MAPPING LAND USE AND LAND COVER CHANGE AND THEIR EFFECTS ON URBAN_PRE URBAN AGRICULTURE IN DEBRE MARKOS TOWN, ETHIOPIA.

THESIS SUBMITED TO

THE SCHOOL OF GRADUATE STUDIES OF ADDIS ABABA UNIVERSITY IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE WARD OF DEGREE OF MASTERS OF ART IN GIS, REMOTE SENSING AND CARTOGRAPHY STREAM

BY:

ZIENA LINGEREH

ADVISOR:

HABTOM BELEW

ADDIS ABABA UNIVERSITY

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By

ZIENA LINGEREH AYELE

(GSR/2325/08)

ADVISOR:

HABTOM BELEW

Addis Ababa University

School of Graduate Studies

This is to certify the thesis prepared by Ziena Lingereh entitled as *"Mapping Land Use Land Cover Changes and its effects on urban and Peri Urban Agriculture in Debre Markos Town"* is submitted in partial fulfillment of the requirements for the Degree of Master of Art in GIS, remote sensing and cartography compiles with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the Examining Committee:

External Examiner ________________________ Signature_______________ Date ____________

Internal Examiner ________________________ Signature_______________ Date ____________

Advisor _________________________________ Signature ______________ Date ____________

Chairman ____________________________ Signature ______________ Date ____________

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Abstract

Land use / Land cover mapping serve as a basic register of land resource for all levels of government, environmental agencies like Ethiopia where agriculture sector has the basic contribution for gross economy, land resource plays a major role in the level of production. *This study emphasize mapping land use land cover change detection and presents results regarding to land use land cover change detection and its effect on urban agriculture in the case of Debre Markos town. To achieve the objective of this thesis integration of recent technology, such as remote sensing and GIS tools and different ancillary data like topography map used as input with ground verification for accuracy assessment. To collect ground truth data for aspect of accuracy assessment stratified random sampling method was used and followed that 250 sample points were collected from these 60%used for classification purpose and 40% were used for accuracy assessment. Change detection Analysis results shown that there was decreased farm land in the last 29 years from -15.4% from (1987 to 2003), -4% from (2003to2016) and -1.24% from (1987to2016) due to expansion of built up areas. The spatial trend of built up areas was a growing trend in the different part of Debre Markos town which accounted area coverage of increment 11.4% in 1987 to 24% in 2003 and 25.4% in 2016 . Therefore, the findings of this study could provide as decision making for urban planning.*

Key words: Land Use Land Cover changes, GIS, Remote Sensing

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List of Abbreviations

AOI	Area of Interest
CSA	Central Statistics Agency
EMA	Ethiopian Mapping Agency
FCC	False color Composition
GIS	Geographic Information System
GLCF	Global Land Cover Facility
IHDP	International Human Dimension Program
LULCC	Land Use Land Cover Change Detection
TM	Thematic Mapper
UA	Urban Agriculture
UPA	Urban and Pre-urban Agriculture
UNDP	United Nation Development Program

CHAPTER ONE

1. INTRODUCTION

1.1 Background

Changes in Earth's natural land cover have been taking place since time immemorial, and have been linked with both innate phenomenon and human intervention. Urban areas now form the foundation of the human experience for the greater part of the Earth's population. Several reports have emphasized that cities today must meet up the desires of increasing populations and growing economies, while at the same time minimizing their environmental impacts. Detailed monitoring of urban land use modify remains costly and challenging, and is often performed on a city-by-city basis that prevents relative analysis of urban trajectories, land use features, or the effectiveness of different plan and policy interventions(K.Kavitha et al., 2012).

Unavoidably, population increase leads to a quick expansion of urban growth, causing changes in land use land cover in many urban areas. The rate of such change is obvious in developing countries with high population increase. These unmanageable urban changes in the region of the Ethiopian towns can build up a large number of communal and physical problems, in addition to the farming lands changed. Recently, information of land use and land cover transformation is highly required to many groups; remotely sensed data can be used as it provides the land cover information. It is also fundamental for estimating levels and rates of deforestation, habitat fragmentation, urbanization, wetland and soil deprivation and many other landscape-level phenomena (Edward et al., 2010).

The understanding of town land change is also important for decision makers and planners. In recent years, urbanization is a main trend in big cities all around the world. The main modify of land use like this type of areas can be referred as other type of land use transferring into urban land. Unfortunately, the predictable survey and mapping techniques are costly and time intense for the estimation of urban expansion and such information is not available for most of the urban centers, mainly in developing countries. As a consequence, increased project attention is being going to the monitoring of urban growth using GIS and remote sensing techniques. Remote sensing is ever more used for identifying and investigation of urban expansion since it is price effective and technologically efficient. Currently, these methods have progressed and have been extensively used in supervision of innate resource and urban forecast (Kennedy et al., 2009).

Mapping land-use and land-cover (LULC) change in an area is vital for many planning and management activities. Improved understanding of LULC patterns will assist planners to properly evaluate complex causes and responses used to better project future trends of human actions and LULC change (Dionyset al., 2010).

Urban agriculture (UA) is an important land-use class and it is a most important source of livelihood for many people and urban dwellers plant plots/bare lands to support financially their earnings and maintain their livelihoods. Though, lands used for UA are becoming gradually scarcer due to high competition from other land uses and the rapid population growth being experienced in many cities of the developing world. Information about land use /land covers change and its consequence on agricultural lands in town area are important for enhancing food security and for proper management of land use (Foeken, 2006). This study was use multi-date satellite images to examine LULC changes and their effects on urban agriculture within Deber Markos town.

1.2 Statement of the problem

Ethiopia is one of the slightest urbanized countries in the world. Even for African standards, the rank of urbanization is low. According to the Population Reference Bureau's *World Population Data Sheet* (2002), while the average level of urbanization for Africa in general was 33% in 2002, Ethiopia had only 15% of its population living in urban areas. Despite of the low level of urbanization and the fact that the country is mainly rural, there is a fast rate of urban growth, which is currently estimated at 5.1% per year (CSA, 1998).

Rapid rate of urban growth lead to rapid changes of land use and cover than ever before, particularly in developing nations, are often characterized by unrestrained urban rambling, land degradation or the transformation of agricultural land to other uses and resulting massive cost to the environment (Sankhala et al., 2014).

Planning problems in the study area include inappropriate land uses due to ignorance or misconception about physical environment changes due to land use changes, urban policy makers be unsuccessful to give due attention to urban agriculture and poor availability of spatial information necessary for urban planning. This improper land use extremely affects the local and/or regional environment, which was ultimately affecting the global environment and it minimize urban greenness (Maru, 2014).

Urban agriculture is an important provider of food production to market. particularly in developing and emerging countries, urban landscapes are generally various and characterized by their sequential unpredictability in cropping patterns, small-scale fields and fast changes due to the urban surrounding area (Smith et al., 1996). However urban agriculture areas are more and more under pressure of population growth and in developing countries, this occurrence was exacerbate by poverty, most important to unbelievable problems of employment, immigration from the rural areas, transportation, and food supply and environment protection.

Land use land cover (LULC) is a global change driver and has distinguished implications to many of the worldwide policy issues (Vitousek et al, 1999). Land use /land cover Change analysis of features of Earth's surfaces important for improved understanding and mapping patterns of land-use and land-cover (LULC) change in an area is important for many planning and management activities but urban policy makers be unsuccessful to give due attention to urban agriculture during urban planning policy reforms and digital change detection in urban environments is a dispute due to three characteristics exceptional to urban areas: (1) urban land-use and land-cover changes usually account for a little amount of the project area and are scattered in different locations; (2) reflectance of surfaces and parallel spectral features between impervious surfaces and other no vegetation land covers are complex; and (3) the spatial resolution of remotely sensed imagery is limited (Kennedy et al. 2009).

Therefore this study aims to develop a change detection procedure suitable for detecting urbanization in a complex urban land use land cover change, based on the comparison of extracted inflexible surface data sets from multi temporal images by carry out different change detection techniques such as unsupervised classification, supervised classification, ,post classification and ground reference or field verification.

According to Mueller et al. (2004) further referred to there are main challenges during classification of land use land cover and when segmenting urban agricultural landscapes. Some of the major reasons for this are (a) numerous small objects may lead to high grey value variation and over segmentation, (b) the low contrast between objects results in under segmentation and, (c) deviation from rectangular shapes prevents the use of fixed geometric rules. However, from the experience of land use land cover classification system can be guaranteed by using during image pre-processing techniques and field verification.

1.3 Justification and Motivation of the Project

Indeed, there is no any studies on land use land cover change within Debre Markos town but studies has been made to document on the assessment of land use land cover dynamics and soil erosion, assessment for sustainable management of land resources (Tegaw, 2007) within Gozamin in werda in the past but it doesn't paying attention within the urban land use land cover change and its effect. Therefore this study focused on urban land use land cover changes and the main motivation of this project is to improve capacity building of Debre Markos municipalities 'will be adjust their plan related to land use land cover that could be upgraded with little hint and effort. In the area of urban planning many researchers have conducted using remote sensing imageries particularly in urban change analysis and the modeling of future growth, land use land cover evaluation, urban heat island research(Basudeb Bhatta,2011). This project provides integration of remote sensing and GIS based multi temporal land use/land cover change data provide information that can be used for assessing the structural variation of land use /land cover patterns, which can be applied for avoiding irreversible and cumulative effects of urban growth, are important to allocation of urban services.

1.4 Objective

1.4.1 General Objective

The main objective of this project is to assess the effects of the land use land cover changes on urban agriculture in Debre Markos town over the three decades period of 1987, 2003 and 2016 by integrated use of Remote Sensing (RS) and Geographic Information System (GIS).

1.4.2 Specific Objectives

Specific objectives of the project are to deliver:

- ✓ Classify the LULC changes in the project area during the time periods of 1987, 2003and 2016.
- ✓ Identify the drivers of land use land cover change in the project area.
- ✓ To examine the characteristics of urban land cover over the study area based on the classification by utilizing GIS technologies and
- ✓ To give awareness areas within the town that may form the bases for hint or sound solution for urban planners and decision makers.

1.5 Significance of the Project

The study was emphasize how remote sensing and GIS technologies were important for classification of different land use land cover change and how land use land cover mapping is vital for making decision and for urban development plan because in the developing countries there is uncontrolled growth of towns and problem of land administration system, similarly this problem also faced in the project area. Therefore to overcome the problems such as: incompatibility of land use services in residential zones, absence of functions required at neighborhood level such as green areas, loss of agricultural lands, demolish of garden land, destruction of important vegetations and improper use of land resources and finally to analyze and understand the driving factors for land use land cover change. In addition to this, the study will try to bring a hint for the town municipalities' and planners about land use data that are important for sustainable environment and to understand the living conditions and standards to maintain the current and the future land use managements. Final beneficiaries of this project will be Debre Markos town societies, especially who live in unplanned areas and whose livelihood depends on urban agriculture.

Knowing land use land cover can assist planners for multipurpose and in time will become an essential bases for all land administration and urban planning functions such as legislators, planners, and state and local government officials to determine better land use policy, to project transportation and utility demand, to identify future development pressure points and areas, and to implement effective plans for regional development. Therefore, the project will be the base for these issues, it put proper land use management for implementation of urban plan and it will be a hint for further projects (Clawson et al, 1965)

1.6 Limitation of the Thesis

The present project is not completely free from limitation. In this project many constraint are faced from data acquiring till to analysis, from these the following are mentioned. To do land use land cover change detection ground truth and verification is very essential but it is difficult to addressee in short period time and small finical support. Even though it is very important this project faced serious problem linked with finical support and time constraints. Mapping urban land use land cover changes is difficult during interpretation and classification of images due to similarity of spectral signature of features.

Regarding to accuracy assessment, due to over lapping of features the overall accuracy become low when we compare Anderson, 1997, overall accuracy which is 85 percent.

1.7 Scope of the Thesis

This project was focus mainly on land use land cover change detection and their effect by integrated GIS and remote sensing data and giving hint about the importance of mapping land use land cover change for urban planning in Debre Markos town boundary and also the accuracy assessment was carryout and putting results, and finally recommendations were raised based on the findings.

1.8 Thesis Structure

This Project comprises six chapters. Chapter 1 sets out the background of the project, Statement problem, Justification of the project, objectives of the project and significant of the project following Chapter 2 Provides project, a literature review which introduces some helpful background of techniques used in this project, and Chapter 3 deals with the description of the project area and methodology of mapping land use land cover change and its effect on urban agriculture.. Chapters 4 deals about data analyze and discuss the results. Finally, Chapter 5 concludes by summarizing the major findings and giving recommendations of the study.

CHAPTER TWO

2. LITERATURE REVIEW

2.1 Land Use Land Cover (LULC)

Land is the most important usual resource, which comprises soil and water and the associated flora and fauna, thus involving the total ecosystem. Knowledge of the spatial distribution of land use and land cover is essential for the planning and management activities. Land use is characterized by the planning, activities and inputs people undertake in a certain land cover type to produce, change or maintain it.

Although the term Land cover and land use are often using interchangeably, their actual meanings are quite distinct. It is important to distinguish this difference, and the information that can be ascertained from each source. Land cover corresponds to the physical condition of the ground surface, for instance forest, grasslands, etc., while land use reflects human activities such as the use of the land, for instance industrial zones, residential zones, etc. Land cover refers to feature of the land surface, which may be natural, semi natural, managed, or manmade. They are directly observable by remote sensor. Land use, on the other hand refers to the activities on land or classification of land according to how it is being used. Not directly observable, inferences about land use can often be made from land cover (Basudeb, 2011).According to Basudeb, the two terms are described as follows:

Land cover refers the biophysical coverage of land like natural areas, forests, buildings, lakes and roads. The term land cover describes the types of resources/features present on the surface of the earth. It is the observed (bio) physical over on the earth’s surface.

Land use refers to the socioeconomic use that is made of land for different purpose such as agricultural use, commerce, residential use, recreational area; at any place , there may be multiple and alterative land uses. It reflects the character of a society’s interaction with its physical environment, fact that becomes obvious when it is possible to see different economic and social systems occupying the similar environments.

Land Use Land Cover Change (LULCC) is a very complicated process, affected by natural and human dimensions. The natural environment is a dominant factor in a way, while human dimensions are repulsive factors. The research on LUCC is a basic precondition of regional LUCC monitoring, driving factor analysis, and even to LULCC prediction. RS (remote sensing) and GIS (geographic information systems) are believed as the most advanced means to obtain land use information because they are real time, impersonal and has wide coverage (Sankhala et al., 2014).

2.2. Purpose of Land Use Land Cover

Remote sensing data can provide land cover information rather than land use information. The properties measured with remote sensing techniques related to land cover, from which land use can be inferred, particularly with ancillary data or a prior (already known) knowledge (Basudeb, 2011).

Identifying, delineating and mapping and subsequent monitoring studies, resources management, and planning activities this identification of land cover establish the baseline from which monitoring activities (change detection) can be performed, and provides the ground cover information for baseline thematic maps(Basudeb, 2011).

According to (Basudeb, 2011) Land use application involves both baseline mapping and subsequent monitoring, since timely information is required to have knowledge on the state of use of current quantity of land and to identify the land use changes time to time. This knowledge helps to developing strategies to balance conservation, conflicting uses, and developmental pressure. Issues driving land use studies include the removal or disturbance of productive land, urban encroachment, and depletion of forest.

In addition, a reason for developing and maintaining a land cover monitoring study is to provide a consistent view of the stock and state of our natural and built resources as they change through time. Knowledge of land use and land cover is important for many planning and management activities concern concerning the surface of the earth. Survival of human race depends on its living in harmony. Many a civilization has perished in the past when its people misused and over and over exploited the land, and interfered with the environment (Kavitha et al., 2012) .Land use refers to ‘man’s activities on land, which are directly related to land’ (Anderson et al., 1976).Land use and land cover change (LULCC) is general term for the human modification of earth’s terrestrial surface. Land use land cover arrangement makes landscape patterns.

Land use land cover change (LULCC) detection is very essential for better understanding of landscape dynamic during a known period of time having sustainable management. Land use land cover changes is a dynamic, widespread and accelerating process, mainly driven by natural phenomena and anthropogenic activities, which in turn drives changes that would impact natural ecosystem. Land use and land cover change, as one of the main driving forces of global environmental change, is central to the sustainable development debate. Land use/land cover change has been reviewed from different perspectives in order to identify the drivers of land use/land cover change, their process and consequences (Zahra et al, .2004)

Land use Land cover studies are multidisciplinary in nature, and thus the participants involved in such work are numerous and varied, ranging from international wildlife and conservation foundations to government researchers and forestry companies. Regional government agencies have an operational need for land cover inventory and land use monitoring, as it is within their mandate to manage the natural resources of their respective regions. In addition to facilitate sustainable management of land, land cover and land use information may be used for planning, monitoring, evaluation of development, industrial activity, or reclamation. Detection of long term changes in land cover may reveal a response to a shift in local or regional climate conditions, the basis of terrestrial global monitoring (Basudeb Bhatta, 2014).

Changes in land cover are examined by environmental monitoring researchers, conservation authorities, and departments of municipal affairs, with interest’s varying from tax assessment to reconnaissance vegetation mapping. Governments are also concerned with the general protection of national resources, and become involved in publicly sensitive activities involving land use conflicts (Basudeb Bhatta, 2014).

According to (Basudeb Bhatta,2014) explanation land use applications of remote sensing include the natural resource management, wildlife habitat protection, baseline mapping for geographic information system (GIS) input, urban expansion or encroachment, routing and logistics planning for seismic/exploration/resources extraction activities, damage delineation (tornadoes, flooding, volcanic, seismic, fire, and terrorist activities),legal boundaries for tax and property evaluation and target detection_ identification of landing strips, roads, clearings, bridges, and land or water interface.

2.2.1 Land Use Land Cover Change

The modification of earth's terrestrial surface by human activities is commonly known as land use land cover change (LULCC) around the globe. Although modification of land by humans to obtain livelihood and other essential has been there for thousands of years, the extent, intensity and rate of LULCC are far greater now than were in the past .These changes are driving forces for local, regional and global level unprecedented changes in ecosystem and environmental processes. Thus land use land cover change plays an important role in the study and analysis of global changed scenario today as the data available on such changes is essentials for providing critical input to decision making of ecological management and environmental planning for future (Zahra et al.2014).

As the population increase and national economics continue to move away from agriculture based system, cities grow and spread. The urban sprawl often infringes upon viable agriculture to productive forest land, neither of which can resist nor deflect the devastating momentum of urbanization. Urbanization has mainly exerted strong pressure on existing land use and the most affected is agricultural lands which are transformed to built up areas in every high rate. City growth is an indicator of industrialization (development) and generally has negative impact on the environmental health of region (Basudeb et al, 2011). The change in land use from rural to urban is monitored to estimate population, predict and plan the direction of urban sprawl for developers, and monitor adjacent environmentally sensitive areas or hazards.

Remote sensing methods can be employed to classify types of land use over large areas in practical, economical, and repetitive fashion. The change is usually detected by comparison between old maps and update remote sensing images.

The land cover change can be divided into two categories (1), Seasonal change, for instance, agricultural lands and deciduous forests change seasonally, (2), Annual change (change over years, for example, deforested areas or newly built towns. Usually annual changes and are mixed within the same images. To detect the annual change (change over years), however, only the real change should be detected, so that two multi date images of almost the same season should be noted that a cycle of seasonal change can be rather complex.

According to (Basuaeb.B,2004) Land use change detection and mapping applications are (1) high resolution imageries to obtain detailed information and (2) multi spectral optical data to make fine distinction among various land use classes.

2.2.2 Land Use Land Cover Mapping

Knowledge of land use and land cover is important for many planning and management activities and is considered an essential element for modeling and understanding the earth as a system. Land cover maps are presently being developed from local to national to global scales. The use of panchromatic, medium-scale aerial photographs to map land use has been an accepted practice since the 1940s. More recently, small-scale aerial photographs and satellite images have been utilized for land use/land cover mapping (Basuaeb, 2004)

Depending on the level of mapping detail, its land use could be described as urban use, residential use, or single-family residential use. The same tract of land would have a land cover consisting of roofs, pavement, grass, and trees. It is important to study of the socioeconomic aspects of land use planning (school requirements, municipal services, tax income, etc.), it would be important to know that the use of this land is for single-family dwellings. Fora hydrologic study of rainfall characteristics, it would be important to know the amount and distribution of roofs, pavement, grass, and trees in this tract. Thus, a knowledge of both land use and land cover can be important for land planning and land management activities (Thomas M.et al, 2004).

Land cover Mapping serves as a basic inventory of land resources for all levels of government environmental agencies, and private industry throughout the world. Whether regional or local in scope, remote sensing offers a means of acquiring and presenting land cover data in a timely manner. Remote sensing techniques are the most practical and cost efficiently system for obtaining a timely regional overview of land cover. Remote sensing data are capable of capturing changes in plant phonology (growth) throughout the growing season, whether relating to changes in chlorophyll content (detectable with VNIR) or structure changes via radar In addition, different Land cover classes are typically mapped from digital remotely sensed data through the processes of image classification (Basuaeb.B. 2004)

2.3 Urban Agriculture (UA)

Urban growth, particularly the movement of residential and commercial land to rural areas at the periphery of metropolitan areas, has long been considered a sign of regional economic vitality and it has been an important research field even in the global view, it was supported as a core project by the International Geosphere-Biosphere Program (IGBP) and by the International Human Dimensions Program on Global Environmental Change (IHDP).

Urban Agriculture (UA) is defined as food production from cropping and animal husbandry in and around the urban area. It is not a novel phenomenon; it is likely as old as the earliest urban settlement. Throughout the globe, agriculture today is increasingly, a part of city landscape. Like many urban trend, agriculture crosses borders north and south and is evidence in both rich and poor countries. It is found in small towns and the major metropolis, in temperate and tropical latitudes, and at sea level and high in the mountains (Bourque, 2000). In 1996, the United Nations Development Program (UNDP) estimates that about 800 million urban residents are involved in commercial and subsistence agriculture in or around cities.

Urban agriculture is an important economic activity central to the lives of tens of millions of people in the world. Urban dwellers cultivate plots/open spaces to subsidize their income and sustain their livelihoods (Foeken, 2006). According to the United Nations (UN), Urban and Pre Urban Agriculture (UPA) is practiced by an estimated 800 million people who raise crops and livestock, or who net fish in towns and cities (UNDP 1996). It has, over the years, contributed significantly to the socio-economic development of urban dwellers, while improving their nutritional security (Egziabher et al. 1994). In developing countries, two out of three urban families are engaged in farming from which they earn their living (IIED 1992). In addition, UA contributes immensely to urban food security (Argenti, 2000, van Veenhuizen, 2006).

According to the Food and Agriculture Organization (FAO), urban and pre-urban farming supply food to 700 million city dwellers about one quarter of the world’s urban population (Marcotullio et al. 2008).The situation was not different in Ethiopia (Egziabher, 1994) stated that the livelihoods of many urban citizens in Ethiopia (e.g. Addis Ababa: economic capital and which accounts for over thirty percent of the total urban population) is heavily dependent on urban farming, but urban policy makers fail to give due attention to urban agriculture during urban planning policy reforms. But according to (Edwards, 2010) as is the case in Ethiopia, urban agriculture can be characterized in to three farming systems on the basis of location. These are the pre-urban, household or homestead gardening, and vacant-space cultivation. The pre-urban cultivation takes place on lands just outside the built up areas of the city. Vacant-space cultivation is done in open spaces usually in residential areas, beside water ways (natural and man-made such as drainage channels), and road sides.

Apart from the food security and income subsidy that both consumers and producers enjoy, A also contributes to flood control, land reclamation and city greening (Altieri et al, 1999), (Obuobie et al, 2006).However, the urban population in developing countries is growing three times faster (3% annually) than the rural population, which is growing at an annual rate of less than 1% (Ruel et al. 1998). The United Nations Population Fund reports that more than half of the world's population (3.3 billion people) will be living in urban areas by 2008, and estimates that this will swell to almost 5 billion by 2030 (Brockerhoff, 2000), This population explosion is expected to put extreme pressure on existing resources/infrastructure and eventually increase urban poverty and food insecurity among urban dwellers (Mink, 1993).

2.4 Urban Land use Changes

The characteristics of cities and their surrounding regions, in turn, help shape globalization; for example, by providing a suitable labor force, making available the required physical and technological infrastructure, creating a stable and accommodating regulatory environment, offering the bundle of necessary support services, contributing financial incentives and possessing the institutional capacity without which globalization cannot occur.

According to the reports of the United Nations Centre for Human Settlements(Habitat, 2001), it has showed most remarked changes in developing countries associated with the migration of rural people to cities for better opportunities. Following this there had been estimated a rapid growth of population in urban areas at an average rate of 2.3% per year between or (2000-2030), (Nations, 2001).

Urban growth, particularly the movement of residential and commercial land use to rural areas at the periphery of metropolitan areas, has long been considered as a sign of regional economic vitality (Yuan et al, 2005). However, its importance becomes unbalanced with impacts on ecosystem, greater economic differences and social fragmentation. It can be defined as the rate of increase in urban population. Dynamic processes due to urban change, especially the tremendous worldwide expansion of urban population and urbanized area, affect both human and natural systems at all geographic scales (Brockerhoff, 2000). The ability to monitor urban land cover and land use changes is highly desirable by local communities and policy decision makers. Due to the increased availability and improved quality of multi spatial-temporal data and new analytical techniques, nowadays it is possible to monitor urban land cover and land use changes and urban sprawl in a timely and cost-effective way (Yang et al, 2003). Therefore, the use of satellite data provides for regional planning and urban ecology.

2.5 Integration of remote sensing and GIS on LULC mapping

2.5.1 Integration with remote Sensing

Remote sensing is a cost-effective technology for mapping land cover and land use and for monitoring and managing land resources. The remote sensing literature shows that a tremendous number of efforts have been made for mapping, monitoring, and modeling land cover and land use at the local, regional and global scales(Chanara.p et al.,2012).

Remote sensing images are often composed of spectral classes that are relatively uniform in brightness levels across several bands. These images are useful to accurate analysis of land use and land cover mapping in part because land cover information can be interpreted more or less directly from evidence visible on aerial and satellite images. Images from these satellites are invaluable to the mapping, monitoring and management of the Earth's resources. Usually, LULC maps have been produced from these remotely sensed data (Luong, 1993).

Remote sensing has a tremendous advantage over ground survey methods due to the large area coverage of its data and the ability to map inaccessible areas (Baban, 1999). The frequency (temporal resolution) at which remotely sensed images are acquired also renders the technology suitable for monitoring LULC changes. Images of the same area acquired on different dates (multi-temporal) can be quickly analyzed to quantify these changes. Remote sensing data thus provides detailed, accurate, cost effective and up-to-date information with respect to different vegetation types and land uses. Remote sensing data have proven to be useful in data-poor regions where recent and reliable spatial information is lacking (Dong et al. 1997).

Many LULC mapping projects have benefited from the rich information provided by remote sensing data, especially Landsat data (Seto et al. 2002, Yin et al. 2005). Landsat represents the world longest continuously acquired collection of space based land remote sensing data. Since its launch in 1972, the Landsat sensor has provided researchers with rich information about our environment. These images provide a valuable resource for people who work in agriculture, geology, forestry, education, regional planning, and mapping and global change research. Accurate information of land use and land cover change is therefore highly essential to many groups. To achieve this information, remotely sensed data can be used since it provides land cover information.

Remote sensing refers to the science or art of acquiring information of an object or phenomena in the earth's surface without any physical contact with it. And this can be done though sensing and recording of either reflected or emitted energy or the information being processed, analyzed and applied to a given problem (Campbell, 2002). Remote sensing of land use/land covers by integrating current knowledge and scientific understanding and provides an outlook for the future. Specific topics emphasize current and emerging concepts in land-use/land-cover mapping, an overview of advanced and automated land-cover interpretation methodologies, and a description and future projection of the major land-cover types of the world (Chanara et al., 2012).

The primarily goal of remote sensing is not only the pursuit of knowledge, but also the application of any knowledge gained. Visual and digital image processing helps this goal further by allowing scientist to manipulate and analyses the image data produced by the remote sensors in such a way as to reveal information that may not be immediately recognizable in the original form (Basudeb, 2011).This integration also provides an important application for mapping land use land cover classification and change detection.

2.5.2 Integration with GIS

GIS data sources which can be referenced spatially can be used in this type of environment such as digital map of soil type, land cover classes, forest species, road networks and many others, depending on the application. It is now being widely used in crop management. Remote sensing and GIS have made huge impacts on how those in the agricultural industry are monitoring and managing crop lands and predicting biomass or yields (Basudeb Bhatta, 2011).

Map products derived from remote sensing are usually critical component of GIS. Remote sensing is an important technique to study both spatial and temporal phenomena and monitoring. Though the analysis of remote sensed data, one can drive different types of information that can be combined with other spatial data within GIS. The integration of the two technologies creates a synergy in which the GIS improves the ability to extract information from remotely sensed and remote sensing in turn keeps the GIS up to date with actual environmental information. As a result large amount of spatial data can now be integrated and analyzed. This allows for better understanding of environment processes and better insight into the effect of human activities .The GIS and remote sensing can thus help people arrive at informed decisions about their environment. Therefore, it is important to realize that GIS and remote sensing can complement, but never completely replace field observation. Actually the appropriate approach is to integrate remote sensing, GIS and field observation in a common denominator so that the maximum possible information can be accumulated and analyses with maximum possible efficiency and reliability.

CHAPTER THREE

3. Material and Methods

3.1 Description of the Study Area

3.1.1 Geographical Location

Debre Markos, the capital of Misrak Gojjam Administrative Zone is located in northwest of the capital city of the federal democratic of Ethiopia, Addis Ababa at a distance of 300 Kms and 265 Kms to the capital of Amhara Nation Regional State, Bahir Dar. Specifically it is located in the Amhara regional state, East Gojjam zone. The town served as the capital city of Misrak Gojjam zone. Until 1995, Debre Markos was the capital city of the province of Gojjam (Debre Markos City Administration, 2016). It has latitude and longitude of $10^0$20'N, $37^0$43'E and altitude of 2,449 meters above sea level and it has moderate temperature. The town is named Debre Markos after its principal church, which was constructed 1869 and is devoted to Saint Mark. The area of Debre Markos Town is 6,556 ha and has oval shape; its Average Annual Temperature is 18.5ºC; Mean Annual Rainfall is 1,380 mm and the existing wind direction is from north to south.

3.1.2 Topography

Debre Markos town characterized by plain flat plain topographic landscape although there have been different rivers and hill shade features towards to peripheral town which are the main constraints for physical expansion of the town. The elevation of town is fail between 2249_2509 (Debre Markos Town Administration).

3.1.3 Population and Language

According to CSA (2007), the population of the town was 62,497. Out of this 29,921 (47.87%) were males and 32,576 (52.1%) were females; 16,325 (26.14%) were within the age group of 0-15 years, 42,185 (67.49%) 16-60 years, and 3,987 (6.37%) 61 years and above. The population growth rate at low variant was 2.4%, while household size in the town is calculated to be 3.2. The majority of the urbanites worshiped Ethiopian Orthodox Tewahido church. 97% of the inhabitants are speakers of Amharic language. The remaining 3% of the inhabitants are speakers of Tigiregna, Agew and Afan Oromo. According to CSA (2013), the population projection figure of the town had been estimated 38291 male and 41689 female inhabitants which is a total of 79980 populations. Area of the town is expected to be 1214.9 sq. Km and 65.82 km/square density. (Debre Markos, town Administration, 2016).

3.1.4 Climate

The agro climatic zone of the Woreda varies from *Kolla, Woina Dega* and *Dega*. The annual rainfall of the Woreda varies from 1000 –1510 mm per year. The Woreda high rainfall season is during *Kiremt* that starts in June and ends in September and short rain season is in, *Belg,* which encompass March, April, and May. Temperature is the major determinant factor for Ethiopian Climate. The mean minimum temperature for the Woreda is 8.5^{0}c to mean maximum temperature of 30^{0}c.The upper part of the Woreda is known for its minimum temperature which result in the prevalence of *Dega* type of climate while the lower part of the Woreda, which has the highest temperature, which is known for its *Kolla* type of climate (Debre Markos Town, 2016).

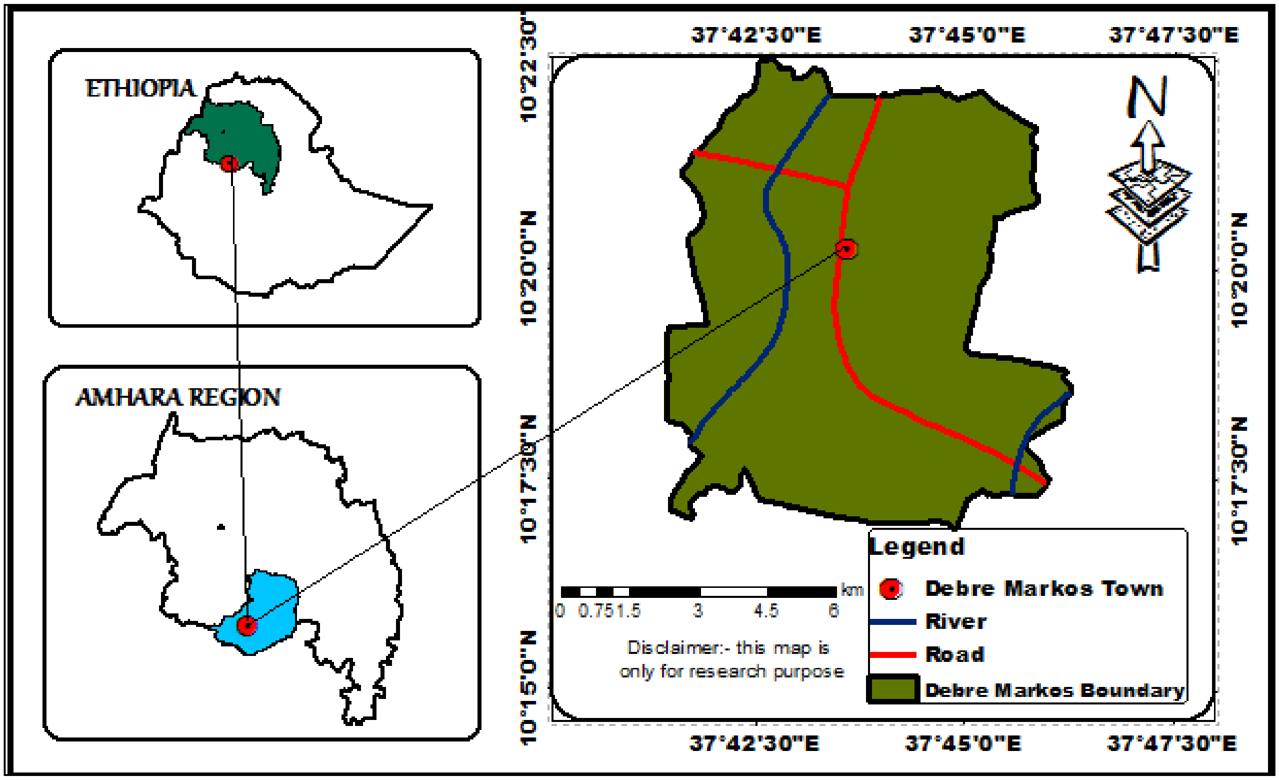


Figure 1 Map of study area

3.2 Methods of the Study

3.2.1 Data sources of the study

3.2.1Acquisition of Data

To meet the objectives of the project, the following data will be necessary. First the administrator boundary of the project area was obtained from (EMA and CSA) and exported as a shape file. In this case, the study site or the study area was selected either through path and raw or longitude and latitude was required.

3.2.1.1 Aerial photographs and satellite images

Aerial photographs and satellite images, known as remotely sensed images, permit accurate mapping of land cover and make landscape features understandable on regional, continental, and even global scales. Temporary phenomena, such as vegetation, farm lands built-up areas, grass lands, forests and water bodies can be studied by comparing images acquired at different times.

The most primitive recognized sources of land use and land cover data for the study area for ground truth purpose aerial photographs was obtained from the Ethiopian Mapping Agency (EMA).

For the recent years, three periods of freely available Landsat images will be use. The raw images obtained from earth Explorer (http://earthexplorer.usgs.gov) for free website which were selected based on ;(i) availability of the data, (ii) cloud cover percentage which were 0 percent cloud cover, and (iii) association with years of major actions in the study area .In order to identify path and raw of the project area, overlaying this shape file over the existing path and raw data file may require. Prior to the overlay, define project and re-projection was perform since the shape file is unknown coordinate system and simultaneously its coordinate system do not much with the shape file that have path and raw information. Totally, three Landsat images of Landsat_5 TM (1987), Landsat_5 TM (2003) and Landsat_8 (2016) were downloaded.

NO	Data type	Date of acquisition	Scale	Source
1	Landsat -5 TM image	1987_01_15	30m ™	Earth Explorer
2	Landsat -7 ETM image	2003-03-08	30m ™	Earth Explorer
3	Landsat -8OLI image	2016_02_16	30m ™	Earth Explorer

Table 1Data type and source

3.2.1.2Ancillary data

Ancillary data were used to improve accuracy of the classification and to support the interpretation of land cover change. In these project topographic maps of the study area at a scale of 1:50,000 and Spot image which was taken 2006 that cover the study area was purchase from Ethiopian Mapping Agency (EMA) for the purpose of ground truth data collection. And vector overlays such as roads, and rivers were obtained from the Central Statistical Agency of Ethiopia (CSA).

3.2.1.3 Field Work

The location of a specific characteristic, such as a land cover type, may be known through field observations that acquire knowledge about the study area from first-hand observation, analysis of aerial photography, personal experience, etc. Field data are considered to be the most accurate data available about the area of study. They should be collected at the same time as the remotely sensed data, so that the data correspond as much as possible. However, all field data may not be completely accurate because of observation errors, instrument inaccuracies, and human shortcomings. Global positioning system receivers were useful tools to conduct ground truth studies and collect training sets. In this project uses hand held GPS to collect feature class types and important coordinates which were training samples. Training samples are sets of pixels that represent what is recognized as a discernible pattern, or potential class. The system was calculating statistics from the sample pixels to create a parametric signature for the class. (Tammy Parece, James Campbell and John McGee, 2014)

Even though field surveying was not error free, a time consuming and expensive task, accurate ground control is essential when mapping using remote sensed data as remotely sensed measurements can only be as reliable as the ground truth on which they are based. In this project fieldwork was implemented in reconnaissance survey by developed a classification scheme either to collect training data for digital classification or for ground verification or validation is part and parcel of applied remote sensing because land cover mapping activities without the support of field investigation is most likely prone to incorporate errors.

3.3 Image pre-processing

Image pre-processing is the term for operations on images at the lowest level of abstraction. These operations do not increase image information content but they decrease it if entropy is an information measure. The aim of pre-processing is an improvement of the image data that suppresses undesired distortions or enhances some image features relevant for further processing and analysis task. (*Kragujevac J. Math*, 2009).In this project, it will be presented some preprocessing techniques of image transformation includes geometric correction or image registration, atmospheric correction and radiometric calibration essentially. In addition, image analysis was carryout by using image analysis window such as adjusts the displayed contrast characteristics of image, adjusts the displayed brightness characteristics of image, adjusts the transparency of image, adjusts the gamma transformation applied to all the three year Landsat image.

In addition to these processes, image filtering small neighboring pixels corresponding to one real object have the same or similar brightness value and to produce a new brightness value in the output image.

3. 3.1 Subsetting of Study area Images

The first step in image pre-processing is image extraction. Some irrelevant parts of the image can be removed and the image region of interest is focused. Taking out the project area from the whole part of the image is important to reduce the size of the image file to include only the area of interest (AOI). This is not only eliminates the extraneous data in the image. But it speeds up processing due to smaller amount of data to process. This is important when utilizing multiband data Such as Landsat TM imagery. This reduction of data is known as Sub setting. In this stage Arc GIS Software was important. In this process each Landsat scene were clipped through by the project area. It has to be done after band stacking or composite image and there was also removing of background color was require.

After Subsetting the study area to correct changes in scene illumination, atmospheric condition, viewing geometry and instrument response characteristics. This involves two steps, taking the digital number (DN) values in each pixel and converting them to radiance and reflectance. The required information will obtain from Meta file and tables that provided by (Chander et al., 2009).

Finally to clear Landsat scenes, a reduction in between scene variability can be achieved through normalization for solar irradiance by converting the spectral radiance, as calculated above, to a planetary or exoatmospheric reflectance. When comparing images from different sensors, there are two advantages to using reflectance instead of radiances. First, the cosine effect of different solar zenith angles due to the time difference between data acquisitions can be removed, and second, it compensates for different values of the exoatmospheric solar irradiances arising from spectral band differences.

3.3.2 Image Enhancement

Image enhancement can be defined as the conversion of the image quality to a better and more understandable level for feature extraction or image interpretation (Basudeb B., 2011).Although radiometric corrections (pre-processing) for illumination, atmospheric influences, and sensor characteristics were done for the suitability of visual interpretation.

Low sensitivity of the detectors, weak signal of the objects present on the earth surface, similar reflectance of different objects and environmental conditions at the time of recording are the major causes of low contrast of the image. Another problem that complicates photographic display of digital image is that the human eye is poor at discriminating the slight radiometric or spectral differences that may characterize the features. The main aim of digital enhancement is to amplify these slight differences for better clarity of the image scene. This means digital enhancement increases the separability (contrast) between the interested classes or features. The digital image enhancement may be defined as some mathematical operations that are to be applied to digital remote sensing input data to improve the visual appearance of an image for better interpretability or subsequent digital analysis (Lillesand and Keifer, 1979).It also valuable to detect and define LULC information classes since different multi temporal images have different spectral characteristics. A proper image enhancement includes multispectral transformation, false color composites and vegetation indices, which is important to achieve information of the area and spectral knowledge. Image enhancement is a method widely used to provide effective display for image interpretation (Cetin, 2009). Therefore, this study, multispectral images were required enhancement using ENVI software and by using Arc map image analysis window. This process was important for visual interpretation using the enhanced images, auxiliary data and intensive ground verification was carried out for deriving training sets to carryout classification features.

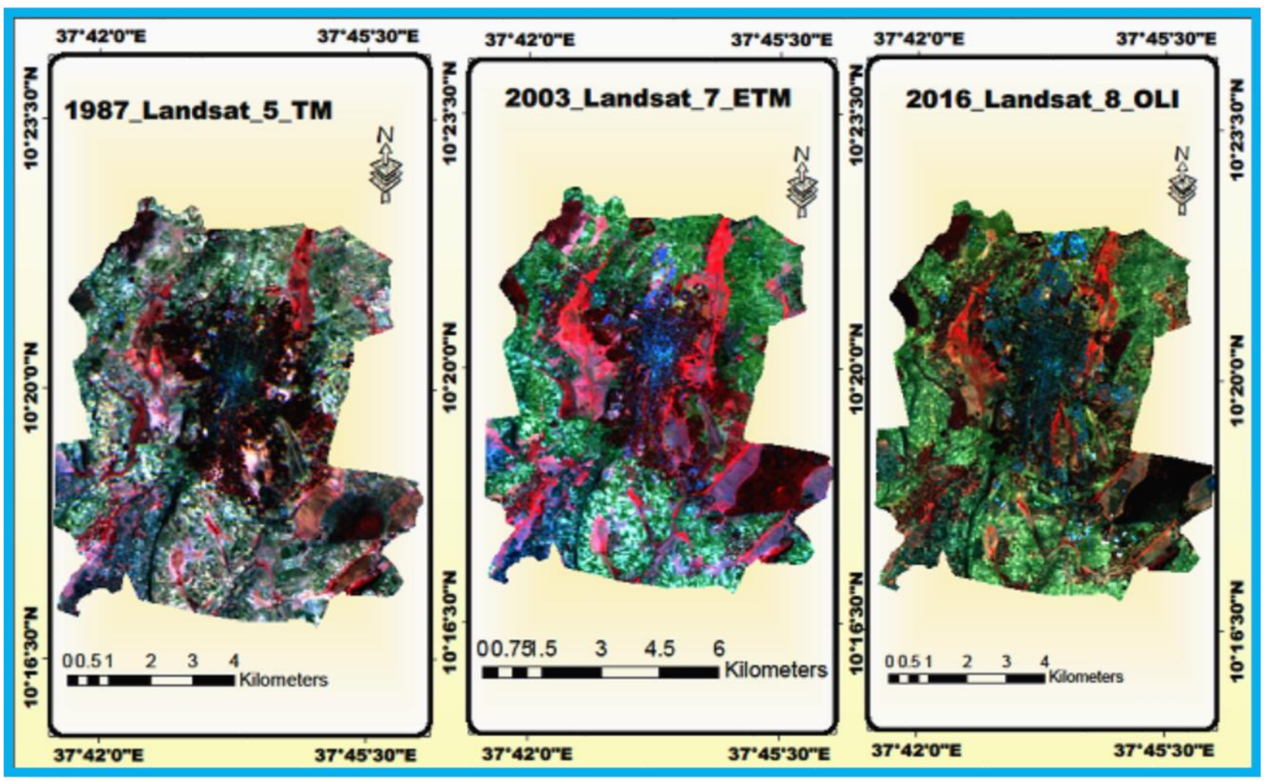


Figure 2 Enhanced image of the study area

3.3.3 Topographic Correction

In mountainous region, topographic map affect that from the difference in illumination the reason is that the angel of the sun and terrine angle produce different reflectance for the same cover type. Hence the classification processes of rugged terrain are seriously affected by topography but this study area is dominated by flat topography because of flattens of the project area the image is free from any shadow that presents due to variation in topographic correction didn't carry out as a preprocessing image correction**.**

3.4 Image Classification

Image classification is the process of sorting pixels into finite number of individual classes or categories of data, based on their DN (pixel) values. Classification of remotely sensed data is used to assign corresponding levels with respect to groups with homogeneous characteristics with the aim of discriminating multiple objects from each other within the image. The level is called class (Basudeb Bhatta, 2011).Classification is the most popularly used information extraction technique in digital remote sensing.

A human analyst attempting to classify features in an image uses the elements of visual interpretation to identify homogenous groups of pixels which represent various features or land cover classes of interests. Digital image classification uses the classification uses the spectral information represented by the digital numbers in one or more spectral bands and attempts to classify each individual pixel based on this spectral information.

Image classification is a procedure to automatically categorize all pixels in an image of a terrain into land cover classes. This concept is dealt under the broad subject, namely, Pattern Recognition. Spectral pattern recognition refers to the family of classification procedures that utilizes this pixel-by-pixel spectral information as the basis for automated land cover classification.

Image classification using remote sensing techniques has attracted the attention of research community as the results of classification are the backbone of environmental, social and economic applications (Lu and Weng, 2007). Image classification is a procedure to automatically categorize all pixels in an image of a terrain into land cover classes. Normally, multispectral data are used to perform the classification of the spectral pattern present within the data for each pixel is used as the numerical basis for categorization. This concept is dealt under the broad subject, namely, Pattern Recognition. Spectral pattern recognition refers to the family of classification procedures that utilizes this pixel-by-pixel spectral information as the basis for automated land cover classification. Spatial pattern recognition involves the categorization of image pixels on the basis of the spatial relationship with pixels surrounding them. Image classification techniques are grouped into two, namely supervised and unsupervised (M.Anji Reddy et al., 2008).

3.4.1 Unsupervised Classification

Unsupervised classification algorithms do not compare points to be classified with training data. Rather, unsupervised algorithms examine a large number of unknown data vectors and divide them into classes based on properties inherent to the data themselves, the classes that result stem from differences observed in the data. In particular, use is made of the notion that data vectors within a class should be in some sense mutually close together in the measurement space, whereas data vectors in different classes should be comparatively well separated. If the components of the data vectors represent the responses in different spectral bands, the resulting classes might be referred to as spectral classes, as opposed to information classes, which represent the ground cover types of interest to the analyst. In this study unsupervised classification will perform using class value to have a general idea about natural clustering of pixels.

The procedure continues until there is no significant change in the location of class mean vectors between successive iterations of the algorithm. Once this point is reached, the analyst determines the land cover identity of each spectral class. A widely used variant on the K-means method for unsupervised clustering is an algorithm called Iterative Self Organizing or data Analysis, or ISODATA (Tou and Gonzalez, 1974). This algorithm permits the number of clusters to change from the one iteration to the next, by merging, split, and deleting clusters. The general process follows that described above for K-means. However, following the assignment of pixels to the clusters, the statistics describing each cluster is evaluated. If the distance between the mean points of two clusters is less than some predefined minimum distance, the two clusters are merged together. On the other hand, if a single cluster has a standard deviation (in anyone dimension) that is greater than a predefined maximum value; the cluster is split in two. Clusters with fewer than the specified minimum number of pixels are deleted. Finally, as with K-means, all pixels are then reclassified into the revised set of clusters, and the process repeats, until either there is no significant change in the cluster statistics or some maximum number of iterations is reached. Therefore, this project uses ISODATA classifier algorithms in which spectral values of pixels are grouped first and then matched by the analyst to information classes. There is no target variable to be predicted and thus no distinction is made between independent and dependant variables. Clustering algorithm partitions the image data into a number of spectral classes and then labels all the pixel of interest as belonging to one of those spectral classes also the levels are purely nominal(class 1, class 2,class 3, class 4 and class 5).

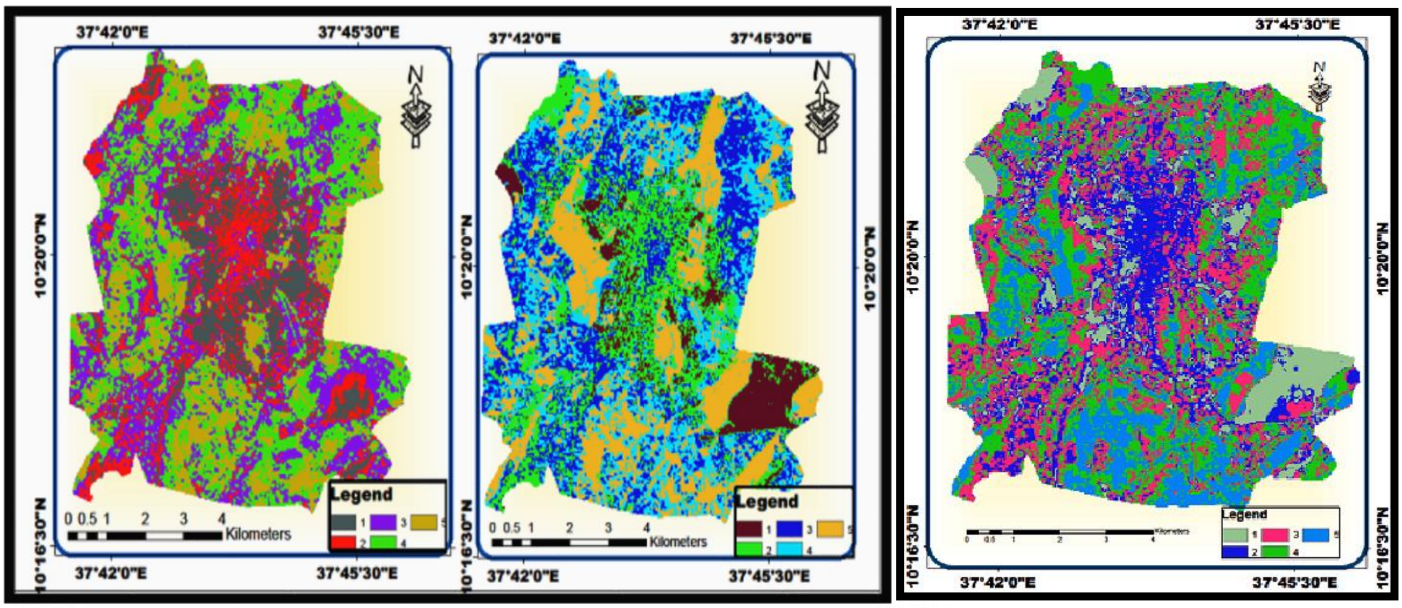


Figure 3 unsupervised classification of study area image right to left respectively (1987, 2003 and 2016)

3.4.2 Development of classification scheme

The classification system was developed by referring (Anderson et al. 1976) classification scheme and has been made to provide as much compatibility as possible with other classification systems currently being used by the various Federal agencies involved in land use inventory and mapping such as Ethiopian Mapping agency. And also based on the prior knowledge of the study area for over 15 years and a brief reconnaissance survey with additional information from written material in the study area, a classification scheme was developed for the study area after (Anderson et al,.1976). The classification scheme developed gives a rather broad classification where the land use land cover was identified by a single digit.

Code	Land Use Land Cover Categories
1	Open area
2	Built up area
3	Farm Land
4	Vegetation
5	Water body

Table 2 Land use land cover classification scheme

3.5 Field Work

3.5.1 Integration with Ground truth and other Ancillary Data

Ground truth is just a terminology term that for surface observation to refer what is actually on the ground that needs to be correlated with corresponding features in the scene. It is important in order to relate image data to real features and materials on the ground. It is also essential for initial supervised classification of an image and to identify location of land cover types.

Based on this; the project provides every effective effort to collect ground truth data by applying field work with knowledge experience of the project area over 15 years and by using ancillary data like topographic map of the project area because ground truth is effective when there is a combination of field work; map and personal experience these areas are known as training sites. The spectral characteristics of these areas are used to train the remote sensing software using decision rules for classifying the rest of image. In the case of classified image, it allows to help determine the accuracy of the classification performed by the remote sensing software and therefore, minimize errors in the classification such as error commission and errors of omission.

Before data collection, first for each classes 50 random sample points was created by using Arc GIS for each cluster to register the type of Land cover /use that would encountered during field work.

For instance, Sample of the random point provided with project area image of 2016.

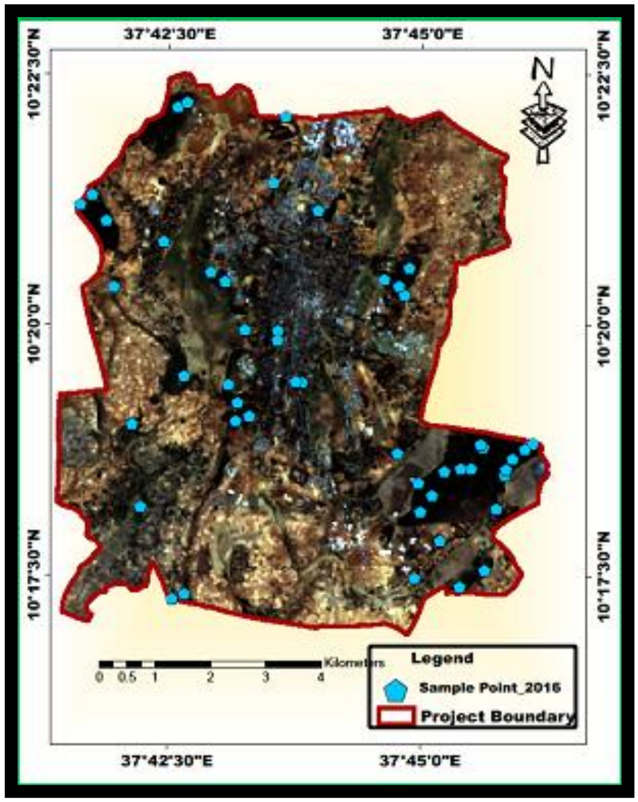


Figure 4.Class_1 Random sample point for image 2016

After the preparation of random sample point for each of class, then extraction of meaningful information and features from the imagery is implemented by using ancillary data which is Google earth, to extract information before field work takes place but it is not sufficient and accurate resulting from extracting exact information from Google earth. Therefore, each class samples features were collected from field work by using handheld GPS. The final goal would be to classification and accuracy assessment and detecting land cover/use change in the project area or to evaluate the impact of change. Therefore the classification of remote sensing imagery becomes more accurate and simplest if the auxiliary data were including with the field work.

Based on this the following samples that represents on the imagery were described in the photograph.

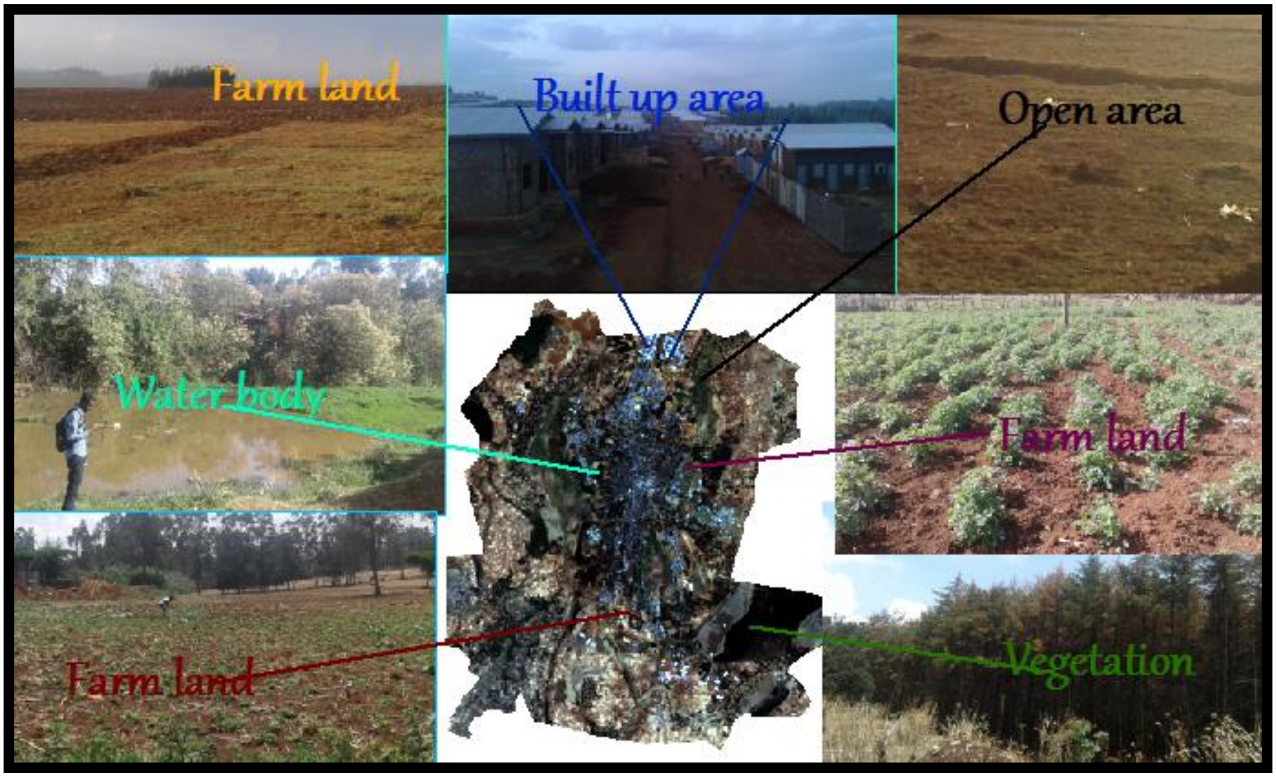


Figure 5 Sample photographs during field work

3.5.2 Image Interpretation

To interpret and identification of targets in remote sensing imagery is performed manually or by visually interpreter. In many cases this is done using imagery displayed in a pictorial or photograph type format independent of what type of sensor was used to collect the data and how the data were collected. Remote sensing images can also be represented in a computer as arrays of pixels with each pixel corresponding to a digital number, representing the brightness level of that pixel in the image (Basudeb. 2011).

Image interpretation on computer screen is important during image classification. In this project image interpretation is performed by examine digital imagery displayed on a computer screen by using false color image composition; it is conducted after data sample collected. For example, landsat 7 ETM (2003) false color composition (FCC) RGB (4, 3, 2)

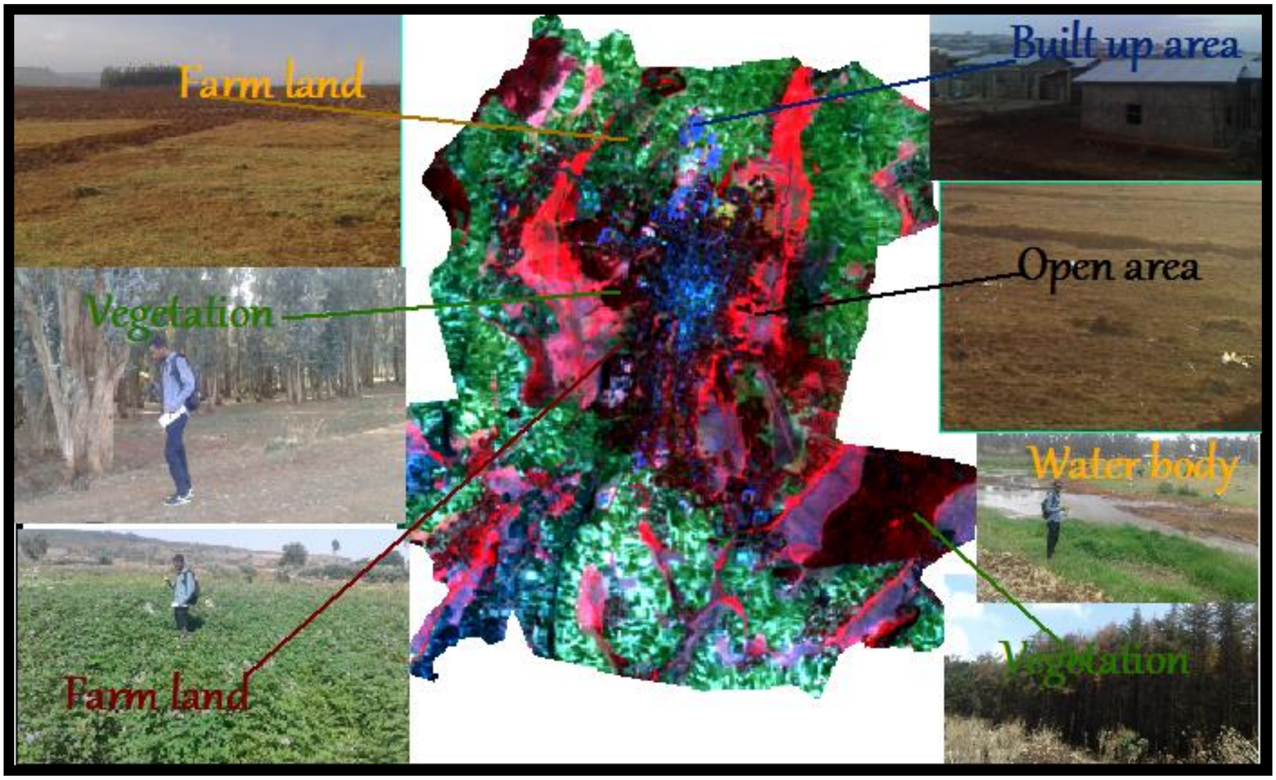


Figure 6 Sample Photographs and interpretation of false color composition (FCC 4, 3, 2)

3.6 Supervised Classification

A supervised classification algorithm requires a training sample (AOI) for each class, that is, a collection of data points known to have come from the class of interest. The classification is thus based on how close a point to be classified is to each training sample. There are different types of supervised classification algorithms these are: maximum likelihood, parallelepiped, minimum distance to mean and spectral angle mapper classification methods and neural net classification.

3.6.1.1Minimum Distance-to-Means Classifier

Minimum Distance-to-Means Classifier is a simple classification strategy. This method first analyses the areas designated in the training and then calculates a mean values in each band for each training class. These mean values define the location of the class center in spectral space (Basudeb Bhatta, 2011). Pixel of unknown identity may be classified by computing the distance between the value of the unknown pixel and each category means. After computing the distance the unknown pixel is assigned to the closest class. This range may be defined by the highest and lowest digital number values in each band and appears as a rectangular area in our two-channel scatter diagram. An unknown pixel is classified according to the category range or decision region in which it lies or as "unknown" if it lies outside all regions. The multidimensional analogs of these rectangular areas are called parallelepipeds, and this classification strategy is refined to by that tongue-twisting name. The parallelepiped classifier is also very fast and efficient computationally.

The minimum-distance-to-means strategy is mathematically simple and computationally efficient, but it has certain limitations. Most importantly, it is insensitive to different degrees of variance in the spectral response data. In the pixel value plotted at point 2 would be assigned by the distance-to-means classifier to the "sand" category, in spite of the fact that the greater variability in the "urban" category suggests that "urban" would be a more appropriate class assignment. Because of such problems, this classifier is not widely used in applications where spectral classes are close to one another in the measurement space and have high variance (Lillesand et al., 1979).

3.6.2 Parallelepiped Classifier

The parallelepiped classifier often termed as multilevel slicing divides each axis of multi spectral feature space. The decision region for each class is defined on the bases of a lowest and highest value on each axis. It considers the range of values in each category training set. This range may be defined by the highest and the lowest digital number values (Thomas M. Lillesand). There are high and low limits for every signature in every band. When a pixel data file values are between the limits for every band in a signature, then the pixel is assigned to that signature's class. In cases where a pixel may fall into the overlap region of two or more parallelepipeds, the pixel can be classified by the order of the signatures, by the defined parametric decision rule or the pixel can be left unclassified. If the pixel does not fall into any one of the parallelepipeds then the pixel can be classified by the defined parametric decision rule or we may leave the pixels unclassified without applying any parametric decision rule.

3.6.3 Maximum Likelihood Classifier

Maximum Likelihood supervised parametric classification is the most powerful classifier and uses in commonly based on statistics (mean, variance /covariance). The maximum likelihood classification method applies the probability theory to the classification task. From the training set classes, the method determines the class centers and the variability in raster values in each input band for each class. This information allows the process to determine the probability that a given cell in the input image belongs to a particular training set class centre, and the size and shape of the class in spectral space. It computes all of the class probabilities for each raster cell and assigns the cell to the class with the highest probability value. This method produces more accurate class assignments than the minimum distance to means method when classes vary significantly in size and shape in spectral space (Basudeb, 2011).

Maximum Likelihood quantitatively evaluates both the variance and the co-variance of the category spectral response patterns when classifying unknown pixels. We may compute the statistical probability of a given pixel value being a member of a particular land class, the computer would calculate the probability of the pixel value occurring in the distribution of class corn then the likelihood of its occurring in class “sand”, and so on. After evaluating the probability in each category, the pixel would be assigned to the most likely class (highest probability value).

Based on the above information, this project image classification was carryout by Maximum Likelihood of classifier because this method is important to Carrey out accuracy assessment. The accuracy assessment was based on training samples and spectral signature of future was applied for classifications whereas the remaining data were use for accuracy assessment. A training dataset is a set of measurements (points from an image) whose category membership is known by the analyst. This set must be selected based on additional information derived from maps, Google Earth, topographic maps, field surveys, aerial photographs, and analyst's knowledge of usual spectral signatures of different cover classes. Selecting a good set of training points is one of the most critical aspects of the classification procedure. However, an attempt is made to provide some guidelines based on my experience and I have been uses ground truth as reference, it is important to understand the features in the real world and to map a mental picture of the type of land cover and land use (Bhaskaran *et al.* 2010). A hand held Garmin GPS receiver was used to collect samples and these samples was important for the accuracy assessment.

After conducting supervised classification, some errors has been clean by post classification techniques. Supervised classification was carry out through Arc map by drawing polygon pixels that were based on field point samples, Knowledge about the features during classification of image 2016,through topographic map of the study area and interpretation of false color image pixels and by interviewing elder peoples during field work.

Totally 50 samples were taken for each classes from these 60 percent of the total samples (250) samples were taken from field. Google Earth image were used to perform user training classification technique whereas the remaining data would be used for accuracy assessment. To select which samples being used for classification and assessment, excel random number generation method was used .Based on selected samples; polygons were drawn using Arc Map for the 1987, 2003 and 2016 image. Polygons which represent the same class merge together as one class and totally four different classes were created namely bare land (1), Built up area/settlement (2), farm land (3), vegetation/grassland, (4) and water body (5). By applying Maximum Likelihood Classifier, the following classified image was produced.

3.7 Post Classification

Post classification filtering generalizes the dataset by removing stray pixel in the image and producing more homogenous class areas. Filtering is recommended to apply on the image data before the accuracy assessment. Therefore, Post classification was perform after conducting supervised classification, Some techniques smooth boundary where as others make generalization or remove small patches of class. In this Project majority analysis was carryout. The Poor performances may occur by image enhancement procedures was attribute use related to the spectral variation due to differences in soil moisture and in vegetation phonology between both scenes. Methods based on classification have been found to be less sensitive at these spectral variations and more vigorous when dealing with data captured at different times of the year. Therefore, it will be the most accurate procedure and present the advantage of indicating the nature of land use land cover changes in the study area.

3.7.1 Accuracy assessments

The results of the land cover classifications derived from remotely sensed data are compared by an accuracy assessment. An accuracy assessment analysis was performed by producing an error matrix that compared the interpreted land cover map and a map contains the result of ground truth investigation.

In the study of image processing the term "accuracy" means a measure of consistency with reliable information in a spatial point with data on the classified image [Jensen 1996].

In this project the following error assessment steps was implementing. These are(1) determine the total number of samples to be collected for each category,(2) design an appropriate sampling scheme,(3)obtain ground reference information at sample locations,(4) produce error matrix and(5)evaluate the error matrices, producer accuracy, user accuracy, commission and omission.

Accuracy assessment was checking the accuracy of the output classified image by comparing a sample of pixels with reference data (Aplin, 2013).Therefore, classification accuracy assessment was an important to assess the accuracy of an image classification, and it is common practice to create a confusion matrix.

There are different ways in which accuracy assessments can be accomplished. (1) To compare the classified images to a reference image. A random set of point is generated and classification results are compared with the true information classes in the reference image. (2) To perform accuracy assessment involves using a GPS. A gain a random set of points in generated over the classified image. Ground_truthing would be performed by going into the field at the location of each randomly generated point. The classification result would then be compared to actual land cover at each point’s location. From the above methods this project, the accuracy assessment is produced by method to two which is by generated random points on the classified image and by performing Ground_truthing on the field but to get accurate spatial data and classification result this project uses Google earth to collect feature type to perform supervised classification before ground truthing is takes place.

Generally the following steps were performed (1) creating random points on Arc map (2) Conversion to kml file to over lay on Google map (3) Collecting features type (4) Producing supervised classification (5) Ground truthing on the field and (6) evaluation of classification errors by producing confusion matrix table.

In the evaluation of classification errors, a classification error matrix is typically formed. This matrix is sometimes called confusion (or contingency) matrix (table). In this table, classification result is given as rows and reference or verification (ground truth) is given as columns for each sample point (Congalton, 1986).

Image classification cannot be considered complete until we obtain an estimate of its accuracy. The interpreter (decoder) has to determine exactly how the object classes in the image correspond to these classes on the project area (terrain) surface.

In a confusion matrix, this classification results was compare to additional ground truth information. The strength of a confusion matrix is that it identifies the nature of the classification errors, as well as their quantities, to comparing the classification to geographical data that are assumed to be true to determine the accuracy of the classification process. Usually, the assumed true data are derived from ground truth. It is usually not practical to ground truth or otherwise test every pixel of a classified image. Classification accuracy assessment was carried out in three years 1987, 2003 and 2016 image was based on supervised classification.

Based on data collection from field and Google earth map, which were not used for classification purpose, first error matrix (confusion matrix) was produced and then producer accuracy, user accuracy, commission and omission were produced. The accuracy of image 1987 and 2003 were analyzed using ground data collected from ortho photo (2003), Spot image (2006) and by using topographic map.

According to Thomas M. Lillesand,et al,(2004),the confusion matrix, it can be seen that the following methods used to determine individual category accuracies;(1)User accuracy is the ratio between the number of correctly classified and the row total, it concerned about what percentage of the classes has been correctly classified. (2) Producer accuracy is the ratio between the numbers of correctly classified and the column total, it is more interested in the second case because it tells us how correctly the reference samples are classified. However, there is more appropriate way of presenting the individual accuracies through both users and producers accuracy for each class. (3) Commission errors is the ratio of the number of pixels classified incorrectly by the total number of pixels in the ground truth class forms an error of commission. (4) Omission is the ratio of the number of pixels classified incorrectly by the total number of pixels in the ground truth class forms an error of omission. (5) Overall accuracy is represents the sum of diagonal metric divided by the total pixel and finally determines the classification accuracy by using chance accuracy.

(6) Chance Accuracy (K_hat) = $\frac{Observed\ accuracy - Chance\ agrement}{1 - Chance\ agrement}$

This statistic serves as an indicator of the extent to which the percentage correct values of an error matrix are due to "true" agreement versus "chance" agreement. As true, agreement (observed) approaches 1 and chance agreement approaches 0, *k* approaches 1. This is the ideal case. In reality, *K_hat usually* ranges between 0 and 1. A chance accuracy of 0 suggests that a given classification is better than a random assignment of pixels. In cases where chance agreement is large enough, chance accuracy can take on negative values-an indication of very poor classification performance.

The kappa coefficient statistic is computed as

$$\hat{k} = \frac{N \sum^{rows} X_{ii} - \sum^{rows} X_{class} * X_{ref}}{N^2 - \sum^{rows} X_{class} * X_{ref}}$$

Where,

N = the total number of Observation

X_{ii} = observation a long diagonal

X_{class} = are observations for classified image

X_{ref} =are the observation for reference data

Generally the following procedure was described in the whole Methodology of the project:

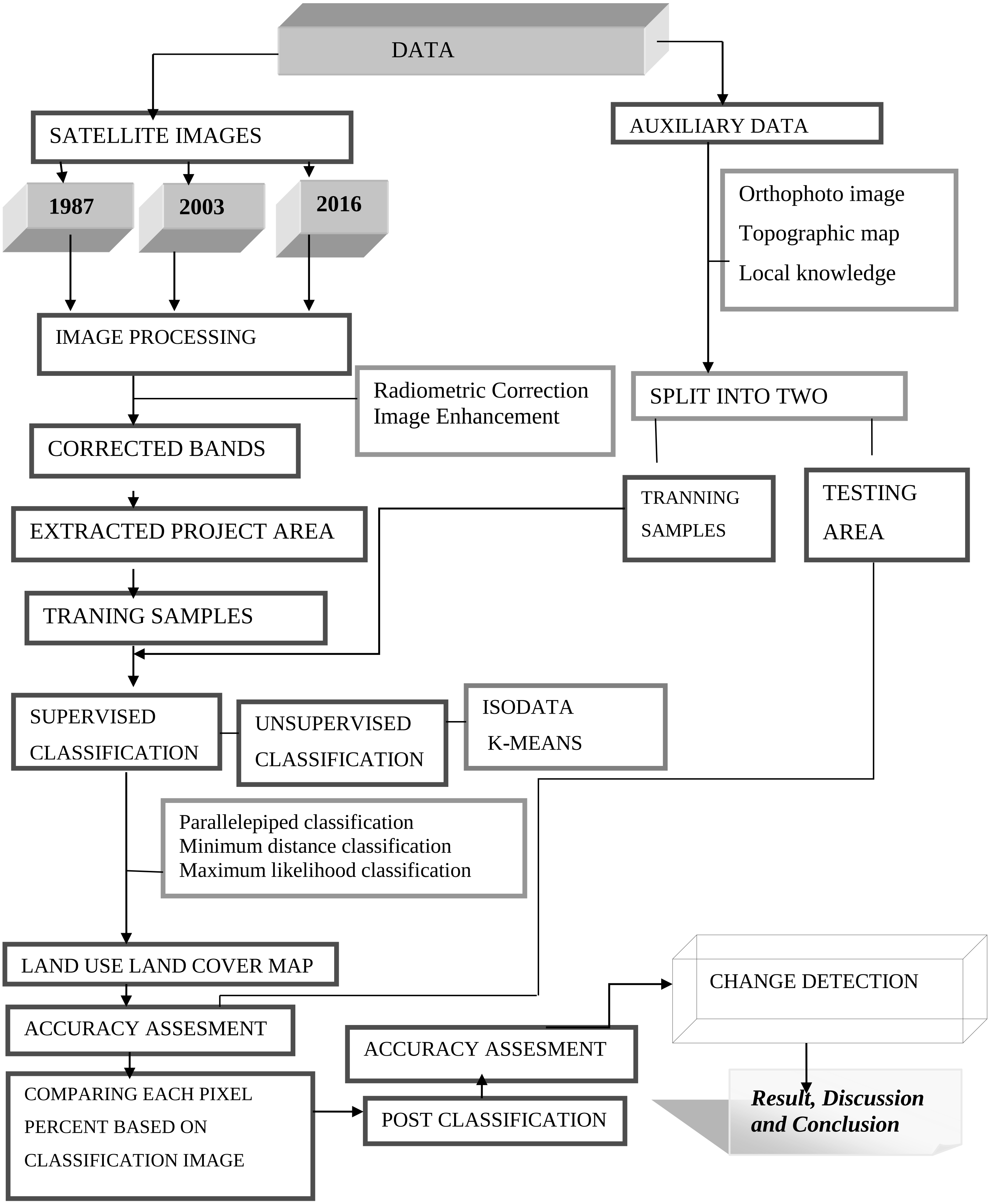


Figure 7 Flow Chart of Methodology

CHAPTER FOUR

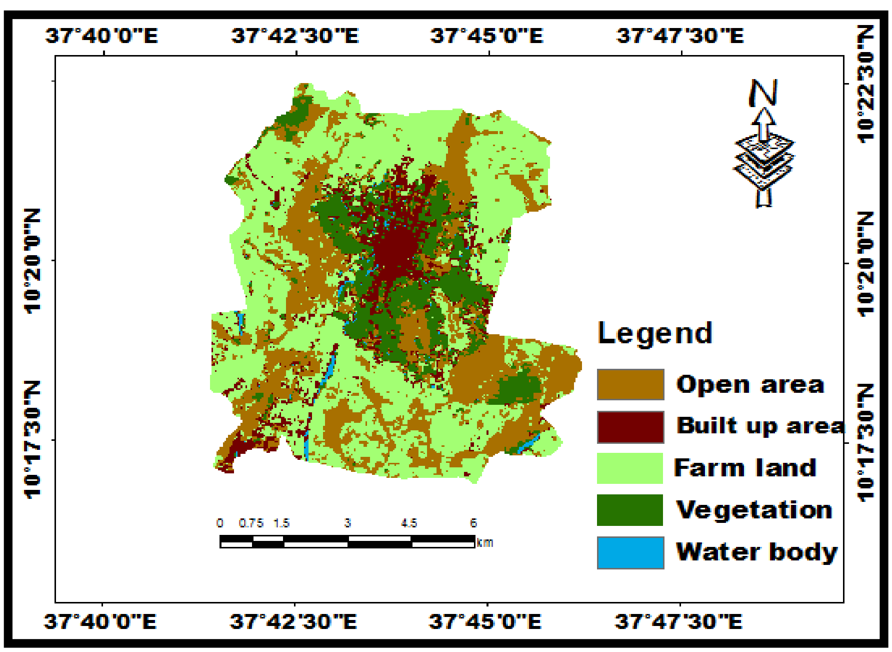
4 RESULT AND DISCUSSION

4.1 Classification and Results of Land use/Land cover Maps

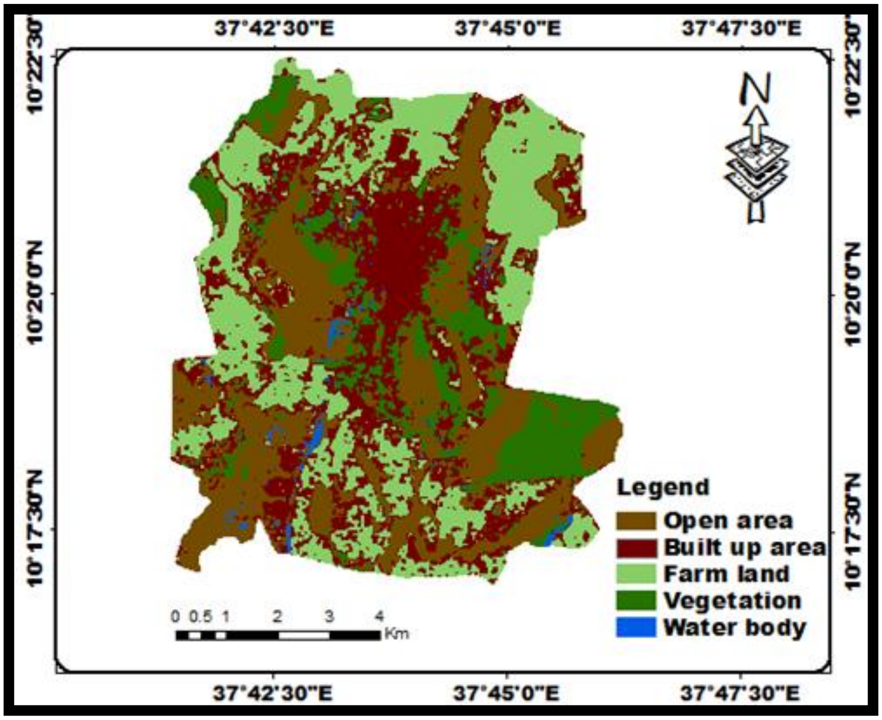
The land cover maps generated after running a maximum likelihood supervised classification as well as a post classification algorithm are presented in figure 8 and Table 3 respectively. As shown from the table 3 transition matrix of LULC in 1987, 55 percent of open area and it constant or remains in 2016.The reminder 45% was transformed and changed to other land use land cover types by 2016, that was 6.6% to built up area uses, 27.08 to farm land uses, 3.65% to vegetation cover and 0.53% to water bodies. In contrast conversion of other land use land cover types to bare lands amounted to only 29% comparing with 45 which open area lost to other land use / land cover.

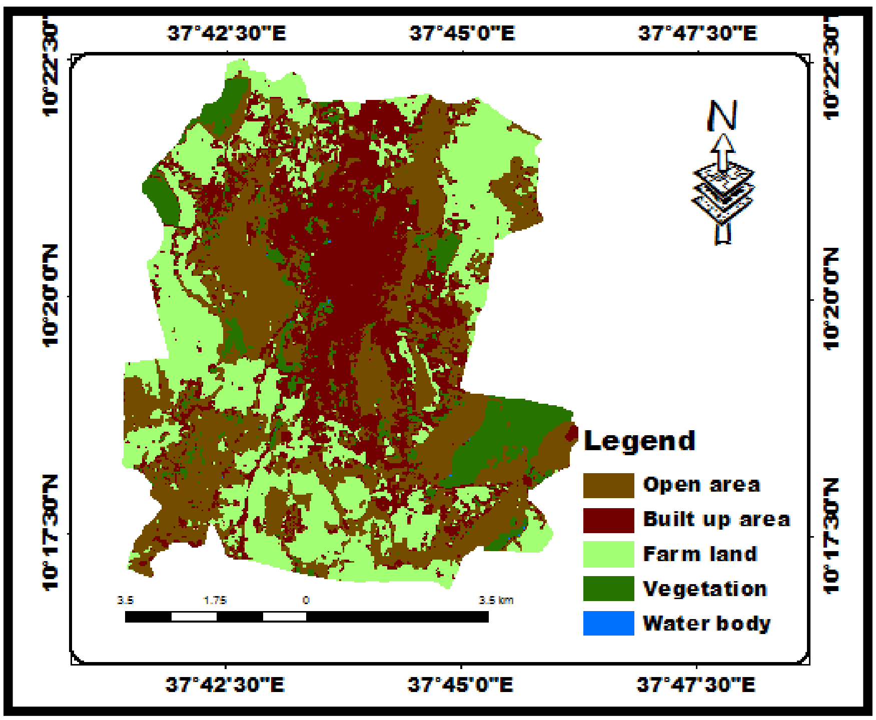
In addition to this about 54.7% that was covered by built up areas in 1987 constantly the same in 2016, the 45.3% was changed into other land use land covers, about 34.3% to open area,7.2% to farm land uses,3.7% to vegetation covers and 0.08% to water bodies. This implies that much of other land use / land cover transformed to build which accounted167% comparing with 45% which built up area lost to other land use/land cover. The change land use land covers in hector and in percentage shows in the following table 3.

(A)



(B)





(C)

Figure 8: Land cover map of Debre Markos for 1987 (a), 2003 (b) and 2016 (c).

4.2. Accuracy Assessment of the Classification maps

Classified land cover maps from remotely sensed images contain various types of errors, it is the responsibility of the researcher to find out those errors so as to make the produced land cover maps become reliable and easily interpretable by users. Once the classified image is integrated into a GIS, to become an information source for urban planners and researchers, accuracy assessment should be processed as it limits the classification results of a remotely sensed imagery data.

The classification accuracy assessment land use land cover result was carryout to assess the accuracy of the classification. The reference data were obtained from sample points which are prepared by considering random sampling that were collected from field observation, using information from key informants during field observation and Google earth.

Based on these classification accuracies, the overall accuracy for the year 1987, 2003 and 2016 are 70.41%, 76 and 81% respectively. Results of user's accuracy in this study showed that in 1987 the maximum class accuracy was 87.2%%, which was built up areas where correctly classified and the minimum was open areas class with an accuracy of 43% as presented in table 4 below. In 2003, the class accuracies range from 58% to 96% where as in the period 2016, it ranges from 74% to 89% as indicated in tables 5 and 6 respectively. The maximum class accuracy (user accuracy) for the year 2003 was 96% which was vegetation and the minimum was open area class with an accuracy of 58% as presented in table 5 below. In 2016 the maximum user accuracy was 89% which was water body where correctly classified and the minimum was built up areas (74%) as showed in table 6.The lowest values of class accuracies were misclassified due to spectral property similarities among other land cover classes. As shown from tables 4 and 5, the user's accuracy was lowest for open area as some of the open area was largely misclassified as built up, vegetation and farm land. In addition table 4_6 shows the detailed result of accuracy assessment of each year and feature class’s classification accuracies result. The kappa coefficient (K_hat) for the year 1987, 2003, and 2016 are 63%, 70% and 90% respectively. According to (Thomas M. Lillesand et al, 2004), when the kappa coefficient is approaches to 1 indicates that the classification is better and if it approaches to negative value indicates that the classification is poor performance. Based on this analysis the kappa coefficients are approaches to 1 therefore the classification is good performance. The three days accuracy assessments all classes (open area, Farm land, built up area and) had relatively high producer accuracies and they had low omission errors. This indicates that the reference sample point was relatively correctly classified. However, the producer accuracy in 2003 for vegetation and water relatively low when compare to the other classes, it indicating that exposed overlap between vegetation and water body and resulting low producer accuracy of the former.

		Ground truth							
Classified Map	Row label	Bare land	Built up area	Farm land	Vegetation	Water body	Grand Total	Commission error	User accuracy
	Open areas	32	4	27	12	0	75	57%	43%
	Built up area	4	48	3	0	0	55	13%	87.2%
	Farm land	4	2	81	12	0	99	31%	82%
	Vegetation	0	10	6	52	10	78	33%	67%
	Water	0	6	0	0	25	31	19.4%	81%
	Grand Total	40	70	117	76	25	338		
	Omission error	20%	31.4%	32%	40%	16%	Overall accuracy=70.41%		Kappa Coefficient =63%
	Producer accuracy	80%	68%	69.23%	68.42%	80%			

Table 3: Confusion matrix for land cover map of 1987

		Ground Truth							
Classified Map	LULC Classes	Open area	Built up area	Farm land	Vegetation	Water body	Grand Total	Commission error	User accuracy
	Open area	42	2	6	12	10	72	42%	58%
	Built up area	4	38	0	8	5	55	31%	67%
	Farm land	3	2	63	8	0	76	17%	83%
	Vegetation	2	0	0	44	0	46	4%	96%
	Water	0	2	3	4	32	41	22%	78%
	Grand Total	51	44	72	76	47	290		
	Omission error	18%	15%	13%	42%	32%	Overall accuracy=76%		Kappa Coefficient =70%
	Producer accuracy	82%	79%	88%	58%	68%			

Table 4: Confusion matrix for land cover map of 2003

		Ground Truth							
Classified Map	Row label	Bare land	Built up area	Farm land	Vegetation	Water body	Grand Total	Commission error	User accuracy
	Open area	68	5	3	7	5	88	23%	77%
	Built up area	7	52	7	4	0	70	26%	74%
	Farm land	7	4	81	4	0	96	16%	84%
	Vegetation	7	4	4	76	0	91	16.5%	84%
	Water	0	0	0	4	32	36	13%	89%
	Grand Total	89	65	95	95	37	381		
	Omission error	24%	20%	15%	20%	16%	Overall accuracy=81%		Kappa Coefficient =90%
	Producer accuracy	76%	80%	85%	80%	86%			

Table 5: Confusion matrix for land cover map of 2016

4.2.1 Land use land cover Analysis result using GIS method

Change detection analysis is done simultaneously for all existed classes. This method exhibited both the number of changed pixels and to whose classes those pixels were assigned. By using this method each year classified images (1987 and2003), (2003 and 2016), (1987 and2016) were analyzed.

4.2.1.1 Land use land cover change between 1987 and 2003

Change detection analysis is used to pattern differ features such as urban expansions land cover change and to analyses the rates of such changes. Below the table shows that the combined change between 1987 and 2003 classified images and there is discussion about different land cover changes that occur in the form partial conversion of one category to the other category class and modification and area coverage with in the study area of the condition of the land cover type within the same category.

As shown from the table 7, there has been an increase of built up areas with respective values 9.9% of the study area in 1987 to 25.5% in 2003 and the change between these two days become 72% indicated in table 7. However, there has been a decrease of agricultural areas as clearly shown in table7. In 1987 agricultural areas covered 39.4% of the study area and it decreased to 33% in 2003, it implies that the decrement between (1987_2003) was accounted (_15.4%). From table 7 below, agricultural land was the most dominant land cover class in the study area but showed a continuous decrease from 39.4% by 1987 to 33% in 2003. Because of the successive decrease of agricultural areas, built up areas have dynamically increased in the study periods.

It is believed that in Debre Markos town there is high migrants that immigrate from rural to urban areas with relation to rapid population growth and shortage of farm lands in rural areas. Similarly vegetation cover dramatically decreased by over 30%. This may be linked with expansion and rapid growth of the town, Horizontal growth of the town and improper use of lands could be for the cause of decrement of urban agriculture. Now a day's Ethiopian urban areas growth is horizontally rather than vertically due to this, farm land and bare lands becoming diminished. As table 7 and the figure shows that except built up areas from (1987_2003) farm land, bare land, vegetation and water body decreased by 15%, 13%, 38% and 18% respectively.

Class	Area(1987)		Area(2003)		change1987_2003	
	ha	%	ha	%	ha	%
Open area	2153.43	32.8	1871.82	25.5	-281.6	-13
Built up area	649.08	9.9	1765.53	26.9	1116.45	+72
Farm land	2588.06	39.4	2189.7	33.4	-398.36	-15.4
Vegetation	1104.27	16.8	678.98	10.4	-425.29	-38.5
Water body	61.93	0.94	50.74	0.77	-11.19	-18
Total	6556.77	100	6556.77	100	------------	-------------

Table 6: Area statistics of the land use and land cover units from 1987-2003

4.2.1.2 Land use Land cover change between 2003 and 2016

The major land uses area in 2003 with large areal coverage were open area, farm land, built up area, vegetation and water body in decreasing order. From this water body covers small amount of land cover class. The major reason for the small amount of water converges might be water body converted to open area and there may be also misclassification of the signal pixel. Water interpretation is one of difficult data processing or classification of images because in the project area most of water bodies were covered by vegetations.Table7 transition matrix shows that 67.8% was open area in 2003 and it constant or remain in 2016.The reminder over 30% was transformed and changed to other land use land cover types by 2016, that was 19.32% to built up area uses, 7.99% to farm land uses, 4.07% to vegetation cover and 0.79% to water bodies. In contrast conversion of other land use land cover types to bare lands amounted to 30.6%. In addition to this about 27.33% that was covered by vegetation in 2003 still the same in 2016, the 72.7% was changed into other land use land covers, about 17.45% to open area,18.2% to built up uses,37% to farm land and 0.039% to water bodies. In contrast conversion of other land use land cover to vegetation cover was small amount it accounted 14.6% compares with 72.7% that lost to other land use land cover classes.

As discussed in the literature review and it was mentioned by different studies like(Basudeb Bhatta, et al. 2011) urbanization has mainly exerted strong pressure on existing land use and the most affected is agricultural lands which is transformed to built up areas in every high rate. In the project area this type of transformation is the main cause of urban agriculture degradation and expansion of urban areas to the periphery areas. Conversion of agricultural land use to other uses becomes a serious problem on urban community food production and food security and it diminished foreign exchange.

	Sum of Count	**LULC(2016)**					
		Column Label					
	Row Label	**Bare land**	**Built up area**	**Farm land**	**Vegetation**	**Water body**	**Grand Total**
LULC(2003)	**Open area**	1506.15	429.03	177.48	90.45	17.46	**2220.57**
		67.8%	19.32%	7.99%	4.07%	0.79%	
	Built up area	292.77	869.85	334.8	50.76	20.97	**1569.15**
		18.65%	55.4%	21.33%	3.23%	1.2%	
	Farm land	145.98	915.89	486.37	15.48	6.93	**1570.65**
		9.2%	58.3%	30.9%	0.98%	0.44%	
	Vegetation	240.66	50.92	509.45	376.83	0.54	**1178.4**
		17.45%	18.2%	37%	27.33%	0.039%	
	Water body	0.27	0.63	0	15.93	1.17	**18**
		1.5%	3.6%	0	91%	6.5%	
	Grand Total	**2185.83**	**2266.32**	**1508.1**	**549.45**	**47.07**	**6556.77**

Table 7: Transition matrix table hector between 2003 _2016.

the above transition matrix table 7 between 2003 and 2016 which is important to analyze amount of changed of land uses to the other and unchanged area size in unite of hector and percentage of change, the yellow shaded represents no change between two years.

Below table 8 the largest share of land use land cover change between 2003 and 2016 in the project area was built up areas which cover more than 40 percent next to water bodies. The main reason with this increment of built up area and water bodies, in the town building expansion was towards farm land areas and high elevation areas but there was no building constructions around flood plain areas near to seasonal rivers due to this reason seasonal rivers were improved and modified to other water bodies and it may be misclassification of water bodies due to overlapping with vegetation. In contrast other land use land cover decreased between 2003_2016 which were vegetation (-53.3%), farm land (-4%), and bare land (-1.7%).

Class	2003		2016		change 2003_2016	
	ha	%	ha	%	ha	%
Open area	2220.57	34	2185.83	33	-34.74	-1.7
Built up areas	1569.15	24	2266.32	34.5	697.17	+44.4
Farm land	1570.65	24	1508.1	23	-62.55	-4
Vegetation	1178.4	18	549.45	8.4	-628.95	-53.3
Water body	18	0.27	47.07	0.72	29.41	+163
Total(ha)	6556.77	100	6556.77	100	-------	---------

Table 8: Area statistics of the land use and land cover units from 3003-2016

4.2.1.3 Land use Land cover change between 1987and 2016

The change detection statistics below are presented in Table 3, there has been an increase of built up areas with respective values 11.46% of the study area in 1987 to 25.4% in 2016. Water body was also shown a consistent increase between the study periods with values presented in table 3 below. However, there has been a decrease of farm land as clearly shown in table 3 which accounted -1.24%. In 1987 farm land covered 37% and in 2016 accounted 36.6% of the study area. The farm land was the most dominant land cover class in the study area but showed a slightly decrease from 37% by 1987 to 36 in 2016. The change detection statistics of farm land uses between (1987_2016) was less, comparing with change between 1987_ 2003(-15.4%) and between 2003_2016 (-4%).The cause for slightly decrement of farm land use might be linked, the contribution of open area because within the study area, there was small farming activities such as potato along lower part of a river, this also causes for increment of seasonal water bodies between the two dates (1987_2016).

Figure 9 Expansion of Horticulture/farm land uses towards open areas

However in the study area, there was expansion of farm land towards open area/sparsely vegetation areas, according field observation there was a general shift or conversion to other uses such as agricultural lands, open area and vegetation shift to built up areas this is may be linked with the need for more buildings over the year has been due to the urban expansion towards the peri-urban areas.

Class	1987		2016		change 1987_2016	
	ha	%	ha	%	ha	%
Open area	2369.97	36.1	1992.96	30.4	-377.01	-16%
Built up areas	751.5	11.46	1668.33	25.4	916.83	+122%
Farm land	2429.01	37	2399.04	36.6	-30.07	-1.24%
Vegetation	982.8	15	466.74	7.1	-516.06	-52.547%
Water body	23.49	0.4	29.7	0.5	6.21	+26%
Total(ha)	6556.77	100	6556.77	100	-------	-------------

Table 9: Area statistics of the land use and land cover units from 1987-2016

In addition, In Deber Markos town livestock keeping is one of urban agriculture and it is the main supply milk production for urban peoples however according to field observation and key informants this type of agriculture become demolished due to shortage of animal feed in the area due to expansion of built up areas towards other land use land covers. As a result, many farmers become out of their former work.

Figure.10 open area and farm land use transformed/converted to built up area.

Change detection statics showed that in 3dayes built up areas class increased more than doubled; representing an increase from (1987_2003) more than 70%, 44.4% in (2003_2016) and from (1987_2016), 122% respectively. It implies that the greater changes is occurred in 16 years or between 1987_2016 (122%) and slightly increase from (2003_2016). In contrast farm lands decrease (from2588.06 to 1508.1ha), representing decreasing to (-15.4%), and (1.24%) and (4%) change rate in 1987, 2003 and 2016 respectively. But the change rate between 1987_2016 was not significantly. Similarly; Vegetation cover dramatically decreased to 38.5% from 1987 _2016), from (2003_2016) by 53% and from (1987_2016) over (50%).

The following bar graph chart shows the change rate of classes between these three days or change in 1987, 2003 and 2016 years respectively.

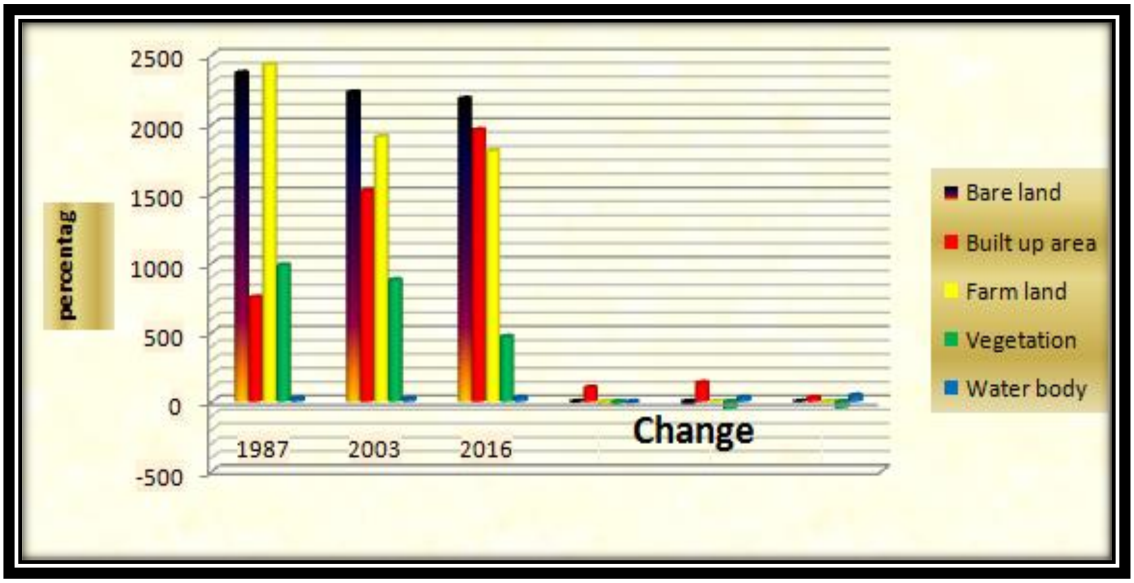


Figure 11 the bar graph showing land use land cover change statistics

4.3 Nature and magnitude of Land use Land cover Change

4.3.1 Land use land cover change in farm land/ Agricultural land

Agricultural lands changes in comparison with changes in other land use/land covers indicates a change detection analysis which performed to reveal LULC conversions from one date to the other. This study was focused on the land use land cover change mainly on agricultural changes. Land cover changes can occur in two forms: conversion of land cover from one category to a completely different category (via forestation, urbanization, etc.), modification of the condition of the land cover type within the same category. This change detection analyses describe and quantify differences between images of the same scene at different times. The classified images of the three dates can be used to calculate the area of different land covers and observe the changes that are taking place in the span of data. Unless there is field verification it is difficult to identify agricultural land use because uncultivated farm land pixels were similar with bare/grass lands but by using different assessment methods was used and significant changes has been observed mainly on agricultural lands and other LULC classes.

Figure 5 and table 6 indicates LULC change of farm land comparing with the other LULC that occurred in the study area between (1987 _ 2016).

The increment in infrastructure development of Debre Markos town from time to time has played a major influence for the expansion of built up areas towards farm land uses. The main focus of this study was assessing and examining the spatial extents of farm land by comparing with different LULC classes within the three study periods. To achieve this, a reclassification was made to generate land use and land cover maps of farm land and none farm land areas as shown in figure 4.2 below. As clearly seen in table 4.5, the proportion of farm land areas in 1987 was 37% of the entire study area. In 2003 the percentage of farm land decrease and it was 24% and in 2016 increase and it reached to 36.6% of area coverage. It shows the positive value when it compare with area coverage with 2003.

Land Cover Class	1987		2003		2016	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Farm Land	2429.01	37	1570.65	24	2399.04	36.6
Non Farm land	4127.76	63	4986.12	76	4157.73	63.4
Total(ha)	6556.77	100	6556.77	100	6556.77	100

Table 10: Farm land and none farm land between1987 - 2016

The study area has experienced spatial increase of different land use and land cover classes such as; built up areas, due to the corresponding horizontal expansion as well as conversion of land cover classes during the distinct study periods. The reclassified images in figure 4.2 showed that there had been a rapid land cover change from farm land areas to none farm land. In both study periods, agricultural areas were the most dynamic classes which contributed to the increase of built up areas. There was a huge decrease of farm land from 1987 to 2003. This was related to the diminished of farm land such as; construction of buildings and construction of schools. The basic reason for the decrement farm land in 1987 as compared to 2003 might linked with, agricultural lands were uses for the forestation program launched by the then government of Dergu.

In addition, the above table shows agricultural lands area coverage was high in 2016 which accounted 36.6% comparing with 2003 which accounted 24%. The reason may linked with the contribution of open areas, because in the study area, there different farming activities along lower course of a river.

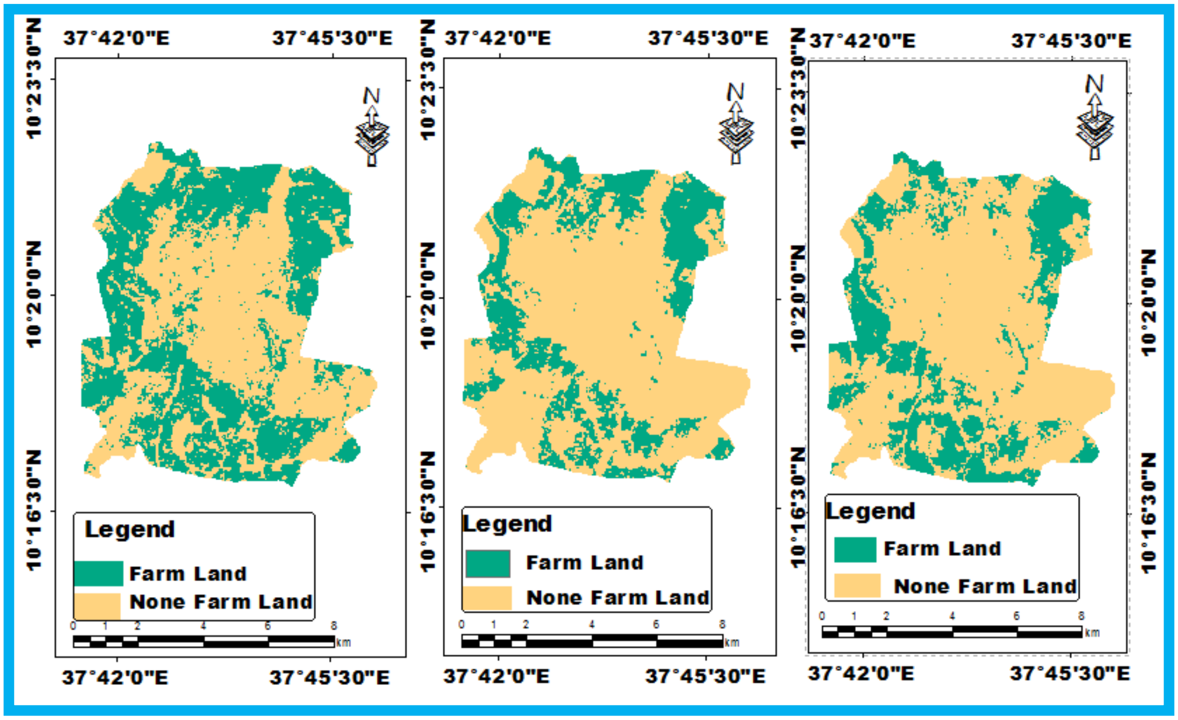


Figure: 12 Farm land and none farm land for 1987 (left), 2003 (middle) and 2016 (right) respectively.

4.3.2 Land use land cover change in Built up area

Based on the objective of this study, which was to map land use land cover change and its effect on urban agriculture thus built up area was more contribute for LULCC on agriculture land because of this the attention was given to build up areas in comparison with other land use/ land cover classes. As the above result shows that built areas was strictly increasing from 1987_2016. The increment of built up areas links with the horizontal growth of the town towards to agricultural areas. Because of this agricultural lands diminished and it transformed to build up uses. In order to examine the nature and the magnitude of the built up areas, a reclassification was made to generate land use and land cover maps of built up and none built up areas as shown in figure 4.2 below. As clearly seen in table 4.5, the proportion of built up areas in 1987 was 11.46% of the entire study area. In 2003 the percentage of built up areas showed more than double increase and it was 24% and in 2016 it reached to 25.4% of area coverage. As the figure shows in the project area urbanization is rapidly increase from year to year (1987_2016).due to high demand of land for different activities such as commercial, residential, educational sectors and other due to suitability of the area, near to rivers areas were not suitable to built settlement, due to this the expansion was towards the agricultural lands. As a result land for urban agriculture becoming in shortage, therefore it leads to urban farm limited land use. Different studies like (Maru A.2014) states that free grazing devastates grasses, forest trees and micro organism under limited, but in the study area some grazing places owned by different private owners this leads to shortage of open space for other farmers and some grazing places transformed to built up areas.

Land Cover Class	1987		2003		2016	
	Area (ha)	%	Area (ha)	%	Area (ha)	%
Built up area	751.5	11.46	1569.15	24	1668.33	25.4
None Built up area	5805.27	89	4987.67	76	4888.44	75
Total(ha)	6556.77	100	6556.77	100	6556.77	100

Table 11: Built up area and none built up area between1987 – 2016

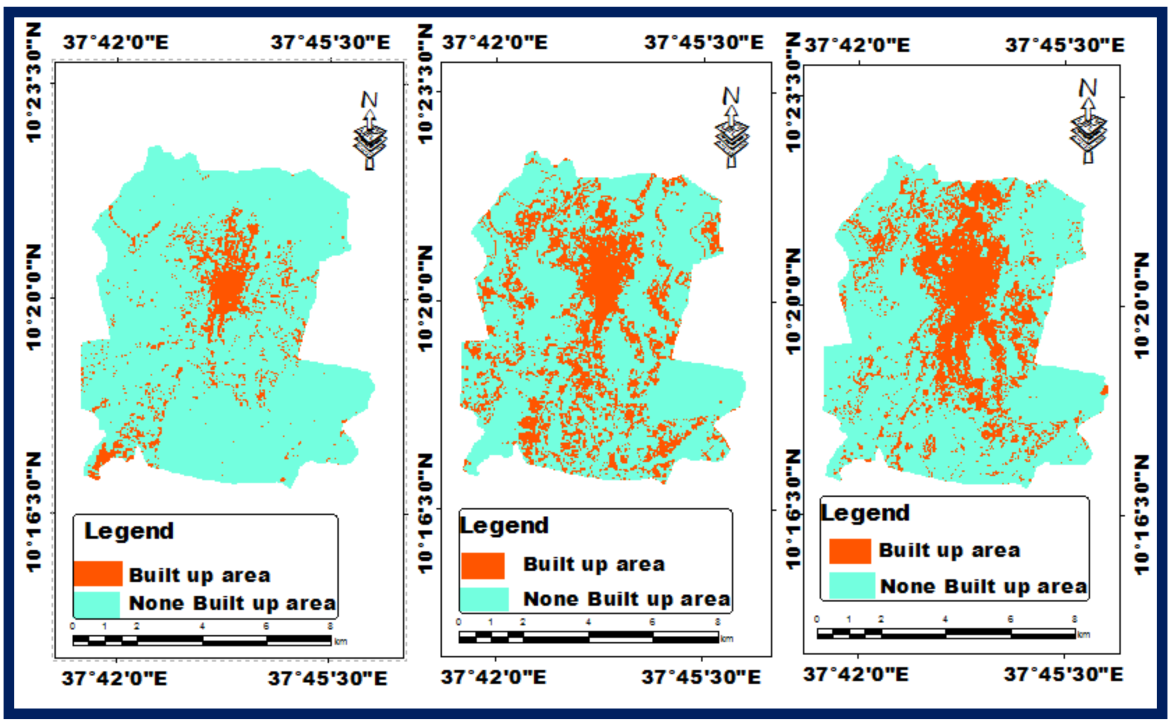


Figure: 13 Built up and none built up areas for 1987 (left), 2003 (middle) and 2016 (right) respectively.

CHAPTER FIVE

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion

Land use land cover has its own adverse and positive effect on spatial resource and change on geo information based on this, this project has been assessed the effects of land use land cover change on urban agriculture.

Even though image classification and interpretation using landsat image is difficult for urban areas, mapping land use land cover is very important to identify LULC changes and its effect in the project area.

Recent land use land cover change is very important especially in developing country like Ethiopia, for effective usage of resource and for data management of natural resource. Planned and managed urban resource and for urban development. Combination of deferent land uses and land cover with urban agriculture which is the most potential for the improvement of urban environment and for urban food security.

Mapping land use land change detection analysis helps for many perspectives related to planning activities; this project tries to address the land use changes and its effect takes place between 1987 and 2003, 1987 and 2016 and 2003 and 2016.It is a common fact that the increment of urban population and horizontal growth of Debre Markos town, put pressure and diminishes on farm land, vegetation and water bodies. This phenomenon was evidenced in the project area since urbanization is associated with built up areas consequently with deforestation. As a result vegetation and farm lands were decreased more than 50% due to the high demand of housing in Debre Markos town.

Remote sensing data are analyzed through along processes using various image preprocessing techniques and methods. This preprocessing of data was helpful to evaluate land use land cover changes in the project area, however to get accurate information during classification process different ancillary data such as orthophot, Spot image, topographic maps has been used.

The assessment of project has been emphasizing the recent technology which is integration of remote sensing, Photogrammetry, orthophoto and GIS technologies. This integration was very effective during classification of different land use land cover change and toper form and analyzes of LULC changes.

The accuracy of assessment of data was based on ground truth which is identify and location of land use land cover features type was field based by using hand held GPS, other ancillary data integrated with personal experience or knowledge of the project area.

According to change detection statistics, the majority of changes is occurred on built up areas and agricultural or farm lands. Built up areas changes increased by over 130% between 1987_2016 and farm lands decreased by over 20% from 1987_2003 and it has adverse effect on urban food security. The main reason for decreasing of agricultural lands was linked with the growth of population and construction of town buildings is towards agricultural land because of this urban and pre urban farmers lose their lands in the town and they relocate to other areas.

5.2 Recommendations

Based on analyses of change detection statistics that provide from the project area, important recommendations can be drawn.

- Land use land cover change detection plays a great role for urban changes and urban planning. Therefore the government and project area town municipalities should emphasize the application of GIS and remote sensing in the process of planning activities.
- The growth of Debre Markos town seems like to horizontally towards periphery area, without planning, therefore planners should give emphasize vertical development of the town.
- Land use Land cover change of the project area would be numerous help in information of policies and programmers were required for developmental planning, therefore the project area administration should initiate and use this type of data to the future.
- Mapping land use land cover change is important for Sustainability and management of natural resource and they are pillars of protection of urban environment. Therefore, the

municipality of Debre Markos town should get accurate up to date information on land use land cover change.

- The government should give attention and initiate land use land cover change projects and related to land use land cover problems should be given effective responses.

Reference

Altieri, M.A .Companion, .N.,Cnizares, K,Murphy C.,Rosset,p.Bouque,M.and Nicholas .C,I.1999.The greening of barriers, urban agriculture for food security in cuba agriculture and human values 16,pp.131_140.

Anderson.J.R.,Hardy.E.E,Roach J.T.,and Witmer R.F (1976).A land use A land cover classification system for use with remote sensing data, geological survey N.964,u.s.

Argentina,O.(2000)feeding the cities, food supply and distribution. Achieving urban food and nutrition security in the developing world.

Baban. S.M.T., 1999.Uses of remote sensing and GIS in developing lake management strategies. Hydrobiology, 395_96.pp 211_226.

Basudeb Bhatta,2011.Remote Sensing and GIS 2nd edition textbook,from (peg 361_378)

Bouque M.2000,Policy option for urban agriculture

Brockerhoff,M, 2000. Achieving urban food nutrition and security in the developing world.

Chandra.P.Gri,Siouxfalls south Dakota, remote sensing of land use and land cover principles and application,(2012).

Debre Markos City Service (2005). General Profile of Debre Markos Town. Debre Markos (Unpublished, translated version).

Dong.Y.Forster.B and Ticehurst.C., 1997, Radar Backscatter analysis for urban environment. International journal of Remote sensing, 18, pp 1351_1364.

Dionys Forster , Tobias Walter Kellenberger , Yves Buehler & Bernd Lennartz (2010) Mapping diversified peri-urban agriculture – potential of object-based versus per-field land cover/land use classification, Geocarto International, 25:3, 171-186, DOI: 10.1080/10106040903243416

Edward, suede.(2010).Ethiopia environment review No 1 forum for environment Addis Ababa Examination for urban agriculture in east Africa.

Egzaiabher,A, G.Lee.Smith, D.G memon, P.A., Mougeot, L.J.A and Sawioc. 1994 cities feeding people. An examination of urban agriculture in east Africa.

FAO, 2001, Urban agriculture and pre urban agriculture, briefing guide for successful implementation of urban agriculture in developing countries and countries of transition.

FAO,2004,The state of food insecurity in the world .Monitoring progress towards the world food summit and millennium development goals

Foeken,D ,2006,To Subsidies my income: urban farming in East Africa town .studies center No 7,the Netherlands.

Habitat, U.N, 2001, Cities in globalization world: global report a human settlement U.N_Habitat Landon.

IIED, 1992, Sustainable cities meeting needs, reducing resources use and recycling .reuse and reclamation.

Kennedy, R.E.et al, 2009,Remote Sensing change detection tools for natural resources managers, understanding concepts and tradeoff in the design of land escape monitoring project Remote Sensing environment 113:1382.

K.Kavitha, C.Prakasam, A.shanthakumri, 2012,Research Scholar of geography, school of earth and atmospheric science, Land use land cover change detection in midtrial district.

Ku,D.,Mousel,P.,Brondizio,E and Moran,E.2004;Change Detection techniques.International Journal of Remote Sensing.

Lu, D and Weng, Q, 2007, A Survey of image classification methods and techniques for improving classification performance, international journal of Remote Sensing, 28(5)823_870.

Luong, P.T, 1993.The detection of land use land cover changes using Remote Sensing and GIS Vietnam. Asian pacific Remote Sensing journal,S.pp.63-66.

M.Anji Reddy, 2008.text book of remote sensing and Geographic information science third edition.

Mather, P.M, 1987, computer processing of Remote Sensed images: A n introduction, John Wiley and sons, 352p.

Mar Cotullio,P.J.,Brai Moh,A.K, and Onlish,.T.R,2008.The impact of urbanization on Soil, in land use and soil resource ,A.K.Braimoh and P.L.G.velk(eds),pp.201-245.

Maru. Abebaw,2014 Environmental perspective of urban Agriculture in the case of Debre Markos town.

Mink,S.D,1993,Poverty,population and environment (New York)

M.Smith, 1996, Urban landscapes and sustainable Cities.

Nations, U 2001world urbanization prospects the 1999 revision .united nation New York.

Ruel.M.T.,Garrett.J.LMorris,S.S.,Mayweul,oshang,A.,engle,P.,MenonP.,Slack,A.D.L,1998.Urbn challenge an nutrition security: A review of food security.

Sankhala,S.,Singh,B.2014,Evaluation of urban sprawl and land use land cover change using Remote Sensing and GIS techniques case study of Jaipur city,India,int.J.Emerging technique Adv.Eng.4(1) 66-72.

Teshome T.2007, Assessement of land use land cover change, dynamics of and soil erosion estimation for sustainable management of land resources in Gozamin wereda.

UNFPA (UNITED NATION POPULATION FUND), 2007Stack of world population: unlashing the potential of urban growth (NEW YORK).

UNDP (UNITED NATION DEVELOPMENT PROGRAM), 1996, urban agriculture food jobs and sustainable cities (NEW YORK).

Vagnneron,I.,2007,Economic appraisal of profitable and sustainability of peri urban agriculture in Bangkok, ecological economics (516-529).

Yang,lxian,G klaver,J.M and deal ,B,2003,Urban land cover change detection through sub pixel imperviousness mapping using Remote sensing data, Photogrammetric Engineering and Remote sensing,69(9)(1003-110).

Tammy Parece, James Campbell and John McGee, 2014, Remote Sensing Arc Map Environment, Classification of a Landsat Image (supervised).

Image pre-processing tool Kragujevac J. Math, 2009, College of Computer Science, Megatrend University of Belgrade, and 11000 Novi Beograd, Serbia (97_107)

Zahra Hassan, Rabia shabbier, sheikh Saeed Ahmed,Amir Haidar Malik,Neelam Aziz,Amna Butt and Summra erum,2004, Dynamics of land use and land cove changes (LULCC) using geospatial techniques :a case study of Islamabad Pakistan.

Appendix

Appendix Sample data collected from field observation and Google earth which were used for classification and accuracy assessment.

OID	Class ID	Longitude	Latitude	Class Name	OID	Class ID	Longitude	Latitude	Class Name
1	1	37.76493	10.3112	Vegetation	126	4	37.75943	10.363	Bare Land
2	1	37.75729	10.31268	Vegetation	127	4	37.70538	10.34744	Built up area
3	1	37.76178	10.31522	Vegetation	128	4	37.74422	10.2946	Farm Land
4	1	37.73906	10.3456	Bare Land	129	4	37.72866	10.31861	Bare Land
5	1	37.76029	10.29173	Bare Land	130	4	37.73421	10.35353	Built up area
6	1	37.7248	10.33269	Built up area	131	4	37.71521	10.32349	Bare Land
7	1	37.75242	10.30641	Vegetation	132	4	37.74556	10.32133	Vegetation
8	1	37.73643	10.33973	Built up area	133	4	37.70069	10.30673	Farm Land
9	1	37.75188	10.30844	Vegetation	134	4	37.72324	10.32865	Bare Land
10	1	37.75566	10.30843	Vegetation	135	4	37.7083	10.32775	Bare Land
11	1	37.76069	10.29217	Bare Land	136	4	37.72686	10.32164	Vegetation
12	1	37.76159	10.29425	Bare Land	137	4	37.69924	10.31741	Bare Land
13	1	37.73449	10.32555	Vegetation	138	4	37.74376	10.31618	Bare Land
14	1	37.72552	10.34516	Bare Land	139	4	37.75372	10.3335	Farm Land
15	1	37.76439	10.31119	Vegetation	140	4	37.76275	10.29277	Farm Land
16	1	37.73828	10.32818	Bare Land	141	5	37.73174	10.29808	Farm Land
17	1	37.76192	10.30523	Vegetation	142	5	37.72557	10.30177	Bare Land
18	1	37.76033	10.30478	Vegetation	143	5	37.7543	10.29081	Vegetation
19	1	37.72121	10.33564	Vegetation	144	5	37.70508	10.33463	Bare Land
20	1	37.71836	10.3373	Vegetation	145	5	37.73097	10.30398	Farm Land
21	1	37.74497	10.32644	Vegetation	146	5	37.71685	10.36324	Farm Land
22	1	37.69781	10.35014	Vegetation	147	5	37.7366	10.28682	Bare Land
23	1	37.76047	10.31241	Vegetation	148	5	37.71894	10.30787	Farm Land
24	1	37.72424	10.33196	Built up area	149	5	37.71568	10.29705	Bare Land
25	1	37.76151	10.30574	Vegetation	150	5	37.72702	10.30223	Bare Land
26	1	37.75947	10.30117	Vegetation	151	5	37.7543	10.2908	Vegetation
27	1	37.7343	10.32739	Vegetation	152	5	37.70508	10.3346	Bare Land
28	1	37.7593	10.31478	Vegetation	153	5	37.73097	10.304	Farm Land
29	1	37.7616	10.3051	Vegetation	154	5	37.71685	10.3632	Farm Land
30	1	37.76225	10.31363	Vegetation	155	5	37.74116	10.3561	Bare Land
31	1	37.75543	10.30699	Vegetation	156	5	37.70789	10.3353	Bare Land
32	1	37.7484	10.30113	Vegetation	157	5	37.71894	10.3079	Farm Land
33	1	37.69756	10.35183	Vegetation	158	5	37.71568	10.2971	Bare Land
34	1	37.71527	10.34306	Built up area	159	5	37.72702	10.3022	Bare Land
35	1	37.74383	10.34174	Built up area	160	5	37.70938	10.3469	Bare Land
36	1	37.76813	10.31271	Vegetation	161	5	37.74506	10.2865	Farm Land
37	2	37.72109	10.3388	Vegetation	162	5	37.71719	10.3484	Farm Land

38	2	37.74497	10.32497	Bare Land	163	5	37.71238	10.3414	Bare Land
39	2	37.69987	10.30052	Bare Land	164	5	37.7308	10.2919	Bare Land
40	2	37.7376	10.33064	Bare Land	165	5	37.69802	10.3071	Farm Land
41	2	37.72553	10.33825	Built up area	166	5	37.69841	10.3482	Vegetation
42	2	37.74328	10.33248	Vegetation	167	5	37.723	10.3026	Farm Land
43	2	37.70835	10.32454	Bare Land	168	5	37.71972	10.3005	Bare Land
44	2	37.73443	10.34731	Built up area	169	5	37.71602	10.2922	Bare Land
45	2	37.6909	10.30581	Farm Land	170	5	37.7605	10.2982	Bare Land
46	2	37.74781	10.31619	Bare Land	171	5	37.73287	10.3267	Bare Land
47	2	37.72829	10.3455	Built up area	172	5	37.75081	10.366	Bare Land
48	2	37.74879	10.31576	Farm Land	173	5	37.73647	10.2855	Farm Land
49	2	37.74043	10.30779	Built up area	174	5	37.73272	10.3025	Bare Land
50	2	37.74026	10.34753	Bare Land	175	5	37.70983	10.3367	Bare Land
51	2	37.70131	10.29045	Bare Land	176	5	37.71566	10.2865	Farm Land
52	2	37.73476	10.31521	Vegetation	177	5	37.7432	10.3046	Bare Land
53	2	37.71378	10.34825	Bare Land	178	5	37.74303	10.3379	Vegetation
54	2	37.7037	10.34588	Vegetation	179	5	37.73532	10.2845	Farm Land
55	2	37.72548	10.32795	Built up area	180	5	37.73405	10.3216	Bare Land
56	2	37.7393	10.32201	Vegetation	181	5	37.76902	10.305	Bare Land
57	2	37.73016	10.32913	Bare Land	182	5	37.72649	10.299	Farm Land
58	2	37.76105	10.29419	water Body	183	1	37.75036	10.3011	Vegetation
59	2	37.7062	10.33306	Farm Land	184	1	37.7248	10.3327	Built up area
60	2	37.73931	10.31289	Vegetation	185	1	37.76335	10.3107	Vegetation
61	2	37.72351	10.35094	Farm Land	186	1	37.76268	10.3105	Vegetation
62	2	37.69912	10.35047	Farm Land	187	1	37.72552	10.3452	Bare Land
63	2	37.74001	10.31238	Vegetation	188	1	37.76439	10.3112	Vegetation
64	2	37.75445	10.29064	Bare Land	189	1	37.73828	10.3282	Bare Land
65	2	37.73904	10.28692	Bare Land	190	1	37.7401	10.343	Vegetation
66	2	37.71967	10.31638	Bare Land	191	1	37.76192	10.3052	Vegetation
67	2	37.71785	10.341	Vegetation	192	1	37.75523	10.3122	Vegetation
68	2	37.73931	10.34942	Bare Land	193	1	37.76033	10.3048	Vegetation
69	2	37.73721	10.33055	Bare Land	194	1	37.76047	10.3124	Vegetation
70	2	37.73105	10.34232	Built up area	195	1	37.75543	10.307	Vegetation
71	2	37.73874	10.30609	Bare Land	196	1	37.69756	10.3518	Vegetation
72	2	37.73265	10.3091	Vegetation	197	1	37.74383	10.3417	Built up area
73	3	37.75832	10.35416	Farm Land	198	2	37.69987	10.3005	Bare Land
74	3	37.73841	10.36646	Farm Land	199	2	37.74434	10.3362	Bare Land
75	3	37.711	10.32576	Bare Land	200	2	37.74781	10.3162	Bare Land
76	3	37.70991	10.29947	Bare Land	201	2	37.74043	10.3078	Built up area
77	3	37.71128	10.32196	Farm Land	202	2	37.74026	10.3475	Bare Land
78	3	37.71299	10.37074	Bare Land	203	2	37.71378	10.3483	Bare Land
79	3	37.69732	10.31636	Bare Land	204	2	37.73061	10.3438	Vegetation
80	3	37.76101	10.29865	Farm Land	205	2	37.73132	10.3332	Built up area

81	3	37.72351	10.36345	Bare Land	206	2	37.7062	10.3331	Farm Land
82	3	37.70304	10.32786	Farm Land	207	2	37.72351	10.3509	Farm Land
83	3	37.7229	10.32925	Bare Land	208	2	37.70664	10.3663	Vegetation
84	3	37.73877	10.36411	Farm Land	209	2	37.73105	10.3423	Built up area
85	3	37.76011	10.30082	Bare Land	210	3	37.73854	10.3256	Farm Land
86	3	37.70398	10.34917	Built up area	211	3	37.70991	10.2995	Bare Land
87	3	37.75431	10.35732	Farm Land	212	3	37.72351	10.3635	Bare Land
88	3	37.7263	10.35537	Bare Land	213	3	37.74771	10.3322	Farm Land
89	3	37.71859	10.28771	Bare Land	214	3	37.7229	10.3293	Bare Land
90	3	37.74836	10.35011	Farm Land	215	3	37.73877	10.3641	Farm Land
91	3	37.7206	10.31273	Farm Land	216	3	37.75431	10.3573	Farm Land
92	3	37.74582	10.35644	Farm Land	217	3	37.7263	10.3554	Bare Land
93	3	37.71798	10.31246	Bare Land	218	3	37.7206	10.3127	Farm Land
94	3	37.75243	10.3633	Farm Land	219	3	37.74868	10.3416	Bare Land
95	3	37.74678	10.32294	Farm Land	220	3	37.71624	10.3148	Farm Land
96	3	37.74099	10.29982	Farm Land	221	3	37.73555	10.3665	Farm Land
97	3	37.7021	10.33697	Farm Land	222	3	37.74099	10.2998	Farm Land
98	3	37.7132	10.30169	Bare Land	223	3	37.697	10.312	Bare Land
99	3	37.75135	10.34441	Farm Land	224	4	37.70209	10.3289	Farm Land
100	3	37.69965	10.32253	Farm Land	225	4	37.69179	10.3136	Bare Land
101	3	37.70604	10.33713	Farm Land	226	4	37.70443	10.3332	Bare Land
102	4	37.70891	10.31424	Farm Land	227	4	37.70538	10.3474	Built up area
103	4	37.7486	10.35486	Farm Land	228	4	37.74422	10.2946	Farm Land
104	4	37.7065	10.33895	Vegetation	229	4	37.73645	10.2889	Built up area
105	4	37.70085	10.32588	Bare Land	230	4	37.71521	10.3235	Bare Land
106	4	37.71238	10.37163	Farm Land	231	4	37.72324	10.3287	Bare Land
107	4	37.7302	10.3068	Built up area	232	4	37.72686	10.3216	Vegetation
108	4	37.74705	10.34644	Farm Land	233	4	37.74376	10.3162	Bare Land
109	4	37.71642	10.31372	Farm Land	234	4	37.75372	10.3335	Farm Land
110	4	37.7333	10.36312	Built up area	235	5	37.71602	10.297	water Body
111	4	37.74155	10.30198	Built up area	236	5	37.7366	10.2868	Bare Land
112	4	37.71693	10.32983	Bare Land	237	5	37.72034	10.2903	Farm Land
113	4	37.7009	10.30972	Farm Land	238	5	37.71142	10.3514	Bare Land
114	4	37.70209	10.32888	Farm Land	239	5	37.73989	10.3333	Bare Land
115	4	37.69302	10.30344	Vegetation	240	5	37.73396	10.3204	Bare Land
116	4	37.71436	10.36351	Built up area	241	5	37.7579	10.3626	Farm Land
117	4	37.71226	10.36163	Farm Land	242	5	37.74746	10.3105	Bare Land
118	4	37.69179	10.31357	Bare Land	243	5	37.71507	10.298	Bare Land
119	4	37.70443	10.3332	Bare Land	244	5	37.75262	10.2975	Farm Land
120	4	37.76244	10.29648	Bare Land	245	5	37.73639	10.3524	Bare Land
121	4	37.70102	10.33249	Farm Land	246	5	37.72346	10.3422	Built up area
122	4	37.74888	10.34891	Farm Land	247	5	37.72374	10.2862	Bare Land
123	4	37.728	10.29921	Farm Land	248	5	37.73922	10.3604	Farm Land
124	4	37.75245	10.34712	Farm Land	249	5	37.71137	10.3361	Bare Land
125	4	37.72189	10.37037	Farm Land	250	5	37.75898	10.2974	Bare Land

***Figure represents 'shaded' sample data used for accuracy assessment (40%) and the other 60% for classification.**