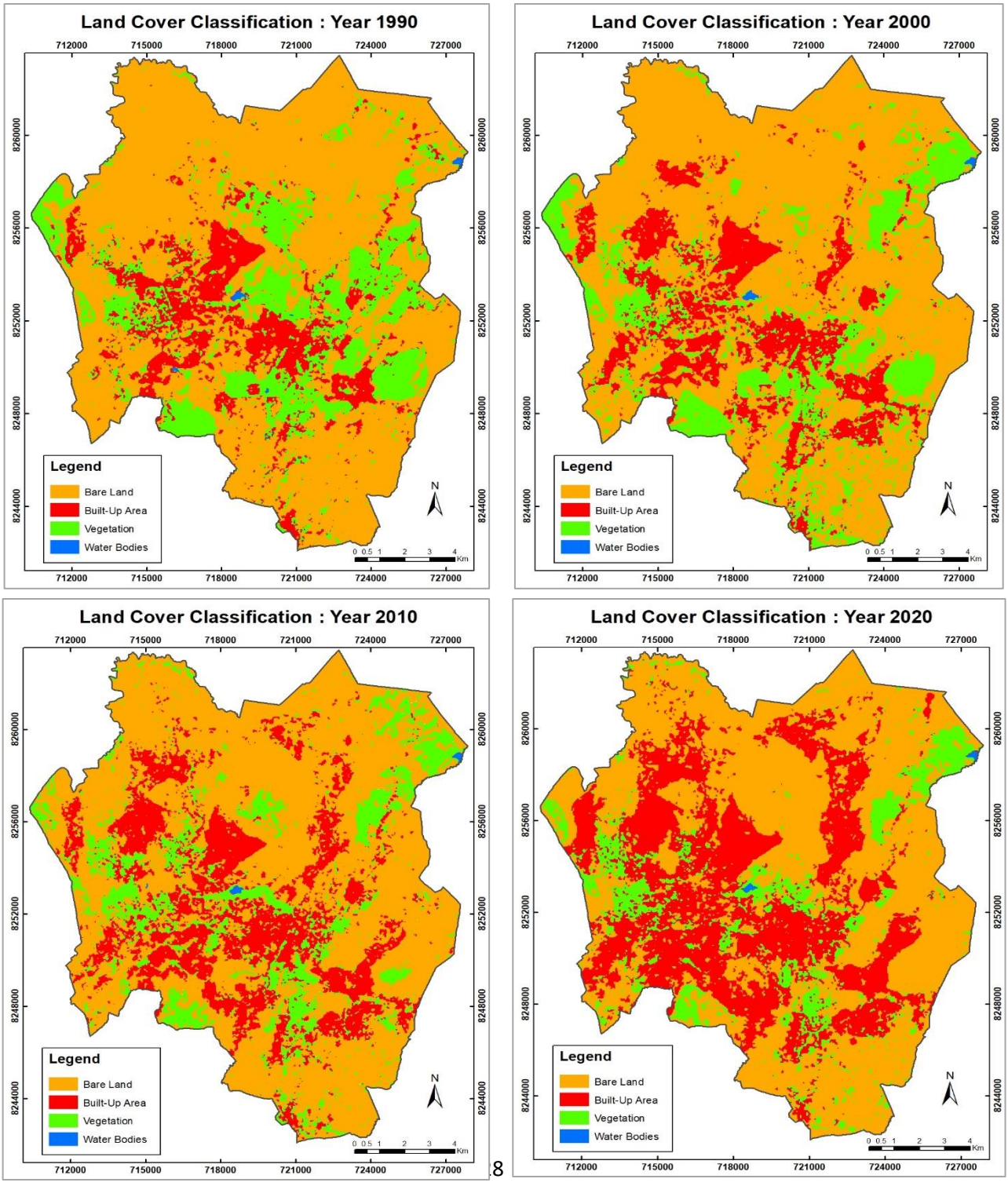


Figure 6. Land Cover Classification maps for Blantyre City from 1990-2020

Table 6 below summarizes the area extent for respective land cover classes of the classified images.

Table 6. Area Statistics of the land cover classes from 1990-2010

Land Cover Class	1990		2000		2010		2020	
	Area($km^{2)}$	%	Area($km^{2)}$	%	Area($km^{2)}$	%	Area($km^{2)}$	%
Built-Up Area	30.9582	12.87	39.3444	16.36	49.9401	20.76	76.4271	31.77
Vegetation	45.3636	18.86	40.1067	16.67	32.7762	13.63	26.1963	10.89
Bare Land	163.8873	68.13	160.8075	66.85	157.5765	65.51	137.6856	57.24
Water Bodies	0.3339	0.14	0.2844	0.12	0.2502	0.10	0.234	0.10
Total	240.543	100	240.543	100	240.543	100	240.543	100

Table 6 shows that built-up areas have increased from 12.87 percent of the study area in 1990 to 16.36 percent in 2000, 20.76 percent in 2010, and 31.77 percent in 2020. However, as seen in table 6, there has been a reduction in vegetation, bare land, and water bodies. Vegetation covered 18.86 percent of the study area in 1990, but it fell to 16.67 percent, 13.63 percent, and 10.89 percent in 2000, 2010, and 2020, respectively. According to figure 4 and table 6, bare land is the most dominant land cover class in the study region, but it has been steadily decreasing since 2000, from 66.85 percent to 65.51 percent in 2010 and 57.24 percent in 2020.

Because of the successive decrease of bare land and vegetation, built-up areas have dynamically increased in the study periods. This could be due to an increase in population growth associated with high demand for land and urban supplies. It is also visible from figure 4.0 and table 6.0 that water bodies have shown a decrease from 0.14 percent of the study area in 1990 to 0.12 percent in 2000 and again showed a negligible decrease of about 0.10 in 2010 and 2020. The small decrease in water bodies and change in built-up areas in 2010 could be related to the Mudi dam situated in Ndirande Township and some other existing dams due to siltation and the subsequent use of these surrounding areas for

agricultural activities. (Wolancho, 2012) had reported a similar study in other parts of Ethiopia and they showed that sediment delivered from agricultural watersheds threatened the life of both artificial and natural water reservoirs. Generally, built-up area, vegetation, and bare land were the most dominant land cover classes that have been observed in the study periods of 1990, 2000, 2010, and 2020, with some significant changes in the last 30 years as illustrated in the classification output maps and table 6.0. The graphical representations below show trends in land cover classes over the past 30 years.

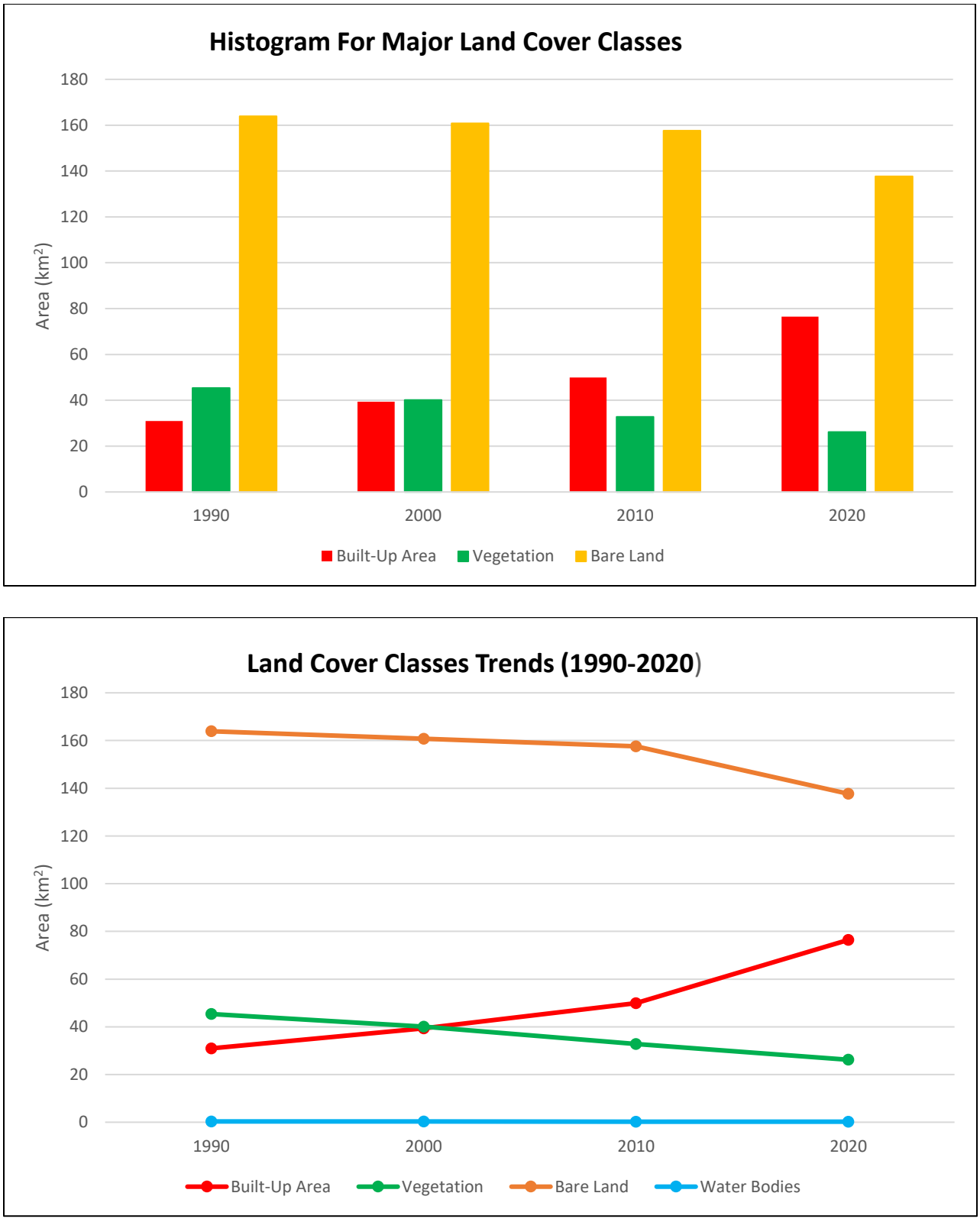
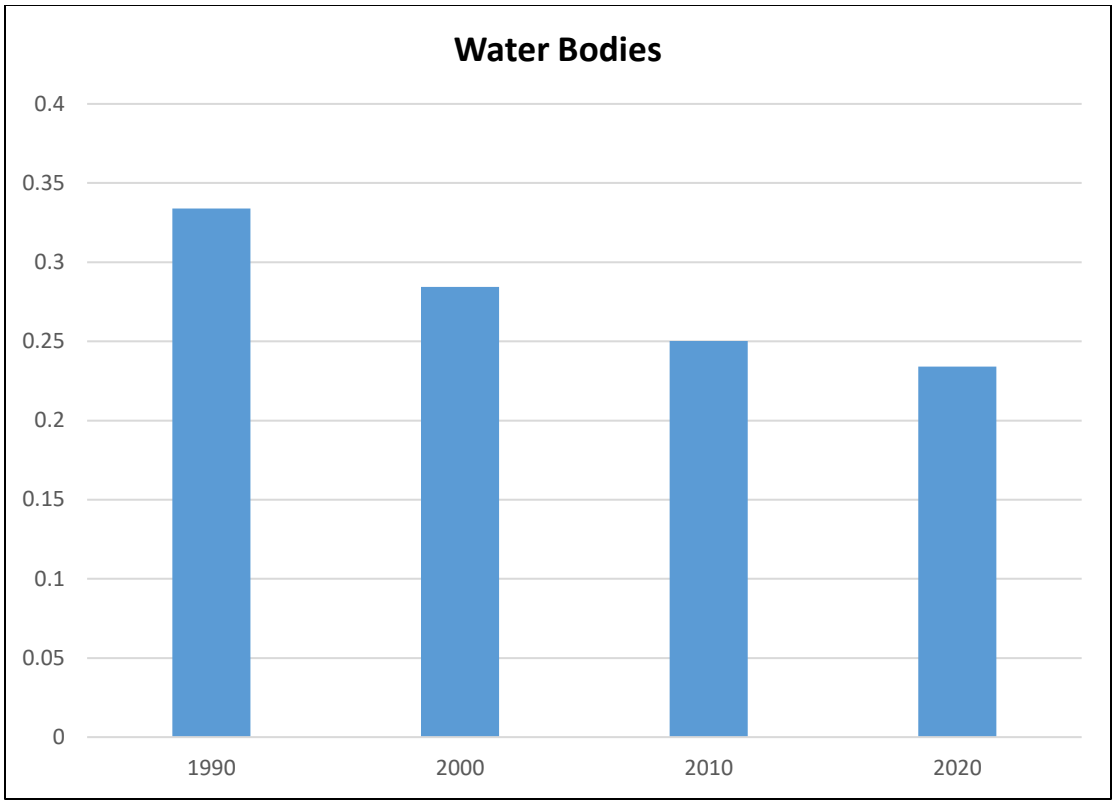


Figure 7. Graphical trends of Land Cover Classes for Blantyre City from 1990-2020



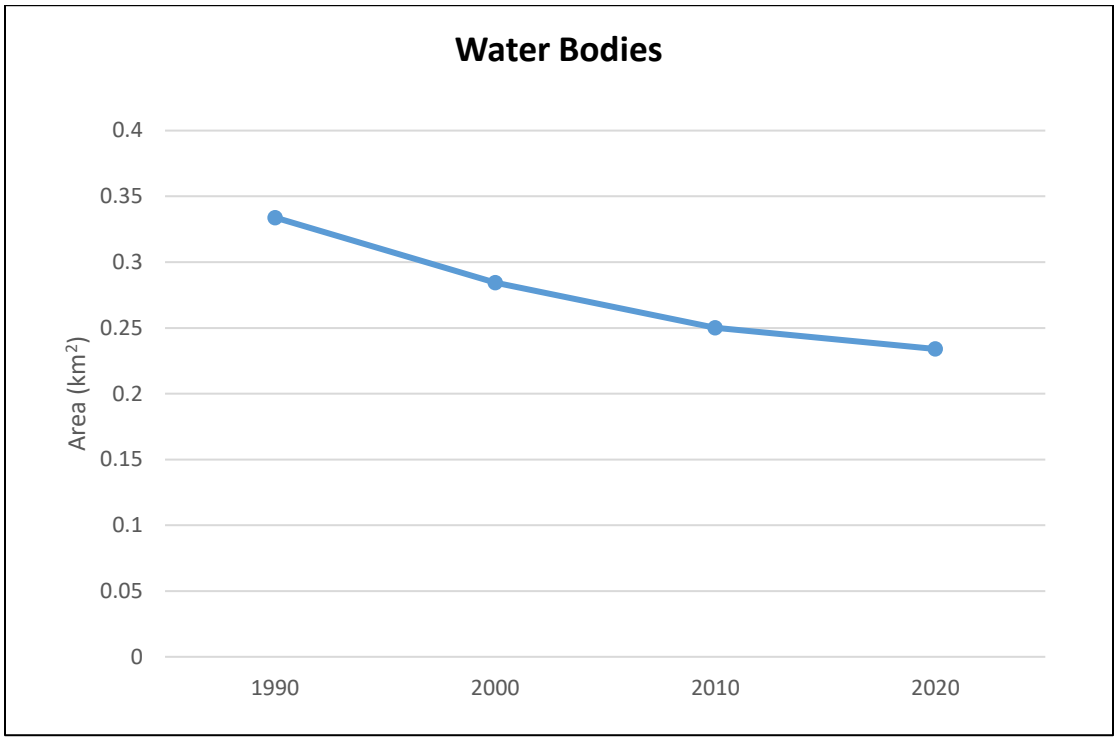


Figure 8. Graphical representations trend of Water bodies class for Blantyre City from 1990-2020

4.2. Accuracy Assessment of the Classification

Because classified land cover maps derived from remotely sensed images contain a variety of errors, it is the researcher's responsibility to identify and correct these errors so that the resulting land cover maps are reliable and easy to understand. Once the classified image has been inserted into a GIS and has become a source of knowledge for urban planners and researchers, accuracy evaluation should be performed because it restricts the classification results of remotely sensed imagery images. To do so, the accuracy of a classified map was evaluated and compared to reference data using an error matrix, as described in section 3.3.2.1, chapter 3. The accuracy assessment in this study was made using the original Landsat images against respective classification outputs for 1990, 2000, 2010, and 2020.

4.2.1 Overall Accuracy

It is calculated by dividing the total number of correctly identified pixels by the total number of reference pixels (that is, the count of the elements along the main diagonal). It displays the tabular error matrix's overall result. Overall accuracies conducted throughout this study were 95% in 1990 (table 7), 85% in 2000 (table 8), 93.33% in 2010 (table 9), and 91.67% in 2020 (table 10). The tables below summarize accuracy assessment conducted upon the classification maps.

Table 7. Confusion matrix for the land cover map of 1990

	Reference Map						
Classified Map	Land Cover Class	Built-Up Area	Vegetation	Water Bodies	Bare Land	Total	User's Accuracy
	Built-Up Area	15	0	0	3	18	83.33%
	Vegetation	0	15	0	0	15	100%
	Water Bodies	0	0	15	0	15	100%
	Bare Land	0	0	0	12	12	100%
	Total	15	15	15	15	60	
	Producer's Accuracy	100%	100%	100%	80%		
	Overall Accuracy	95%					
	Kappa Coefficient	0.9333					

Table 8. Confusion matrix for the land cover map of 2000

	Reference Map						
Classified Map	Land Cover Class	Built-Up Area	Vegetation	Water Bodies	Bare Land	Total	User's Accuracy
	Built-Up Area	15	1	0	5	21	71.43%
	Vegetation	0	14	3	0	17	82.35%
	Water Bodies	0	0	12	0	12	100%
	Bare Land	0	0	0	10	10	100%
	Total	15	15	15	15	60	
	Producer's Accuracy	100%	93.33%	80%	66.67%		
	Overall Accuracy	85%					
	Kappa Coefficient	0.8000					

Table 9. Confusion matrix for the land cover map of 2010

	Reference Map						
Classified Map	Land Cover Class	Built-Up Area	Vegetation	Water Bodies	Bare Land	Total	User's Accuracy
	Built-Up Area	13	0	0	2	15	86.67%
	Vegetation	1	15	0	1	17	88.24%
	Water Bodies	0	0	15	0	15	100%
	Bare Land	1	0	0	12	13	92.31%
	Total	15	15	15	15	60	
	Producer's Accuracy	86.67%	100%	100%	80%		
	Overall Accuracy	93.33%					
	Kappa Coefficient	0.9111					

Table 10. Confusion matrix for the land cover map of 2020

	Reference Map						
Classified Map	Land Cover Class	Built-Up Area	Vegetation	Water Bodies	Bare Land	Total	User's Accuracy
	Built-Up Area	15	0	0	3	18	83.33%
	Vegetation	0	15	0	1	16	93.75%
	Water Bodies	0	0	15	0	15	100%
	Bare Land	0	0	0	11	11	100%
	Total	15	15	15	15	60	
	Producer's Accuracy	100%	100%	100%	73.33%		
	Overall Accuracy	91.67%					
	Kappa Coefficient	0.8889					

4.2.1.1 User's Accuracy

The number of correctly categorized pixels in each class (class) divided by the total number of pixels in that category of the classified image is referred to as users' accuracy (row total). It denotes the likelihood that a pixel categorized into a particular category on the ground corresponds to that category.

Results of user's accuracy in this study showed that in 1990 minimum class accuracy was 83.3%, which was the built-up area, and the maximum were vegetation, water bodies, and bare land classes with an accuracy of 100% as presented in table 7 above. In 2000, the class accuracies range from 71.43% to 100% whereas, in the period 2010, it ranges from 83.33% to 100%, and lastly in 2020 it ranges from 86.67% to 100% as indicated in tables 8, 9, and 10 respectively. The lowest values of class accuracies were misclassified due to spectral property similarities among other land cover classes. In addition to this, the spatial resolution of Landsat data could influence the image classification. High spatial resolution imagery from satellite sensors such as IKONOS and QuickBird, according to (Zhou et al., 2009), becomes more reliable and accurate for detailed urban land cover mapping at very fine scales.

4.2.1.2 Producer's Accuracy

Producer's accuracy refers to the number of correctly classified pixels in each class (category) divided by the total number of pixels in the reference data to be of that category (column total). This value represents how well reference pixels of the ground cover type are classified. As showed in table 8, bare land was significantly misclassified as compared to the other land cover classes over the study periods. Built-up areas had the lowest producer's accuracy of 86.67%. The lowest values for built-up areas were misclassified due to the similar spectral properties of different land cover classes such as bare lands and vegetation

4.3. Normalized Difference Vegetation Index

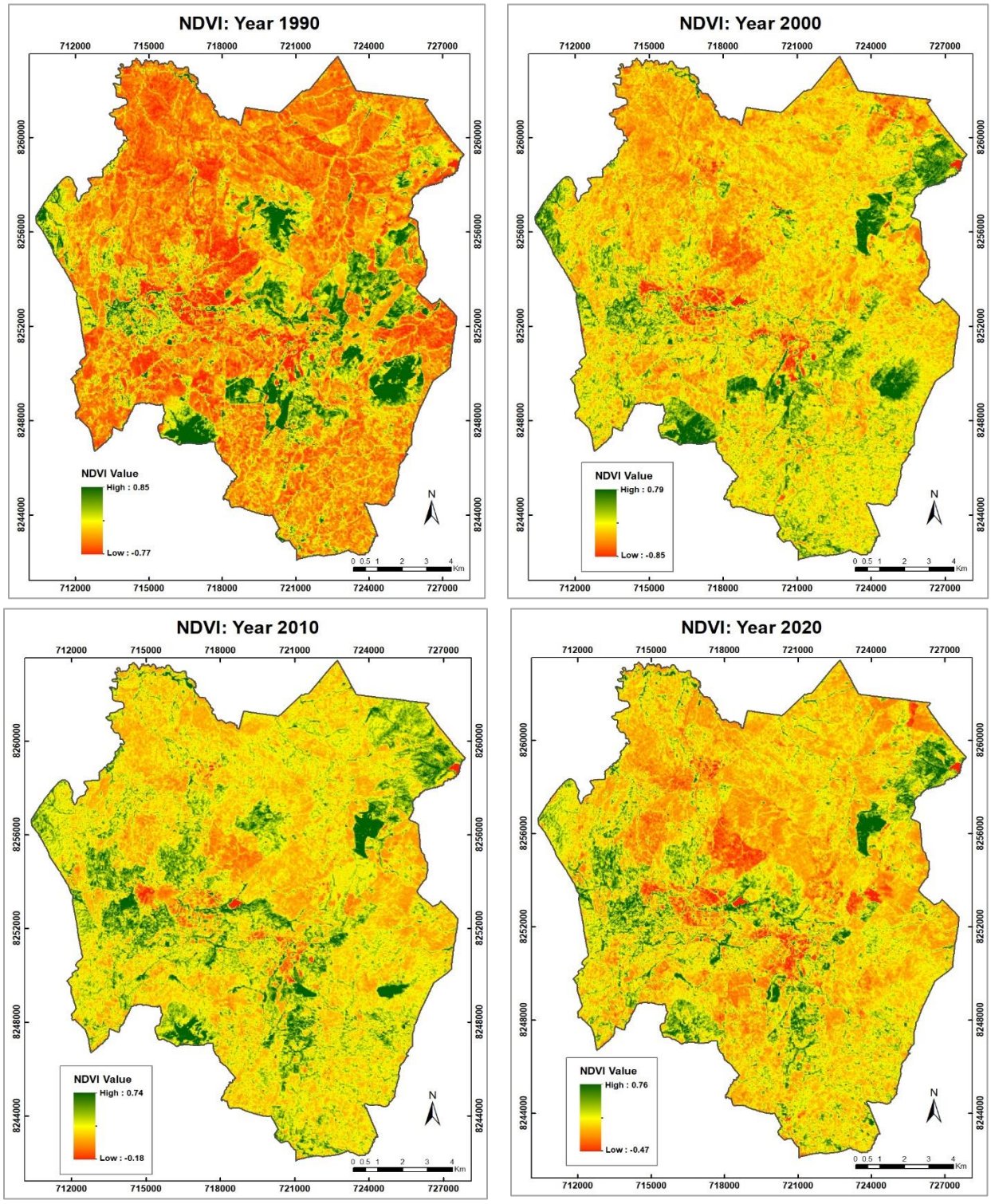


Figure 9. Normalized Difference Vegetation Index (NDVI) for Blantyre City from 1990-2020

Table 11. NDVI Values (Low and High) 1990-2020

	NDVI Value	
Year	Low	High
1990	-0.77	0.85
2000	-0.85	0.79
2010	-0.58	0.74
2020	-0.47	0.76

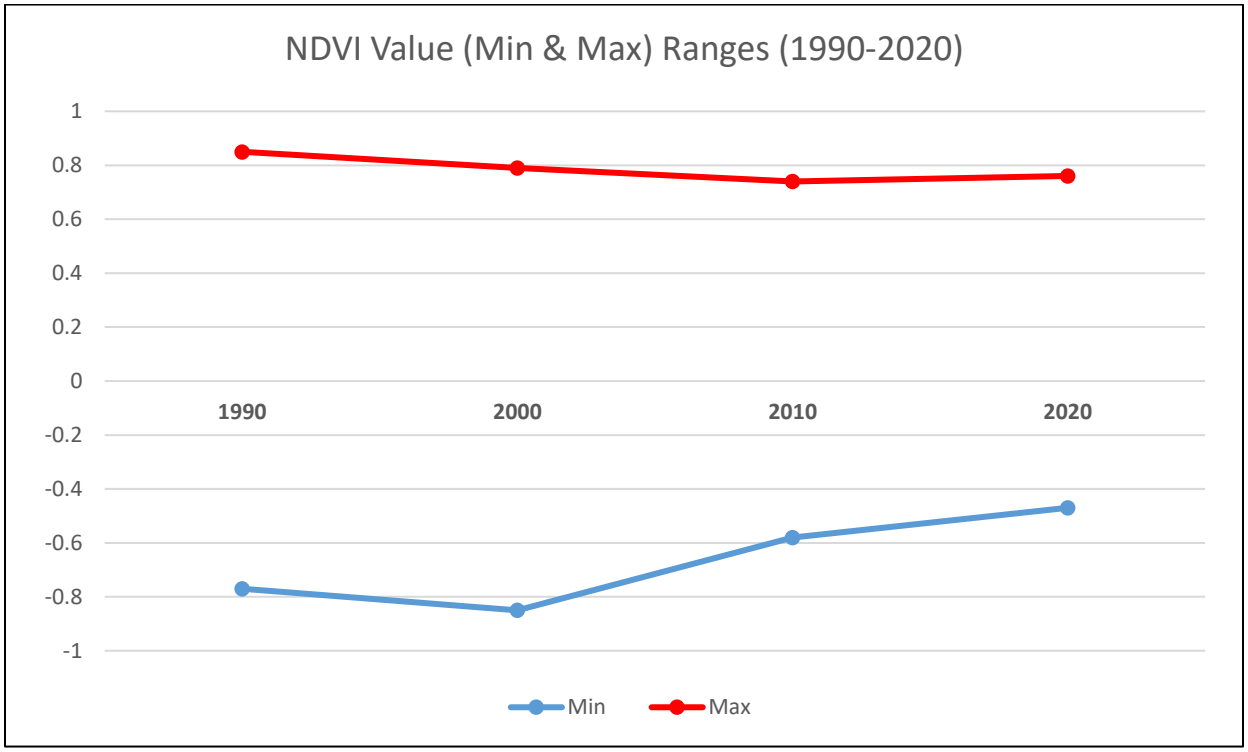


Figure 10. Normalized Difference Vegetation Index (NDVI) graphical trends for Blantyre City from 1990-2020

Satellite sensors that monitor wavelengths of light absorbed and reflected by green plants are used in remote sensing phenology studies. Plant leaves contain pigments that highly absorb visible (red) light wavelengths. Near-infrared light, which is invisible to human eyes, is reflected by the leaves themselves. Many satellite sensors monitor red and near-infrared light waves reflected by land surfaces. Raw satellite data about these light waves were converted into vegetation indices using mathematical formula (NDVI). For each image element, a vegetation index is an indicator that describes the greenness, relative density, and health of the vegetation.

The NDVI scale runs from +1.0 to -1.0. NDVI values range from -1 to 0 represent Water bodies, -0.1 to 0.1 represent Barren rocks, sand, or snow. Moderate NDVI values correspond to sparse vegetation, such as shrubs and grasslands, or senescing crops (approximately 0.2 to 0.5). High NDVI values (approximately 0.6 to 0.9) indicate dense vegetation, such as that found in temperate and tropical forests, or crops at the height of their growth cycle. The slight increase trend for the graph representing minimum NDVI values recorded for the four study periods implies a decrease in moisture and water content on the surface across the study area. Whereas, a slight decrease trend for the graph representing maximum NDVI values recorded for the four study periods implies that there has been a depletion in vegetation cover thus the maximum NDVI value exhibited an overall decreasing trend over time. Despite that, there was a slight increase in Maximum NDVI value to 0.76 in 2020 from 0.74 in 2010.

4.4. Normalized Difference Built-up Index

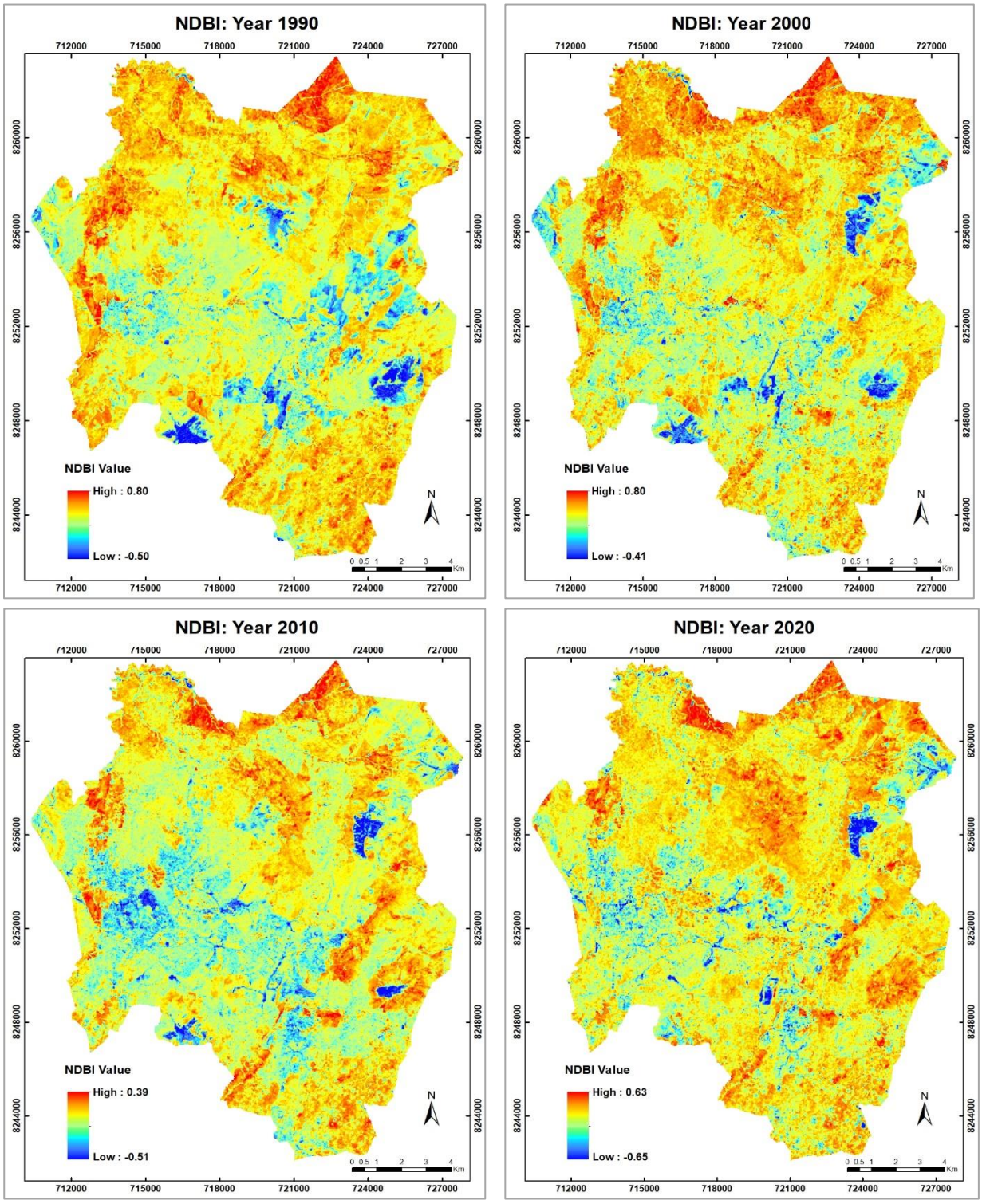


Figure 11. Normalized Difference Built-Up Index (NDBI) for Blantyre City from 1990-2020

Also, the Normalized Difference Build-up Index value lies between -1 to +1. A negative value of NDBI represents water bodies whereas a higher value represents build-up areas. NDBI value for vegetation is low.

4.5. Land cover changes of Built-up areas

The growth of built-up areas has been influenced by the increase in infrastructure development of Blantyre City over time. The study's main goal was to determine and examine the spatial extents of built-up areas over the four-time periods. To accomplish this, land use and land cover maps of built-up and non-built-up areas were reclassified, as seen in figure 12 below. As shown in table 12, built-up areas accounted for 12.87% of the total study area in 1990. Built-up areas increased slightly from 16.36% percent in 2000 to 20.76% in 2010. Finally, in 2020, it had hit 31.77% of the total area exhibiting a rapid change from 1990.

Table 12. Built and non-built-up areas between 1990 – 2020

Land Cover Class	1990		2000		2010		2020	
	Area($km^{2)}$	%	Area($km^{2)}$	%	Area($km^{2)}$	%	Area($km^{2)}$	%
Built-Up Area	30.9582	12.87	39.3444	16.36	49.9401	20.76	76.4271	31.77
Non-Built-Up Area	209.5848	87.13	201.1986	83.64	190.6029	79.24	164.1159	68.23
Total	240.543	100	240.543	100	240.543	100	240.543	100

Owing to the corresponding urban growth as well as the conversion of land cover classes over the various study times, the study area has seen a spatial increase of different land use and land cover classes such as built-up areas. The reclassified images in figure 12 below revealed a dramatic shift in land cover from non-built-up to built-up areas.

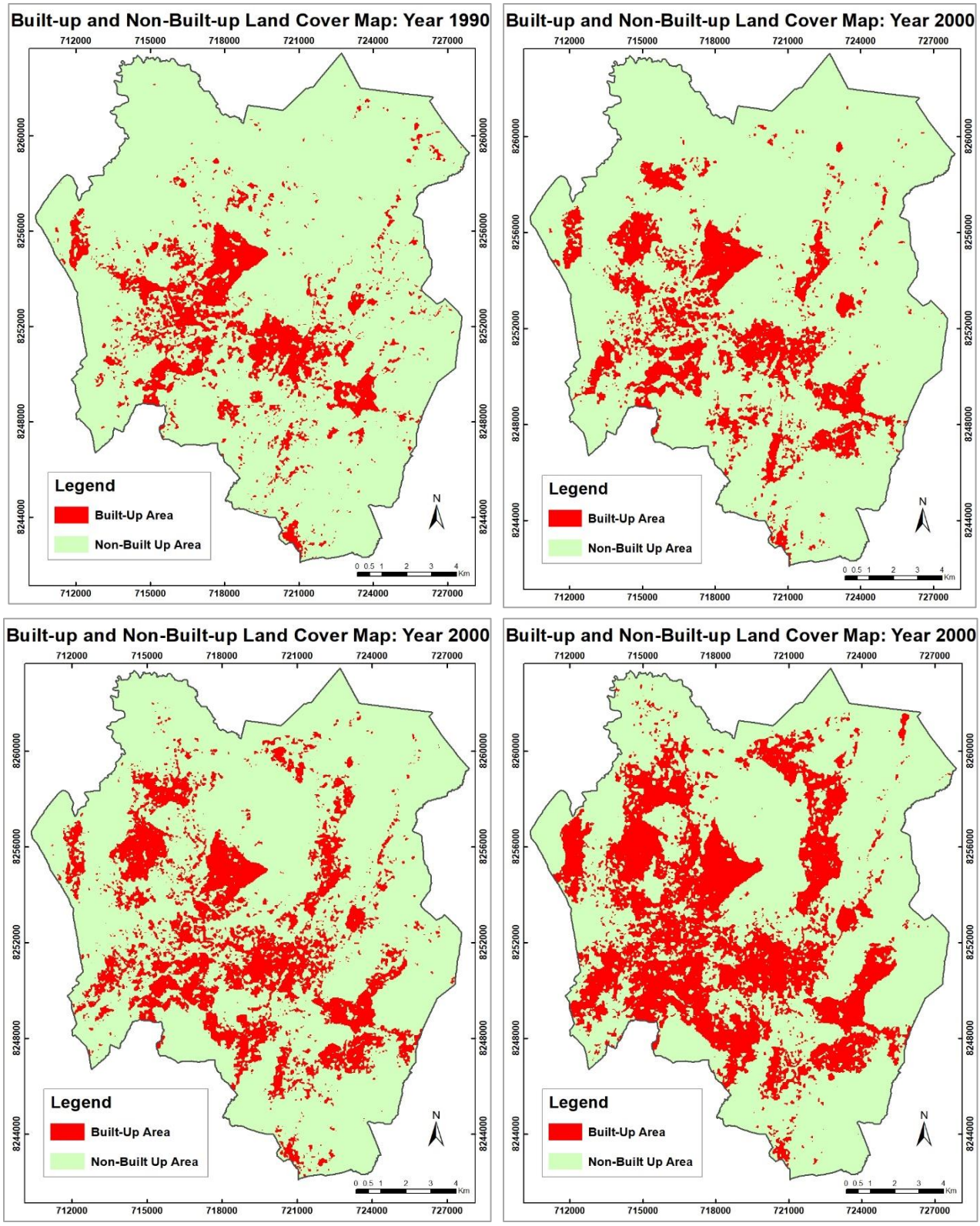


Figure 12. Built-up and Non-built-up areas Land cover maps for 1990-2020 respectively

4.6. Change Detection Analysis

Change Detection Statistics tool was used to compile a detailed tabulation of changes between two classification images (1990 and 2020). the analysis focused primarily on the initial state classification changes; that is, for each initial state class, the analysis identifies the classes into which those pixels changed in the final state image. Table 13 below gives an account of the transitions in land cover classes from 1990 to 2020 complementary to masked classification images illustrated in figure 14 generated using change detection tool in ENVI 5.3.

Table 13. Land Cover class transitions from the initial state (1990) to the final state (2020)

	Initial State (1990)						
Final State (2020)	Land Cover Class	Vegetation	Built-Up	Water Bodies	Bare Land	Row Total	Class Total
	Vegetation	11.49	2.10	0.09	12.51	26.19	26.20
	Built-Up	6.58	24.38	0.01	45.44	76.41	76.43
	Bare Land	27.28	4.47	0.01	105.90	137.66	137.69
	Water Bodies	0.01	0.00	0.22	0.00	0.23	0.23
	Class Total	45.36	30.96	0.33	163.90		
	Class Changes	33.88	6.58	0.11	58.00		
	Image Difference	-19.17	45.47	-0.10	-26.21		

The "Class Total" row shows the total surface area in square kilometers (km^2) in each initial state class. The "Row Total" column shows a class-by-class summary of all the final state surface areas that fell into the initial state classes. The "Class Changes" row shows the total surface area that changed class. The "Image Difference" row shows how a class has either grown or shrunken whereby positive values mean to gain and negative values mean loss.

From the table above there have been losses in vegetation, bare land and water bodies over the past three decades, a total surface area of 19.17km^2 for vegetation has been lost, 26km^2 for bare land was lost as well, and lastly, water bodies had shrunken by 0.1km^2. There has been tremendous growth in the built-up area, and from the table above it grew by 45.47km^2.

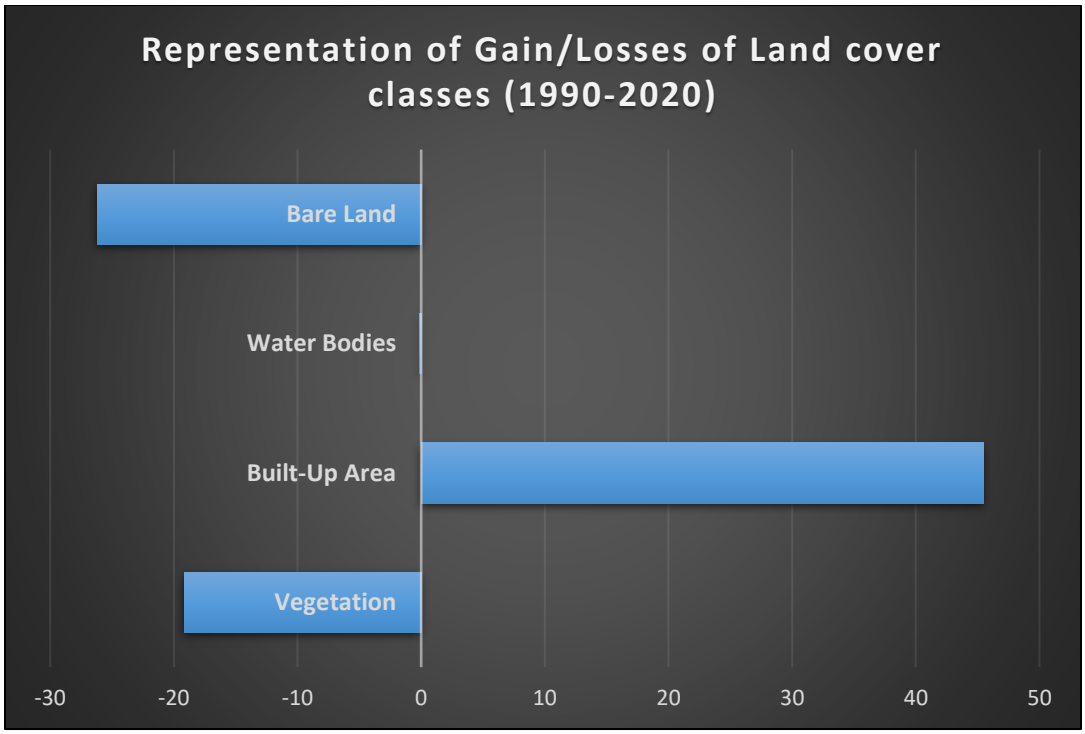


Figure 13. Gains and losses of the land cover classes from 1990-2020.

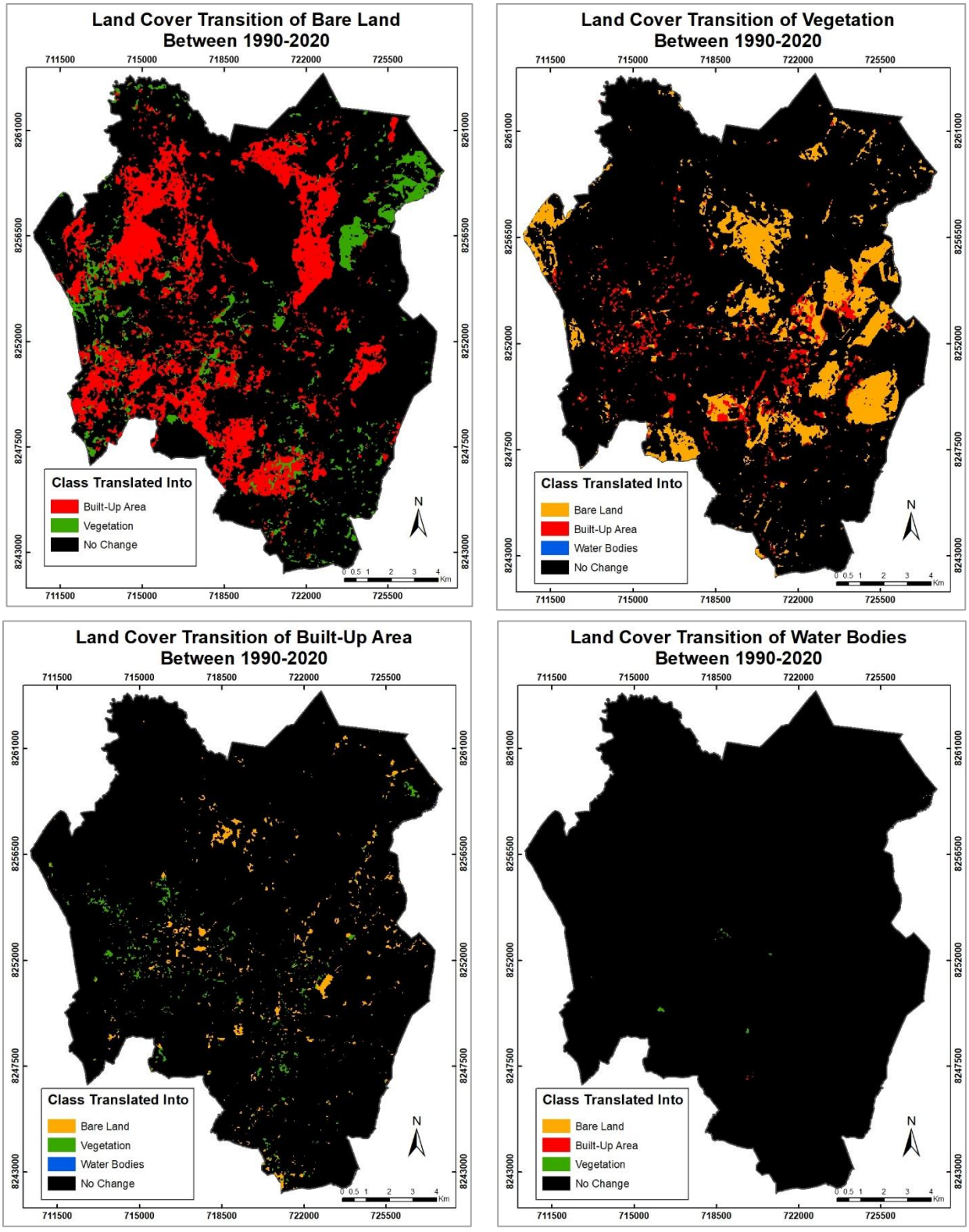


Figure 14. Land Cover Classes transition maps of Bare Land, Vegetation, Built-Up Area and Water Bodies between 1990-2020

From figure 14 above, with visual interpretation, it is evident that a lot of bare land area from 1990 has translated into built-up area and vegetation to a smaller extent. This manifests a tremendous growth of built-up facilities and reduction of bare land in Blantyre City over the past three decades. A considerable translation of surface area for vegetation to bare land as well has been highlighted in the land cover transition map for vegetation. This implies that there have been numerous deforestations of natural forests and habitats thus exposure of previously vegetative areas into bare lands. This has a lot of consequences as far as biodiversity is concerned as the environment is degraded. There has been an insignificant transition in the built-up areas over the past 30 years in the study area, this implies that most of the built-up facilities were permanent, however, a few of built-up areas into 1990 had translated into vegetation and bare lands. This could be associated with economic developments as well as deagglomeration where some built-up infrastructures might have been reallocated. The transition of water was negligible due to the smaller portion of water bodies over the study area; however, it can be depicted that some of the water bodies translated into vegetation and built-up area. This shows that there has been depletion of water bodies due probably due to human and industrial activities in Blantyre City.

4.6.1. Land Cover Classes Distribution by 2050

Below is the graphical representation of the land cover classes projected to 2050 based on trends from 1990 -2020

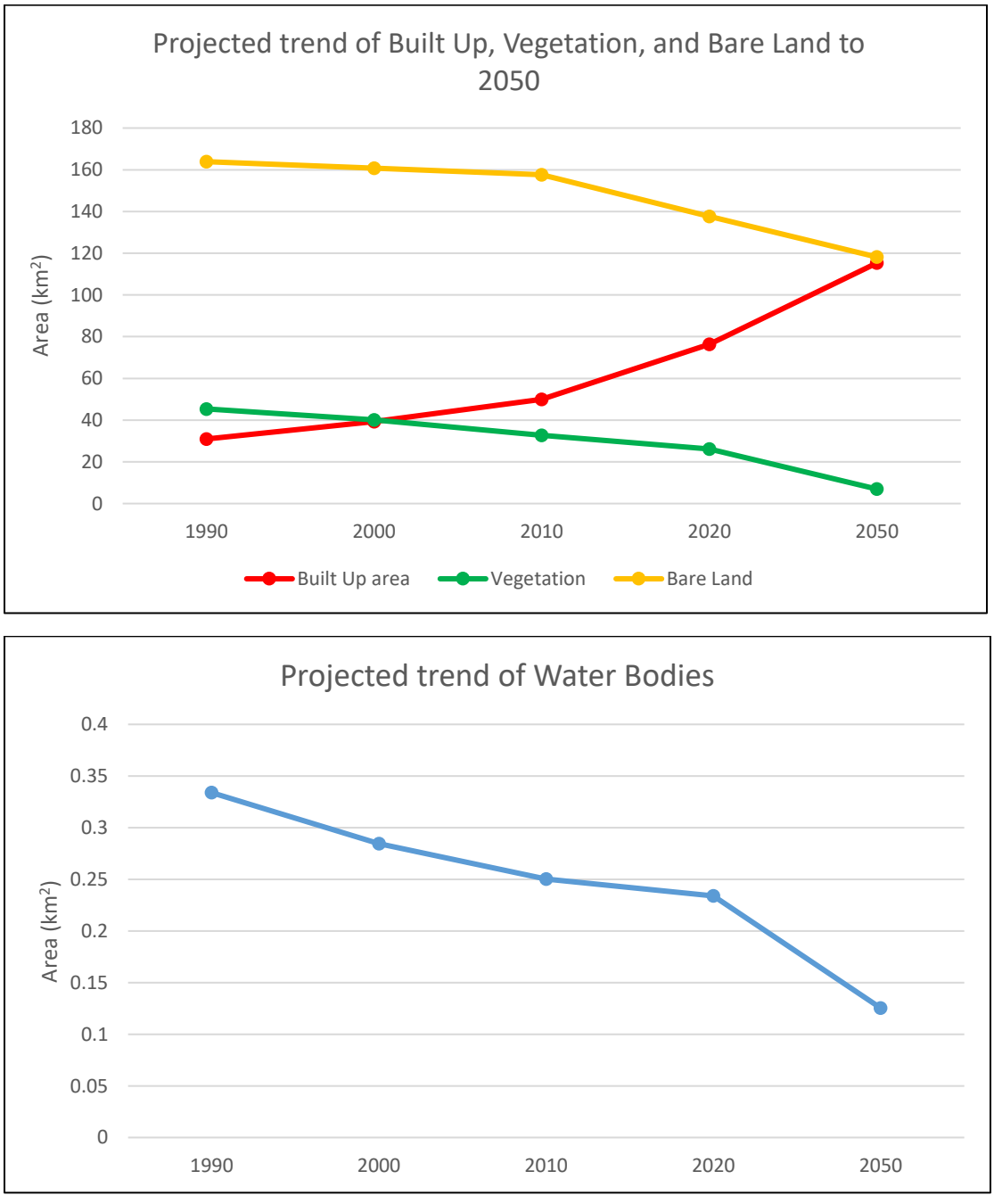


Figure 15. Graphical projections of Land cover classes to 2050

Table 14 below summaries predicted land cover classes by the year 2050 based on trends from 1990 -2020

Table 14. Predicted 2050 Land cover classes distribution for Blantyre City

Predicted 2050 Land Cover Classes distribution		
Land Cover Class	Area (km^2)	Percentage (%)
Built Up area	115.31853	47.95
Vegetation	6.93612	2.88
Bare Land	118.16298	49.12
Water Bodies	0.12537	0.05
Total	240.543	100

5. CHAPTER 5: DISCUSSIONS

5.1. Trends in Urban Land Use

Over the last 30 years, there have been more anthropogenic-induced urban land-use changes in Blantyre City, according to the findings. Over the study period, vegetation, bare ground, and water bodies have all decreased, while built-up area land has increased. From 2010, the growth of the built-up area has been higher, which may be attributed to the national development plan encouraging the accelerated development of Blantyre City as well as rapid population growth, which necessitates the need for land for settlement. Furthermore, the excessive growth in the built-up area suggests a rise in the city's impervious surfaces (Xu et al., 2020). Increased impervious surfaces reduce groundwater recharge and raise solar radiation reflected into the atmosphere, leading to environmental issues such as urban flooding and global warming. This growth puts the city in jeopardy and necessitates better management to ensure long-term urban development.

The loss of vegetation in this analysis corresponds to the loss of green spaces (such as natural forests and parks). As a result of the loss of vegetation, environmental services such as air and water purification, flood prevention, and climate control, including urban cooling, are impacted. According to (L. Y. Wang et al., 2018), rapid urbanization also induces soil erosion, which contributes to gullies and loss of fertile land which sustain plant species including crops.

Between 2010 and 2020, the number of people living in cities increased dramatically. This was in connection with the development of built-up areas such as factories, small urban centers, and other urban facilities as far as infrastructure development is concerned. The shrinking amount of bare land puts tremendous strain on land suitable for urban growth (Saadani et al., 2020). Hundreds of families are said to have constructed their homes illegally in the city, including wetlands, steep slopes, and river/stream buffer zones. Multiple hazards, such as floods and landslides, threaten such unplanned settlements, which have risen in frequency and severity in recent years as a result of climate change and variability (Sudmeier-Rieux et al., 2015). People have encroached into areas vulnerable to multiple hazards in Mzuzu City, northern Malawi, in a similar situation.

5.2. Dynamics of Land Use and Land Cover Classes

According to (Genet, 2020), the degree of disruption caused by human actions on natural resources is reflected in the change in land-use rate. Blantyre City's land-use density has notable spatial differentiation characteristics. The high land-use intensity is mostly concentrated in the central west and east of Blantyre City, where there are transition zones for built-up areas, bare land, and vegetation (which corresponds to agriculture and forest areas). The terrain is relatively flat, and the climate is suitable for crop growth, particularly in the central east of Blantyre City. The central part of Blantyre City was dominated by farmland and forest areas in 1990 as shown by increased coverage of vegetation on the classification output. However, by 2020 there has been an increase in a built-up area and bare land over the central west and east of Blantyre City, this manifest rapid population growth in the study area as well as deforestation coupled with clearance of land for settlement.

5.3. Validation of the Results

The accuracies of change detection results, according to (Chakraborty et al., 2017), are highly dependent on several factors, including the availability and quality of ground truth data, the complexity of the study area's landscape, the change detection methods or algorithms used, as well as classification and change detection schemes. The overall accuracy of all four classification maps was proximately 91%, representing an error margin of 9%. The classification errors in the results are due in part to impure training samples that capture mixed land use and land cover types since accurate training and validation samples are critical for classification accuracy as articulated by (Zhao et al., 2016). The classification accuracies of vegetation and water bodies were the highest from 1990 to 2020, according to the users' and producers' accuracy of the land cover classification data. This may be because the vegetation and water bodies in the area were made up of homogeneous pixels that could be easily differentiated from the different land cover types.

6. CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusion

At all spatial and temporal scales, changes in land use and land cover have a variety of consequences. It has been one of the big problems for environmental change and natural resource management as a result of these impacts and influences. To forecast future trends, set decision-making processes, and create alternative scenarios, it's crucial to understand the dynamic interactions between changes and their drivers over time and space.

This research was carried out using a combination of GIS and remote sensing techniques. These methods were applied to identify and evaluate changes in land cover classes. In the first section, satellite data for the study periods of 1990, 2000, 2010, and 2010 was collected, and land cover maps were generated using remote sensing techniques and a maximum likelihood supervised image classification algorithm. Processes for assessing the accuracy and detecting changes have also been completed. The overall accuracy of the land use and land cover maps produced in this study was above the minimum threshold, which was considered appropriate.

The study found that the proportion of built-up areas has risen based on classification results. It increased from 12.87% in 1990 to 16.36% in 2000, then 20.67% in 2010 and 31.77% in 2020, the built-up area trend has been steadily changing. Along with vegetation, bare land was a significant factor in this large-scale conversion to developed areas. From 68.13% in 1990 to 66.85% in 2000, 65.51% in 2010, and finally 57.24% in 2020, the value of bare land has been steadily declining. Vegetation, on the other hand, has been steadily declining since 1990, with a value of 18.86% in 1990, 16.67% in 2000, 13.63% in 2010, and 10.89% in 2020. The conversion of vegetation and bare land to built-up areas could be related to the increment of population and faster economic development in Blantyre City. Accuracy assessments of classified images showed better results with an overall accuracy of 95% in 1990, 85% in 2000, 93.3% in 2010, and 86% in 2020.

The results of the change detection study revealed that built-up areas increased by 45.47km^2 from 1990 to 2020, while bare land, vegetation, and water bodies decreased by 26.21km^2, 19.17km^2, and 0.1km^2 respectively. The bulk of the increase in built-up areas was explained by vegetation and bare land, according to the contribution of land cover groups to the overall increase. With the rapid development of infrastructure, the tourism industry, and population growth mentioned in the results section, the trend and scale of changes in built-up areas are likely to continue.

6.2. Recommendations

GIS and remote sensing are critical resources in land use and land cover change studies, according to the findings of this research. As a result of the findings of this study, the following are suggested as potential research directions:

Increased population in Blantyre city has contributed to unplanned and squatter settlements which elicit hazards and disasters such as landslides, flooding, epidemics etc. Urban planners and related stakeholders must embark on strategic urban planning for sustainable urban development by adopting GIS and Remote Sensing Technology to evaluate land use dynamics.

To generate high-quality land cover maps, high-resolution imageries such as IKONOS and QuickBird must be used. Since urban areas have diverse and heterogeneous characteristics, mapping these areas with high-resolution imagery provides better details. Furthermore, using ancillary data as ground truth obtained using GPS from the field improves image classification accuracy.

The performance of land-use models for future forecasts could be improved by incorporating social-economic data, land policy, biophysical, and human factors. As a result, developers, decision-makers, and stakeholders need to ensure that land is used efficiently.

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