ANALYZING THE INFLUENCE OF URBANIZATION ON AGRICULTURAL LAND USING REMOTE SENSING AND GIS METHODS

Case Study: Morogoro Municipality

By

Tatu Juma Mhode

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CERTIFICATION

The undersigned certify that they have supervised and proof read the dissertation and recommend for acceptance by The Ardhi University a dissertation document entitled **"Analyzing the influence of urbanization on agricultural land using remote sensing and GIS methods."** In fulfilment of the course GS 393-dissertation Examination.

Dr. Guido Uhinga
(supervisor)
Date:
x

Dr. Zakaria Ngereja
(supervisor)
Date:

DECLARATION AND COPYRIGHT

I, Tatu Juma Mhode declares that this dissertation is my own original work and that to the best of my knowledge, it has not been presented to any other university for a similar or any other degree award except where acknowledgement has been made in the text.

Tatu Juma Mhode.

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DEDICATION

I dedicate this dissertation to my beloved mother Mrs. Mwanahamisi Juma Kiswanya and my uncle Mr. Mahmoud Mkuyu for their frequent support and diligent efforts in my upbringing from my childhood to date for their support they provided. I also wish to dedicate this dissertation my fellow friends for their encouragement in my education oddys.

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ABSTRACT

Morogoro Municipality is one the fast-growing town in Tanzania. It experiences rapid urban growth due to increasing human population, high demand of land for settlement, commercial activities and other activities which require land resources, These reasons have caused transformation of agricultural land into settlement and other human activities, which have led to agricultural loss of land suitable for agriculture and cause some problems. Such as food insecurity. this dissertation aims to assessing the influence of urbanization on the loss of agriculture land in Morogoro municipality from 2013 to 2021 by using GIS and remote sensing methods. Data source for the study were Landsat image which includes the Landsat 8 OLI of 2013,2017 and 2021. In additional the administrative boundary of Morogoro Municipality was obtained from diva GIS were used to extract areas of interest. By using GIS and remote sensing methods the map showing the total urbanized area of Morogoro Municipality time period of land cover was produced. The total urbanized area increased from 90.4347km^2 in 2013 to161.0748km^2 in 2021 out of 540km^2 of Morogoro municipality, with the average of annual urbanization rate of 8.8 km^2/year. This has caused the agriculture land loss in Morogoro municipality were the total of agriculture area decreased from 46.7471km^2 in 2013 to 43.0092km^2 at an average annual agriculture rate 0.4672km^2. This indicate that rapid urbanization growth is affect agriculture land cover. Land surveys must ensure that there are available surveyed plots for development to avoid loss of agriculture. The result obtained is limited to the data type and the methodology used, therefore may not provide the general conclusion, this is because the image used is characterized by low resolution which contain less information to identify features especial the built-up area and agriculture area. Also, the information was derived using a pixel-based classification instead of object-based classification.

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LIST OF ABBREVIATIONS

USGS	United States Geological Survey
GDP	Growth Domestic Product
GIS	Geographical Information System
LULC	Land Use or Land Cover
OLI	Operation Land Imager
UN HABITAT	United Nation Human settlement Programme

CHAPTER ONE

INTRODUCTION

1.1 Background

Urbanization is a rapid increasing of the population of an area that can be influenced by increasing of the economic growth. that can lead to the changes in the land use and land cover patterns of an area. Population growth is becoming more serious in urban areas as its leads to the adverse effects on the agricultural land. Land transformation is one of the most important fields of human induced environmental transformation, with an extensive history dating back to antiquity (Fazal, 2000). Since Neolithic times, the modification of the earth by human action mainly involved impacts on the soil and biotic resources. Land transformation did not stop but, rather, accelerated and spread with the beginning of the Industrial Revolution., the globalization of the world economy and the expansion of population and technological capacity land transformation also as lead to land for agricultural activity are loss. now Tanzania country facing this phenomenon.

Tanzania agricultural sector contributes nearly one third of the country GDP and employ 75 percent of population has potential to increase income and improve livelihoods. Feed the future, the united states government global hunger and food security initiative support plan led by Tanzania, to reduce poverty and improve nutrition, Tanzania is focusing on agriculture as a means to achieve economic growth. its plans incorporate private sector engagement including the southern Agriculture growth corridor of Tanzania initiative, a public private partnership to increase agriculture business investments in the country southern corridor (Blanco.H, 2009)Land use, land cover and agricultural fields’ changes globally, the world’s population is becoming more in urban areas are the most agricultural effects on urbanized (Gowthaman & K.D, 2017). So due to the impact of urbanization in the economy can lead to the decline of the country GDP. To assessing the impact of urbanization on agricultural land its can use the various technique

Remote sensing and GIS techniques can be used to analyze the impact of urbanization on agricultural land by providing detailed information on land use changes, such as the conversion of agricultural land to urban land. These techniques can also be used to assess the impact of urbanization on crop productivity and soil health, as well as to identify areas at risk of urbanization. Additionally, GIS can be used to create maps and visualizations to help decision-makers understand the extent and implications of urbanization on agricultural land.

Overall, remote sensing and GIS are powerful tools that can provide valuable insights into the impact of urbanization on agricultural land and can be used to inform land use policies and management strategies.

There has been a number of studies that have used remote sensing and GIS techniques to analyze the impact of urbanization on agricultural land. According to (Mohammad, M, M, Mehrjard, & G, 2017) the study aimed to provide a comprehensive understanding of the extent and pattern of urbanization and its effect on agricultural with the aim of informing future urban planning and land use decisions. (Chen, Zhan., & Q.L., 2016) the study aimed to provide comprehensive understanding of the extent, pattern, and dynamic of urbanization and its impact agricultural land in china, and inform policies for sustainable urban and agricultural development. (Mao, Ma, & X, 2015), the study aimed to assessing the changes in agricultural land and drivers of those changes, and to evaluate the effectiveness of policies aimed at mitigating the negative impact of urban sprawl on agricultural. (Tripathi, Pandey, & J.P., 2018), which used satellite imagery and GIS to track the conversion of agricultural land to urban land in India and found that urbanization had a significant impact on crop productivity and soil health. These studies establish that remote sensing and GIS techniques are powerful tools for analyzing the impact of urbanization on agricultural land, and that urbanization can have significant negative impacts on crop productivity and soil health.

1.2 Statement of the problem

Rapid growth of urban area has negatively impacted areas initially used for agriculture. This has resulted into food insecurity, among others, vegetable fruit and other crops and therefore contributing to shortage of food in urban area. Morogoro municipality is one of the areas where agriculture has been much affected by urbanization. Area that were used to cultivate crops such as maize, vegetable and fruits have now been transformed into residential area. The rate of urbanization is be seen, in terms of the increasing number of built up area. This is because no studies have been conducted to determine the rate of urbanization in the area. this study therefore seeks to determine the rate of urbanization in the Morogoro municipality area to inform action against the unprecedented urbanization trend

1.3 Objective

1.3.1 Main objective

The main objective is to assess the influence of urbanization on agricultural land in Morogoro Municipality

1.3.2 Specific objectives

i. To analyse land use /land cover dynamics of Morogoro Municipality for period of 2013-2021
ii. To determine rate of agricultural land loss due to urbanization in Morogoro Municipal

1.4 Research questions

Completion of this research will answer the following questions;

i. What are the land cover and land use of Morogoro municipal?
ii. To what extent has land cover has changed?
iii. To what extent has urbanization affected Agricultural land?
iv. What is the rate of change of land use land cover in Morogoro Municipality?

1.6 Significance of the research

i. The results will help decision makers on the effect of urbanization on agricultural land loss.
ii. The results will help decision making related to sustainable urban planning.

1.7 Beneficiaries of the research

i. Planners, the research can help the planners to conduct sustainable urban planning without affecting the area which are suitable for agriculture activities.
ii. Decision makers, also the research can the decision maker to make the decision on conducting the land transformation without affecting the agricultural land.

1.8 Study area

The study area is Morogoro municipality in Morogoro region. Morogoro region is one of Tanzania's 31 administrative region and consist of 8 districts. The population of Morogoro municipality is estimated to be 458,000 inhabitants with annual urban population growth (2022) of 4.09 and 540kmsqr.according to the 2022 population census, there were 28.7 percent. Morogoro municipal council will have the highest population density which in every kilometer square cover 743 people. agriculture activities and industrial are the regional economy. the main pursuits are small scale agricultural (production of food and cash crop for sustenance).

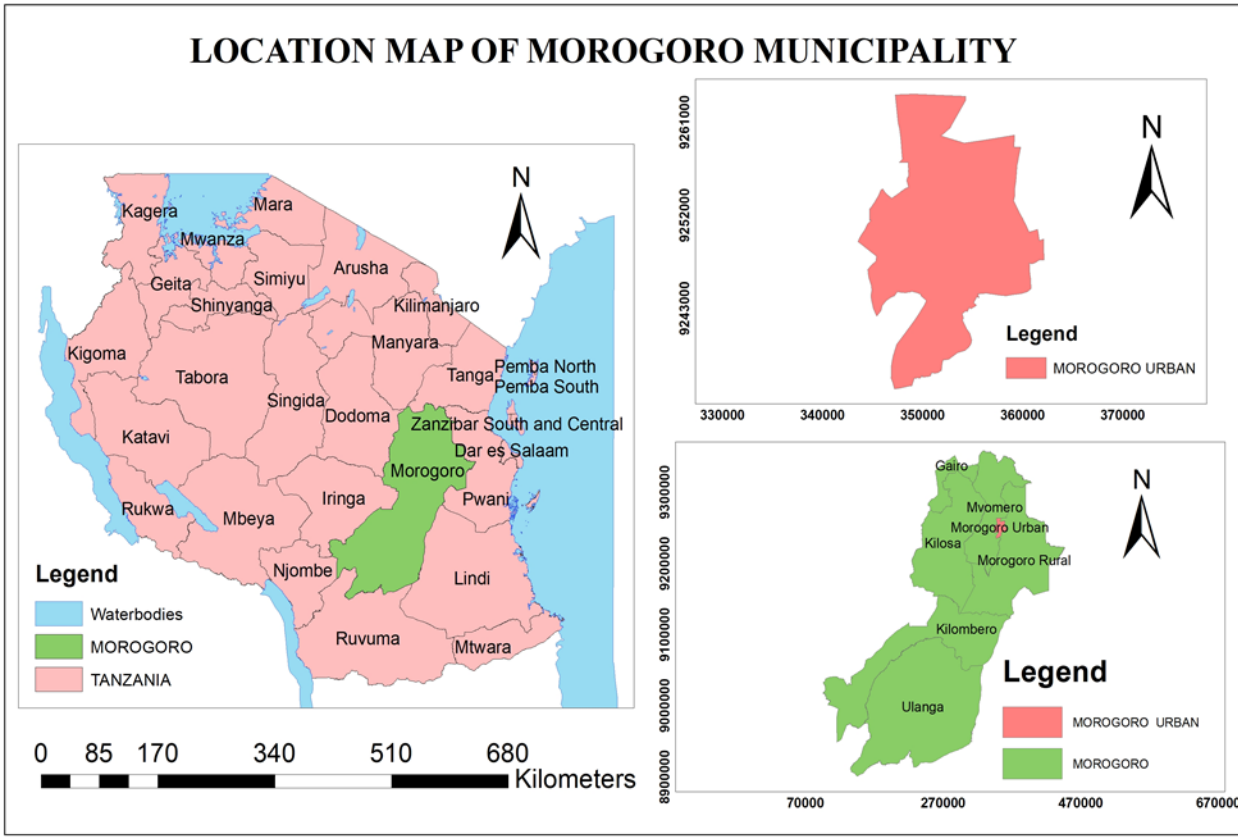

Figure 1.1 : Location map of Morogoro Municipality

CHAPTER TWO

LITERATURE REVIEW

2.0 Spatial urban growth

Spatial urban growth refers to the expansion of the built-up areas including human settlement due to gradual increase in the proportion of people living in certain area. Urban growth can be quantified either in terms of the level of urban development relative to the overall population of the population increasing (UNFPA, 2007).

2.1 Modelling of land cover/land use

Modelling is an analytical process conducted in conjunction with a geographical information system (GIS) in order to describe basic processes and properties for a given set of spatial features. From modelling the abstraction of real-world feature is created known as a model. The role of GIS in modelling are preparing data files, pre and post-processing of data for input to the model and displaying the model results in map form.

2.2 Image pre processing

Preparation of data for subsequent analysis, correction of deficiencies and Removal of flaws which make the part of preprocessing is important because it improves the quality of image as the basis for later analyses that will extract information from the image. Image pre-processing operations are also referred to as image restoration and rectification (Lillisand, Kiefer, & Chipman, 2007). The pre-processing techniques are concerned with the removal of data errors and of un-wanted or distracting elements of the image. There are various pre-processing processes which are;

- Inspecting characteristics and quality of data by displaying, summarizing and presenting histograms and other statistical summaries
- Compensate for radiometric errors.
- Geometric corrections.

a. Geometric correction

The geometric correction process is normally implemented as a two-step procedure. First, those distortions that are systematic or predictable are considered. Second, those distortions that are essentially random or unpredictable are considered. Random distortions and residual unknown systematic distortions are corrected by analyzing well-distributed ground control points (GCPs) occurring in an image. Once the coefficients for these equations are determined, the distorted image coordinates for any map position can be precisely estimated (Lillisand, Kiefer, & Chipman, 2007).

b. Radiometric error

Radiometric error is affecting the Digital Number (DN) stored in an image. Radiometric corrections involve improving the surface spectral reflectance, emittance, or back scattered measurements obtained using remote sensing system. They are caused by sensor Errors which are due to mechanical, electronic or communication failures of sensors and due to atmospheric errors, which are caused due to atmospheric constituents' interaction with EMR. Radiometric errors affect the Digital Number (DN) stored in an image (Lillisand, Kiefer, & Chipman, 2007).

2.3 Image classification

Image classification is the process of assigning pixels to nominal, which results to the thematic classes (Mather & Koch, 2011). The principle of image classification is that a pixel is assigned to a class based on its feature vector by comparing it to the predefined clusters in the feature space where by doing so all image pixels results in a classified image. This is also a process in which the (human) operator instructs the computer to perform an interpretation according to certain conditions. Image classification is based on the different spectral characteristics of different materials on the earth's surface.

Ground truthing

Ground truthing refers to the process of gathering or collection of information of locations for training and validation samples (Rehna & Natya, 2016). A ground truth is the term used to refer to information on location provided by observation for training and validation samples. The sources of ground truth are field observations, in situ spectral measurements, descriptive reports, Aerial reconnaissance and photography, Maps and satellite data with various height.

Spectral pattern is a set of radiance measurements from various wavelength bands for each pixel. Classification procedures can be based on Spectral pattern (spectral pattern recognition), Spatial patterns (spatial pattern recognition), Temporal patterns (temporal pattern recognition).

Spectral pattern recognition uses pixel-by-pixel spectral information as a basis for automated classification. (Rehna & Natya, 2016).

Computer assisted classification is one among the classification methods, the other ones be manual and object-oriented method (Rehna & Natya, 2016) Depending on the interaction between the analyst and the computer during the classification, there are two types of classification which are supervised classification and unsupervised classification.

2.3.1 Supervised classification

In supervised classification the operator defines the spectral characteristics of the classes by identifying sample areas (training areas). Supervised classification requires that the operator to be familiar with the area of interest. The operator needs to know where to find the classes of interest in the area covered by the image. This information can be derived from the general area knowledge of from dedicated fields of observations.

- Stages for performing supervised classification.

  The analyst identifies representative training sites and develops a numerical description of the spectral attributes of each feature imaged (Rehna & Natya, 2016) The training effort is both an art and a science. It requires close interaction between the image analyst and the image data. It requires substantial reference data and a thorough knowledge of the geographic area represented by the data. The training stage is important as it determines the quality of the information generated through classification. It helps to yield quality classification results; training data must be representative and complete but also to include all spectral classes and to include all information classes to be discriminated. In the training stage is where the;

  - The number of classes are identified
  - The Training sample per each class
  - The selecting and identifying validation samples and training samples. The validation samples are the samples that are used to qualify the performance. The training samples are the samples used to create the model. Training samples are always 70% of all samples while the validation samples are 30% of all samples.

class separability

This is the statistical measure between two signatures and can be calculated by Euclidean distance, Divergence, Transform divergence and Jeffries. (Rehna & Natya, 2016)

i. Classification stage.

Training sites are used to categorize each pixel in the image data into the land feature class it most closely resembles. A number of mathematical approaches exist for this purpose i.e. spectral pattern recognition. Select appropriate classification algorithm Example Minimum Distance to means classifier, Parallelepiped classifier, Random Forest classification, Maximum Likelihood classifier. The actual classification is done here. 16 Classifiers. A computer program that implements a set of procedures for image classification. There are different methods/strategies to image classification. Example ML classification, composed of various sets of procedures. A proper selection of a classifier is required for good accurate results. The classifier selected was; Random Forest Classification. This performs both regression and classification task and handle large dataset efficiently also, provides a higher level of accuracy in predicting outcomes over the decision tree algorithm (Rehna & Natya, 2016). It can handle binary features, categorical features and numerical features. There is little pre-processing that needs to be done also, the data does not need to be transformed or rescaled. Among the disadvantage is that large number of trees can make the algorithm too slow and ineffective for real-time prediction and works on tabular data.

ii. Output stage.

In this stage Presentation of the results of the categorization process. The output must effectively convey the interpreted information to its end user. The output might be in the form of Graphic files, Tabular data, and Digital information file. It is in this place where Accuracy assessment is done. Accuracy assessment determines the correctness of a classified image based on pixel groupings. Example the categories of real world features presented. The results of classification are assessed using a confusion matrix.

User accuracy Probability that a certain reference class has also been labelled as that class. In other words, it tells us the likelihood that pixel classified as a certain class actually represents that class.

Producer accuracy. Probability that a sample point on a map is that particular class. It indicates how well the training pixels for that class have been classified (Rehna & Natya, 2016)

Principle of image classification scheme

Pixel is assigned to a class based on its feature vector, by comparing it to predefined clusters in the feature space. Doing this for all image pixels results in a classified image. The crux of image classification in comparing it to predefined clusters, which require definition of clusters and methods of comparison Definition of clusters is an interactive process and is carried out during the training process. Comparison of individual pixels with the clusters take place using classifier algorithms (Rehna & Natya, 2016)

Classification scheme

This shows how the classes will be chosen during the process of image classification. There are several classification schemes and one of them is Anderson's classification scheme. This was developed for the use with remote sensing data both aircraft and satellite based. The advantages of this are can be used for many applications by selecting the level of the detail desired and many of the classes are not separable over large areas using remote sensing observations. (Rehna & Natya, 2016)

Levels of Anderson classification scheme are;

i. **Level one** Urban built up areas, Agriculture, Rangeland, forest, water areas
ii. **Level Two** Residential commercial, industrial, croplands, and pasture.
iii. **Level three** Single-family units and multifamily units.

Classes chosen during the process of image classification. The classes can be chosen;

i. Based on pixel information.

Based on pixel information and are classified as pre-pixel classification, sub pixel classification, pre-field classification, contextual classification, knowledge-based classification and combination of multiple classifications

ii. Based on training samples.

Based on use of training samples and are classified as supervised classification and unsupervised classification. Supervised classification methods require input from an analyst. The input from analyst is known as training set.

All the supervised classifications usually have a sequence of operations that must be followed

- Defining of the Training Sites.
- Extraction of Signatures.
- Classification of the Image

General steps for classifying the satellite image

The process of satellite image classifications typically involves five steps which are.

i. Selection and preparation of the image data depending on the cover types to be classified, the most appropriate sensor, the most appropriate dates of acquisition and the most appropriate wavelength bands should be selected.

ii. Definition of the clusters in the feature space where two approaches are used which is supervised and unsupervised classification.

iii. Selection of classification algorithms where the operators needs to decide on how the pixels (based on their DN) are assigned to the classes.

iv. Running the actual classification which is done once the training data have been established and the classifier algorithm is selected. This means that based on its DN values, each pixel in the image is assigned to one of the predefined classes.

Validation of the result

This process is done once the classified image has been produced its quality is assessed by comparing it to reference data (ground truth). This requires selection of sampling technique of a sampling technique, generation of an error matrix and the calculation of error parameters. (Rehna & Natya, 2016)

2.3.2 unsupervised classification

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. In unsupervised classification, it first groups pixels into “clusters” based on their properties. Then, you classify each cluster with a land cover class. The two basic steps for unsupervised classification are:

- Generate clusters
- Assign class

The algorithm of unsupervised classification;

- Iso Data classification
- K -Means classification

2.3.3 accuracy assessment

Accuracy assessment refers to the process that measures the agreement between a standard assumed correct and a classified image unknown quality (Campbell, 2007). These target accuracies often tend to be based upon the influential work of Anderson. Typically, the specified requirements take the form of a minimum level of overall accuracy, expressed numerically by some index such as the percentage of cases correctly allocated, and a desire for each class to be classified to comparable accuracy. For an overall accuracy should be greater than 70% to classification to be accurate. Additional features typically called for are the provision of more than one measure of classification accuracy (Mausel, D.lu., & E, 2003).

2.3.4 Land use

Land use refers to the purpose the land serves, for example, recreation, wildlife habitat or agriculture, residence; it does not describe the surface cover the ground. For example, a recreational land use could occur in a forest, shrub land, grasslands or on manicured lawns. Land use is commonly defined as a series of operations on land, carried out by humans, with the intention to obtain products and/or benefits through using land resources (Guan, et al., 2011)

2.3.5 Land cover

Land cover refers to the surface cover on the ground, whether vegetation, urban infrastructure, water, bare soil or other; it does not describe the use of land, and the use of land may be different for lands with the same cover type. For instance, a land cover type of forest may be used for timber production, wildlife management or recreation; it might be private land, a protected watershed or a popular state park. Land cover is commonly defined as the vegetation (natural or planted) or man-made constructions (buildings, etc.) which occur on the earth surface. Water, ice, bare rock, sand and similar surfaces also count as land cover (Guan, et al., 2011).

The analysis of satellite image for determination of the extent of change of land cover features is very important for implementation of different land development plans for sustainable development (Anderson, Hardy, & Roach, 1972).

2.4 Change detection

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Mausel, D.lu., & E, 2003)Some typical change detection includes land use land cover change, Forest or vegetation change, landscape change, urban change and environmental change. The output of change detection should provide information about.

- Area change and change rate.
- Spatial distribution of changed types.
- Change trajectories of land-cover types.
- Accuracy assessment of change detection results.

i. Techniques used for change detection

- Image algebra methods which use a reference/threshold to detect change and involve some techniques such as image differencing, image regression, image rationing and vegetation index differencing.
- Classification methods which based on the classified images and some of the techniques used are post-classification comparison and artificial neural networks.
- Advanced models which convert image reflectance values into physically based parameters or fractions which are easy to interpret and some of the techniques used is the spectral mixture analysis YYJK, T6.
- Transformations method which reduce data redundancy and some of the techniques used are Principal component analysis (PCA) and tasseled cap transformation

ii. Procedures for performing change detection

- Image selection.
- Image registration

- Radiometric corrections
- Multi temporal analysis

2.5 The effect of urbanization on agricultural land by using GIS and remote sensing techniques from other related studies

Different studies have been conducted to show how urbanization as affected to the agricultural land. Study to investigate the impact of urbanization on cropland in China's Yangtze River Delta region using remote sensing and GIS techniques (Chen, Liu, Yang, & Li, 2015). On this study they used remote sensing data and GIS techniques to analyze land use/cover changes in the region from 1985 to 2010. The researchers used statistical analysis to identify the impact of urbanization on cropland and to determine the intensity of urbanization that had the most significant impact on cropland loss. The study recommends the implementation of policies to promote sustainable land use management and to protect agricultural land from further loss due to urbanization.

The other related studies to this research are to estimate the impact of urbanization on agricultural land in the Pearl River Delta region, China (Gao, Li, Chen, & Hu, 2018). The study used remote sensing data and GIS techniques to analyze land use/cover changes in the region from 2000 to 2015. The researchers used statistical analysis to identify the impact of urbanization on agricultural land and to determine the intensity of urbanization that had the most significant impact on agricultural land loss. The study recommends the implementation of policies to protect agricultural land from further loss due to urbanization and to promote the sustainable use of land resources.

The other studies to this research are Agricultural land use changes and its impact on food security: A study using remote sensing and GIS techniques in India (Mallick, Kumar, & Singh, 2012). To investigate the impact of urbanization on agricultural land use changes and its impact on food security in India using remote sensing and GIS techniques. The study used remote sensing data and GIS techniques to analyze land use/cover changes in the region from 2000 to 2019. The researchers used statistical analysis to identify the impact of urbanization on agricultural land and its impact on food security

CHAPTER THREE
METHODOLOGY

3.0 Overview

This chapter describe overall the method ranging from data collection to result. It includes the data acquisition, data preprocessing and data analysis method that were used in obtaining the result. This study adapts the image processing like training sample, image classification and accuracy assessment on data processing and performing change detection toward to achieving the main object. The step by step process performance in this study is summarized in figure 2.

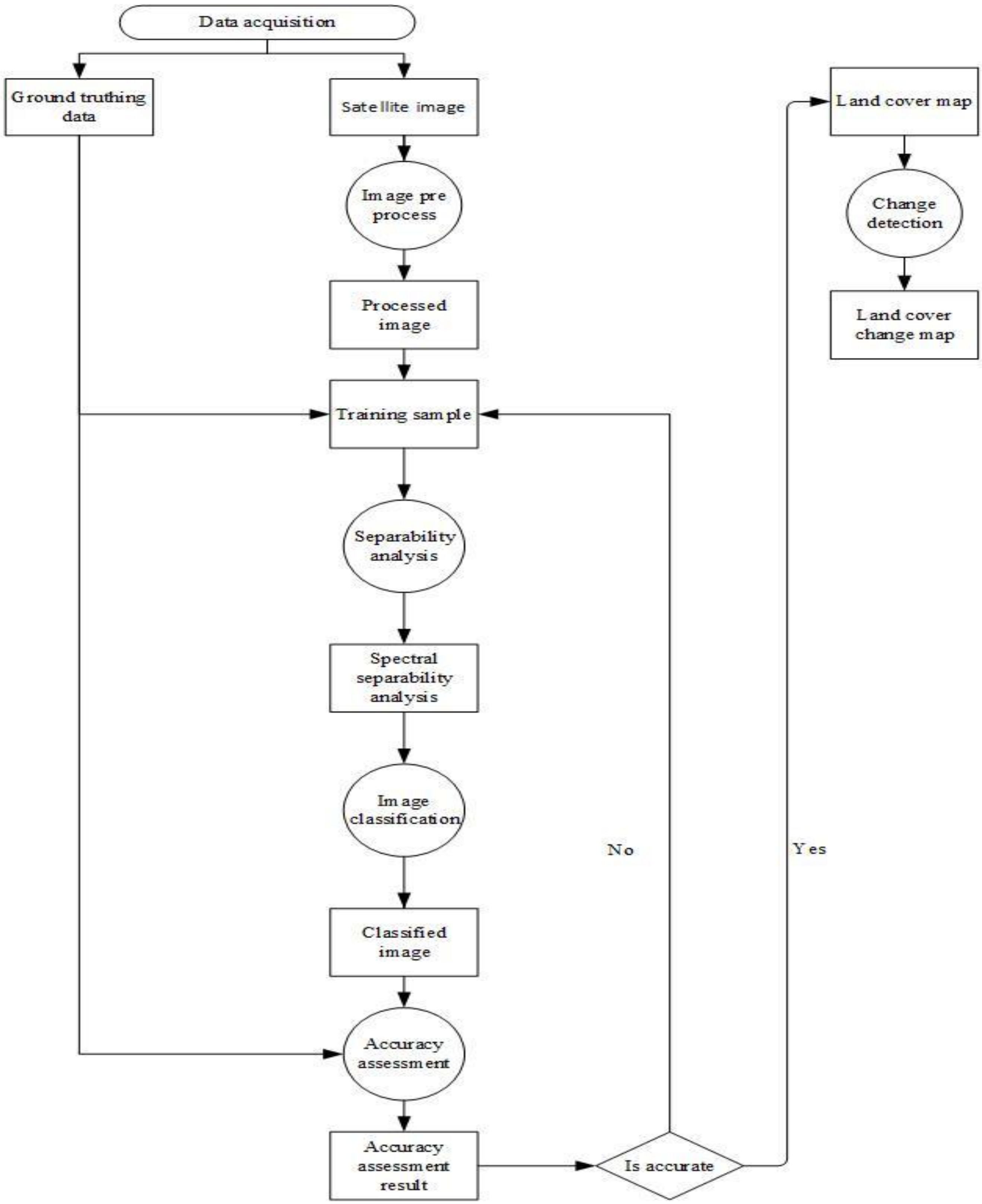

Figure 3. 1 Flow chart of assessing land cover changes

3.1 Data Acquisition

The data used in this study are Landsat 8 OLI data ground truthing data and administrative boundary data. the Landsat data are obtained from USGS explorer where these data are used in image classification and analysis of changes on the land cover are used in spatial and spectral observation. Table 1 show characteristic of data

Table 3.1: characteristic of data

Data	Date	Format	Source	Uses
Landsat 8 OLI image	2013 2017 2021	TIFF	USGS (http://earthexplorer.usgs.gov)	Spatial and spectral observation
Ground truthing data		csv	Field data collection	Accuracy assessment
Administrative boundaries		shape file	DIVA-GIS (https://www.diva-gis.og)	Extraction of the area of interest

3.2 Image Pre-Processing

The stage of Pre-processing was performed for the purpose of converting digital number (DN) to surface reflectance and followed by layer stacking process which performed by combining pre-processed bands of Landsat images to produce a single stacked layer in a TIFF format. With the bands of same resolution, the raster layer was containing band 1, 2,3,4,5,6 and 7 were selected. Band 10 were not selected because they were panchromatic 29 which have 30m resolution and thermal band for the Landsat 8 OLI images. The stacked processed image was re-projected into UTM 36S using WGS 84 datum purposely to eliminate the negative coordinates from Landsat 8 OLI coordinate system. The intention of re-projection was to make the images to bear the same coordinates as the area of interest.

3.3 Ground truthing data utilization

At this stage, satellite image with high resolution which are google earth pro was used to collect ground truth data for training sample and validation process of the feature classes as existed on the ground and its coordinates. During ground truthing 361 data of different land cover were collected and used for the current satellite image which is Landsat 8 OLI of 2021. The ground truth data were divided into two groups whereby 70% was used for training sample during image classification and 30% was used for validation of classified image during accuracy assessment.

3.4 Sub setting of an image

The process of obtaining the area of interest for classification was accomplished through sub setting, it was done on the Landsat 8 OLI images to obtain the representation of the project area on the images by adding the shape file of Morogoro Municipality area. The extraction by mask algorithms were used to clip the area of interest from re-projected stacked images.

3.5 Image classification

The method of Supervised classification was employed as a technique of image classification where feature classes were assigned into pixels, and the algorithm used was maximum likehood it performs both regression and classification task and it can handle large dataset efficiently. Each pixel is assigned to the class that has the highest probability.

Its accurate classifier (take most variable into consideration and also takes variability of classes into accounts by covariance matrices). It was involved in the selection of classification scheme, selection of training sample, generation of signature files, evaluation of signature files and performing the supervised classification. The classification processed can be summarized in the following steps;

i. Selection of Classes

Anderson level I classification scheme was used during selection of land cover classes which was based on the available ground truth data and resolution of the image used. Due to the nature of project area three classes were used to represent features as follows;

- Bare land
- Vegetation
- Built up area

ii. Selection of Training Sample

The training samples were collected by using rectangular polygon icon tool which were used to select small part of the class that was identified and positioned by using the ground truthing data that were collected basing on the selected classes of ground features for Landsat 8 OLI image of 2021. For other Landsat 8 OLI image of 2013 and 2017 the spectral reflectance was used to facilitate selection of training samples based on different band combination. The number of pixels based on number of bands was used to select training sample.

iii. Generation of Signature Files

After selection of training samples from each class, in addition each class were merged and renamed accordingly. Signature files tend to describe classes and their respective feature's locations and value determining the general class value used in the classification processes.

iv. Selection of Classification Algorithm

After spectral classed being defined in the feature space the maximum likelihood algorithm was used to decide how the pixels are assigned to the classes and then performing the classification.

3.6 Accuracy assessment

The accuracy of the classified image of 2021 was assessed by confusion matrix which uses validation data from ground truth as reference, the classified images of 2013 and 2017 was assessed by confusion matrix which uses random points from the google earth as the reference.

3.7 Change detection

The post classification comparison method was used to detect area changes and rate changes whereby land cover map of 2013 was compared by land cover map of 2017 and land cover map of 2017 was compared by land cover map of 2021

CHAPTER FOUR

RESULTS ANALYSIS AND DISCUSION

4.1 Image classification results

The process of classification was done completely based on the classification scheme, selecting of training sample, generation of signature files. The different number of pixels were assigned to the high probability specific class in order to determine the accuracy of the process.

4.2 Accuracy assessment results

The accuracy assessment was performed by computations of confusion matrices. The accuracy assessment of Landsat 8 OLI of 2021 was 75% of Landsat 8 of 2017 was 87% and Landsat 8 of 2018 was 78.51%. The table 2 represents confusion matrices and Total accuracy for Landsat 8 OLI of 2017.

Table 4.1: Accuracy assessment for land cover map of 2017

OID		Agriculture	sparse vegetation	built up	bare land	Total (user)
1	Agriculture	27	2	1	0	30
2	Sparse vegetation	0	42	4	0	46
3	Built up	1	4	68	12	85
4	Bare land	0	0	1	38	39
5	Total(producer)	28	48	74	50	200

$$overall\ accuracy\ = \frac{total\ number\ of\ correct\ pixels}{total\ number\ of\ reference\ pixel} \times 100\%$$

$$= \frac{27 + 42 + 68 + 38}{200} \times 100\%$$

The overall accuracy is 87%

Table 4. *2:* Accuracy assessment for land cover map of 2021

oid		agriculture	sparse vegetation	built up	bare land	total (user)
1	Agriculture	22	6	1	1	30
2	sparse vegetation	0	34	0	0	34
3	built up	1	12	72	26	111
4	bare land	0	1	1	23	25
5	total (producer)	23	53	74	50	200

$$overall\ accuracy\ = \frac{total\ number\ of\ correct\ pixels}{total\ number\ of\ reference\ pixel} \times 100\%$$

$$= \frac{22 + 34 + 72 + 23}{200} \times 100\%$$

The Overall accuracy is 75%

Table 4. *3:* Accuracy assessment of land cover map for 2013

OID	Class Value	agriculture	sparse vegetation	built up	bare land	Total
1	Agriculture	20	3	1	0	24
2	sparse vegetation	4	57	6	1	68
3	built up	0	2	50	9	61
4	bare land	0	0	8	39	47
5	Total	24	62	65	49	200

$$overall\ accuracy = \frac{total\ number\ of\ correct\ pixel}{total\ number\ of\ reference\ pixel} \times 100\%$$

$$overall\ accuracy = \frac{20 + 57 + 50 + 39}{200} \times 100\%$$

The overall accuracy is 83%

4.3 Land cover map

During the classification of the images four land cover were detected and classified which were Bare land, built up, sparse vegetation and agriculture and the different land cover maps of different years were obtained. Land cover maps of 2013, 2017 and 2021.

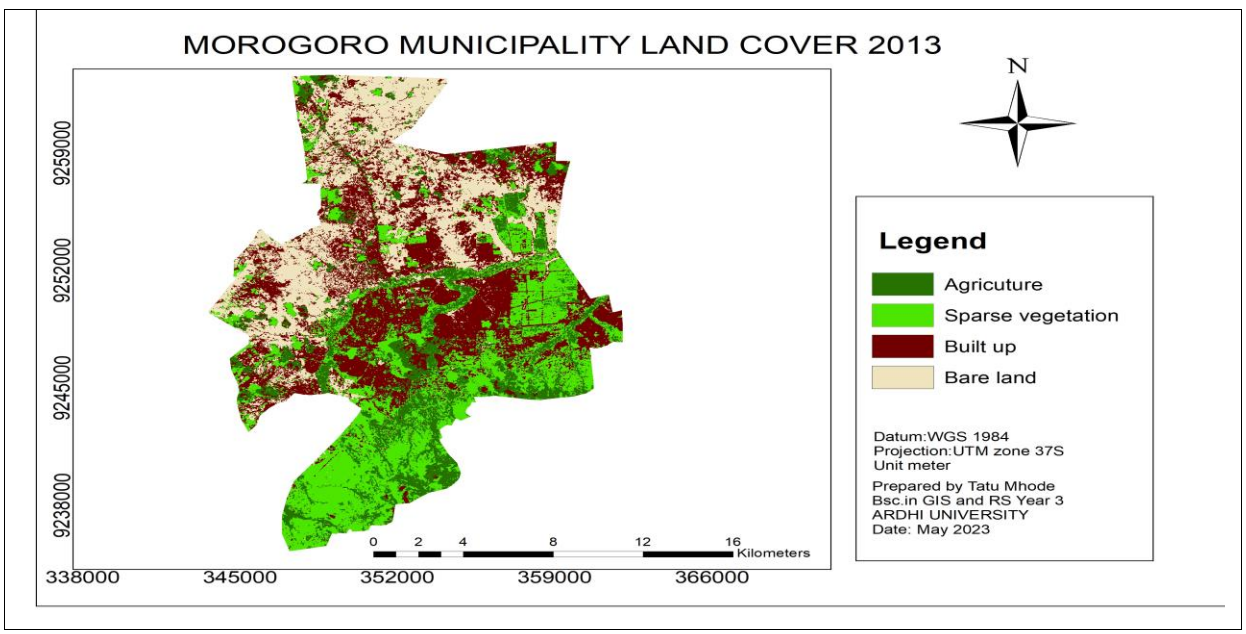

Figure 4. 1: Morogoro Municipality land cover map for 2013

Figure 4.1 shows, most of the area was covered sparse vegetation bare land and built up where 79.4295kmsqr,73.6578km square and 90.4347km square, respectively. And the Agriculture was occupied by 46.7471km square out of 540 km square of Morogoro Municipality.

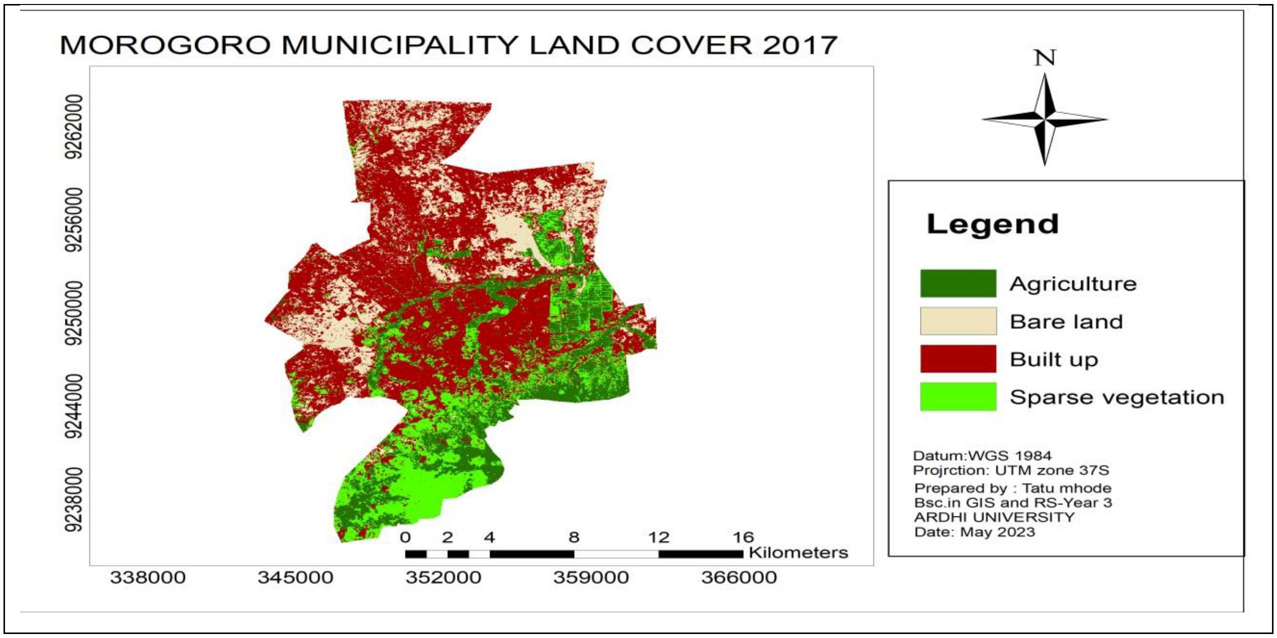

Figure 4. 2: Morogoro Municipality land cover map for 2017

Figure 4.2 shows, most of the area was covered built up and sparse vegetation where 142.776km square and 51.7419km square respectively. The Agriculture was occupied by 46.7471km square and bare land was occupied 49.5486km square out of 540 km square of Morogoro Municipality. The built-up area was increased by 54.3413 km square compared by 90.4347 km square of 2013 and agriculture was decreased by 2.5445km square.

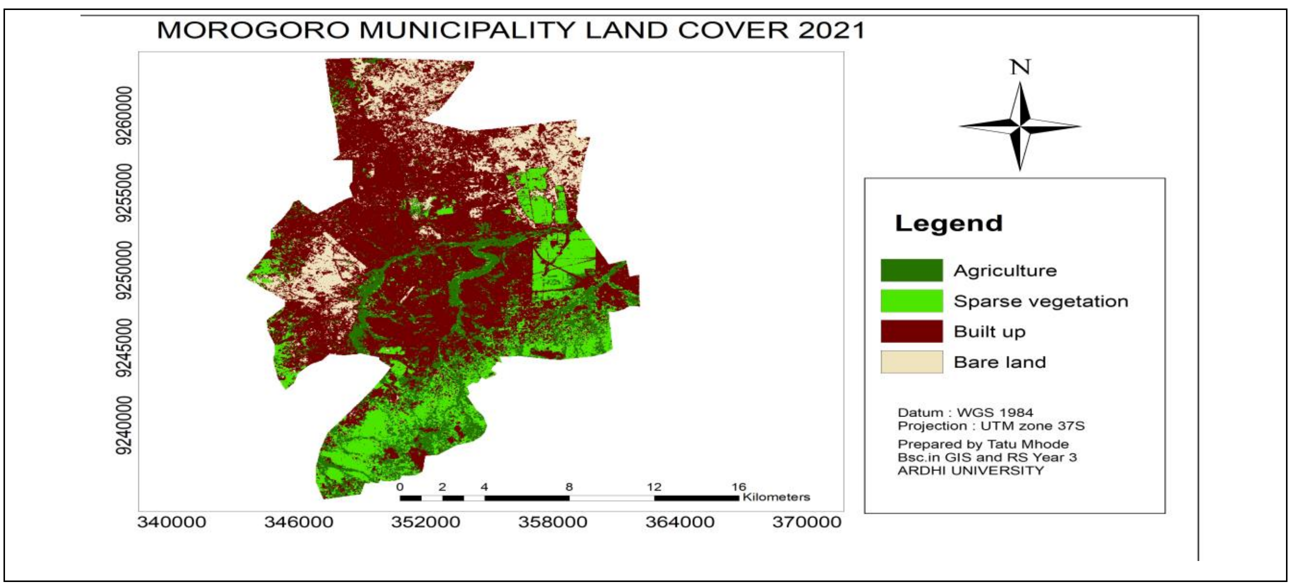

Figure 4. 3: Morogoro Municipality land cover for 2021

Figure 4.3 shows, most of the area was covered built up and sparse vegetation where 161.0748km square and 48.771km square respectively. The Agriculture was occupied by 43.0092km square and bare land was occupied 35.4096km square out of 540 km square of Morogoro Municipality. Whereas built up area was increased by 18.2988km square compared by 142.776 km square of 2017 and agriculture was decreased by 1.1934km square.

4.4 Graph representation of land cover

The graphs show the rate of land cover in every year. The below figure shows the graph of 2013,2017 and 2021.

Figure 4. 4: The land cover for 2013,2017 and 2021

4.5 land cover change

The results show the change of Morogoro Municipality land cover for the year 2013-2017, 2017-2021 and 2013-2021. It shows how land covers changed from one type to another and it is well defined in the legend. Figure 4.5, Figure 4.6 and Figure 4.7 Shows the land cover change of Morogoro Municipality in the years 2013-2017, 2017-2021 and 2013-2021 respectively

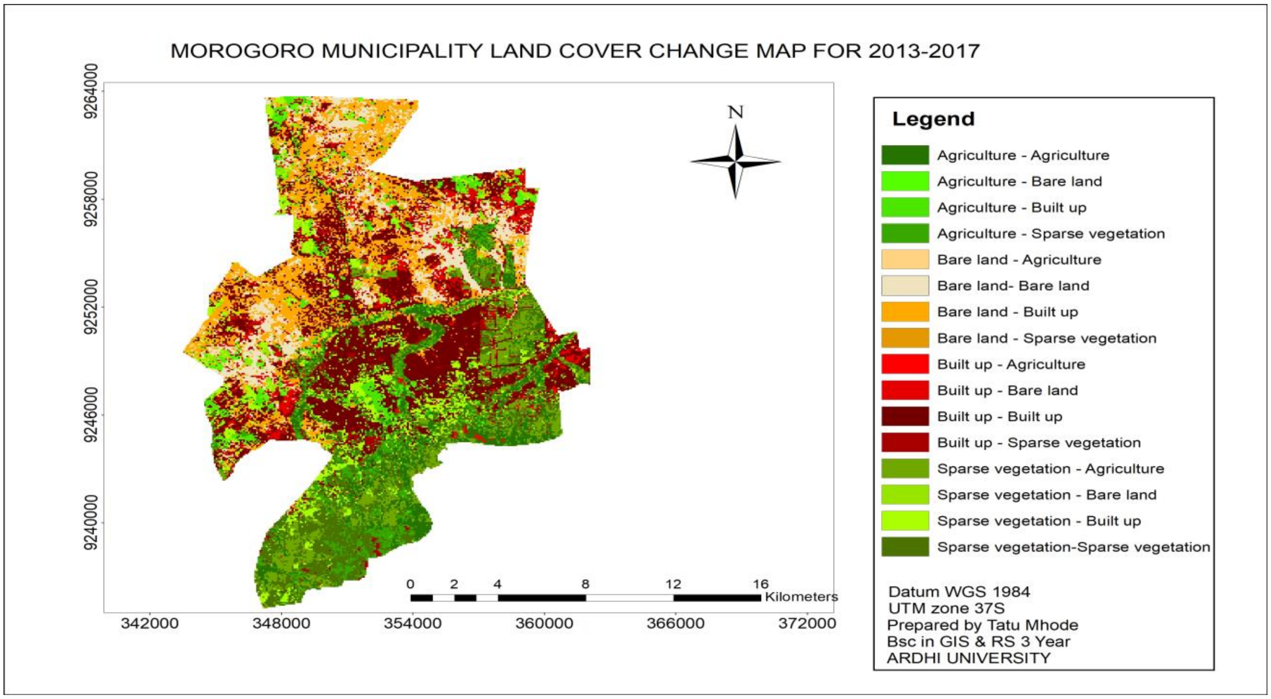

Figure 4.5: Morogoro Municipality landcover change for 2013 -2017

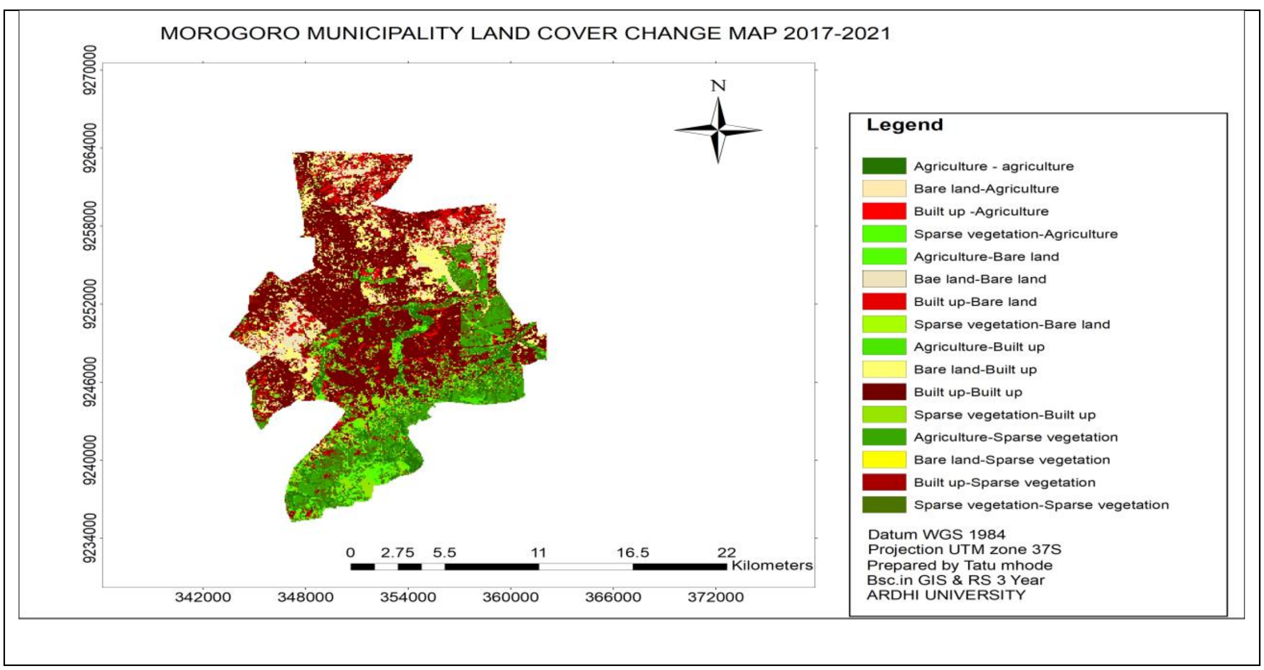

Figure 4. 6: Morogoro Municipality land cover change for 2017-2021

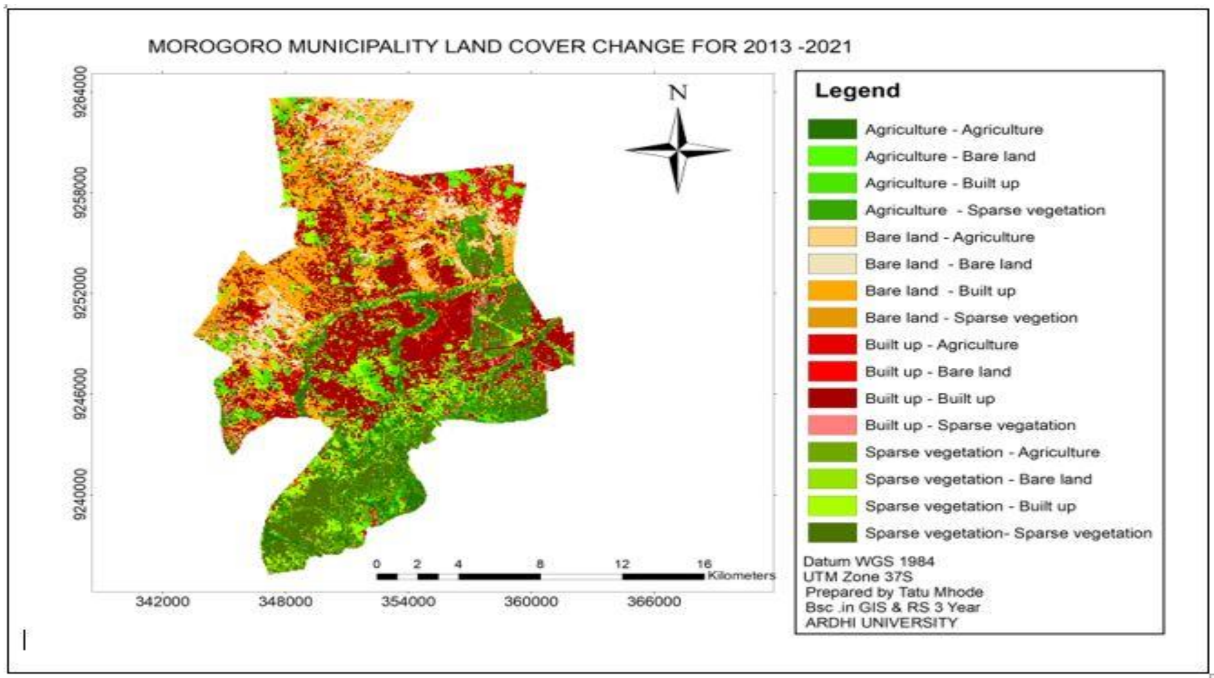

Figure 4. 7: Morogoro Municipality of land cover change for 2013 to 2021

4.6 Rate of land cover change

The tables were made in order to make the interpretation easier during analysis. the below are the tables that shows the land cover change between 2013 and 2017, the land change from 2017 and 2021 and the land cover change from 2013 and 2021.

Table 4. 4: The rate of land cover change for 2013-2017.

Class	Area (km²) 2013	Area (km²) 2017	Area change (km²)	Rate (km²/year)
Agriculture	46.7471	44.2026	-2.5445	-0.6361
Sparse vegetation	79.4295	51.7419	-27.6876	-6.9219
Bare land	73.6578	49.5486	-24.1092	-6.0273
Built up	90.4347	142.776	52.3413	13.0853

From the above table the ate of land cover changes from 2013 to 2017 wee as follow the built-up area increases by 13.0853km²/year, agriculture area was decreases by 0.6361km²/year, sparse vegetation decreases by 6.9219km²/year and bare land was decreases by 6.0273km²/year.

Table 4.5: The rate of land cover change for 2017-2021

Class	Area (km^2) 2017	Area (km^2) 2021	Area change (km^2)	Rate (km^2/year)
Agriculture	44.2026	43.0092	-1.1934	-0.29835
Sparse vegetation	51.7419	48.771	-2.9709	-0.742725
Bare land	49.5486	35.4096	-14.139	-3.53475
Built up	142.776	161.0748	18.2988	4.5747

From the above table the ate of land cover changes from 2017 to 2021 whereas follow the built-up area increases by 4.5747km^2/year, agriculture area was decreases by 0.20835km^2/year, sparse vegetation decreases by 0.742725km^2/year and bare land was decreases by 3.53475km^2/year.

Table 4 .6: The rate of land cover change for 2013-2021

Class	Area (km^2) 2013	Area (km^2) 2021	Area change (km^2)	Rate (km^2/year
Agriculture	46.7471	43.0092	-3.7379	-0.4672
Sparse vegetation	79.4295	48.771	-30.6585	-3.8323
Bare land	73.6578	35.4096	-38.2482	-4.781
Built up	90.4347	161.0748	70.6401	8.83001

From the above table the ate of land cover changes from 2013 to 2021 were as follow the built-up area increases by 8.83001km^2/year, agriculture area was decreases by 0.4672km^2/year, sparse vegetation decreases by 3.8323km^2/year and bare land was decreases by 4.781km^2/year

4.6.1 Graph representing the rate of land cover change

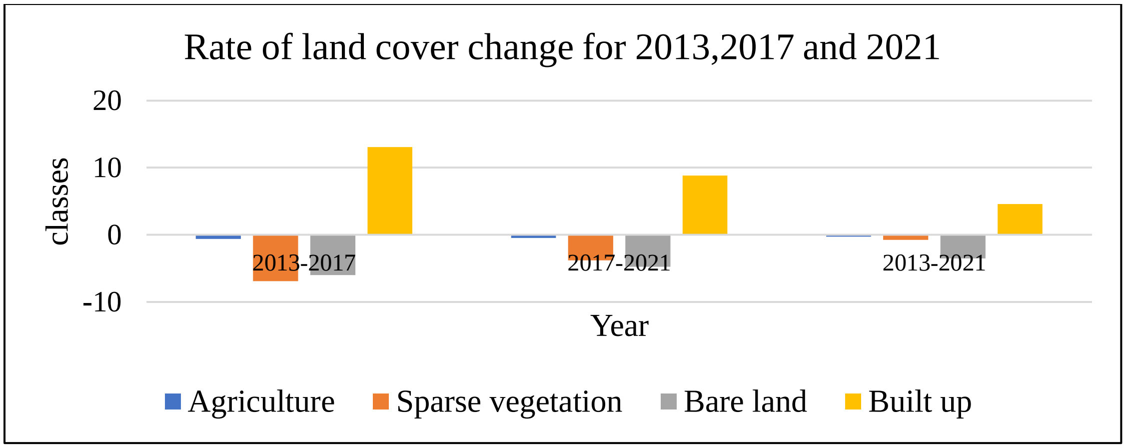

Figure 4. 8: The rate of land cover change for 2013,2017 and 2021

4.6.2 Relationship between urban area /built up and agriculture area

The graph that created are showing the relation between urban area and agriculture area. the below show the relation between agriculture and urban area

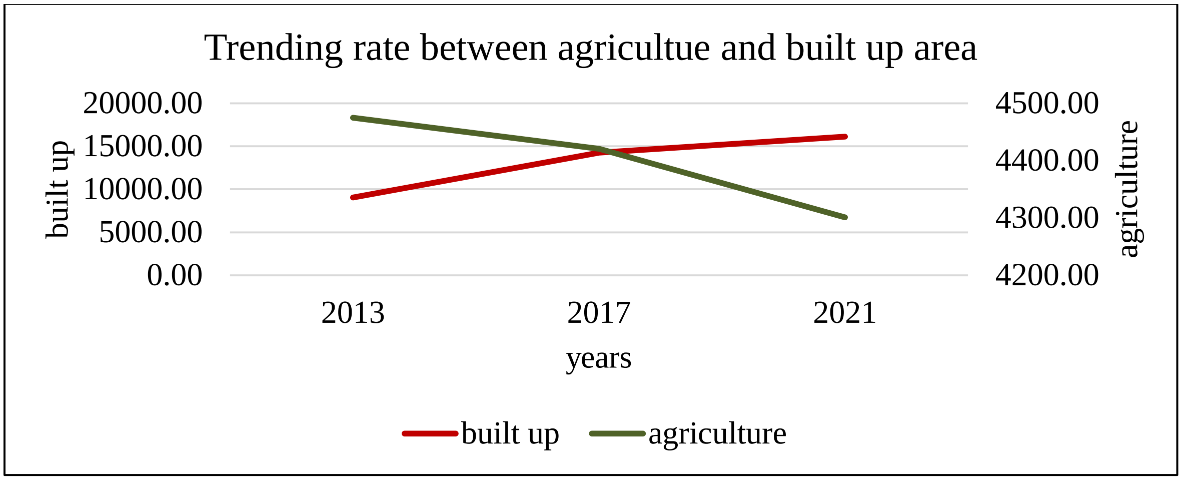

Figure 4. 9: Relationship between built up and agriculture area

Figure 11 show the relationship between urban area/built up and agriculture area where as when the urban area increases agriculture area decreases. the trending analysis of urban area is to increase due to change of the years according to rate of change urban area can change for 8.830017km²/year and agriculture area can decreasing 0.4672km²/year.

4.7 Change from agriculture to built up

The table ware made in order to make the interpretation easier during analysis. table 8 that show area of change from agriculture to built up, between 2013 and 2021,

Table 4 .7: The area that changes from agriculture to built up

year	Agriculture -built up(km²)
2013-2021	14.2123

CHAPTER FIVE
CONCLUSION AND RECOMMENDATION

5.1 Conclusion

GIS software has been applied to identify and analyze the urbanized area in Morogoro Municipality, this is contributed by the availability of remote sensing data Landsat image from different year that facilitate the analysis of spatial urban growth and agriculture land loss in Morogoro Municipality .According to the analysis it shows that there has been rapid growth of built up area which affect the agriculture activities in Morogoro Municipality . the result obtained is limited to the data types and the methodology used, therefore the study has shown that not only agriculture land that is affected by urbanization but other types of landcover like vegetation and bare land, the trend shows that when agriculture decreases and the urban area increases and the agriculture land loss for eight years is 4.94%.

5.2 Recommendation

- Morogoro Municipality land officers must ensure the speed of surveying, when the conducting land uses change must consider the area of agriculture activities must not be affected and cannot change their use in order to control loss of agriculture land.
- Further study can be done to analyze the effect of urbanization on agriculture land in Morogoro Municipality by using high resolution satellite image in which the information on the feature is derived from the group of pixels instead of pixel based to improve the classification result
- Software used are ArcGIS and Quantum GIS so for further study can used other software like google earth engine and R software during data analysis.

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