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MODELING DEFORESTATION ALTERED BY DEVELOPMENT INFLUENCES OF URBAN AREAS TO PERI- URBAN AREAS

A Case Study of Songea Urban District

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BSc Geoinformatics

Dissertation

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A Case Study of Songea Urban District

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A Dissertation submitted to the Department of Geospatial Science and Technology in partially fulfilment of the requirements for the award of Bachelor of Science in Geoinformatics (BSc.GI) of Ardhi University

CERTIFICATION

The undersigned certify that he has read and hereby recommend for acceptance by Ardhi University dissertation entitled **"Modeling Deforestation Altered by Development Influences of Urban Areas to Peri- Urban Areas"** in partial fulfillment of the requirement for the Degree of Bachelor of Science in Geoinformatics, Ardhi University, Dar es Salaam.

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Mr. Joseph Maziku

(Supervisor)

Date...

DECLARATION AND COPYRIGHT

I Mwandosya Salvatory J hereby declare that, the contents of this dissertation are the results of my own findings through my study and investigation, and to the best of my knowledge they have not been presented anywhere else as a dissertation for diploma, degree or any similar academic award in any institution of higher learning.

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ABSTRACT

Urban growth is a dynamic process that involves significant changes in land use and land cover at the local level. The population has been rapidly increasing, leading to exponential urbanization in various parts of the country, including Songea urban district in Ruvuma region. This urban growth and development trend have significantly impacted the dynamics of land use and land cover in peri-urban areas due to expansion and development activities. Forest clearing for agricultural expansion, production of charcoal, and clearing for building materials have intensified to meet the demands of the growing town. Consequently, these anthropogenic activities have led to alterations in forest reserves. The main objective is to model deforestation of Songea Urban District.

This research utilized remote sensing and GIS techniques to create land use/land cover maps for Songea urban area in 2006, 2011, 2016, and 2022. Landsat satellite images were classified using supervised classification with the Maximum Likelihood algorithm. Five land use/land cover classes were identified: built-up areas, forests, bare land, vegetation, and farmland. Population data from 2012 and 2022 were obtained from the National Bureau of Statistics website to support the analysis.

This analysis used ArcMap software to detect changes in land cover between 2006 and 2022 within a specific district. The aim was to identify significant changes that occurred over a 15-year period. Additionally, population density analysis was conducted using 2022 population data to explore its correlation with urban growth. To predict future land uses, a subset of the built-up land cover class from 2006, 2011, and 2016 was employed. A linear trend line analysis method was used to create a linear model, forecasting land use patterns for the next 10 years starting from 2016.

Based on the main objective of this study, linear trend model of built-up land class ($Y= 8057.8x + 10523$) was prepared to describe the deforestation status of the Songea urban district. The analysis concludes, high urbanization rate consumes most land covers, with built-up areas growing at a rate of 8,000 hectares every five years. By 2026, they are predicted to cover 80% of the district. This study recommends the use of remote sensing datasets and techniques to monitor urban growth trend in order to support proper design of policies to secure forest resources around towns. Lastly, other researchers are encouraged to use high resolution datasets like Quick Bird in order to improve the accuracy of the analysis in built-up expansion trends.

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LIST OF ABBREVIATION

NBS	National Bureau of Statistics
SMD	Survey and Mapping Division
USGS	United States Geological Survey
ML	Maximum Likelihood Classifier
LULC	Land Use Land Cover
RS	Remote Sensing
OLI	Operational Land Imager
AOI	Area of Interest

CHAPTER ONE

INTRODUCTION

1.0 Chapter Review

This chapter describes the background of the research, the related studies that have been done by other scholars, statement of the problem that influences the study of the research, main and specific objectives of the research, significance, beneficiaries, expected outputs, limitation and the study area of the research.

1.1 Background

Forest is referred to an area occupied by different kinds of trees, shrubs, herbs and grasses maintained for productivity of wood and non- wood materials (Moran & Ostrom, 2005). Deforestation is the clearing, destroying, or otherwise removal of trees through deliberate, natural, or accidental means. Peri-urban areas are zones of transition from rural to urban land uses located between the outer limits of urban and regional centers and the rural environment. Also referred to location immediately adjacent to a city or urban area.

Several studies carried out on matter of deforestation into Natural Forest reserves all over the world have addressed many of common reasons for the matter, some of factors are like clearing for agriculture, consumption of forest products, encroachment and forest fires. Specifically on the research subject, Rural-urban migration is one of the major drivers of land use land cover dynamics within an area of interest been reflected as the result of growth of population and other socio-economic human activities carried out within a city or town. Figure 1.1 shows how urbanization creates high demand for charcoal from rural areas that influence deforestation. (Source of image: (Kideghesho, 2015))

Figure 1.1: Production of charcoal from rural areas

Growth of population for Dar es Salaam city is directly related to population growth in its peri-urban areas. Between 1978 and 1988 the population in the study peri-urban areas increased three times in Pugu, nine times in Chanika, and two times in Buyuni and Kisarawe (Kombe, 2010) . This migration pattern reflects negative effects on forest reserves which mainly caused by demands from urban areas can be food demands, construction materials or industrialization, where by spatial expansion of the built-up areas, agricultural activities, non-agricultural activities and other illegal activities around and within forest reserves are influenced and hence cause deforestation catastrophe. An example to this pattern is illustrated by figure 1.2 where mangrove forest is destructed to facilitate paddy cultivation in Rufiji. This shows high Demand for agricultural land.

Figure 1.2: Destruction of mangrove forest for paddy cultivation in Rufiji

Songea is one among fastest growing towns in Africa with an estimated 2020 population of 353,000 and is projected to grow by 110% to 740,000 in 2035 (Forum, 2020). This attributed the choice of case study in order to reflect and assess Songea's peri- urban areas activities that affect or predicted to affect Matogoro natural forests as the effect of increase in population and other town demands related to the matter.

1.2 Statement of the Problem

Forests are very important natural resources which have role on conserving our environment, regulating climate, preventing soil erosion and reducing evaporation; that is to say forest provide habitat for animals and livelihood to humans. Increased anthropogenic activities such as logging, agricultural activities, hunting and forest encroachment have altered forest cover. Furthermore, the increase in population, economic activities and other development programmes in urban areas has resulted in over exploitation of forests in peri urban areas for settlements, agriculture and fulfillment of other demands from urban areas. Deforestation is a serious environmental, social and economic problem which affects millions of people who depend on forest goods and services. Hence the research intends to address the problem by modeling the extent of deforestation of Matogoro forest reserve and to predict the situation in the coming years if the problem is not properly addressed in order to support the design of policy responses and effective monitoring of the reserve.

1.3 Objectives

1.3.1 Main Objective

The main objective of the research is to prepare a deforestation model of Songea urban district.

1.3.2 Specific Objectives

- To determine land use/ land cover maps of the study area through image classification (2006,2011,2016&2022).
- To assess changes in land use and land cover of the area from 2006-2022.
- To determine urban growth trend of the area of interest in a period of 15 years.

1.4 Research Questions

- What is the land- use /cover types of the study area for the flowing years 2006,2011, 2016 &2022?
- What changes of land cover types have occurred between 2006 and 2022?
- What is the rate of change of the urban area (urban growth) for the past 15 years?

1.5 Study Area

Songea is the capital of Ruvuma Region in southwestern Tanzania, one among five districts in Ruvuma Region. it is bordered to the north by the Songea Rural District, to the east by the Namtumbo District, to the south by Mozambique and to the west by the Mbinga District. According to the 2022 Tanzania National Census, the population of the Songea Urban District was 286,285. The city is poised to experience significant economic growth in the near future as the Mtwara Corridor opens up in a few years (Ndembwike, 2006). Seedfarm, Msamala, Bombambili and Lizaboni are among urban wards of the district while, Matogoro, Mletele and Ndilimalitembo are the most peri- urban wards of Songea affected by urban trend influences. Matogoro forest reserve is located in Matogoro ward, one among 21 wards of Songea Urban district. Figure 1.3 describes study area location map

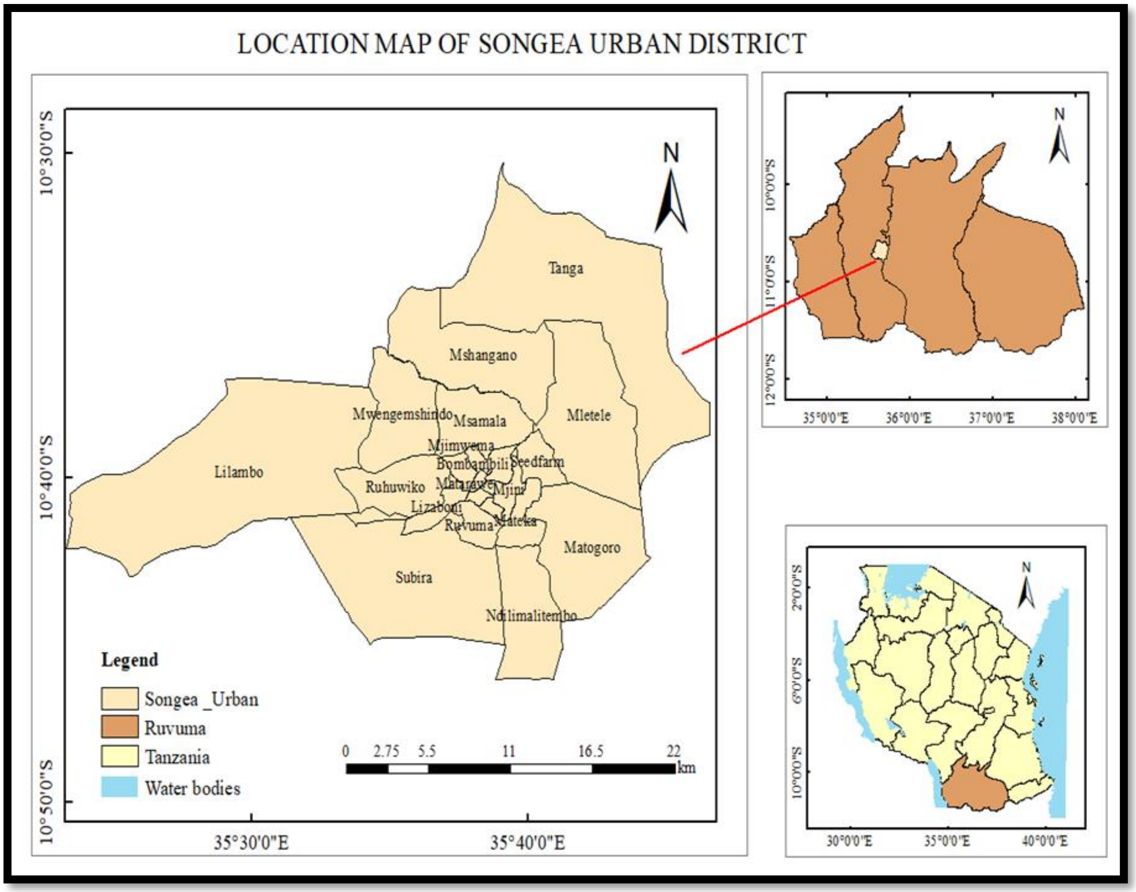


Figure 1.3: Study area location map

1.6 Significance of the study

- To support effective and efficient forest resources monitoring and management to have positive yield on resources and services from forests to boost development.
- To assist policy makers
- To increase awareness to societies near forest reserves on importance of forest resources.

1.7 Beneficiaries of the study

- Policy makers; on making effective policies to govern natural forest resources
- Management authority; to identify most prone areas to deforestation so as to take appropriate actionable plans and targets to prevent or fight against illegal activities within reserves. To come up with effective management plan
- Citizens; to increase awareness on forest resources management since they are beneficial to all.

1.8 Scope and Limitations

This research is valid to the cities and towns with high growing rate in terms of population and economic activities that increase demands for settlement, food products, building materials and other important necessities. Also, research study is limited to the towns with forest reserves in their outer boundaries.

CHAPTER TWO

LITERATURE REVIEW

2.0 Chapter Review

This chapter provides different literature about different relevant topics which were reviewed in this course of conducting this research. Such topics include remote sensing, land cover and land use mapping, change detection and land cover prediction.

2.1 Remote Sensing

Remote sensing is the science and art of obtaining information about an object area or phenomenon through the analysis of data acquired by a device that is not in contact with the object area or phenomenon under investigation (Paul, 2004).

It involves two main processes which are data acquisition and analysis of the data acquired by using various electromagnetic energy sensor system. It involves the study of earths features from images taken from space using satellites or from nearer the earth using aircrafts (Paul, 2004).

Remote sensing is the process of detecting and monitoring the physical characteristics of an area by measuring its reflected and emitted radiation at a distance (typically from satellite or aircraft). Special cameras collect remotely sensed images, which help researchers "sense" things about the Earth (USGS). Some examples are:

Cameras on satellites and airplanes take images of large areas on the Earth's surface, allowing us to see much more than we can see when standing on the ground.

Sonar systems on ships can be used to create images of the ocean floor without needing to travel to the bottom of the ocean and,

Cameras on satellites can be used to make images of temperature changes in the oceans.

Some specific uses of remotely sensed images of the Earth include:

Large forest fires can be mapped from space, allowing rangers to see a much larger area than from the ground.

Tracking clouds to help predict the weather or watching erupting volcanoes, and help watching for dust storms.

Tracking the growth of a city and changes in farmland or forests over several years or decades and,

Discovery and mapping of the rugged topography of the ocean floor (e.g., huge mountain ranges, deep canyons, and the "magnetic striping" on the ocean floor)

2.2 Satellite Imagery

These are images of the earth collected by imaging satellites operated by governments and businesses around the world. There have been a number of satellite missions launched into space. The first images from space were taken in 1946. The first Landsat program started in 1972. These images have many applications such as in agriculture, forestry, geology, education, cartography and planning (Nasa, 2020). Interpretation and analysis of these images are done by using specialized remote sensing software such as Erdas imagine 2014 and GIS software. Landsat being the oldest continuous earth observing satellite imaging program and it is collected at 30 m resolution. The Landsat 8 and Landsat 9 satellites are currently in orbit.

2.2.1 Landsat 5

On March 1, 1984, NASA launched Landsat 5, the agency's last originally mandated Landsat satellite. Landsat 5 was designed and built at the same time as Landsat 4 and carried the same payload: the Multispectral Scanner System (MSS) and the Thematic Mapper (TM) instruments. (Nasa, 2020).

Landsat 5 operated at 705 Km altitude, with polar and sun - synchronous orbits, inclined at 98.2° with 16 days as its repeat coverage time and lastly Landsat 5 was Decommissioned in January 2013 (Nasa,2020)

For this research, TM sensor imagery were downloaded for the years 2006 and 2011 for further analysis. The table 2.1 entails the Landsat 5 TM specifications (Source: ResearchGate)

Table 0.1: Landsat 5 TM spectral bands

Landsat 5 TM		
Bands	**Wavelength (micrometers)**	**Resolution(meters)**
Band 1- Blue	0.45-0.52	30
Band 2- Green	0.52-0.60	30
Band 3- Red	0.63-0.69	30
Band 4- Near Infrared (NIR)	0.76-0.90	30
Band 5- Shortwave Infrared (SWIR) 1	1.55-1.75	30
Band 6- Thermal	10.40-12.50	120*(30)
Band 7- Shortwave Infrared (SWIR) 2	2.08-2.35	30

2.2.2 Landsat 8

Landsat 8 is the eighth-generation satellite of the Landsat program. It was launched on 11th February 2013. The satellite has two instruments, namely, the Operational Land Imager (OLI) for imaging in the visible and near infrared spectrum and Thermal Infrared Sensor (TIRS) for imaging in the thermal infra-red region (Vhengani, et al., 2015). The band information for the OLI and TIRS are shown in table 2.2

Table 0.2: Landsat 8 spectral bands

Band No	Colour	Wavelength (nm)	Spectral resolution (m)
Band 1	Blue	433 – 453	30
Band 2	Blue	450 – 515	30
Band 3	Green	525 – 600	30
Band 4	Red	630 – 680	30
Band 5	NIR	845 – 885	30
Band 6	sSWIR	1560 - 1660	30
Band 7	lSWIR	2100 - 2300	30
Band 8	Pan	500 – 680	15
Band 9	Cirrus	1360 - 1390	30
Band 10	TIR	10300 - 11300	100
Band 11	TIR	11500 - 12500	100

The Landsat 8 spacecraft is orbiting at an altitude of 705 km above mean sea level and has an inclination of 98 degrees from the North Pole at a revisit period of 16 days. Both OLI and TIRS have swath width of 185 km. these images are free of cost ad are downloaded from the United States Geological Survey (USGS) Earth Explorer. The level 1 of these images are radio metrically and geometrically corrected (Vhengani, et al., 2015). The 2016 and 2022 satelite images were downloaded from Landsat 8 OLI instrument for research analysis.

2.3 Image classification

Image classification is the process of assigning land cover classes to pixels. For example, classes include water, urban, forest, agriculture, and grassland (GISGography, 2022).

The 3 main types of image classification techniques in remote sensing are: Unsupervised image classification, Supervised image classification and Object-based image analysis.

Unsupervised and supervised image classification are the two most common approaches. However, object-based classification has gained more popularity because it's useful for high-resolution data (GISGography, 2022).

2.3.1 Supervised classification

This is a type of classification that requires a prior knowledge of the area. It uses the training sample data of known classify pixels of unknown identity. Here the analyst selects representative samples of known cover types (Paul, 2004).

In supervised classification, you **select representative samples** for each land cover class. The software then uses these **"training sites"** and applies them to the entire image.

The three basic steps for supervised classification involves selecting training areas, generating signature file and lastly classifying image (GISGography, 2022)

Finally, the last step would be to use the signature file to run a classification. From here, you would have to pick a classification algorithm such as: Maximum likelihood, Minimum-distance, Principal components, Support vector machine (SVM) or Iso cluster.

2.3.2 Unsupervised Classification

This does not require a prior knowledge of the study area, the computer automatically groups the pixels into separate clusters based on their spectral signatures (Paul, 2004). The analyst only specify a number of classes.

Overall, unsupervised classification is the most basic technique. Because you don’t need samples for unsupervised classification, it’s an easy way to segment and understand an image (GISGography, 2022).

The two basic steps for unsupervised classification are Clusters generation and classes assigning.

According to GISGeography by using remote sensing software, we first create “clusters”. Some of the common image clustering algorithms are: K-means and ISODATA.

The next step is to manually assign land cover classes to each cluster. For example, if you want to classify vegetation and non-vegetation, you can select those clusters that represent them best (GISGography, 2022).

2.3.3 Object-based image analysis

Supervised and unsupervised classification is pixel-based. In other words, it creates square pixels and each pixel has a class. But object-based image classification groups pixels into representative vector shapes with size and geometry (GISGography, 2022).

Here are the steps to perform object-based image analysis classification: perform multiresolution segmentation, select training areas, define statistics and lastly classify.

Object-based image analysis (OBIA) segments an image by grouping pixels. It doesn’t create single pixels. Instead, it generates objects with different geometries. If you have the right image, objects can be so meaningful that it does the digitizing for you (GISGography, 2022).

In Object-Based Image Analysis (OBIA) classification, you can use different methods to classify objects. For example, you can use:

SHAPE: If you want to classify buildings, you can use a shape statistic such as “rectangular fit”. This tests an object’s geometry to the shape of a rectangle.

TEXTURE: Texture is the homogeneity of an object. For example, water is mostly homogeneous because it's mostly dark blue. But forests have shadows and are a mix of green and black.

SPECTRAL: You can use the mean value of spectral properties such as near-infrared, short-wave infrared, red, green, or blue.

GEOGRAPHIC CONTEXT: Objects have proximity and distance relationships between neighbors.

Basically, for this research, Supervised classification technique was employed for image classification. In supervised classification the user or image analyst "supervises" the pixel classification process. The user specifies the various pixels values or spectral signatures that should be associated with each class. This is done by selecting representative sample sites of a known cover type called **Training Sites or Areas.** The computer algorithm then uses the spectral signatures from these training areas to classify the whole image (Klaus, Norman, & Gerrit, 2009).

On the other side, Maximum likelihood classifier was opted in, this is because The Maximum Likelihood (ML) classifier considers not only the cluster centers but also the shape, size and orientation of the clusters. This is achieved by calculating a statistical distance based on the mean values and covariance matrix of the clusters. The statistical distance is a probability value: the probability that observation x belongs to specific cluster. A cell is assigned to the class (cluster) to which it has the highest probability.

The assumption of most ML classifiers is that the statistics of the clusters follow a 'normal' (Gaussian) distribution (Klaus, Norman, & Gerrit, 2009).

2.4 Class Separability analysis

Refers to measure on how collected class representatives are not mixed. It is the degree that class representatives do not overlap or mixed up. A separability analysis can be performed on the training data to estimate the expected error in the classification for various feature combinations (Landgrebe, 2003). The results may suggest that some of the initial features be dropped before classification of the full image. Most common measures of separability are based on how much the intra- class distributions overlap (probabilistic measures). These involves Jeffries- Matusita distance, Bhattacharya distance and the Transformed divergence. There are several ways to perform separability analysis, this study uses transformed divergence method to evaluate class separability.

Transformed divergence is the simplest statistic to understand which yields real values between 0 and 2, where 0 indicates complete overlap between the signatures of two classes, and 2 indicates a complete separation between two classes.

2.5 Validation of the image classification results / Accuracy Assessment

After the image classification, validation of the classification results is followed to assess the accuracy of the process been done. Image classification results in a raster file in which the individual raster elements are class labelled. As image classification is based on samples of the classes, the actual quality of the result should be checked. This is usually done by a sampling approach in which a number of raster elements of the output are selected and both the classification result and the true world class are compared. Comparison is done by creating an ‘error matrix’, from which different accuracy measures can be calculated. The ‘true world class’ is preferably derived from field observations. Sometimes sources of an assumed higher accuracy, such as aerial photos, are used as a reference (Klaus, Norman, & Gerrit, 2009).

2.5.1 Kappa Statistics

The Kappa statistic is used to control only those instances that may have been correctly classified by chance. This can be calculated using both the observed (total) accuracy and the random accuracy. Kappa can be calculated as: Kappa = (total accuracy – random accuracy) / (1 – random accuracy), also Kappa is referred to the repeatability of the classification process to achieve the same results. Kappa coefficient in image classification Ranges from 0 to 1 where 1 provide indication that the results achieved are completely repeatable and 0 indicates that the results are of random chance (Sim, 2005)

2.6 Land use land cover mapping

Although the terms land cover and land use are often used interchangeably, their meaning are quite very clear. Land cover mapping refers to the process of classifying and categorizing different types of land cover on the Earth's surface. It involves the identification and delineation of various land cover classes, such as forests, urban areas, agricultural fields, water bodies, grasslands, and barren land, among others (Giri, 2012). This mapping is typically done using remote sensing techniques, such as satellite imagery, aerial photography, and LiDAR data. While Land use refers to the purpose the land serves such as recreation, cultivation, fishing, grazing etc.

2.7 Modeling in Remote Sensing (MIRS)

In remote sensing, modeling refers to the process of creating mathematical or computational representations of the physical processes involved in the acquisition and analysis of remotely sensed data. Remote sensing models simulate the interactions between electromagnetic radiation and the Earth's surface or atmosphere to understand and interpret the observed data (Schowengerdt, 2011).

Some of key aspects of modeling in remote sensing involves, Radiative Transfer Models: Radiative transfer models simulate the interaction of electromagnetic radiation with various elements of the Earth's surface and atmosphere. These models account for factors such as solar radiation, atmospheric scattering and absorption, surface reflectance, and emission. They help understand how different materials or objects interact with light at different wavelengths, enabling the interpretation of remote sensing data. Other key aspect of modeling is Image Formation model

Image Formation Models: Image formation models simulate the process of converting raw sensor measurements into meaningful images. These models take into account sensor characteristics, such as spatial resolution, spectral response, and geometric distortions. By incorporating sensor parameters and imaging geometry, image formation models help generate georeferenced and orthorectified images.

2.7.1 Change Detection

This is the process of analyzing multi-temporal remotely sensed images acquired over given geographic location at different times for identifying the changes associated to particular location. The process involves identification of difference in the state of an object or phenomenon at different times of acquisition or observation. Accurate and timely change detection associated to earth’s surfaces helps in establishing relationship between mankind and environmental changes which help in managing and utilization of resources. Change detection utilizes the multi-band dataset which depends much on the data sources such as Thematic Mapper (TM), SPOT, Radar and Advanced very High- Resolution Radiations. (Chuvieco & Huete, 2010)

There are several techniques employed in change detection, including: **Image algebra method** where the change is detected using some techniques such as image regression, image differencing and image rationing

Advanced models, here the image reflectance values are converted into physically based parameters that are easily interpreted.

Classification method, this is based on the classified images as an input and the techniques used are post classification comparison and artificial networks.

Transformation method, this reduces data redundancy and some techniques used is Principal Component Analysis. (PCA)

2.7.2 Linear Trend analysis

Linear trend analysis is a statistical method used to analyze the relationship between a dependent variable and time. It involves fitting a straight line to a series of data points over time and examining the direction and strength of the trend. This technique helps identify whether the variable is increasing, decreasing, or remaining constant over a given time period. By using methods such as least squares regression. (Kutner, Nachtsheim, Neter, & Li, 2020)

Linear trend analysis provides valuable insights into the behavior and direction of the dependent variable over time. It is widely used in various fields, including economics, finance, environmental science, and social sciences, to study and forecast trends.

Here are the key steps involved in linear trend analysis:

Step 1, Data Collection: Gather the time series data, ensuring that each observation is associated with a specific time point.

Step 2, Plotting the Data: Create a scatter plot of the data points, with the time on the x-axis and the dependent variable on the y-axis. This visual representation helps identify any potential patterns or trends.

Step 3, Fitting the Trend Line: Use regression analysis to fit a straight line to the data points. The line represents the estimated trend in the dependent variable over time.

The most common method used is the least squares method, which minimizes the sum of the squared differences between the observed data points and the predicted values on the line.

Step 4, Assessing the Trend: Analyze the slope (steepness) of the trend line to determine if the variable is increasing, decreasing, or remaining constant over time. A positive slope indicates an increasing trend, a negative slope indicates a decreasing trend, and a slope of zero represents a constant trend.

Step 5, Evaluating the Strength of the Trend: Assess the goodness of fit of the trend line to determine how well it represents the data. Common measures include the coefficient of determination (R-squared), which indicates the proportion of the variance in the dependent variable explained by the trend line.

Step 6, Making Predictions: Once the trend line is established, it can be used to make predictions about future values of the dependent variable based on the time component.

2.8 Review of Deforestation

Deforestation is an alarming environmental issue with significant global implications. It involves the permanent removal of forests and their transformation into non-forest areas. This destructive practice has devastating consequences on biodiversity, climate change, and local communities. The loss of forests disrupts ecosystems, leading to the extinction of plant and animal species. Additionally, deforestation contributes to climate change by releasing large amounts of carbon dioxide into the atmosphere. It also disrupts water cycles, leading to soil erosion and decreased agricultural productivity. The exploitation of forests for timber, agriculture, and urbanization needs urgent attention and sustainable solutions to protect our planet's invaluable forest resources. (Shoumatoff, 1992)

2.8.1 Drivers of the deforestation

The drivers of deforestation are complex and multifaceted, involving a combination of economic, social, and political factors (Kumar, 2010).

Here are some of the key drivers commonly associated with deforestation:

Agriculture and Livestock Expansion: The conversion of forests into agricultural land, particularly for large-scale commercial agriculture and livestock production, is a major driver of deforestation. The demand for commodities like soy, palm oil, beef, and timber drive the clearing of forests to make way for these lucrative industries.

Logging and Timber Extraction: Unsustainable logging practices, both legal and illegal, contribute to deforestation. Timber extraction for commercial purposes, including the production of furniture and construction materials, leads to the degradation and destruction of forests.

Infrastructure Development: The construction of roads, dams, mining operations, and other infrastructure projects often involves clearing forests. These projects can open up previously inaccessible areas for further exploitation and contribute to the fragmentation of forest ecosystems.

Fuelwood and Charcoal Production: In many regions, particularly in developing countries, the reliance on wood for cooking and heating drives deforestation. High demand for fuelwood and charcoal places significant pressure on forests, especially in areas with limited access to alternative energy sources.

Population Growth and Poverty: Rapid population growth, coupled with poverty and the lack of sustainable livelihood options, can drive communities to clear forests for subsistence agriculture, fuelwood collection, and other basic needs. Poverty alleviation and sustainable development are crucial in addressing this driver

2.8.2 Effects of deforestation

Deforestation has a wide range of significant effects on the environment, biodiversity, climate, and local communities. Here are some of the key effects of deforestation (Beresford-Kroeger, 2012)

Loss of Biodiversity: Deforestation is a major driver of species extinction. Forests are incredibly biodiverse ecosystems, housing a vast array of plant and animal species. When forests are cleared, many species lose their habitat, leading to population declines and, in some cases, extinction. This loss of biodiversity can disrupt ecosystems and have cascading effects throughout the food chain.

Climate Change: Forests play a crucial role in mitigating climate change. They act as carbon sinks, absorbing and storing significant amounts of carbon dioxide (a greenhouse gas) from the atmosphere. When forests are cleared, this stored carbon is released back into the atmosphere, contributing to the greenhouse effect and exacerbating climate change. Deforestation is a significant contributor to global carbon emissions.

Soil Erosion and Reduced Agricultural Productivity: Trees help hold the soil in place, preventing erosion and maintaining its fertility. When forests are cleared, particularly on slopes or in fragile ecosystems, the exposed soil is prone to erosion by wind and water. This leads to decreased agricultural productivity, as fertile topsoil is washed away, reducing soil quality and causing long-term damage to agricultural lands.

Loss of Livelihoods and Cultural Heritage: Forests provide essential resources and livelihoods for millions of people, especially indigenous and local communities who depend on forests for food, medicine, shelter, and cultural practices. Deforestation threatens their way of life, displacing communities, disrupting traditional knowledge systems, and undermining their cultural heritage.

Increased Risk of Forest Fires: Forests that have been cleared or fragmented are more susceptible to wildfires. Without the natural buffer provided by intact forests, fires can spread more easily and become more intense. Deforestation, coupled with climate change, contributes to an increased risk of forest fires, leading to further loss of forest cover and exacerbating air pollution.

CHAPTER THREE

METHODOLOGY

3.0 Chapter Overview

This chapter describes all the methods, techniques and tools that were used to execute the research. It explains how the research is going to be conducted from data collection, data reading, conversions or pre-processing and data processing until the main objective is met.

3.1 Brief description of methods

In order to attain the goal of this research, Landsat imagery of 2006, 2011, 2016 and 2022 are acquired from Landsat 5 TM and landsat8 OLI platform from USGS earth explorer, land cover maps are then prepared after image pre- processing and processing stages (image classification) have been effectively performed. From land cover maps of respective years prepared, change detection map (2006-2022) was derived from them followed by several analysis in hand together with comparison with population data (2012&2022) of the study area to reflect its impact to peri-urban area. Lastly after validation of land cover maps with high resolution image from Google earth, linear trend analysis is followed, and built-up area prediction model of Songea urban is derived by linear trend line prediction method. The methodology workflow chart in figure 3.1 describes the research workflow.

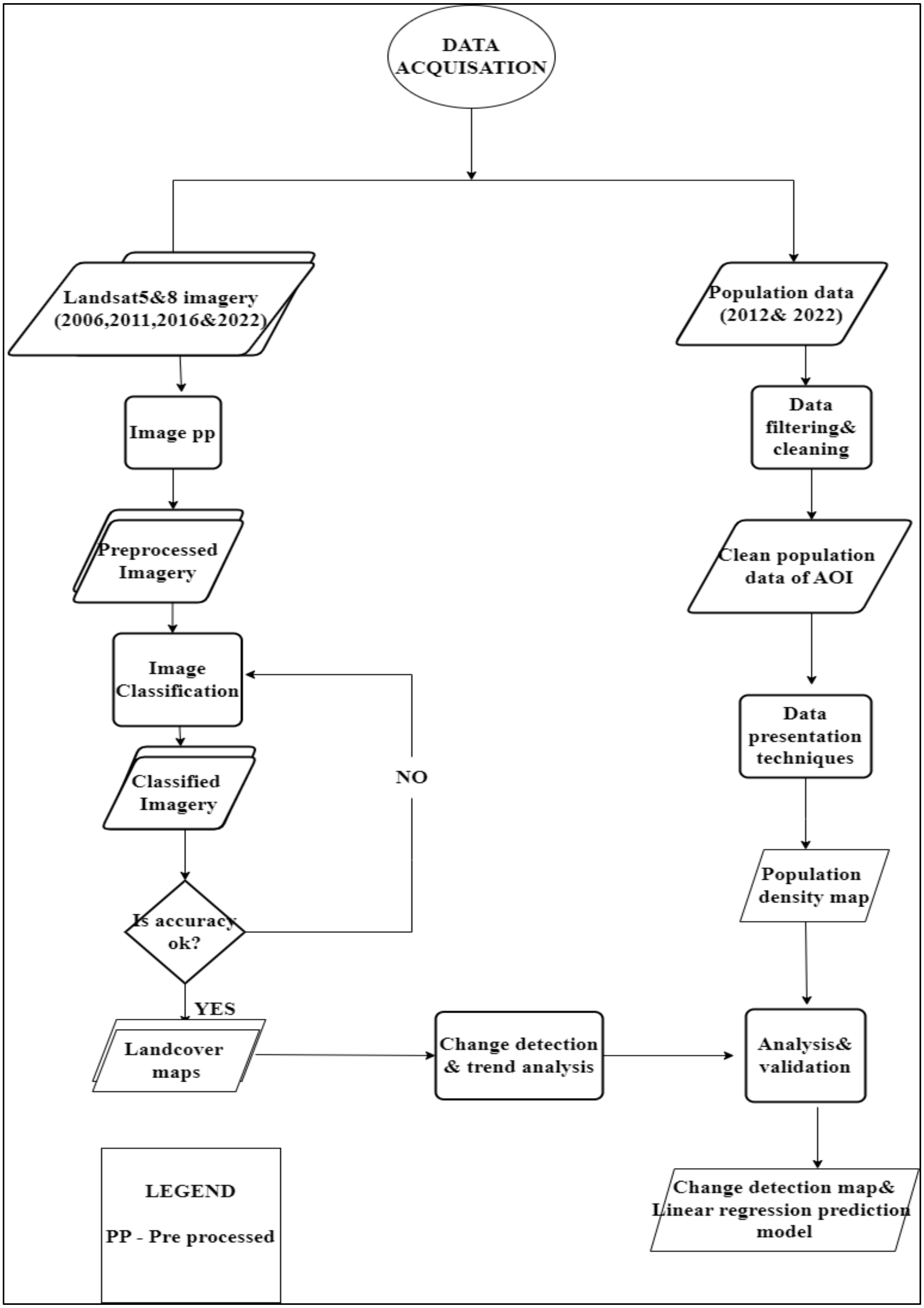


Figure 3.1: Methodology Workflow chart

3.2 Data collection and data sources

According to the research, various dataset has been analyzed and more semantic data related to the theme were selected to be utilized. Table 3.1 shows various useful data to be used in the research together with description of data sources, characteristics and their uses

Table 0.1: Data types, sources and characteristics

S/N	DATA TYPES	SOURCES AND CHARACTERISTICS	USES
1	Landsat 5 TM Images (2006&2011)	Source: USGS Earth Explorer (TIFF format, 30m resolution)	Analysis of land covers, trends and prediction models preparation
2	Landsat 8 OLI Images (2016& 2022)	Source: USGS Earth Explorer (TIFF format, 30m resolution)	Analysis of land covers, trends and prediction models preparation
3	Population data of Songea district (2012&2022)	NBS, Tanzania Excel format	Assessment of urban growth resulting to peri-urban development.
4	High resolution imagery	Google earth	Ground truthing and validation.

3.3 Software packages

In accomplishment of the desired research various software were utilized to assist various steps in production of outputs for analysis. Table 3.2 presents software used with their purpose in task accomplishment.

Table 0.2: Software used and their purpose

SOFTWARE	PURPOSE
ArcMap 10.8 and Qgis 3.8.2 Zanzibar	For visualization of the map, map preparation, clipping of the area of interest, change detection and other geoprocessing
Erdas Imagine 2014	For image classification and other pre processing
Microsoft excel	For trend line analysis and prediction

3.4 Methods

3.4.1 Data Collection

The data used in this study include Landsat 5 TM (2006&2011) and Landsat 8 OLI (2016&2022) images. Also Census Population data of Tanzania of 2012 and 2022. Landsat data were downloaded from USGS Earth explorer website, with path and rows 168/067. Population data were downloaded from NBS official website.

3.4.2 Pre processing

Here the data were prepared for analysis. For the Landsat data the process involved were layer stacking, reprojection, clipping/ subsetting of the study area ready for the classification. From Census General report of 2012 and 2022 population data of Songea urban district were extracted to be used for population distribution and density analysis.

Layer stacking , reprojection and clipping of the study area were done in Erdas imagine 2014 environment. Layer stacking was purposely done in order to join single bands of the image to create a mult-band image. Followed by reprojection of the image to match with the coordinate system of the shapefile of the study area boundary. Area of the interest (study area) was clipped from the image in order to work with AOI in classification.

3.4.3 Image classification

A set of multiband images were classified using supervised classification technique. T raining samples were collected from google earth image of the area of the study for obtaining sufficient number of samples for training during classification. Five classes which are bareland, vegetation, Farmland, Built-up and Forest. Supervised classification was used in this study where the training samples were clustered to assign pixels to classes. An algorithm used during classification was the maximum likelihood classifier. Figure 3.2 shows the screenshot of the image classification in Erdas imagine software.

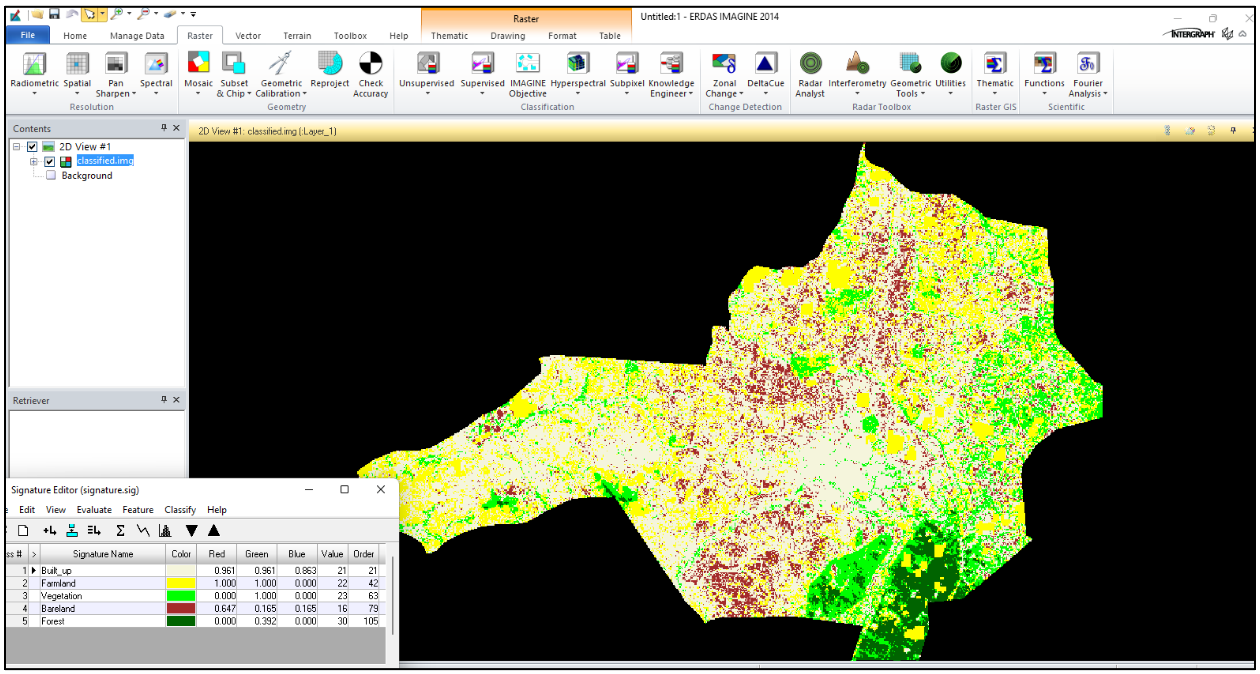


Figure 3.2: Classification in Erdas Imagine 2014

Separability analysis was done before the whole process of classification, class samples collected were imported in the Erdas Imagine 2014 software and evaluated before creation of the signature files in order to assess class separation and independency to avoid mixed class errors.

Kappa statistics and Error Matrix: After classification, accuracy of the results was also assessed through error matrix, and kappa statistics for each classified image. Signature file and classified images were imported in the process of assessing the accuracy of the classification and the process was done in the Erdas software using accuracy assessment tool.

3.4.4 Change Detection

Land covers were used in change detection analysis as inputs. ArcMap software was used in performing land cover change analysis by post classification method, whereas 2006 land cover was compared with near recent land cover of 2022, period of at least 15 years was more significant to study and identify clearly land cover changes through map and graph visualization. Land covers which were used to perform change detection analysis were of the same season and area to avoid confusion which may be caused due to other factors like weather differences and climatic condition. This analysis is very much helpful to identify various changes occurring in different classes of land use like increase in built up area or decrease in forest covers

3.4.5 Linear Trend line Analysis

Trend line analysis, is the linear analysis which would be helpful in predicting the future. For this case study Class of built-up area has been selected for quantification of the linear model. Change analysis has identified significant increase in built up which in one way or the other can alter more the variation of other land classes. Trend line analysis has been done from classified images of 2006, 2011 and 2016 basing on built up area covers on respective years. Table 3.3 shows area covers of built -up class of the years 2006, 2011 and 2016 respectively.

Table 0.3: Trend of Built- up areas in 2006, 2011 & 2016

YEAR	BUILT UP AREA IN HECTARES
2006	16940.34
2011	29918.7
2016	33055.92

Trend data of the built-up areas above as shown in table 3.3, were plotted in Microsoft Excel and then from the graph, trend line linear equation with its coefficient of determination (R^2) were obtained and used for trend line analysis and future prediction.

3.4.6 Future prediction

Future urban growth prediction will be based on trend line prediction from trend line analysis, by observing the urban growth of the area from 3 different years of 2006, 2011 and 2016. Since we will have best results given by a linear trend, the built-up area for the next coming years will be estimated. Various trend line was fitted to predict the built -up area growth of the study area, the best result was given by a linear trend line of an equation (3.1) and coefficient of determination (3.2) as indicated below.

$$Y = 8057.8x + 10523 \quad (3.1)$$

$$R^2 = 0.8894 \quad (3.2)$$

This linear trend line model will be used to predict built-up areas in 10 years to come from 2016, and the validation or quantification of the model will be done by using prepared land cover values of built up with their respective years.

3.4.7 Population density

Population density refers to population of the place over its bounded area. Population density links with urban growth whereas high populated regions are likely to be more developed than others. Population density of Songea urban district was prepared to show wards with high density than the others and their influences to other development.

CHAPTER FOUR

RESULTS AND ANALYSIS

4.0 Chapter Overview

This chapter presents all of the results obtained from methodology of the research and the results were analyzed accordingly. Maps, graphs and tables are the visualization and various analysis techniques utilized to meet the desired purpose of the study.

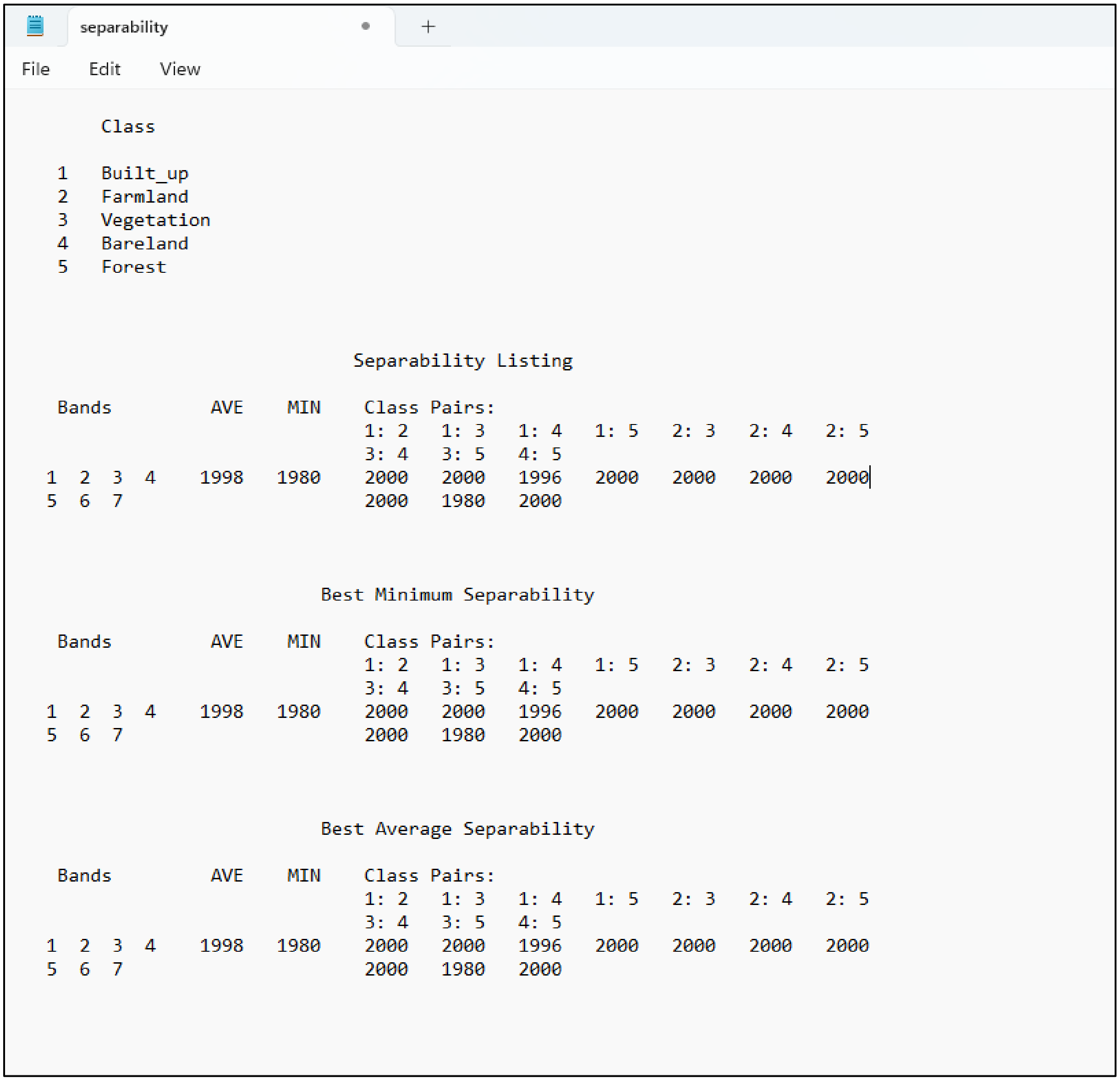
4.1 Classification Accuracy Assessment

This is very important stage of classification where we get the validity of our products ready for various analysis. Classification assessment consists of separability analysis, error matrix and kappa statistics.

4.1.1 Separability analysis

It refers to measure on how collected class representatives are not mixed. It is the degree that class representatives do not overlap or mixed up. There are several ways to perform separability analysis, this study uses transformed divergence method to evaluate class separability. This analysis is done before classification in order to assess the quality of sample to be used as training datasets for the whole process of classification for more accurate results.

Transformed divergence is the simplest statistic to understand which yields real values between 0 and 2, where 0 indicates complete overlap between the signatures of two classes, and 2 indicates a complete separation between two classes. Figure 4.1 shows summary report of class separability.



```
separability
File   Edit   View

       Class

   1   Built_up
   2   Farmland
   3   Vegetation
   4   Bareland
   5   Forest


                       Separability Listing

   Bands        AVE    MIN    Class Pairs:
                              1: 2   1: 3   1: 4   1: 5   2: 3   2: 4   2: 5
                              3: 4   3: 5   4: 5
  1  2  3  4   1998   1980    2000   2000   1996   2000   2000   2000   2000
  5  6  7                     2000   1980   2000


                    Best Minimum Separability

   Bands        AVE    MIN    Class Pairs:
                              1: 2   1: 3   1: 4   1: 5   2: 3   2: 4   2: 5
                              3: 4   3: 5   4: 5
  1  2  3  4   1998   1980    2000   2000   1996   2000   2000   2000   2000
  5  6  7                     2000   1980   2000


                    Best Average Separability

   Bands        AVE    MIN    Class Pairs:
                              1: 2   1: 3   1: 4   1: 5   2: 3   2: 4   2: 5
                              3: 4   3: 5   4: 5
  1  2  3  4   1998   1980    2000   2000   1996   2000   2000   2000   2000
  5  6  7                     2000   1980   2000
```

Figure 4.1: Class separability Report

4.1.2 Error matrix

It refers to the statistical measure of assessing accuracy of the classification (producer's, user's and overall) by comparing the reference data against classification results. Figure 4.2 shows summary report of accuracy assessment.

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	60	60	60	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
Vegetation	8	16	8	100.00%	50.00%
Bareland	4	4	2	50.00%	50.00%
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
Built_up	14	15	13	92.86%	86.67%
Farmland	5	4	4	80.00%	100.00%
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
	0	0	0	---	---
Forest	9	1	1	11.11%	100.00%
Totals	100	100	88		

Overall Classification Accuracy = 88.00%

----- End of Accuracy Totals -----

Figure 4.2: Accuracy Assessment summary Report

4.1.3 Kappa Statistics

It refers to the repeatability of the classification process to achieve the same results. Ranges from 0 to 1 where 1 provide indication that the results achieved are completely repeatable and 0 indicates that the results are of random chance. Kappa statistics of the 2006 classified image was 0.8006 meaning that there is high probability of the results to be repeatable. It is important to consider the specific context of your image classification task when interpreting the Kappa value. The nature of the dataset, the complexity of the categories, and the number of annotators or models involved all play a role in determining how to interpret the Kappa value. Figure 4.3 shows kappa statistics summary report.

```
accuracy
File    Edit    View
---------------------

Overall Kappa Statistics = 0.8006

Conditional Kappa for each Category.
------------------------------------

    Class Name             Kappa
    ----------             -----
  Unclassified            1.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
    Vegetation            0.4565
      Bareland            0.4792
                          0.0000
                          0.0000
                          0.0000
      Built_up            0.8450
      Farmland            1.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
                          0.0000
        Forest            1.0000

                 ----- End of Kappa Statistics -----
```

Figure 4.3: Kappa Statistics summary Report

4.2 Land Cover Distribution and comparison chart

Landcovers/ land use maps prepared from accurate classified images (2006,2011,2016&2022) were analyzed to understand area coverage of each land cover class from all images. Summary of land cover classes area coverage distribution and their comparison is presented in the table 4.1 and more visually in graph as observed in figure 4.4.

Table 0.1: Comparison Table of Land Use/ Land Cover 2006, 2011, 2016 & 2022

LU/LC	AREA IN HECTARES				PERCENTAGE (%)			
	2006	2011	2016	2022	2006	2011	2016	2022
FARMLAND	13150.98	13905.9	4553.37	594.09	22.64706	23.94917	7.842259	1.023089
BUILT -UP	16940.34	29918.7	33055.92	37764	29.17265	51.52691	56.93214	65.0338
FOREST	12685.86	2030.76	681.21	3225.15	21.84609	3.497438	1.173246	5.554066
BARELAND	14137.2	5317.2	4275.09	6001.2	24.34541	9.157447	7.362978	10.33473
VEGETATION	1154.88	6891.66	15496.38	10483.83	1.988798	11.86903	26.68938	18.05432
TOTAL	58069.26	58064.22	58061.97	58068.27	100	100	100	100

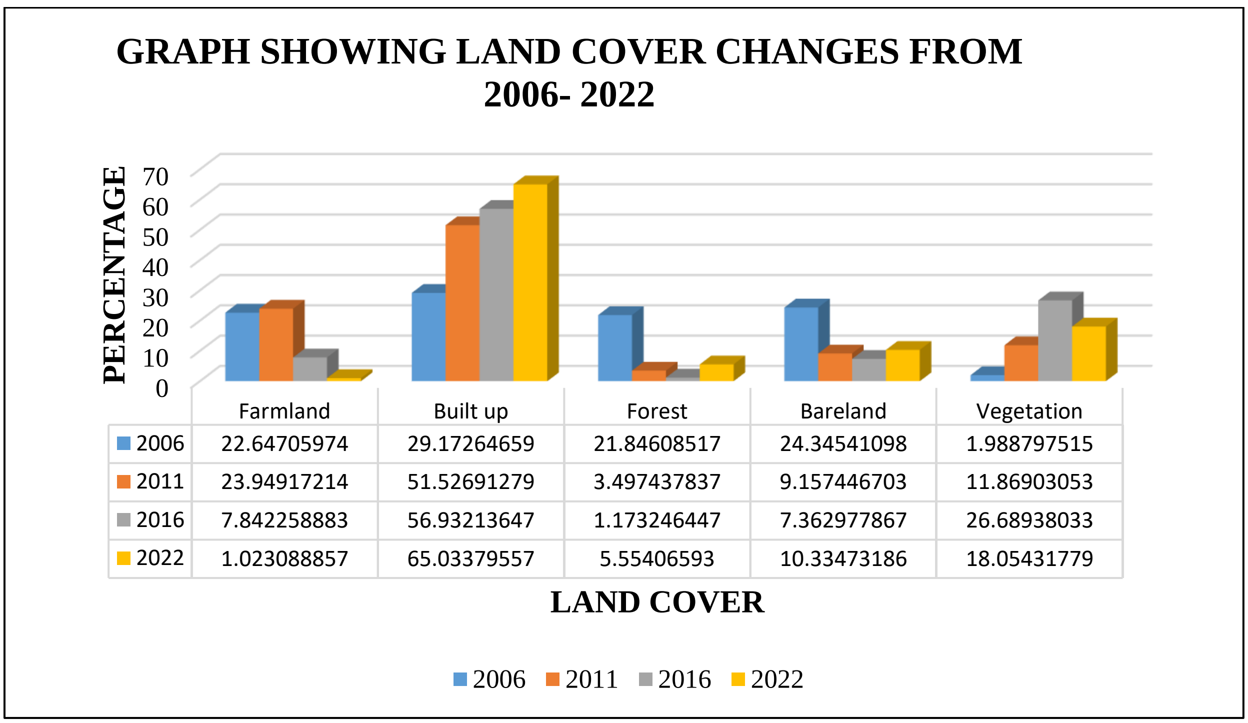


Figure 4.4: Comparison of Land use/Land cover of 2006, 2011, 2016 and 2022

From 2006-2022 period, built up areas have been growing more drastic as it is attributed by development aspects of the town including overall population increase and advancement of social services provision.

Growths of Songea town attributed the significant decrease of farmland class, this is very certain as to the most of urban areas these activities are not supported and strictly restricted by the council and shifted to peri-urban areas.

Bare land cover observed to decrease from 2006 to near present since more built- up areas evolved from the district.

Also, as expected forest cover decreased due to several factors but much possible is due to anthropogenic acts done by peri-urban people attributed by urban demands.

This unexpected increase in vegetation class can be just because of some reasons, for example some land turned from agriculture land were not developed for a time also the amount of rain the town receives.

4.3 Land cover Maps

The LULC maps were classified using supervised method with Maximum likelihood classifier algorithm and classes selected were Farmland, Built-up, Vegetation, Forest and Bare land. LULC maps of Songea urban district of 2006, 2011, 2016 and 2022 were produced. Clipped maps of respective years are as shown in figures 4.5, 4.6, 4.7 and 4.8. Full scaled maps are attached to the appendix.

4.3.1 Land cover map of 2006

Land cover map of 2006 shows dominant land cover classes as farmland and forest covers covering 13150.98 and 12685.86 Hectares respectively of the total area of 58069.26 Hectares. People involved themselves more in agricultural activities. Classified image of 2006 has accuracy of 88% and Kappa value of 0.8006. Figure 4.5 shows land cover of Songea urban in 2006.

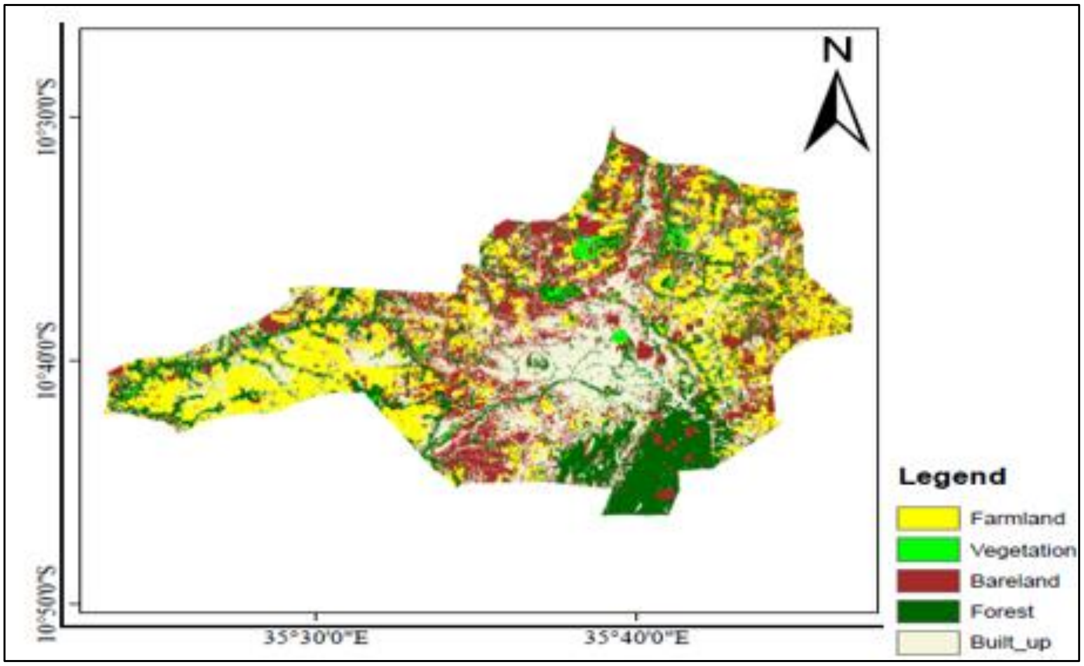


Figure 4.5: Land cover of Songea urban in 2006

4.3.2 Land cover map of 2011

Land cover map of 2011 shows significant decrease in forest covers also there is increase in built up areas. Classified image of 2011 has accuracy of 87% and Kappa value of 0.7877. Figure 4.6 shows land cover of Songea urban in 2011.

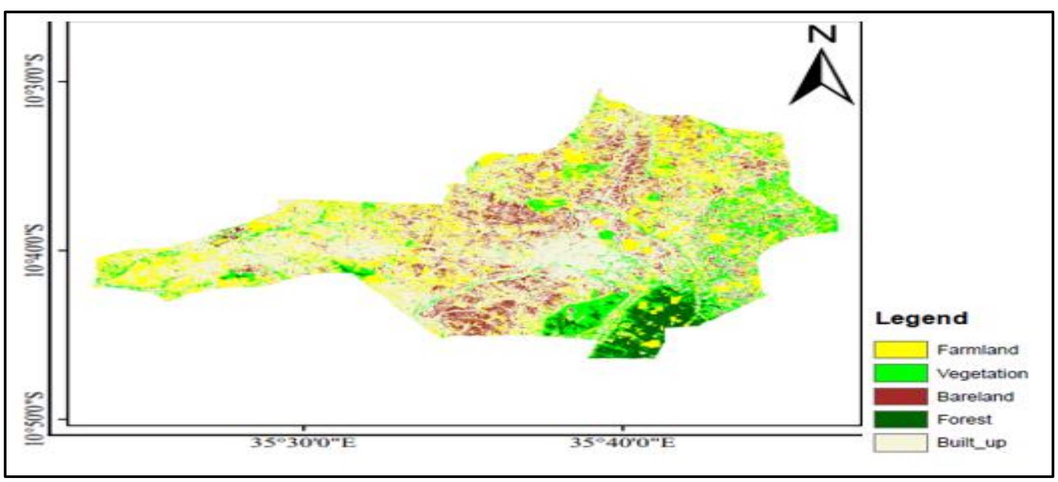


Figure 4.6: Land cover of Songea urban in 2011

4.3.3 Land cover map of 2016

Land cover map of 2016 shows significant decrease in farmland class from 24% to 8% also there is slight increase in built up areas. Classified image of 2016 has accuracy of 90% and Kappa value of 0.8445. Figure 4.7 shows the landcover map of 2016

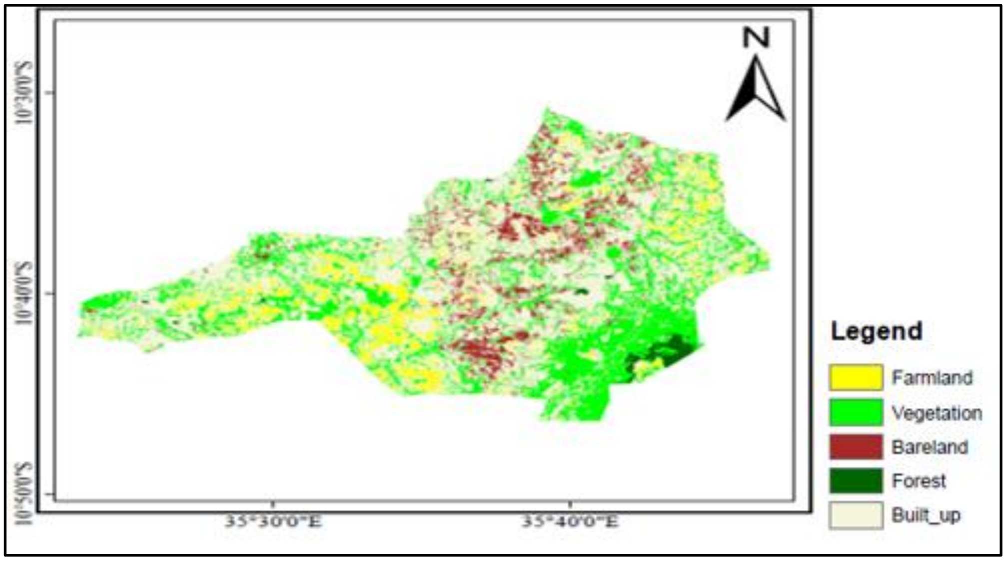


Figure 4.7: Land cover of Songea urban in 2016

4.3.4 Land cover map of 2022

Land cover map of 2022 shows significant decrease in farmland class from also there is increase in built up areas from 57% in 2016 to 65% in 2022. Classified image of 2022 has accuracy of 94% and Kappa value of 0.8865. Figure 4.8 shows the landcover map of 2022.

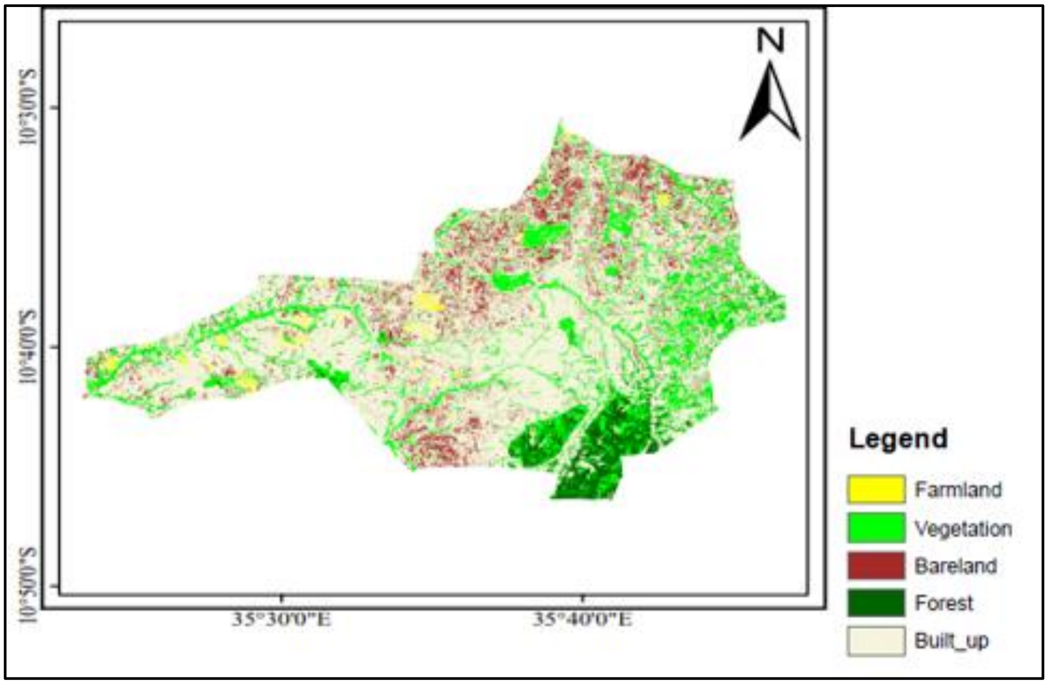


Figure 4.8: Land cover of Songea urban in 2022

4.4 Change detection map

Change map was prepared from land cover maps of 2006 and 2022 Period of at least 15 years is more significant to observed many lands cover changes that happened in the town These observed changes and shifts are more likely attributed by factors like population increase, urbanization and improvement of social services. Change detection map is attached to the appendix of this research

4.4.1 Change detection graph

Change detection graph is to put more clarity and understanding of the land classes changes and shifts from about 15 years period (2006-2022) built up land class is seen to cover very large part of the town as can be seen the changes from other classes to built-up are more significant than others. Change detection graph is shown on figure 4.9 below

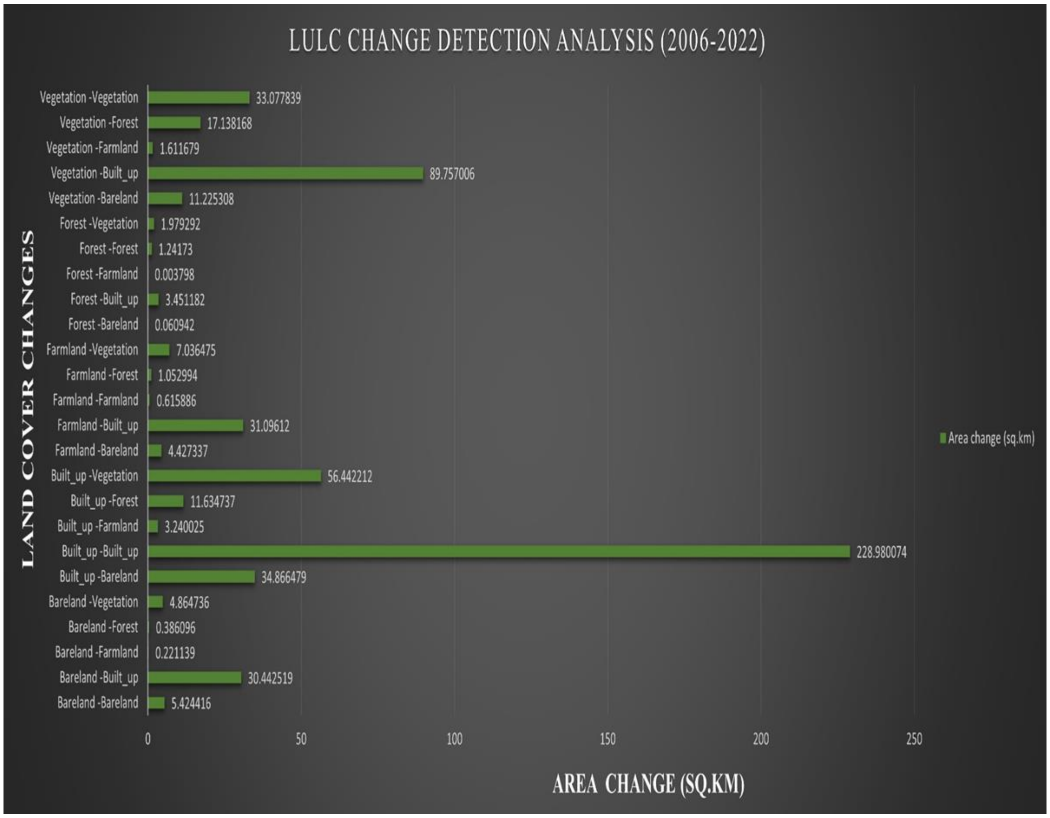


Figure 4.9: Change detection graph (2006 – 2022)

4.5 Population density map

From 2022 census data of songea urban district that consists of 21 wards, population density density map was prepared in order to assist the analysis. 2022 population data were used since the are not far much from present, wards with higher population density such as Seed farm, Bombambili, Mjini, Mjimwema and Msamala were proportional with their large number of built-up land cover class. Population density map is as well attached to the appendix part of the research.

4.6 Land cover change Rate analysis

In this part, rate of change of land cover classes were calculated from area coverage of each class from respective years to observe the trend variation of land cover classes in respective compared years. After subtracting Positive value of the rate indicates the increase and negative value of the rate indicates the decrease of the area coverage of certain class. Table 4.2 summarizes the rate analysis.

Table 0.2: Land cover change rate between 2006, 2011 & 2016

LU/LC	Change area 2006/2011 (hectares)	Change area 2006/2016 (hectares)	Change area 2011/2016 (hectares)
FARMLAND	754.92	-8597.61	-9352.53
BUILT-UP	12978.36	16115.58	3137.22
FOREST	-10655.1	-12004.65	-12004.65
BARELAND	-8820	-9862.11	-1042.11
VEGETATION	5736.78	14341.5	8604.72

4.7 Trend analysis

Trend analysis graph in this part based on built up class land cover areas in terms of Hectares against respective years. The graph shows, the trend of built-up class from 2006 to 2016 is linear because the area increases with the increase in time. Figure 4.10 below shows trend of built-up land cover class

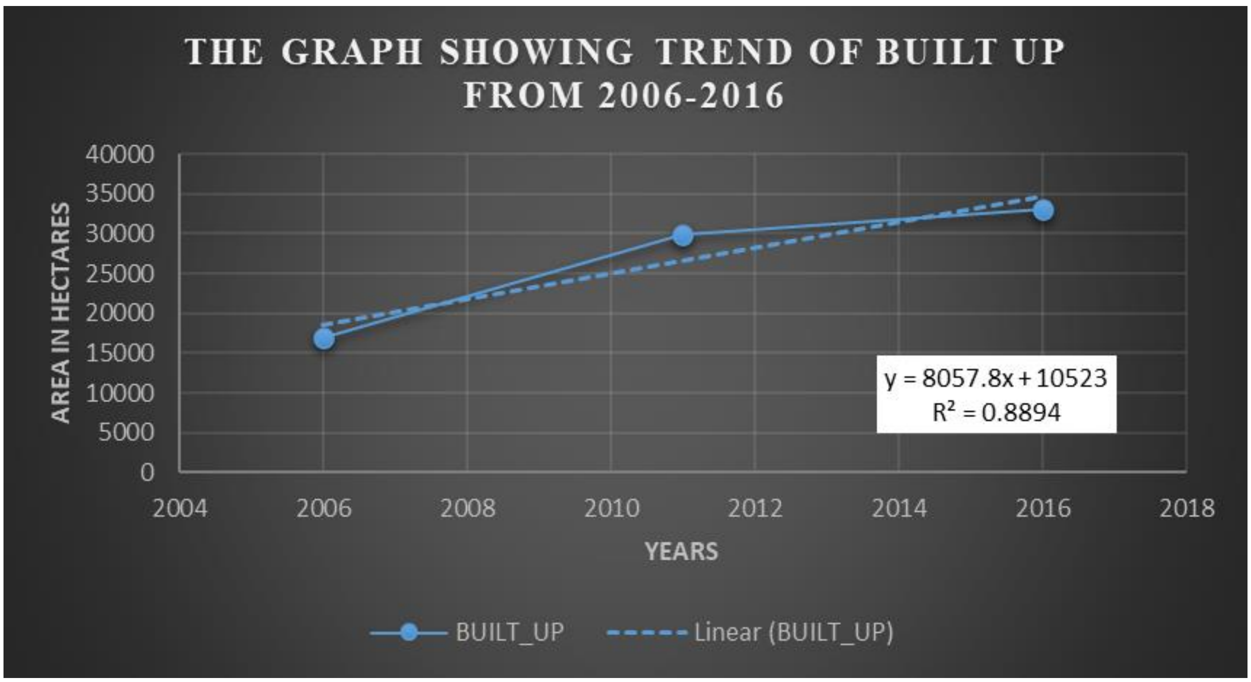


Figure 4.10: Trend of Built-up from 2006 -2016

From equation (3.1), $Y = 8057.8x + 10523$, this means the rate of built-up area will be 8057.8 hectares per 5 years which is equal to 1611.56 hectares per one year.

R^2 (coefficient of Determination) measures how well a statistical model predicts an outcome. It ranges from 0 to 1, 0 means the model does not predict the outcome, between 0 and 1 means that model partially predicts the outcome and 1 means the model perfectly predicts the outcome. The value of 0.8894 indicates the prediction of outcome is high.

4.8 Trend line prediction

Future built- up land cover prediction was based on the obtained trend line equation obtained earlier on the linear trend line analysis. Prediction done for the coming 10 years from the year 2016 to 2026 as described in the table 4.3 below also, prediction can be well visualized through the graph as well shown in figure 4.11.

Table 0.3: Area to be used for Built up in the coming 10 years

YEARS	AREA TO BE USED BY BUILT UP (HECTARES)
2016	33055.92
2017	36307.96
2018	37919.52
2019	39531.08
2020	41142.64
2021	42754.2
2022	44365.76
2023	45977.32
2024	47588.88
2025	49200.44
2026	50810.5

From the table 4.3 above, indicates that by the year 2026 there will be 50810.5 hectares occupied by built-up class out of 58061.97 hectares total. This trend reflects large decrease of other land cover classes including forest cover which may result to deforestation catastrophe of Matogoro forest. The prediction made, assumed all factors which contributes to urban growth to be constant.

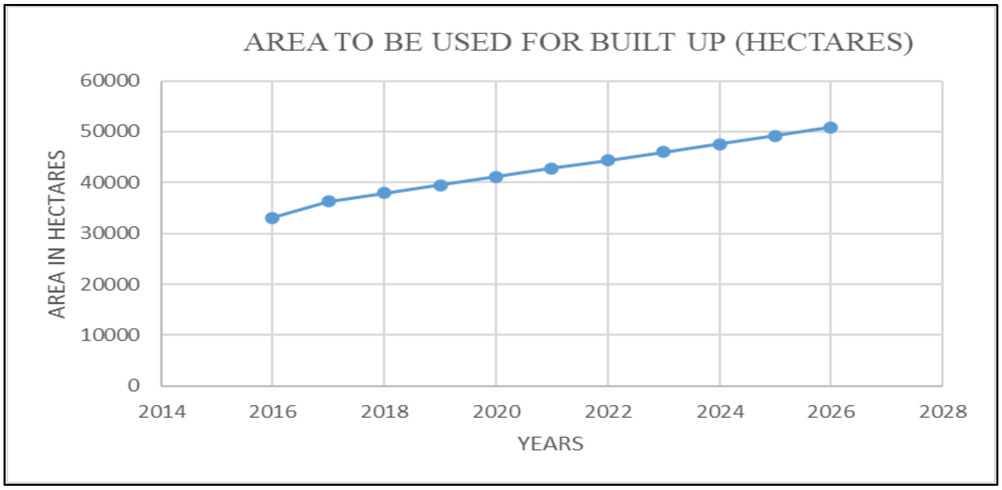


Figure 4.11: Trend for built-up in the next 10 years from 2006

4.9 Model validation

To validate the linear model produced, the built-up data of 2011 were used. Calculations are summarized below as follows.

From the model equation (3.1):

$Y = 8057.8x + 10523$

Where by X represents interval in time (years)

Y represents built-up

When Y = 29918.7

29918.7= 8057.8(X) + 10523

X = (29918.7-10523) / (8057.8)

X = 2.4 ~ 2 which is approximately to the second year of 2011.

Hence model is validated.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.0 Chapter Overview

This chapter describes a conclusion that is drawn from the result obtained in the previous chapter. Furthermore, here the author provides a suggestive idea to enhance a better result derived from the study methodology and results.

5.1 Conclusion

Based on the main objective of this study, linear trend model of built-up land class (Y= 8057.8x + 10523) was prepared to describe the deforestation status of the Songea urban district. The analysis concludes, high urbanization rate consumes most land covers, with built-up areas growing at a rate of 8,000 hectares every five years. By 2026, they are predicted to cover 80% of the district. Also, the study describes population density distribution of Songea urban wards in order to understand the relationship between population increases and built-up areas increases, whereas from analysis it is observed that people shift to centers or towns with good social services and suitable influences for other development aspects. Lastly, in order to support appropriate and quick responses by management concern the prediction of land cover up to 2026 was done through linear trend line analysis and prediction model, that highlighted to have more built-up land covers nearly to cover total area in the coming 10 years.

5.2 Recommendations

This study recommends the use of remote sensing datasets and techniques to monitor urban growth trend in order to support proper design of policies to secure forest resources around towns, also for further researches on urban trend, high resolution datasets like Global High Resolution Urban Data from Landsat from Social Economic Data And Application Center (SEDAC) in NASA and Quick Bird dataset are suggested to be utilize to study and research urban areas covered with a lot of built-up areas in order to support proper design of policies, urban planning and monitoring process in order to secure forest conservation areas as they are very essential in providing livelihood condition to human and other living organisms. Management concern and other stakeholders should focus on investing on purchasing high resolution remote sensing Datasets and employ more skilled personnel in order to be capable in monitoring effectively forest reserves rather than relying much on physical monitoring customs like physical patrols and inspections.

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APPENDICES

APPENDIX 1 : Accuracy Assessment Reports

```
          CLASSIFICATION ACCURACY ASSESSMENT REPORT
          -----------------------------------------
Image File : e:/desertatation/data/2006/classified/classified2006.img
User Name  : MWANDOSYA
Date       : Fri Jun 16 10:25:15 2023
ERROR MATRIX
-------------
ACCURACY TOTALS
----------------
          Class   Reference  Classified  Number      Producers   Users
           Name      Totals      Totals  Correct      Accuracy   Accuracy
     ----------  ----------  ----------  -------     ---------   -----
   Unclassified          60          60       60           ---      --
            ---     ---
     Vegetation           8          16        8       100.00%   50.00%
       Bareland           4           4        2        50.00%   50.00%
       Built_up          14          15       13        92.86%   86.67%
       Farmland           5           4        4        80.00%  100.00%
         Forest           9           1        1        11.11%  100.00%
         Totals         100         100       88
Overall Classification Accuracy =     88.00%
           ----- End of Accuracy Totals -----
KAPPA (K^) STATISTICS
---------------------
Overall Kappa Statistics = 0.8006
Conditional Kappa for each Category.
------------------------------------
    Class Name             Kappa
    ----------             -----
  Unclassified            1.0000
    Vegetation            0.4565
      Bareland            0.4792
      Built_up            0.8450
      Farmland            1.0000
        Forest            1.0000
           ----- End of Kappa Statistics -----
```

CLASSIFICATION ACCURACY ASSESSMENT REPORT

Image File : e:/desertatation/data/2011/mpya/classified/classified.img
User Name : MWANDOSYA
Date : Fri Jun 16 09:29:34 2023

ERROR MATRIX

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	56	56	56	---	--
Bareland	12	3	2	16.67%	66.67%
Built_up	23	29	22	95.65%	75.86%
Farmland	4	7	4	100.00%	57.14%
Vegetation	2	4	2	100.00%	50.00%
Forest	3	1	1	33.33%	100.00%
Totals	100	100	87		

Overall Classification Accuracy = 87.00%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.7877

Conditional Kappa for each Category.

Class Name	Kappa
Unclassified	1.0000
Bareland	0.6212
Built_up	0.6865
Farmland	0.5536
Vegetation	0.4898
Forest	1.0000

----- End of Kappa Statistics -----

CLASSIFICATION ACCURACY ASSESSMENT REPORT

Image File : e:/desertatation/data/2016/mpya/classified/classified_2016.img
User Name : MWANDOSYA
Date : Sat Jun 17 00:28:49 2023

ERROR MATRIX

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	55	55	55	---	--
Built_up	15	19	15	100.00%	78.95%
Farmland	5	7	4	80.00%	57.14%
Bareland	17	11	10	58.82%	90.91%
Vegetation	3	1	1	33.33%	100.00%
Forest	5	7	5	100.00%	71.43%
Totals	100	100	90		

Overall Classification Accuracy = 90.00%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.8445

Conditional Kappa for each Category.

Class Name	Kappa
Unclassified	1.0000
Built_up	0.7523
Farmland	0.5489
Bareland	0.8905
Vegetation	1.0000
Forest	0.6992

----- End of Kappa Statistics -----

```
            CLASSIFICATION ACCURACY ASSESSMENT REPORT
            -----------------------------------------
Image File :
e:/desertatation/data/2022/mpya/classified/classified_2022.img
User Name  : MWANDOSYA
Date       : Thu Jun 15 23:52:14 2023
ERROR MATRIX
-------------
ACCURACY TOTALS
----------------
          Class   Reference Classified Number     Producers  Users
           Name      Totals     Totals Correct     Accuracy  Accuracy
     ----------  ---------- ---------- -------    ---------  -----
   Unclassified          64         63      63          ---    ---

       Farmland           0          0       0          ---    ---
     Vegetation           2          5       2       100.00%  40.00%
       Bareland           5          3       3        60.00% 100.00%
         Forest           5          2       2        40.00% 100.00%

       Built_up          24         27      24       100.00%  88.89%
         Totals         100        100      94
Overall Classification Accuracy =     94.00%
           ----- End of Accuracy Totals -----
KAPPA (K^) STATISTICS
---------------------
Overall Kappa Statistics = 0.8865
Conditional Kappa for each Category.
------------------------------------
    Class Name             Kappa
    ----------             -----
  Unclassified            1.0000
      Farmland            0.0000
    Vegetation            0.3878
      Bareland            1.0000
        Forest            1.0000
      Built_up            0.8538
           ----- End of Kappa Statistics ----
```

APPENDIX 2: The LULC maps of Songea district

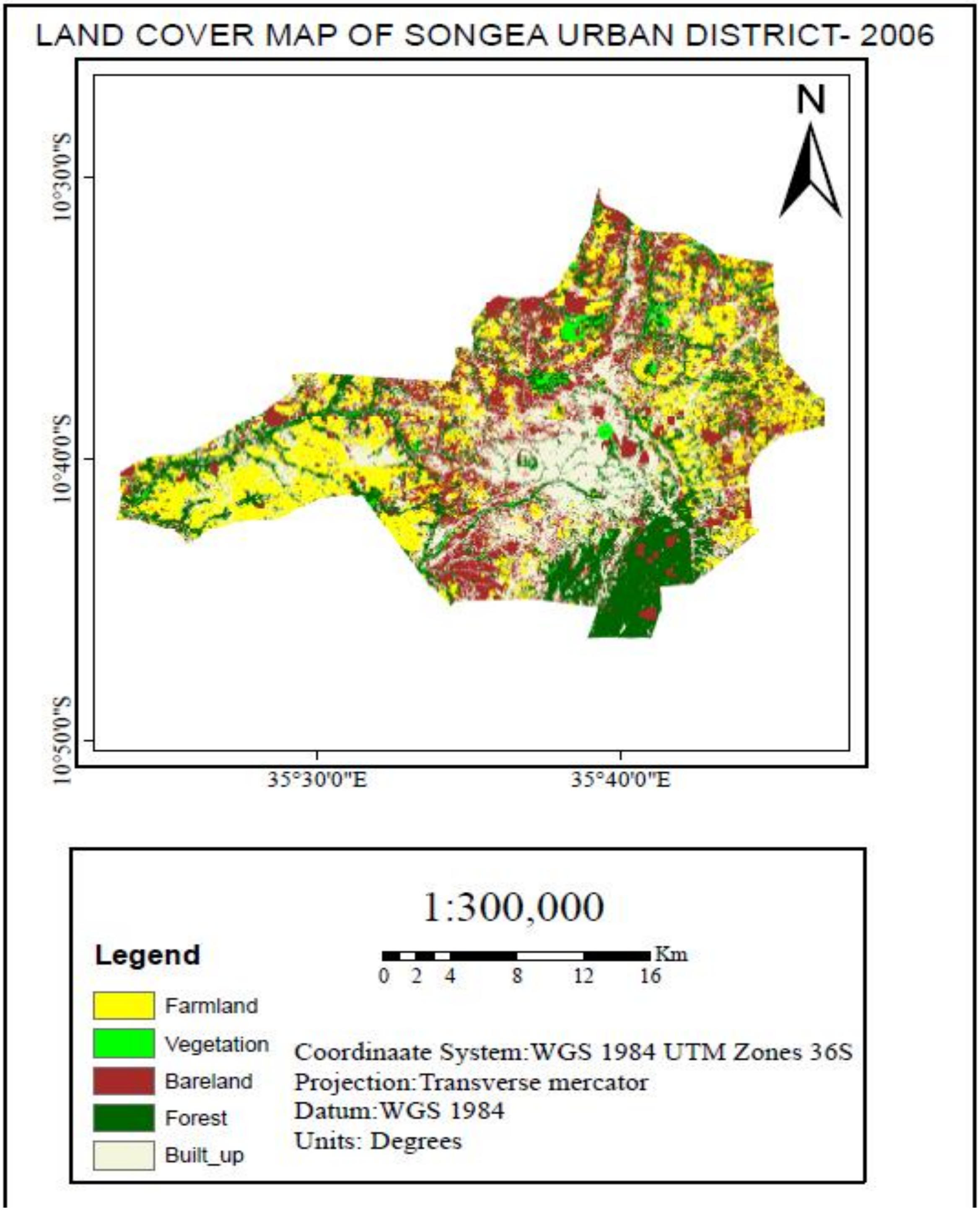

Figure 1: The LULC map of Songea urban of 2006

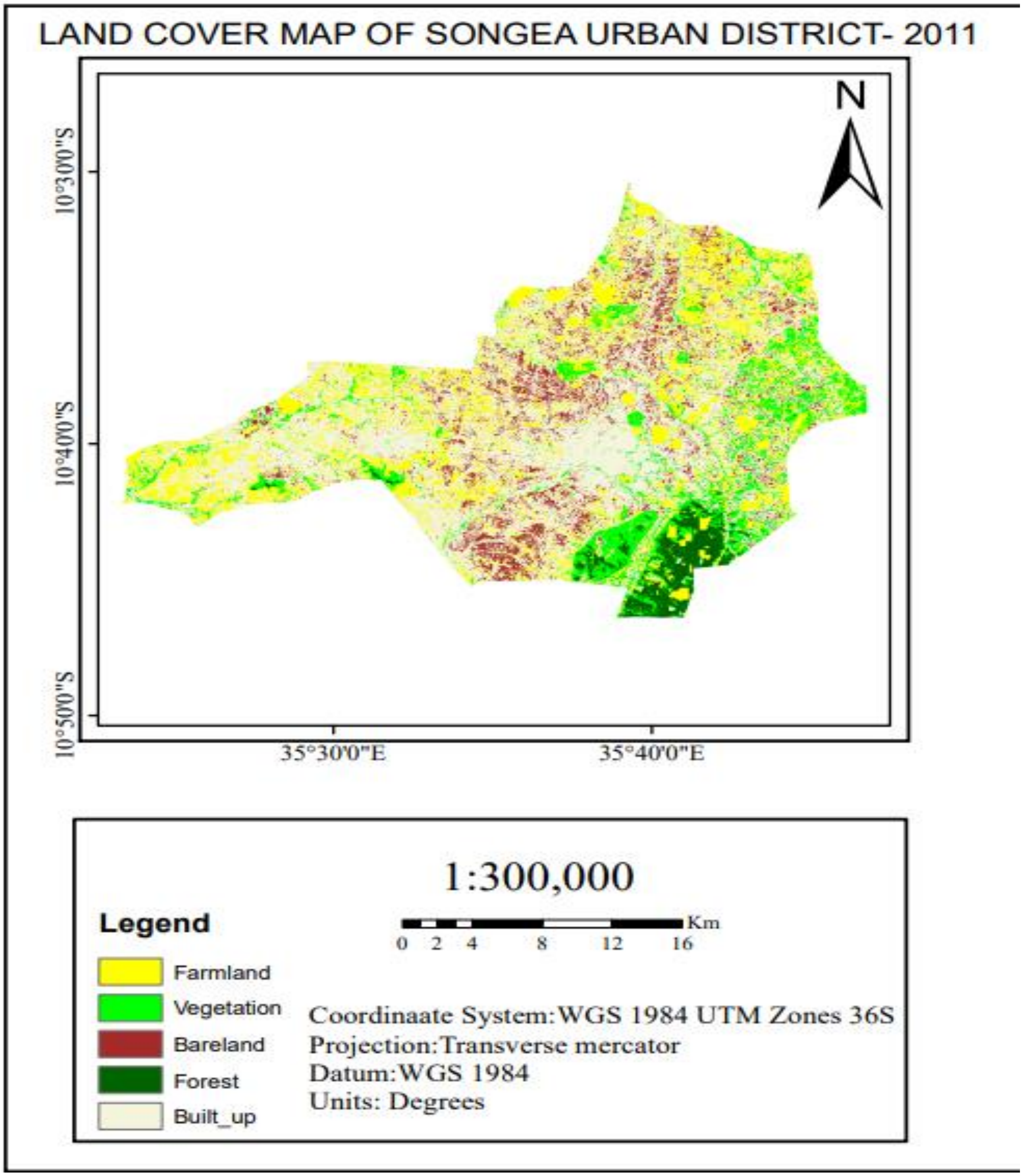

Figure 2: The LULC map of Songea urban of 2011

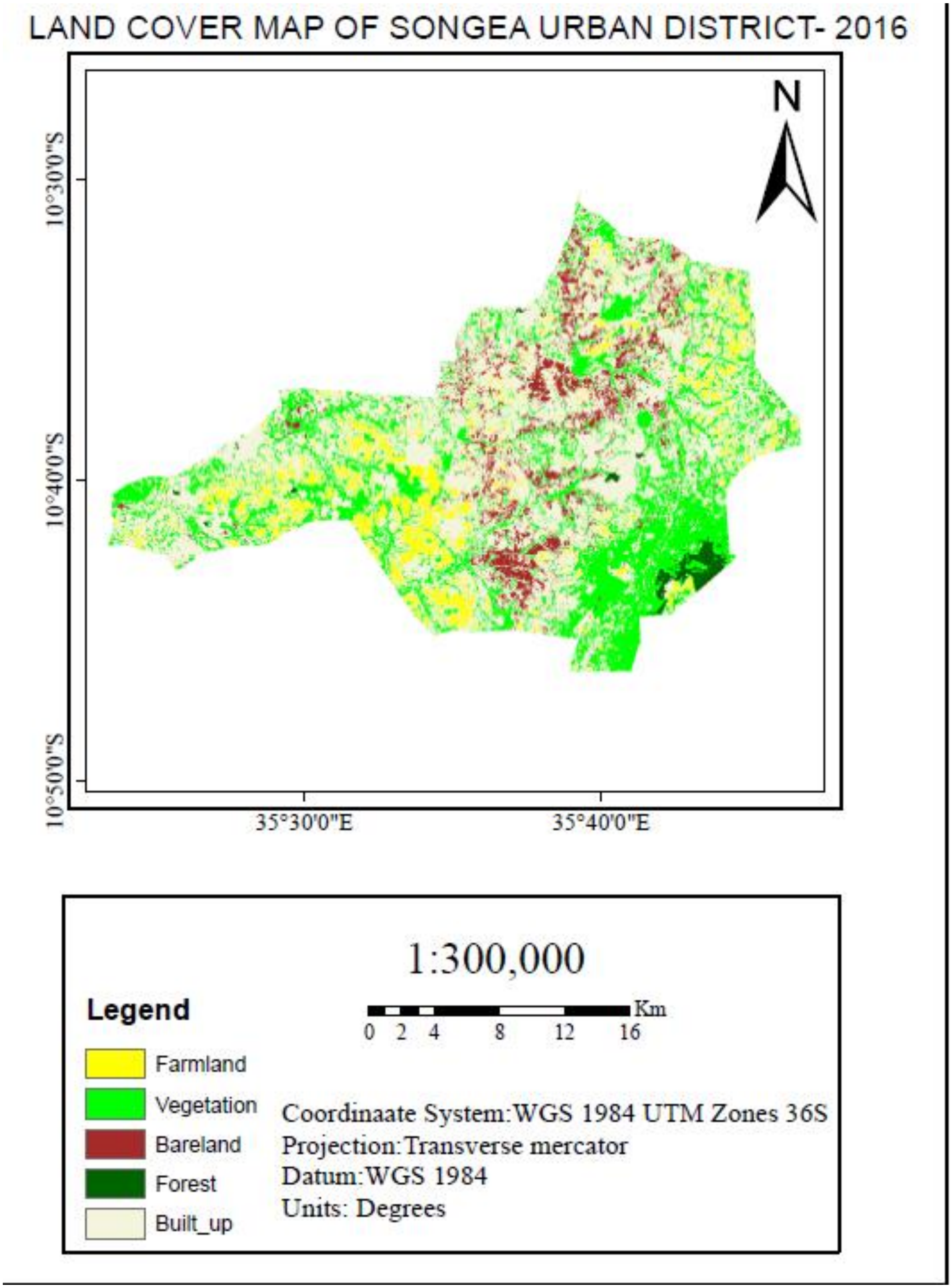

Figure 3: The LULC map of Songea urban of 2016

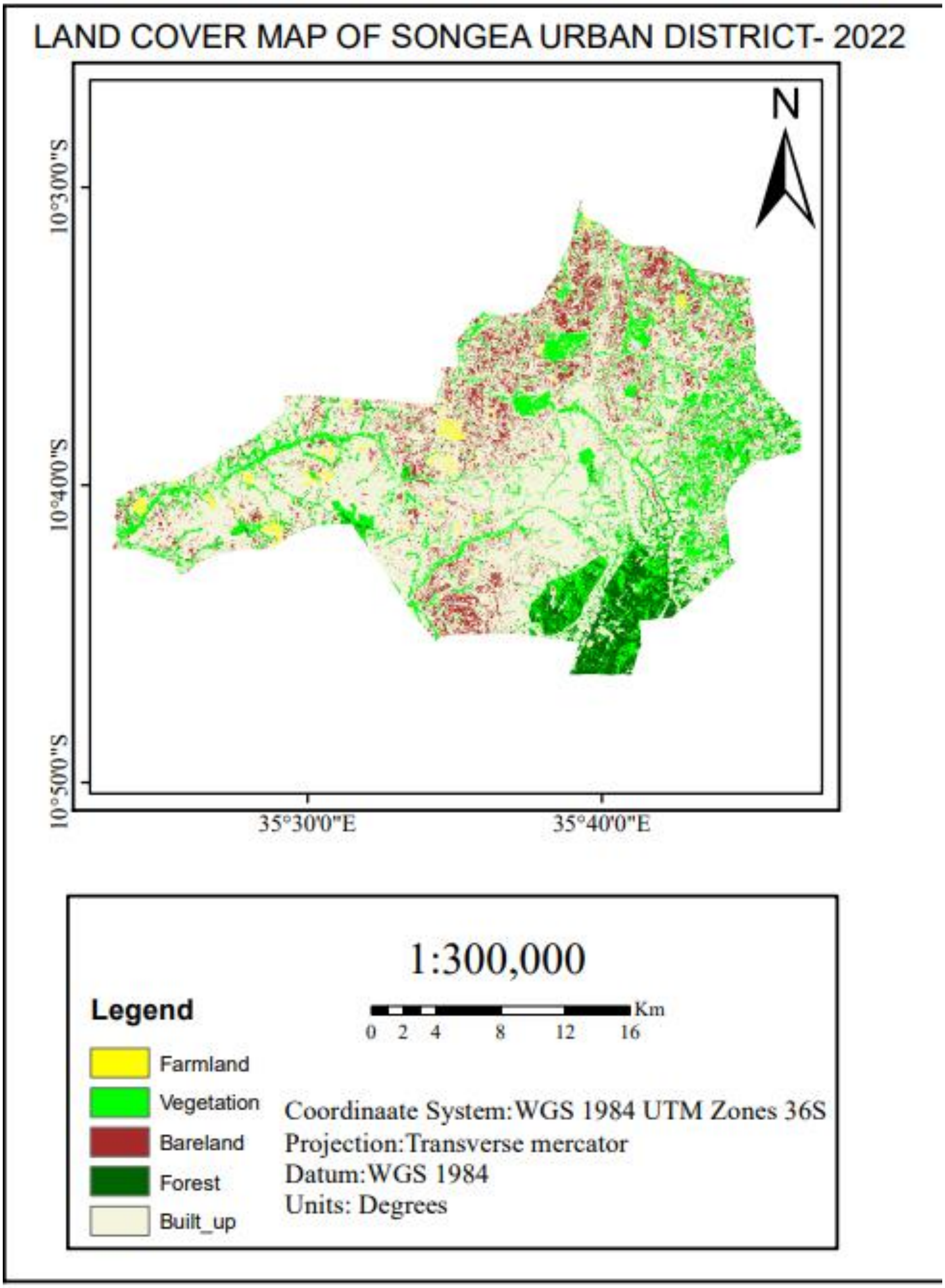

Figure 4: The LULC map of Songea urban of 2022

APPENDIX 3: Change detection map and graph

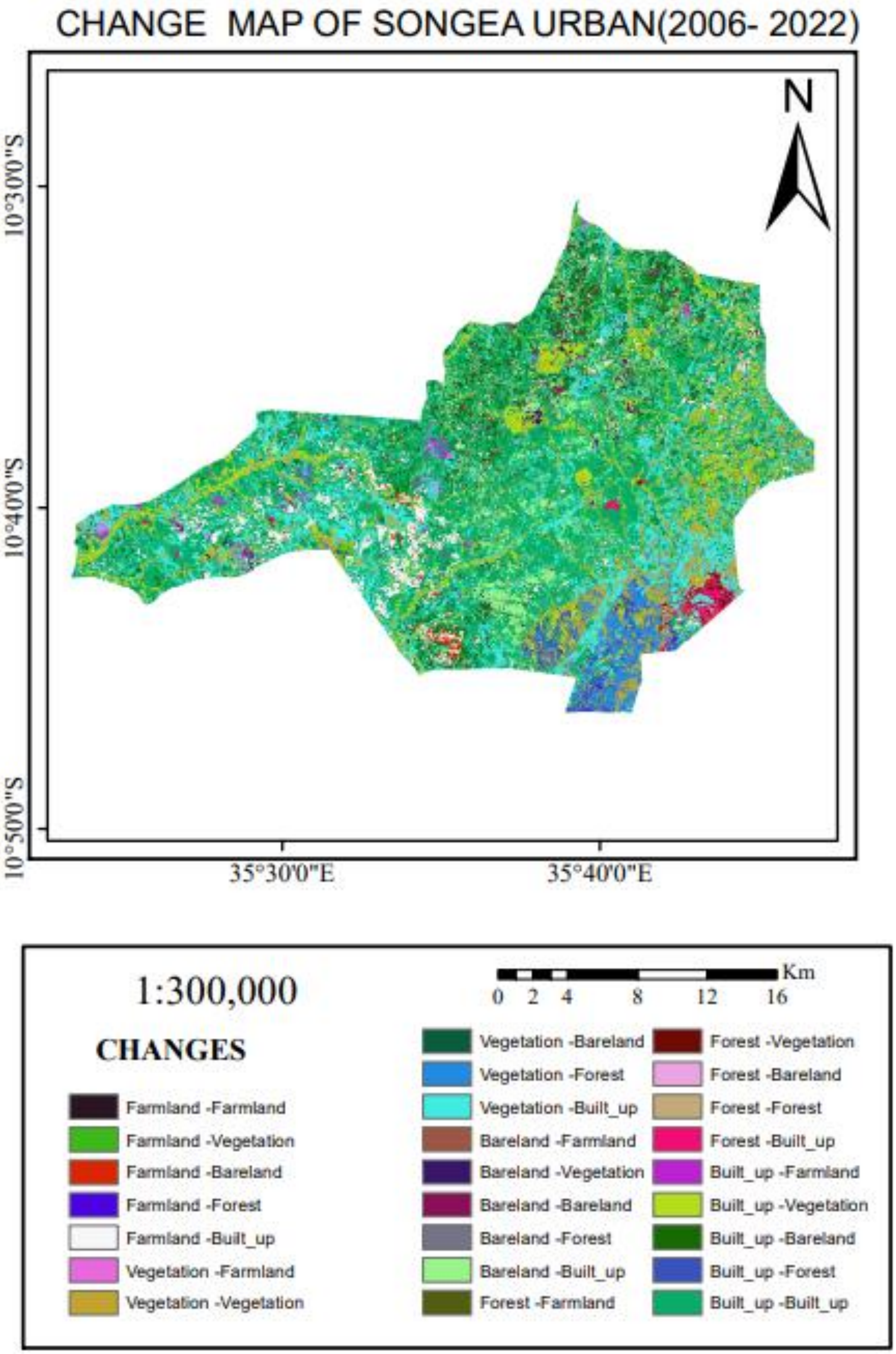

Figure 5: Change detection map of Songea urban (2006-2022)

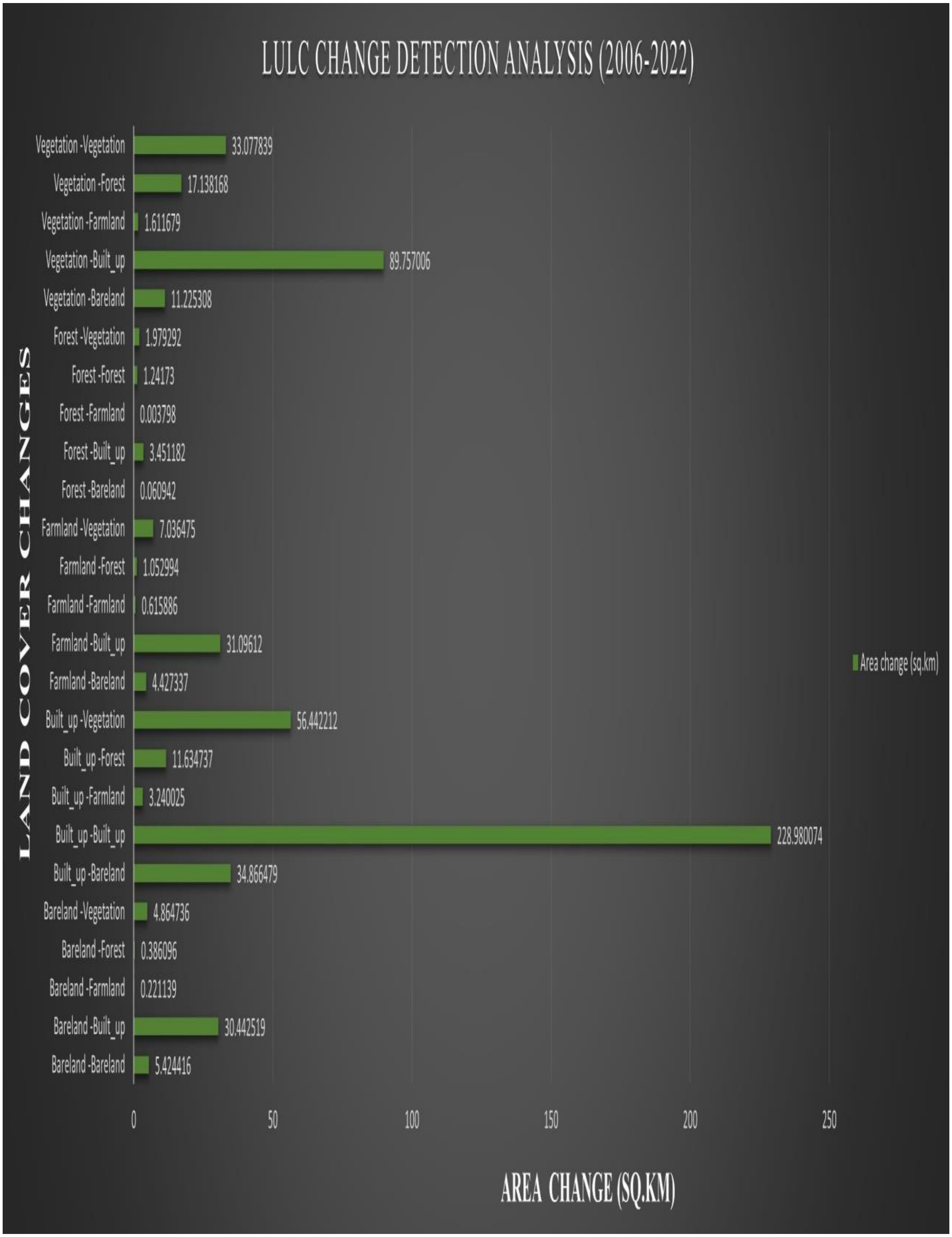

Figure 6: LULC change detection analysis graph

APPENDIX 4: Songea urban population data and Population density map

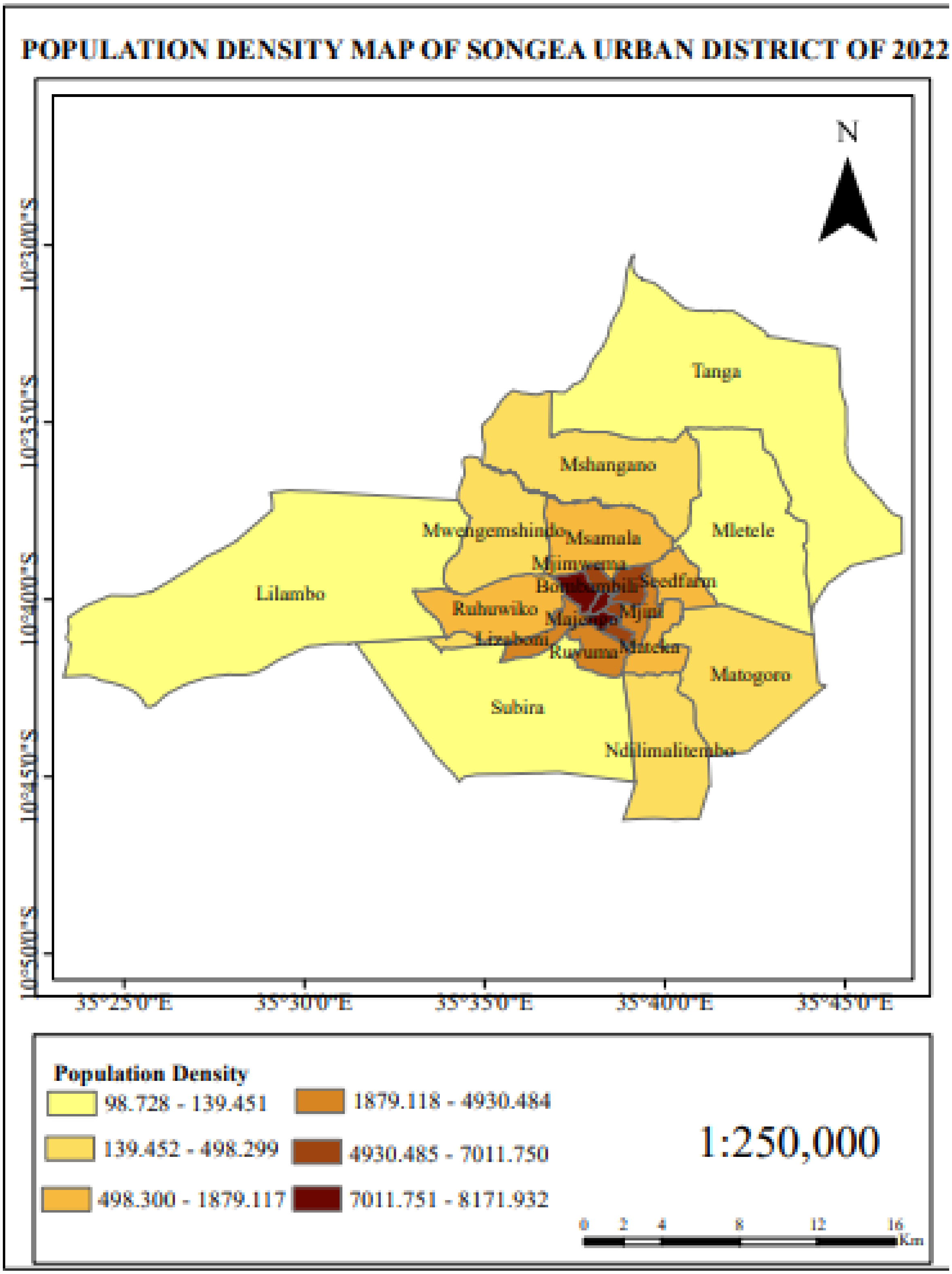

Figure 7: Population density map of 2022

Table 1: Songea urban district Population data in wards (2012 &2022)

Ward_Name	Population_ 2022	Population_2012
Misufini	3719	4599
Mfaranyaki	8114	9115
Mjini	7419	9443
Majengo	6599	7400
Tanga	14780	8754
Msamala	33822	18920
Mletele	6804	5331
Seedfarm	11963	6228
Ruhuwiko	21787	7377
Mshangano	22042	8205
Ruvuma	27514	13543
Subira	8520	7662
Lilambo	12642	11981
Mateka	7158	13537
Ndilimalitembo	9284	1609
Mwengemshindo	4539	2601
Mjimwema	19640	12055
Bombambili	25130	28058
Matogoro	7692	5127
Lizaboni	20120	14815
Matarawe	6997	6949