ADDIS ABABA UNVERSITY INSTITUTE OF TECHNOLOGY

SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

LAND USE AND LAND COVER CHANGE DETECTION ANALYSIS USING REMOTE SENSING AND GEOGRAPHIC INFORMATION SYSTEM: A CASE STUDY OF HOSAENA TOWN SOUTHERN ETHIOPIA.

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FEBRUARY 2019

A Thesis Submitted to the School of Civil and Environmental Engineering of Addis Ababa University in partial fulfillment of Degree of Masters of Science in Geodesy and Geomatics

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Declaration

I declare that this thesis which I submitted to the school of Civil and Environmental Engineering of Addis Ababa University Institute of Technology in partial fulfillment of Degree of Masters of Science in Geodesy and Geomatics is my own work. The thesis has not been submitted previously to qualify for any academic award .I was cared for the academic rights of others in the processes of thesis work.

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FEBRUARY

2019

Ethiopia

ACKNOWLEDGMENTS

My astonishing thanks go for my Almighty God and lord Jesus Christ.

A special gratitude goes to my advisor Dr Worku Zewdie(Phd) for his support and supervision. Helped me when I had problems with my analysis, corrected my thesis at several occasion and you have always been tolerant and encouraged me to add new information.

I would like to thank the Ministry of Urban Development and Construction scholarship program for the funding two year salary in which my study goes to end. I would also like to thank the Mr .Andinet, Geodesy and Geomatic coordinator Dr. Berhan Gessesse(Phd) Remote sensing and Geographic information and Dr.Tulu Bash (Phd) Geodesy and Photogrammetry teachers.

I would also like to thank those stack holders support me in the data collection from providing spatial and attribute data my friends Berhanu G/mariam,Worku ,Mamo for their support and suggestions.

Finally, I would like to thank my parents Ato Eromo Laelago and w/ Abaynshi Addis, my sisters and brothers Dinkinesh, Martha, Selamnash, Genet, Samuel, Henok, Bestega Mishamo Negist and Elisa Eromo who were always supporting and encouraging me with their best wishes.

Abstract

This research was conducted to analyze the land use land cover changes (LULC) for the Hosaena town. For any LULC change analysis acquisition of multi temporal data is vital in order to detect the changes over the time. For this purpose satellite images (Landsat 2000, 2010 and 2018) have been used for retrieving information, adopting image classification method. In addition accuracy analysis has been done by comparing the reference data with the classification results to evaluate the effectiveness of the image classification .

The changes between the defined years was evaluated using land use Land cover maps that belongs to different years adopting cross tabulation and overlay analysis methods., The result indicates that the main changes in the study area were the transformation of Agricultural lands and Grass land were converted into Built up lands in the study area. Accordingly, around 96.6 ha of area of Agricultural land were transformed to build up in the last two decades. The results of this specific study have shown that remote sensing and geographic information system were important tools to studies land use and land cover change. Therefore, based on the findings of this study, the following recommendations are recommended. The use of course imagery does not fit for high level of accuracy of urban features as they are complex and heterogonous. Hence, adopt high resolution imageries such as IKONOS and Quick Bird for generating quality land cover maps. Hence, the output of detailed maps is important to the planners, decision makers and stakeholders for efficient utilization of land.

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LIST OF ACRONOMY

ANN - Artificial Neural Network

CORINE- Co-ordination of Information on the Environment

CSA - Central Statistical Agency

DEM - Digital Elevation Model

ETM- Enhanced Thematic Mapper

HFEDB   Hadiya Finance Development Bureau

GIS - Geographical Information System

GLCF - Global Land Cover Facility

KLM-Keyhole Markup Language

LCM - Land Change Modeler

LULC –Land Use Land Cover Changes

MCE - Multi Criteria Evaluation

SNNPR- Southern Nation Nationalities People Region

TM-Thematic mapper

USGS - United States Geological Survey

Table of Contents

Index of Table

Index of figure

CHAPTER ONE

1.1 INTRODUCTION

Urbanization is universal phenomena and the most powerful and visible anthropogenic force that brought change in land use land cover in global level and rapid urbanization is the manifestation of developing world in the 21century (RLU, 2007). Since 1970s urban studies in developing countries are becoming more attentions due to the creation of big cities (Barros, 2004) that has been used for engaging more residents. Land use land cover changes are the cumulative consequence of human and natural phenomena such as agricultural expansion, trade, population growth and consumption pattern, urbanization, economic development, science and technology and other factors (RLU,2007).Associated with the rapid expansion of urbanization, a lot of land has been converted from farmland to urban land which has negative effect on other land cover classes, such as agricultural lands, non built areas, forests and others (Solomon 2006).

Ethiopia has the second largest population in Africa having a total population of over 100 million. It has an average 2.3% annual population growth and 4.6% of average annual urban growth rate (Haregeweyn et al, 2012). In spite of its low urbanization rate compared to other African countries, however the impact of land use and land cover changes becoming a big challenge to the country .According to Central Statistical Agency (CSA, 2015) the growth of urban populations is attributed to three factors: natural growth, migration to existing urban centers and project sites and statistical growth of urban population due to upgrading of rural villages to towns and formal expansion of existing urban areas. Upgrading of rural villages to urban is the major manifestation of Hosaena town in the last two decades.

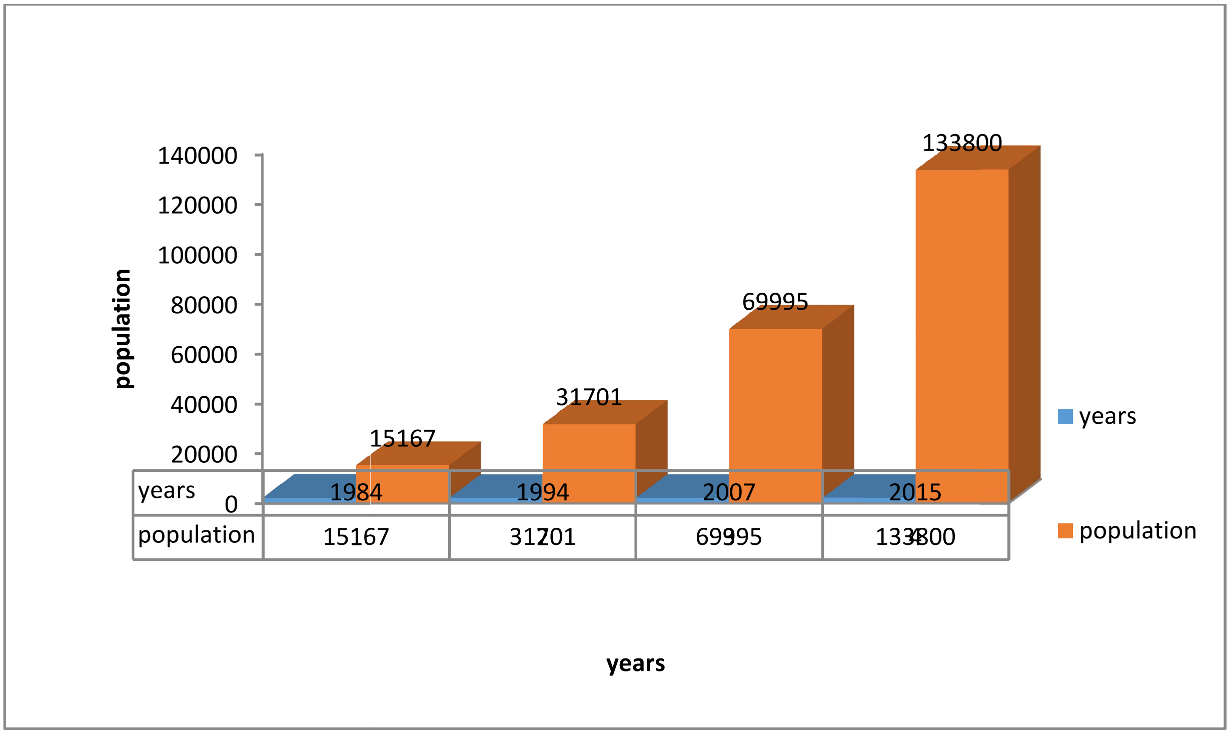


Figure 1.1 Population's size of Hosaena town (source: CSA…..2015)

As land is a scarce natural resource and best possible use is essential to meet the growing demands for indispensable human needs and benefit; as rapid urban expansion has great impacts on the pre-urban areas in terms of shifting the function of the land (Redman and Jones, 2004).Global and local land use land cover change studies were focused on the understanding of processes of land cover change and developing prediction models in the context of global warming and climate changes. There have been many studies in land use land cover change and urban expansion in Ethiopia ,(Fekadu,2015, urban expansion in the fringe area complicated livelihood of the farmers and declined human capitals and recommended that urban expansion should be participatory willingness based and promissory to all stockholders Nigusse,2017 farmers livestock declined because of farm lands and shortage of grass ,the critical case in sebata was land insecurity and forced farmers in the fringe area to sell their own land with lower prices . The researcher was showed that farmers in the study area benefited from the urban expansion like access to road, electricity, market even if the skill gap limited farmers benefit. All focused on the relationship between social economic factors, population density, rising local incomes may be associated with higher local land use intensity and suburbanization (Margo 1992). Percent of area in reserve/protected area and biophysical, Life zones, Median slope, Median soil agricultural and total forest cover. On the other hand, very few studies have focused on the dynamics of land use land cover change over time and space and predict future change patterns using change [Sahalu 2014] The built up increment and agricultural land continuous decreasing in Bahar Dar and recommended that using high resolution satellite images allow to achieve higher accuracy .Hence spatio–temporal, pattern recognition and predicting future urban changes using satellite images needs further research in Ethiopia. In view of the fact that changes detection is dynamic in its approach, in technological advancement and big data availability for change detection; improved methodological approach enhances assessment of urban expansion (Weng, 2010) explained remote sensing provides the necessary information in a timely and cost-effective way compared to the customary field survey approach for change detection which is costly and time consuming.

Hosaena is well known in the region for production of wheat, Teff, maize, cereal crops and recently bamboo attracted investors (HFEDB, 2010). Still expansion of town to formerly agricultural lands through continuous construction of illegal housing is now becoming the usual activities. City sprawling, as it does for others, making Hosaena nebulous which in turn will create various problems ranging from impeding provision of basic and municipal service to fully preventing Hosaena’s development ,Ergando (2011). Any urban area expanding without the frame of the city’s development plan make basic infrastructure inaccessible (UN Habitat iii, Report 2016). This might be the reason for the absence of basic urban services like fixed telecommunication line, electricity and four wheel driving roads in some squatted areas of the town. Squatting activity, although rapidly changed the surrounding agricultural land into built up area, it affected the pre-urban farmers and their families, but brokers and squatters benefited. This work quantify horizontal expansion pattern of Hosaena Town over the years. Generally the study tries to detect the growth patterns and to map the observed changes and more specifically evaluate and quantify spatio-temporal dynamics of Hosaena Town by integrating remote sensing, Geographical Information System (GIS).

1.2 Statement of the problem

Ethiopia is the least urbanized countries in the world (UN-Habitat reports, 2009). Rural – urban migration (Tegene, 2011) and recently infrastructural development (Ayela, 2017) accelerated urbanization processes. However, this expansion of urbanization is not well planned and horizontal expansion is the major challenges of towns and cities in the expense of other land uses. Most towns' in Ethiopia are expanding horizontally following the routes of roads and railway networks (Fekadu, 2015). The Sprawl is moving to unsettled peripheries at the expense of agricultural lands and areas of natural landscapes and other surrounding ecosystems (Lowton, 1997).

Hosaena is among the towns of Ethiopia that has been facing a similar trend of unplanned expansion. It is considered as one of the best financial transaction and access center in the southern Ethiopia (cities review report, 2015). However urban sprawling would have significant impact on the surrounding ecosystem resulting in loss of agricultural land, devastation of forest cover, water depletion and other benefits generated from the land. Because of this rapid growth on the pre-urban, planners and policy makers lack accurate, timely and cost effective urban land use data which is most essential to make decision concerning land resource management. The spontaneous spatial expansion of the town goes to sub urban areas currently outstretched the administrative area of town up to 5-10km under the name of Hosaena town administration (Ergando, 2011).

This paper assesses the horizontal expansion of Hosaena and surrounding with the expense of other land uses; as there is limited study conducted within the area. The previous studies focused on horizontal expansion of Hosaena town to the fringe and explaining the cause and effects but not addressed the land use and land cover change using remote sensing and geographic information system or using spatio-temporal data to quantify and evaluate growth pattern of Hosaena Town.(Fikadu,2015;, Ergando,2011 ; Tesfaye, 2014).

Therefore, this study will provide information on issues of land use and land cover change and dynamics in relation to Built up ,vegetation cover and Agricultural land change and envisage future trend using spatio-temporal analysis in the study area. Mainly, such information is critical for establishing land use and land cover data monitoring strategy through which proper policy intervention be adopted in the growth plan of Hosaena Town.

1.3 Objective

The main objective of this study was to detect and analyze land use and land cover changes in Hosaena Town by integrating remote sensing techniques and geographic information system. The specific objectives of this study were to:

- Map the land use land cover of Hosaena town and surrounding
- Evaluate temporal land use/ land cover changes of Hosaena town.

1.4 Significance of the study

The findings of this study will contribute greatly to the benefit of Hosaena town considering that up-to-date data and information plays vital role in proper planning of the town in relation to the needs of the population, surrounding agricultural communities while maintaining the natural integrity of the environment. It also provides basic information on the urban growth pattern of the Hosaena Town. In addition, this study identified the rate of urban growth pattern in Hosaena Town. Moreover, it evaluates the integration of remote sensing and GIS methodologies, tools to quantify rate and growth pattern of Hosaena town. The output of this research will also be used an initial input for building land use database of the town for future land use planning and management.

1.5 Overview of the Study

The thesis divided into five chapters. The first chapter introduces the background information of the research, the statement of the problem, objectives, research questions, and scope. The second chapter reviews main research outputs related to this study. Third chapter highlights all the procedures and techniques applied for image classification and land use land cover mapping using Arc GIS and. Fourth chapter deals with results and discussions, land cover maps, change detection and accuracy assessments of the classification are discussed in detail. The last chapter five presents conclusions and recommendations. In this section, key findings and critical points that need further treatment has been forwarded as a recommendation for future work.

1.6 Research Questions

The main research question that is addressed by this research includes:

What are the dominant factors that contributed for change ingrowths pattern of Hosaena Town over the years?

What are the relationships between the lands uses land cover changes?

How can remote sensing and geographic information system help in answering these questions?

1.7 Scope and Limitation of the Study

This paper gives insights into how Hosaena area changed in the last 18 years using GIS and Remote Sensing. This approach can be used as potential analytical tools to detect and analyze LULC change in urban area and focused only on the physical change analysis. This study will not include detail attribute factors like human and other factors in detail due to resolution of Satellite Images, Budget and Time.

CHAPTER TWO

2. CONCEPTUAL FRAMEWORK

Different studies in human and physical factors contributed for the natural resources alteration. In the last decades' research on sustainable management of natural resource generated opportunities for new technology in different fields of studies. Scientist throws in cost effective innovations in order to monitor and wisely manage natural resources. Predominantly satellite missions of 1972 on ward contributed a lot for acquiring of land use and land cover change (LULC) information and change monitoring. *Land cover* "describes the physical state of the land surface: as in cropland, mountains, or forests" (Meyer 1995, Moser 1996,). Meyer and Turner (1994) add: "it embraces, for example, the quantity and type of surface vegetation, water, and earth materials (Meyer and Turner 1994). Moser (1996) notes that: "The term originally referred to the type of vegetation that covered the land surface, but has broadened subsequently to include human structures, such as buildings or pavement, and other aspects of the physical environment, such as soils, biodiversity, and surfaces and groundwater" (Moser 1996). *Land use* concerns the function or purpose for which the land is used by the local human population and can be defined as the human activities which are directly related to land, making use of its resources or having an impact on them" (FAO 1995).There are causes and impacts of land use land cover changes in the socio-economic situation and an integrated approach of geographic information system and remote sensing technology are cost effective approaches to land use land cover change detections(Weng,2010).

There are advanced data, methods and techniques used to change detection using remotely sensed data that includes: Linear spectral mixture analysis , hybrid change detection and artificial neural network (ANN), integrated GIS and remote sensing methods and spectral–structural image differencing ,etc (2013 Abdullah). The USGS image archive is also helpful for researchers to easily obtain historical data for land use land cover analysis from earth explorer or other sites. These datasets provide information for mapping the physical characteristics of urban areas and monitoring of temporal changes in urban biophysical features (Haack et al., 1997; Jensen and Cowen, 1999, (Weng, 2010).

2.1 Definitions of Land Use and Land Cover

The terms land use and land cover have been used often interchangeably in literature, though they represent different things. The term land cover refers to the physical cover of the land. It can be defined as the biophysical state of the earth's surface and immediate sub-surface, including biota, soil, topography, surface water and groundwater and human structures (Turner et al., 1995). On the other hand, land use is the purpose for which human is using the land cover type Turner, B.L., Meyer, W.B. and (Skole, 1994). It describes the human activities on the land such as agriculture, forestry or building construction that modify land surface processes including biogeochemistry, hydrology and biodiversity .Research on LULC are important to put an outline on and parameterization of urban growth pattern and to identify a driving force for land use land cover change . However, the major challenges in LULC change analysis is to link behavior of demographic information with the biophysical information in the appropriate spatial and temporal scales.

Human activities generally affect the land cover of an area mainly through shifting land use patterns by a variety of social causes which can be resulted in land cover changes that includes biodiversity loss, water pollution , trace gas emissions and other processes that come together to affect climate and biosphere (Riebsame, Meyer, and Turer,1994).Hence, in order to use land optimally, it is not only necessary to have the information on existing land use land cover but also the capability to monitor the dynamics of land use resulting out of both changing demands of increasing population and forces of nature acting to shape the landscape.

Generally, land use and land cover changes have a wide range of impacts on environmental and landscape attributes including the quality of water, land and air resources, ecosystem processes and functions (Rimal, 2011). Therefore, remote sensing data and geographic information system are vital to provide accurate, timely and detailed information for detecting and monitoring changes in land use and land cover.

2.2 .Causes of Land Use and Land Cover changes

Understanding the mechanisms leading to LULC changes in the past is crucial to understand the current changes and predict future LULC dynamics. Hence, LULC change research needs to deal with the identification, qualitative description and parameterization of factors which drive changes in land use/land cover as well as the integration of their consequences and feed backs (Hussein Ali, 2009). As a result, underlying causes also tend to be complex, formed by interactions of social, political, economic, demographic, technological, cultural, and biophysical variables. Accordingly, major causes of land use/land cover change are natural variability, economic and technological factors, demographic factors, institutional factors, cultural factors and globalization. Natural variability, natural environmental changes interact with the human decision making processes that cause land use/land cover change while economic and technological factors influence land use decision making by altering prices, taxes etc. on land use inputs and products.

According to Lambin et al. (2003), land-use change is driven by a combination of the following fundamental high level causes. These are resource scarcity leading to an increase in the pressure of production on resources, changing opportunities created by markets, outside policy intervention, loss of adaptive capacity and increased vulnerability, and changes in social organization, in resource access, and in attitudes. Some of the fundamental causes leading to land use and land cover change are mostly endogenous, such as resource scarcity, increased vulnerability and changes in social organization and exogenous factors such as changing market opportunities and policy intervention.

2.3 Impacts of Land use Land Cover changes

Land use land cover change may result in environmental, social and economic impact of greater damage than benefit to the area when there is improper conversion of one land use to new land use types(Moshen A,1999).Therefore, data on the land use change are of greater importance for planners in monitoring the consequences of land use and land cover .The economic and spatial distribution of population can occur through conversion from one land use to another, for instance, converting farming lands into residential, industrial, commercial or recreational use.

2.4 Integration of Remote sensing and GIS

Remotely sensed data can be used to extract thematic information to create geographic information layers through image interpretation mechanism like, manual, automated or retain the digital format (Weng, 2010).Remotely sensed data also aid geographic information system in extraction of cartographic information like line, polygon during edge detection, pattern recognition and segmentation. In addition, remotely sensed data are cost effective data source to revise base maps (Ehlers1988). Cartographic representation is the area of application of remote sensing images as an input for geographic information system. Geographic information system assists remote sensing process particularly in images processing from selecting area of interest, preprocessing, processing and image classification.

2.5 Image classification

Image classification belongs to a very active field in computing research, that of pattern recognition. Image pixels can be classified either by their multivariable statistical properties, such as the case of multi-spectral classification (clustering), or by segmentation based on both statistics and spatial relationships with neighboring pixels (Liu and Mason, 2009). Generally, statistical classification can be catalogued into two major branches: unsupervised and supervised Image classification is the most popularly used information extraction techniques in digital remote sensing. General image classification procedures include (Gong and Howarth, 1990b): 1) Design image classification scheme: they are usually information classes such as urban, agriculture, forest areas, etc. Conduct field studies and collect ground information and other ancillary data of the study area. 2) Preprocessing of the image, including radiometric, atmospheric, geometric and topographic corrections, image enhancement, and initial image clustering.(3) Select representative areas on the image and analyze the initial clustering results or generate training signatures.(4) Image classification supervised mode: using training signature; unsupervised mode: image clustering and cluster grouping (5) Post-processing: complete geometric correction & filtering and classification decorating. (6) Accuracy assessment: compare classification results with field data (Caetano (2009).

2.5.1 Pixel Based Classification

The content of reflected solar radiation received by detectors depends not only on the type of earth surface features but also on sun elevation angle and topography and aspect (Qian Yu et al. 2006). Relief lines perpendicular to the light direction are emphasized, and the ridges or valleys may be over- or underemphasized depending on their orientation (Tayyebi et al.2009). Thus, slope gradient and aspect influence received reflectance. Surface cover type is the same; any variation in reflected energy received by the sensor can be attributed to variations in topography, resulting in illumination differences due to slope gradient and aspect. This results in lengthened clusters of the training samples with degree of elongation depending on the locations where samples are taken. This causes bias and results in non-normal distribution of the training samples, which is not ideal for classification (Law K.H. et al 2004). Qian Yu et al (2006) evaluated the ability of the high spatial resolution airborne Digital Airborne Imaging System (DAIS) imagery for detailed vegetation classification at the alliance level with the aid of ancillary topographic data and object based analysis by fractal network approach. Gao .Y and Zhang (2006) utilized DEM based topographic correction upon LanSat ETM+. In traditional classification of multispectral data, the maximum likelihood classifier is considered to provide the best results since it take into consideration the shape, size and orientation of a cluster. Based on the class mean and the variance-covariance matrix, an unknown pixel is assigned to the most likely class. The classification method assumes that the training samples are normally distributed. This ideal situation, however, may not occur in mountainous areas. Within a given cover type, variations in reflected energy might be considerable due to variations in illumination, resulting in non-normal distribution of the training samples. The distribution of the training samples may be biased towards either fully illuminated or shaded slopes. Conese et al (1993) proposed principal component analysis to overcome the topographic effect. Lees and Ritman (1991) used decision-tree rules to map vegetation in hilly areas. Besides, the spatial complexity and internal heterogeneity of natural and semi-natural nature tend to cause non normal distribution of their spectral response in medium resolution images. Taking into consideration just the statistic assumptions of classification algorithms, the non-normality of the individual spectral bands would advise the use of normalizing the spectral bands by the total intensity. In the present paper normalization of the individual spectral bands is implemented for removing the variations in the solar illumination angle. Mulder (1981) demonstrated that decomposition into intensity variation and spectral color variation can be used meaningfully for feature extraction. Elevation differences between ridges and valley bottoms cause climatic variations, which influence the land cover and land use types. In studying such areas, a combination of RS, GIS and expert knowledge of the area is needed to improve spectral classification.

2.5.2 Object oriented classification

The fundamentals of an object-oriented approach are image objects. Image objects are contiguous regions in an image. Image objects can be connected to a hierarchical network, where they are attributed with a high-dimensional feature space. Objects are created by image segmentation, which is the subdivision of an image into separate regions. This segmentation can be realized as an optimization process. Regions of minimum heterogeneity given certain constraints have to be found. Segmentation (Baatz and Mimler, 2002) allows both segmentations based on primary features (gray tone and shape) and (after an initial classification) the more advanced classification-based segmentation.

2.6 Supervised Classification Algorithms

There are different algorithms for supervised classification; the classic classifiers are minimum distance, parallel pipelined and maximum likelihood methods. Each classifiers uses different statistical approaches for the classification, for this research the maximum likelihood approach is used because it gave better results for the study area.

2.6.1 Maximum Likelihood Algorithm

The maximum likelihood algorithm uses a maximum likelihood procedure derived from Bayesian probability theory; it applies the probability theory to the classification process. This method is a supervised method which uses the training sites, from these sites it determines the class center and the variability in the raster values in each band for each class. This helps to determine the probability of the cell to be belonging to a particular class defined using the training sites. The maximum likelihood classifier computes the class probabilities and classifies the cell where the probability is higher (Smith, 2011).

2.6.2 Minimum Distance Algorithm

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 (.Lillesand. Chapman,2004). In spite of this limitation, the minimum-distance-to-mean Classifier quires only a moderate amount of computation in its decision making. The decision is valid in most cases if the training samples fed into the computer are representative. Besides, no assumptions about the distribution of pixel values are required for these samples (Gao, 2009).

2.6.3Parallel pipelined Algorithm

The parallelepiped classifier is a very simple supervised classifier that is in principle trained by inspecting histograms of the individual spectral components of the available training data. While the parallelepiped method is, in principle, a particularly simple classifier to train and use, it has several drawbacks. One is that there can be considerable gaps between the parallelepipeds; pixels in those regions will not be classified. By comparison the minimum distance and maximum likelihood classifiers will label all pixels in an image, unless thresh holding methods are used. Another limitation is that prior probabilities of class membership are not taken account of; nor are they for minimum distance classification. Finally, for correlated data there can be overlap of the parallelepipeds since their sides are parallel to the spectral axes (Richards. Xiuping Jia, 2005).

2.7 Change Detection Analysis

Change detection is the process of identifying differences in the state of an object or phenomenon through observing its variation overtimes by using remote sensing techniques. Change detection is currently being used to monitor natural processes such as long-term effects from changes in climate due to astronomical causes as well as short term processes including vegetation succession and geomorphologic processes (Story and Congalton, 1986). It is also used to monitor anthropogenic effects such as deforestation, agricultural expansion, urbanization and human induced climate change (Story and Congalton, 2009). Similarly, environmental changes are a reflection of how the land has been managed and change detection methods can help to evaluate these practices (Brothers and Fish, 1978).

There are four aspects of change detection which are important when monitoring natural resources and urban growth patterns namely: detecting the changes that have occurred, identifying the nature of the change, ensuring the area extent of the change and assessing the spatial pattern of the change (Pathak, 2014).

2.8. Land use and Land cover Change Studies in Ethiopia

Ethiopia's is one of the agricultural based economies with traditional farming system and with the growth of urban population as the result of inland migration from rural area to urban are in search of better life. Recently proclaimed land leas policy attracted interest for study land use and land cover changes and its impacts in Ethiopia to design management and monitoring policies. Researches on land use and land cover change in Ethiopia involved in different disciplines depending on the availability of data and tools to perform analysis. However, most of the studies have focused on deforestation, the expansion of cultivated land, dry land spatio temporal change, degradation, river catchments and watersheds, natural ecosystems and forests as well as the associated consequences Tekle (2001) (Amsalu et al (2007); Bewket and Abebe (2013)),Zewdie and Csaplovics (2017) .However, urban growth pattern studies in cities of developing countries like Ethiopia were limited. There are few studies that have been reported such as); Bekalo,2009),(Sahel,2014), fekadu(2015) Kidane(2017) urban expansion in the fringe area affected physical, financial ,human assets and recommended that urban expansion should be participatory and promissory to all stockholders.)…. On the other hand urban growth and dynamics using different models relatively studied in larger cities like Addis Ababa Bakelo(2009),(urban growth was following the vicinity of roads and industry sites .This studies used the combination of geographic system with spatial metrics and integrated data of population, infrastructure and housing data for analysis and draw that agricultural land were converted into built up area and urban Land allocation policy and unplanned urban sprawls at the urban fringes. Bahir Dar (Sahel, 2014).) And Mekele,(kidane 2017). Studies conducted by these authors indicated the urban expansion studies without high resolution satellite images impossible to achieve higher accuracy

CHAPTERTHREE

3. Methodology

3.1. Description of the study area

Hosaena Town located in south west of Addis Ababa about 232km away via Alemgena-Butajira route, 280km via Wolkite route, and 305km via Zway. Hosaena Town.is also located 168km away from Hawassa (the regional capital of SNNPR) via Halaba-Angecha and 203km via Halaba. The geographic location of Hosanna is 7° 33’8” North latitude and 37° 51’ 20” East longitude. The administrative area of Hosaena Town is about7202.32hectares, from these area 4,585.48 hectares of the town has been well master planed

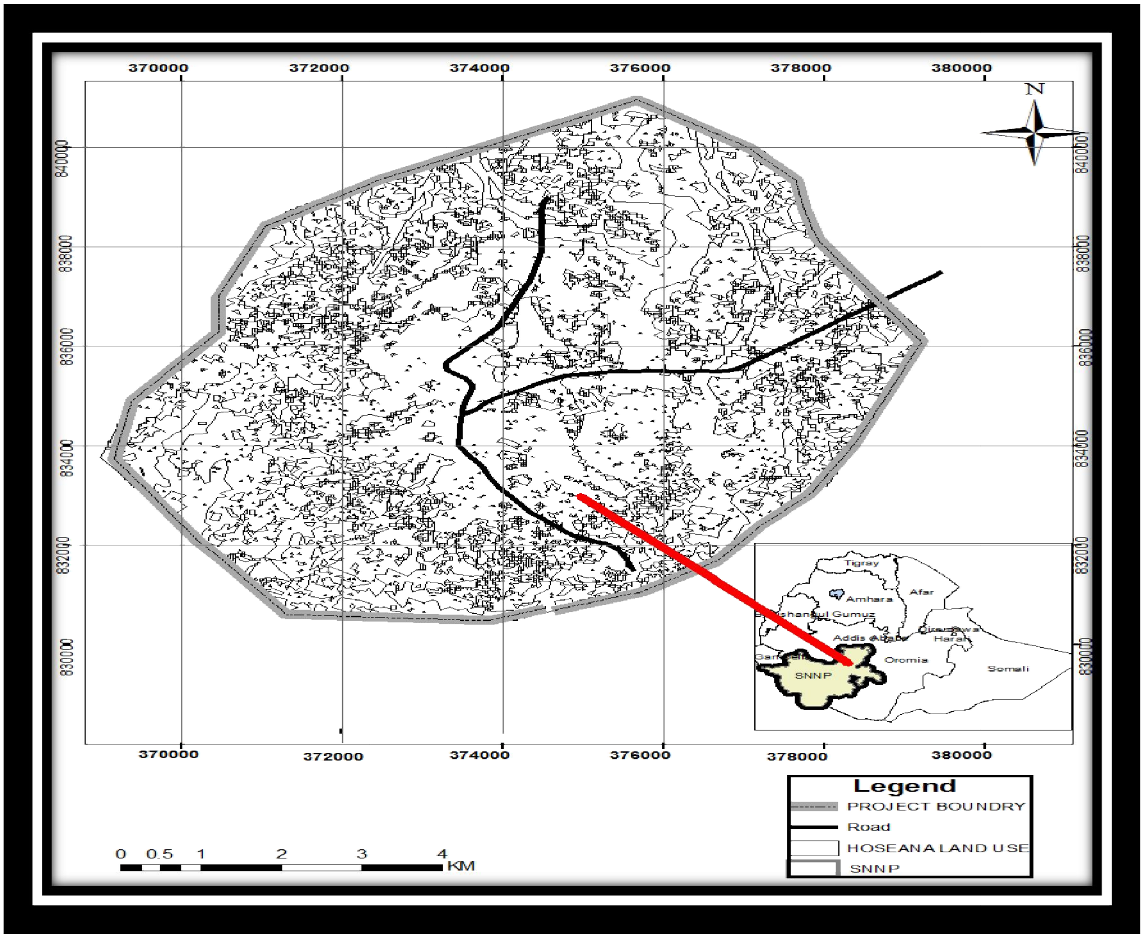


Figure 3.1 STUDY AREA MAP

3.1.1. Population

The total population of Hosanna was 13,467 and 31,701 in 1984 and 1994 respectively (CSA; 1984, 1994). Within ten years time, the town's population reached 69,957(more than double) (CSA, 2007). Based on CSA 2007, at the end of 2010, the population size is 89,251. The 2018 population of the town is projected to reach 148,847(Solomon, 2014 and MUDH, CSA 2017.

3.1.2. Climate

The altitude of the town ranges from 2140m to 2380mabove mean sea level. This shows that the town is mainly characterized by highland ('dega') climatic conditions.

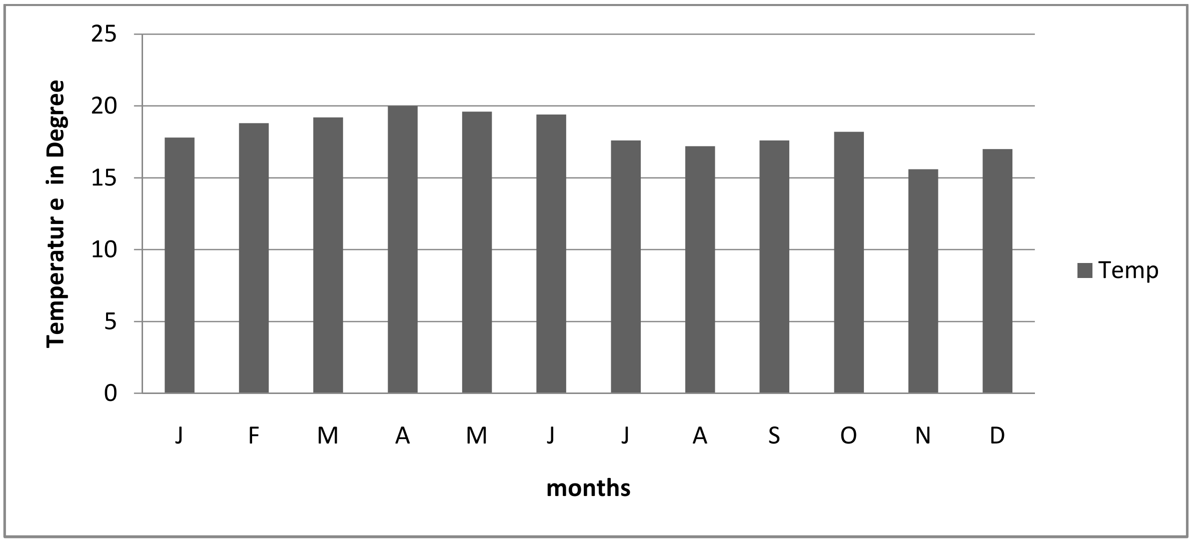


Figure 2.1.1 Mean monthly Temperature of Hosaena town (2010-2018

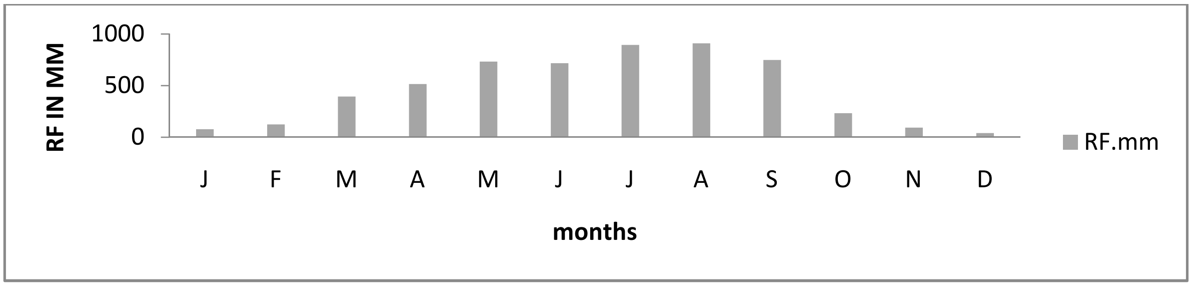


Figure 3.1.2 Mean monthly rain fall distribution of Hosaena town (2010-2018)

3.1.3. Topography

Hosaena town is found at the Southern edge of the western plateau of the physiographic region (Mulugeta, 2001). Its location on a topographically high place makes the town to divide the Ghibe Omo and Rift Valley lakes drainage basins. The elevation within the town ranges from 2,400 m near Hosanna Hospital, currently called Queen Eleni Hospital, and 2,200m at Teklehaimanot Church above the sea level. The average elevation is 2,300m from the mean sea level. The town is prone to flooding and soil erosion due to its high gradient from its peak at the site of the hospital to the low land part of the open market area during the rainy seasons.

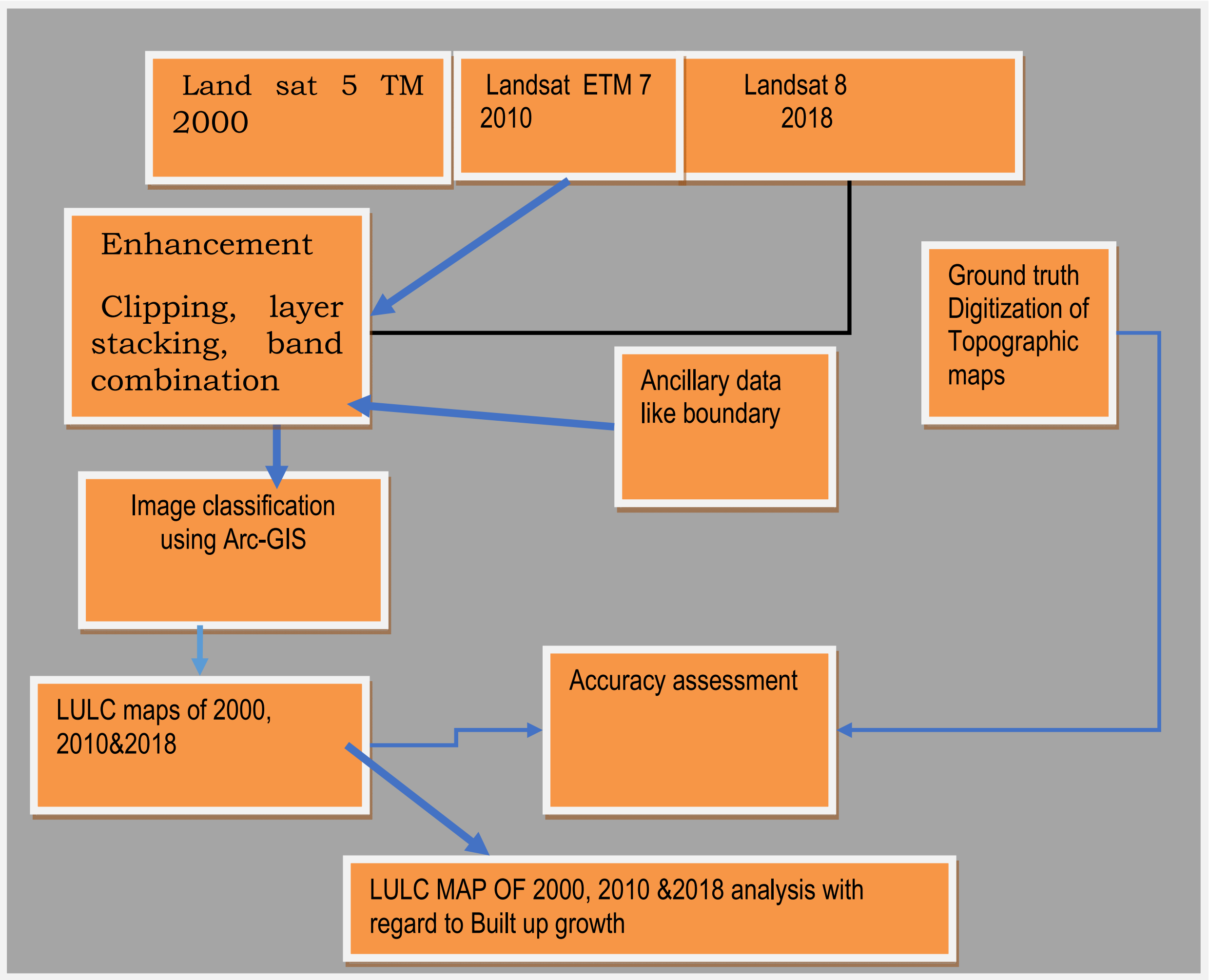


Figure 3.2 General Research Approach

Table 3.1 General Land sat Information

Date	Date acquired	Space craft id	path	row	Sensor id
2000	2-February 000	LANDSAT_7	169	55	"ETM"
2010	14Feb 2010	LANDSAT_5	169	55	"TM"
2018	18 Feb2018	LANDSAT_8	169	55	OLI_TIRS

Table 3.2 Land sat image properties

Landsat5,7 AND 8 (TM sensor)	Wavelength (micrometers)	Resolution (meters)
Band 1	0.45 - 0.52	30
Band	2 0.52 - 0.60	30
Band 3	0.63 - 0.69	30
Band 4	0.76 - 0.90	30
Band 5	1.55-1.75	30
Band 6	10.40 - 12.50	30
Band 7	2.08 - 2.35	30

3.2.2 Software Used

The following software's were used for this study;

(a) ERDAS Imagine 2015 - this was used for displaying and subsequent processing and enhancement of the image. The land LULC classes were also developed using this software.

(b) ArcGIS 10.4.1 - This was also used to compliment the display and processing of the data. This was also used for change detection analysis.

(c) Other's Microsoft Word 2007 and Microsoft Excel 2007.

3.2.3 Pre-processing

Raw satellite image will not be directly utilized for features identification and other related applications due to the limitation to properly indentify each features of the image. Hence, pre-processing is done before the main data analysis and extraction of information. Pre-processing involves two major processes: geometric correction and radiometric correction or haze removal. Remote sensing imageries are inherently subjected to geometric distortions. Accordingly, in this study the following pre-processing was performed:

Step1, Projecting from WGS 1984 to local datum Adindan UTM ZONE 37,

Step 2Using project boundary clipping /subset to study area,

Step 3 Removing cloud using image masking and

Step 4Band combinations Example; Land sat 8 bands 5-4-3(R-G-B), Land-sat TM bands 4-3-2 (R-G-B) and ETM+ 4-3-2 (R-G-B) because multispectral image bands assist in subsequent human interpretation or machine analysis. There are many option of radiometric correction for this study histogram equalization and haze reduction methods employed using ERDAS Imagine 2015. First select tagged image file format (tiff) from the data source and adding the data then raster tab radiometric (which is the collection of tools for adjustment of brightens value of image finally haze removed.

3.2.4. Training and Test Point Collection

Training areas/sample objects which are typical representatives of the classes were collected using high resolution images; existing land cover maps, analyst's personal experiences and knowledge of the physiographical nature of the area. In addition, image enhancement and composition were applied for better discriminating the land cover classes. Training samples for 2000,2010 and 2018 images were collected using topographic maps for each classes ,agriculture ,87 ,Built up 76 ,water 8, open space 51 vegetation/forest 55 and totally 277 polygons also accuracy testing points were randomly collected from Topographic maps and field data collection.

Table 3.2.4 Random Test points

Land use	2000	2010	2018
Agriculture land	80	168	59
Built up land	86	51	66
Grazing	51	29	56
forest	59	61	72
Water bodies	20	30	24

Generally 912 points were used to test the accuracy of the classified images of the 2000, 2010 and 2018.

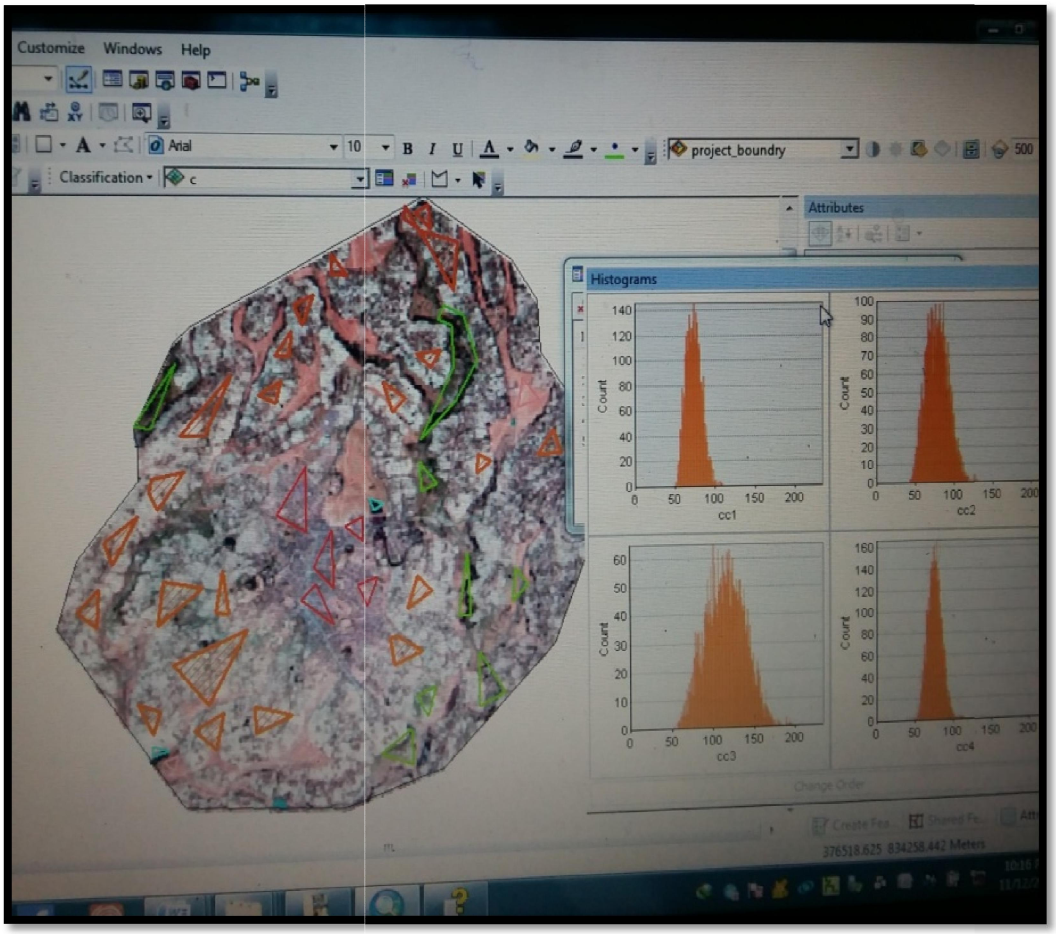


Figure 3.2.4 Training Sample Histogram

3.2.6. Accuracy Assessment

Accuracy assessment is a general term for comparing a classification to geographical data that are assumed to be true, in order to determine the accuracy of the classification process. It is performed by comparing a map created by using remote sensing image classification and analysis to a reference data based on varies information sources such as original mosaic images. An interpretation is then made of how close the newly produced map from the remotely-sensed data relates the reference map. Even though the basic approaches to accuracy assessments look as if relatively straight and simple a variety of errors encountered when data capturing from remotely sensed imageries.

. The error matrix allows us to be able to calculate a variety or accuracy metrics from our data. The columns normally represent the reference data, while the rows indicate the classified image. It also provides an excellent summary of the two types of thematic error that can occur, namely, omission and commission. *Errors of omission* occur when a feature is left out of the category being evaluated; *errors of commission* occur when a feature is incorrectly included in the category being evaluated. An error of omission in one category will be counted as an error in commission in another category. Most of the classification accuracy measurements are derived from confusion matrix. However, the most popular one is the correctly allocated cases in a percentage. Based on this, the *user or consumer accuracy* (CA) is computed using the number of correctly classified pixels to the total number of pixels assigned to a particular category. It takes errors of commission into account by telling the consumer that, for all areas identified as category X, a certain percentage are actually correct (schuckman2018). The *producer's accuracy* (PA) informs the image analyst of the number of pixels correctly classified in a particular category as a percentage of the total number of pixels actually belonging to that category in the image. Producer's accuracy measures errors of omission.

The first step or tasks were collection of test points for each land use land cover classes using topographic maps 2000 and 2010 digitization and GPS points for 2018 finally calculating the accuracy of classified and reference points.

CHAPTER FOUR

4. 1 RESULTS AND DISCUSSIONS

This part includes an overall methods, techniques and materials used to achieve the research objectives. This includes image acquisition, classification, accuracy assessment using classified images and ground truth data. It also encompasses change detection analysis like area calculation, field data collection to image processing like preprocessing of data, remote sensing image classification and change detection analysis.

4.1.1. Data

There are different input data to reach desired goals. However, it is highly depends on the availability of input data and quality of information that can be extracted from the imagery. The data sets used in this study were satellite images obtained from USGS(https://earthexplorer.usgs.gov/) In this study Landsat imageries of Landsat 5 TM, Landsat 7 ETM and Landsat 8 OLI were employed and acquired in the same season and the same level of resolution for the periods 2000,2010and 2018 .Also shape files of study area that includes administrative boundary, river and roads were obtained from Ethiopian Geospatial Information Institute. The images were spatially referenced in the Universal Transverse Mercator (UTM) projection with datum World Geodetic System (WGS) 1984 UTM zone 37N. The images were extracted to Tiff formats for processing.

4.1.2 Data Analysis

The comparison of the LULC statistics assisted in identifying the percentage change, trend and rate of change between 2000, 2010 and 2018. In achieving this, the first task was to develop a table showing the area in hectares and the percentage change for each year (2000, 2010 and 2018) measured against each LULC type. Percentage change to determine the trend of change can then be calculated by dividing observed change by sum of changes multiplied by 100. To obtaining total change or gain or loss of the each land use with the total area of gained area divided by total area of study and multiplied by 100

4.2. Land Covers Classes

In almost any classification process, it is rare to find clearly defined classes that one would like. Before collecting training samples, the land cover classes should be known so as to make the classification easier (Bekalo, 2009).Accordingly, five major land cover classes were identified in the study area.

Table 1.2 Land covers class of the study area

Land cover classes	Description
Built up land	Consists of Urban fabric, Industrial, commercial and transport units, Mine, dump and construction sites, and artificial non-agricultural vegetated areas, roads
Agricultural land	Arable land, Permanent crops, Pastures and Heterogeneous agricultural areas
forest	Forests, Shrub and/or herbaceous vegetation association
Grazing land/Grass land	Dense and degraded
Water bodies	Water courses, water bodies, lake ,dam

4.3. Classification and results of Land cover Maps

The land cover maps generated for the three study periods are analyzed. The figures, shows there has been an increase of built up areas with respective values 5.24% of the study area in 2000 to 13.52% in 2010 and 21.46% in 2018 indicated in figure, 4.3.1, 4.3.2 and 4.3.3 Vegetation cover is increasing from 2000 -2018 and Grass land have also shown a consistent decrease between the study periods.

However, there has been decrease of agricultural areas as clearly shown in figures 4.3.1, 4.3.2and 4.3.3. In 2000 agricultural areas covered 77.5% of the study area. From figure 4.3.1 below and agricultural lands was the most dominant land cover class in the study area but showed a continuous decrease from 77.5% by 2000 to 53.54% in 2018. Urban expansion dynamically increased as the result of the successive decrease of agricultural areas in study periods.

This could be due to an increase of population growth associated with high demand for urban land. Water bodies have shown an increase from0.073 % of the study area in 2000 to 0.14% in 2010.

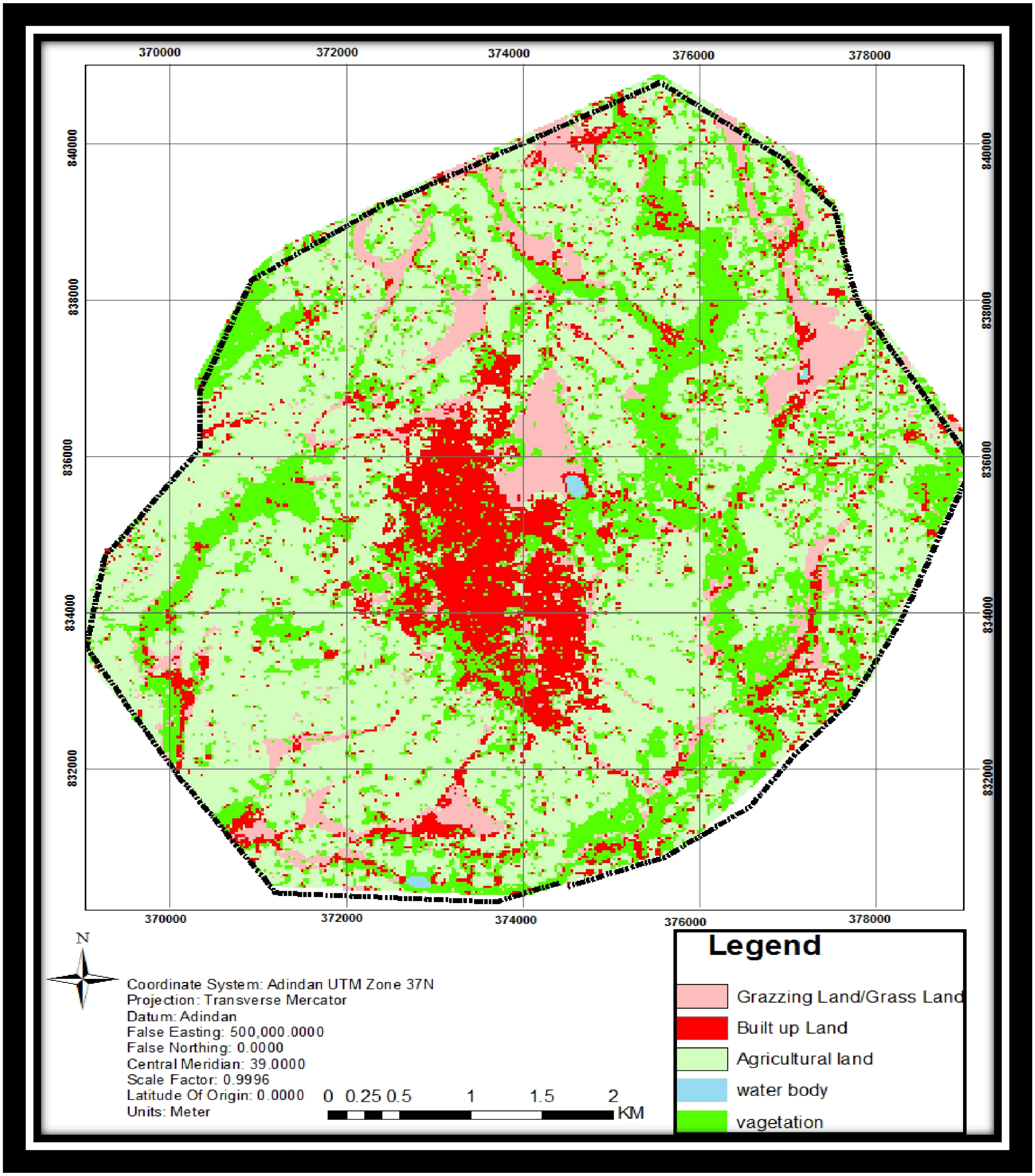


Figure 4.3.1 Land cover map of Hosaena for 2000

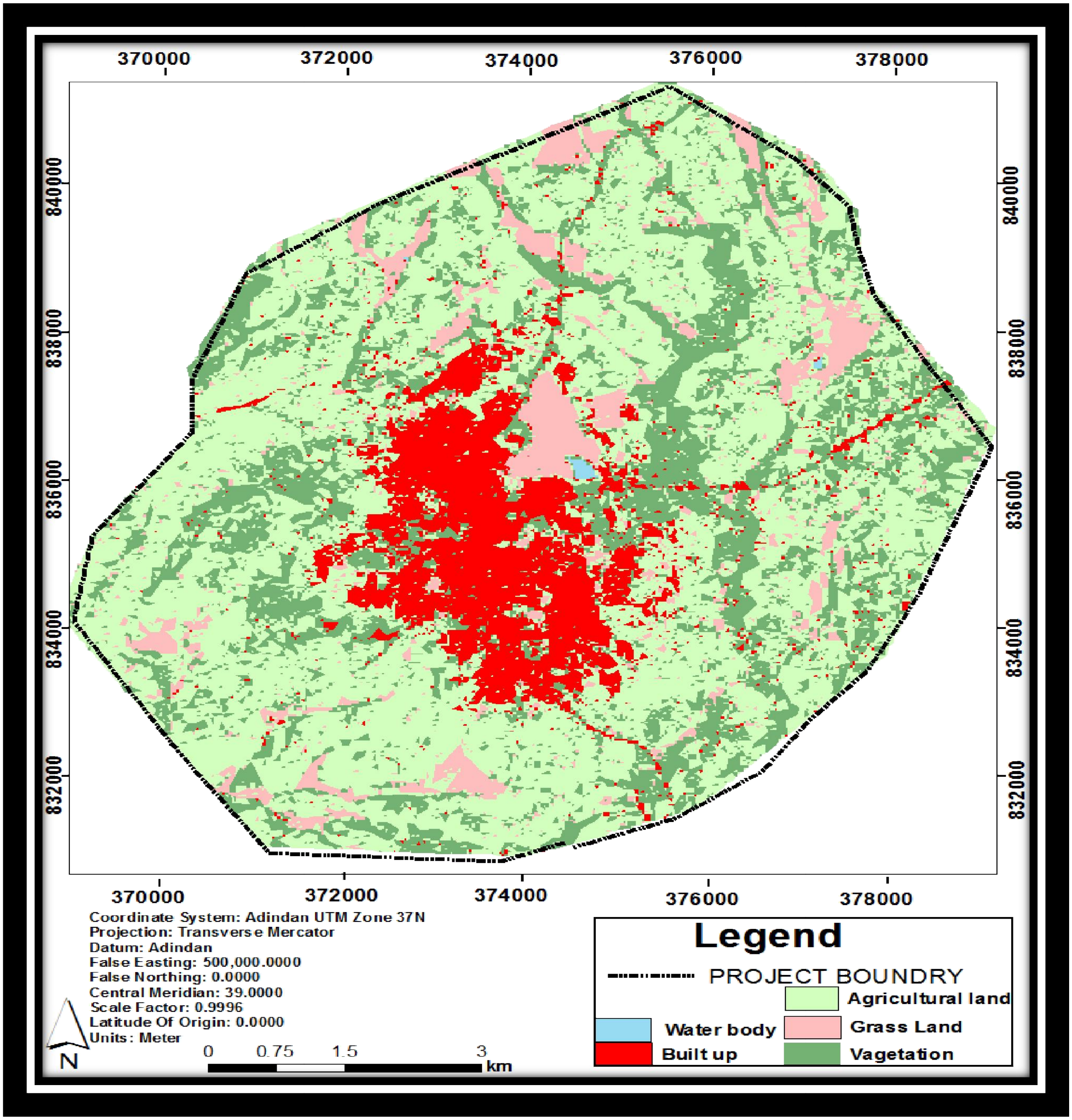


Figure 4.3.2 Land cover map of 2010

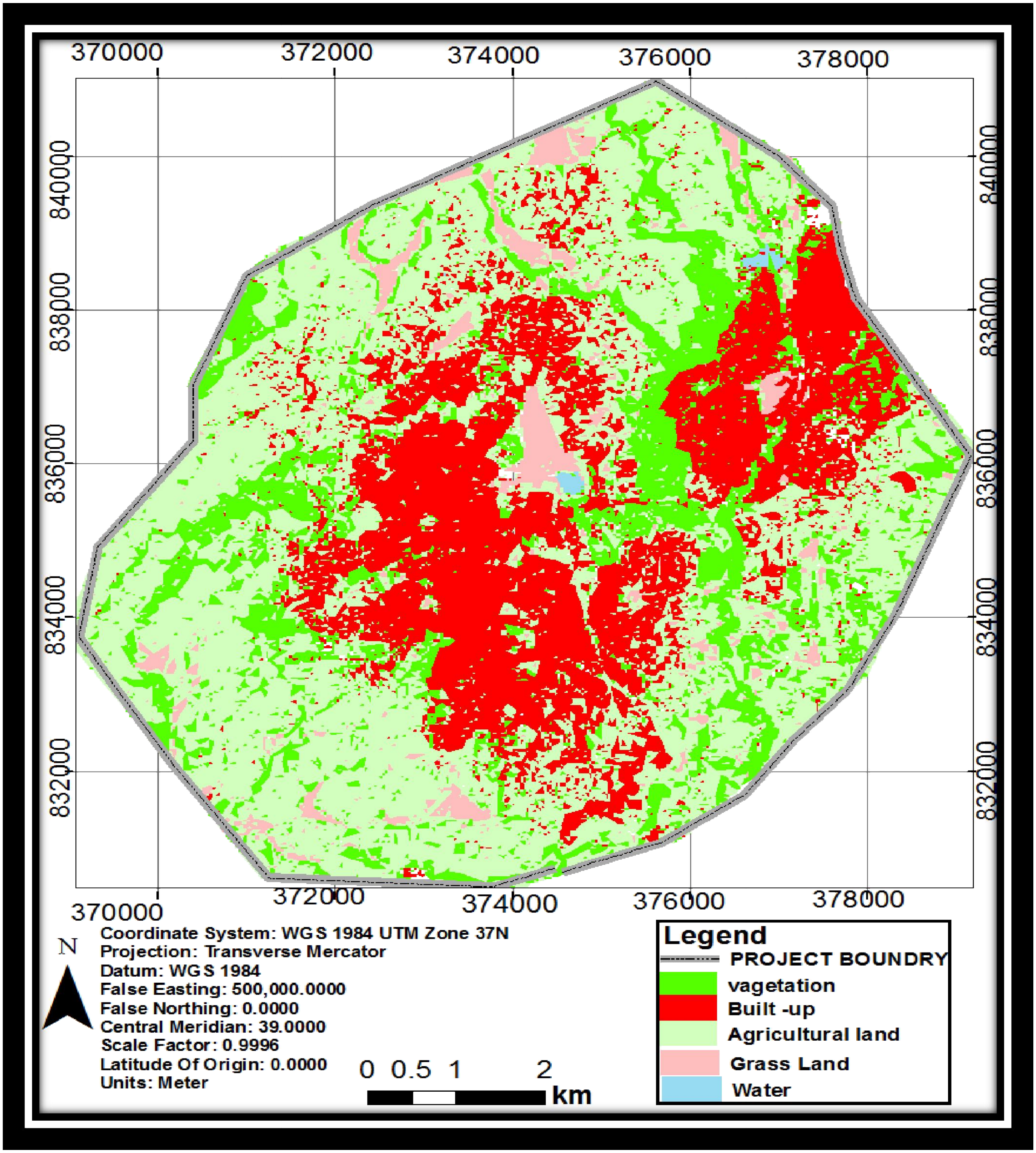


Figure 4.3.3 Land cover map of 2018

Grazing lands also showed a continuous decreasing within the different study periods as indicated in figures 4.3.1, 4.3.2 and 4.3.3 above. Generally, agricultural areas and somehow forest areas were the most prevailing land cover classes that has been observed in the study periods of 2000, 2010 and 2018

Table 4.3 Area information of the land use and land cover units from 2000-2018

Land cover classes	2000		2010		2018	
	Area (ha)	%	Area in Hectare	%	Area in Hectare	%
Built up areas	366.86	5.24	973.648	13.52	1547.30	21.46
Water Bodies	5.24	0.073	10.58	0.14	50.014	0.69
Forest/vegetation	742.771	10.31	1144.17	15.89	1397.29	19.40
Grass land	502.33	6.98	396.06	5.5	353.57	4.91
Agricultural	5585.289	77.55	4677	64.95	3855.64	53.54

4.4. Accuracy Assessment of the Classification

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 incorporated into a GIS, to become an information source for urban planners and researchers, accuracy assessment is supposed to process as it limits the classification results of a remotely sensed imagery data. To do so, the accuracy of a classified map has to be assessed and compared with a referenced data using an error matrix .The accuracy assessment in this study was made using the Topographic map and Global position system(GPS) for the study periods of 2000, 2010 and 2018.

4.4.1. User's Accuracy

User accuracy sometimes consumer accuracy refers to the number of appropriately classified pixels in each class grouping divided by the total number of pixels that were classified in that category of the classified image (row total). It represents the probability that a pixel classified into a given category actually represents that category on the ground. Results of user's accuracy in this study showed that in 2000 the maximum class accuracy was 100%, which was water where correctly classified and the minimum was vegetation with an accuracy of 69% as presented in table 4.4.1 below this shows that some pixels were misclassified as a agricultural land . In 2010, the class accuracies range from 67% to 100% whereas in the period 2018, it ranges from81 % to 100% as indicated in tables 4.4.2 and 4.4.3 respectively. The lowest values of class accuracies were misclassified due to spectral property similarities among other land cover classes. Particularly vegetation and agricultural land spectral similarities affected vegetation class accuracy. As shown from tables 4.4.1, 4.4.2 and 4.4.3 the user's accuracy was lowest vegetation in 2000. Vegetation misclassified in2010 and 2018 periods' .Generally agricultural land and vegetation cover were misclassified in the study periods. Furthermore, the time of image acquisition has a great role for such misclassification problems. Landsat images may be the most common data source for land use/cover classification, even in the study of urban landscapes because of the Landsat program's relatively long history of space-based data collection at global scale. However, the relatively coarse spatial resolution often cannot meet specific project requirements of urban land use/cover classification, especially in a complex urban-rural interface (Jensen and Cowen, 1999; Lu and Weng, 2005). Land sat data could have an influence on the image classification. According to Zhou et al (2009) for detailed urban land cover mapping at very fine scales, high spatial resolution imagery from satellite sensors such as IKONOS and Quick Bird become more accurate.

4.4.2. Producer's Accuracy

Producer's accuracy refers to the number of correctly classified pixels in each class (category) divided by the total number of pixels in the reference data to be of that category (column total are classified. As showed in table 4.4.1 water were largely misclassified as52 % because the number of training sample were lower .vegetation became a low accuracy of 57.32 following water however water lower classification is also 30% not solved in the 2018 may be Agricultural land reflectance similarity leads to lower accuracy of the vegetation or Forest misclassified .The lowest values for Agricultural as compare with other land use land cover the best producer accuracy in the study period 2000-2018.

4.4.3. Overall Accuracy

It is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. It shows overall results of the tabular error matrix it is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. It shows overall results of the tabular error matrix. The overall accuracies performed in this study period 2000 was 81.2% (4.4.1), in 2010 was 82% (4.4.2 and during 2018 it was 94 %(4.4.3) .As mentioned by Anderson et al (1976) for a reliable land cover classification, the minimum overall accuracy value computed from an error matrix should be 85%. However, Foody (2002) showed that this baseline makes no meaning to be internationally acceptable standard for accuracy. This is because a universal standard is not precisely related to any specific study area. Foody (2002) also, illustrious that Anderson et al (1976) do not explain in detail about the criteria of map evaluation for universal applications. Moreover, Lu et al (2004) noted that the accuracies of change detection results highly depend on many factors, such as: availability and quality of ground truth data, the complexity of landscape of the study area, the change detection methods or algorithms used as well as classification and change detection schemes. So, the overall accuracies for both maps were above 85% based on Anderson's criteria.

Table 4.4.1 Confusion matrix for land cover map of 2000

Reference data									
classified		Agricultural land	Grass land	Built up	Vegetation	Water	Total	100%	USER ACCURACY
	Agricultural land	77	3	6	9	1	96	80.2%	
	Grass land	2	45	5	2	0	54	83.3%	
	Built up	0	5	73	2	1	81	90.1%	
	Vegetation	1	4	10	45	7	67	67.1%	
	Water	0	0	0	0	11	11	100%	
	Total	80	57	94	58	20	309		
		96.25%	78.97%	77.67%	77.58%	55%			
		PRODUCER ACCURACY							
		81.2%	OVER ALL ACCURACY						

Table 4.4.2 Confusion matrix for land cover map of 2010

		Reference data							
classified		Built up land	Agricultural land	Grass land	Forest	Water	Total	100%	USER ACCURACY
	Built up land	42	3	0	3	0	48	88%	
	Agricultural land	6	152	4	22	0	184	83%	
	Grass land	1	1	23	1	0	26	88%	
	forest	2	12	2	35	1	52	67%	
	Water Bodies	0	0	0	0	29	29	100%	
	Total	51	168	29	61	30	339		
		82%	90.47%	79.3%	57.37%	96%			
		PRODUCER ACCURACY							
		82.89%	OVER ALL ACCURACY						

Table 4.4.3 .Confusion matrix for land cover map of 2018

Reference data									
classified		Agricultural land	Built up	Vegetation	Grass land	Water	Total	100%	USER ACCURACY
	Agricultural land	57	2	0	1	2	62	91.9	
	Built up land	0	63	0	0	2	65	96.9	
	Forest	2	0	72	0	14	88	81.8	
	Grass land	0	1	0	56	0	57	98.2	
	Water Bodies	0	0	0	0	6	6	100.0	
	Total	59	66	72	57	24	278		
		97	95	100	98	25			
		PRODUCER ACCURACY							
	94%	OVER ALL ACCURACY							

4.5. Land Cover Changes of Built up Land

Hosaena Town fast improvement of the infrastructure from time to time has played a major role for the expansion of built up areas. The main focus of this study was assessing and examining the spatial expansion of built up areas within the 2000, 2010 and 2018. To achieve this, built-up and non built-up newly reclassified land use land cover were shown in 4.5.1, 4.5.2 and 4.5.3 below.

The proportion of built up areas increase from the base year 2000 5.2 % and 2010 13.52% and finally reached to 21.46% in 2018.this shows that urban expansion from time to time in the study area or the built up land expansion with the expense of the other land cover is very high and alarming.

Table 4.5 Built and non built-up areas between 2000- 2018

Land cover classes	2000		2010		2018	
	Area (ha)	%	Area in Hectare	%	Area in Hectare	%
Built up areas	366.86	5.24	973.65	13.52	1547.3	21.46
Non Built up areas	6835.63	94.90648	6228.81	86.47985	5657.514	78.5211
Total	7202.49		7202.458		7202.814	

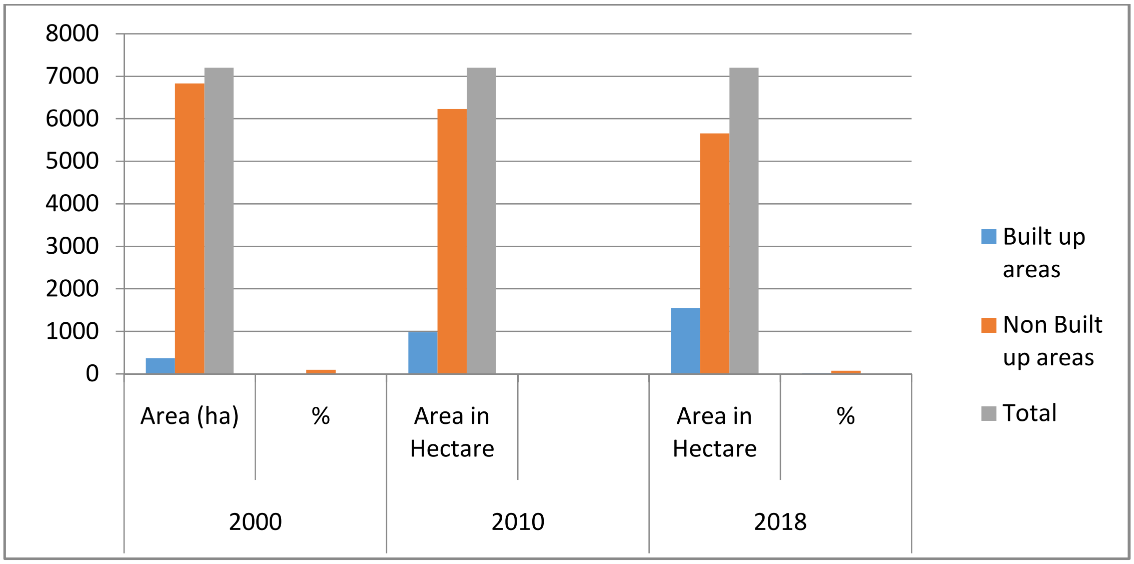


Figure4.5.1.1 BUILT UP AND NONE BUILT UP

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 covers classes during the study periods. The reclassified images in figure 4.5.1, 4.5.2 and4.5.3 showed that there had been a rapid land cover change from non- built up areas to built-up areas. In study periods, agricultural areas were the most dynamic classes which contributed to the increase of built-up areas. This was related to the increase of built up areas such as; illegal housing was raised particularly in the last five years south Africa returned migrant participated in the illegal land marketing(Ergando2011). Following this a lot agricultural land and Grazing land areas were converted to built-up areas.

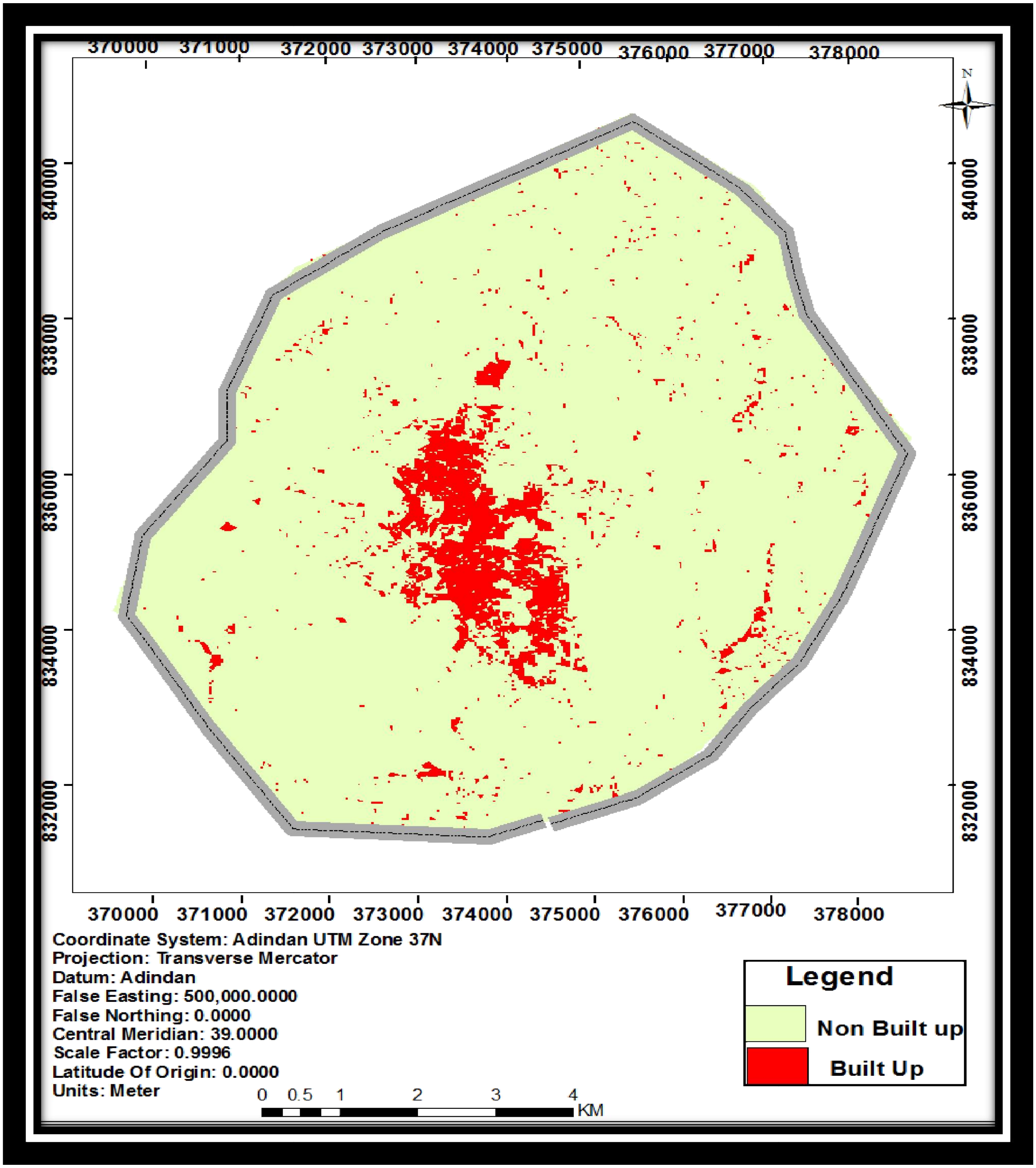


Figure .4.5.1 Built up and Non Built up 2000

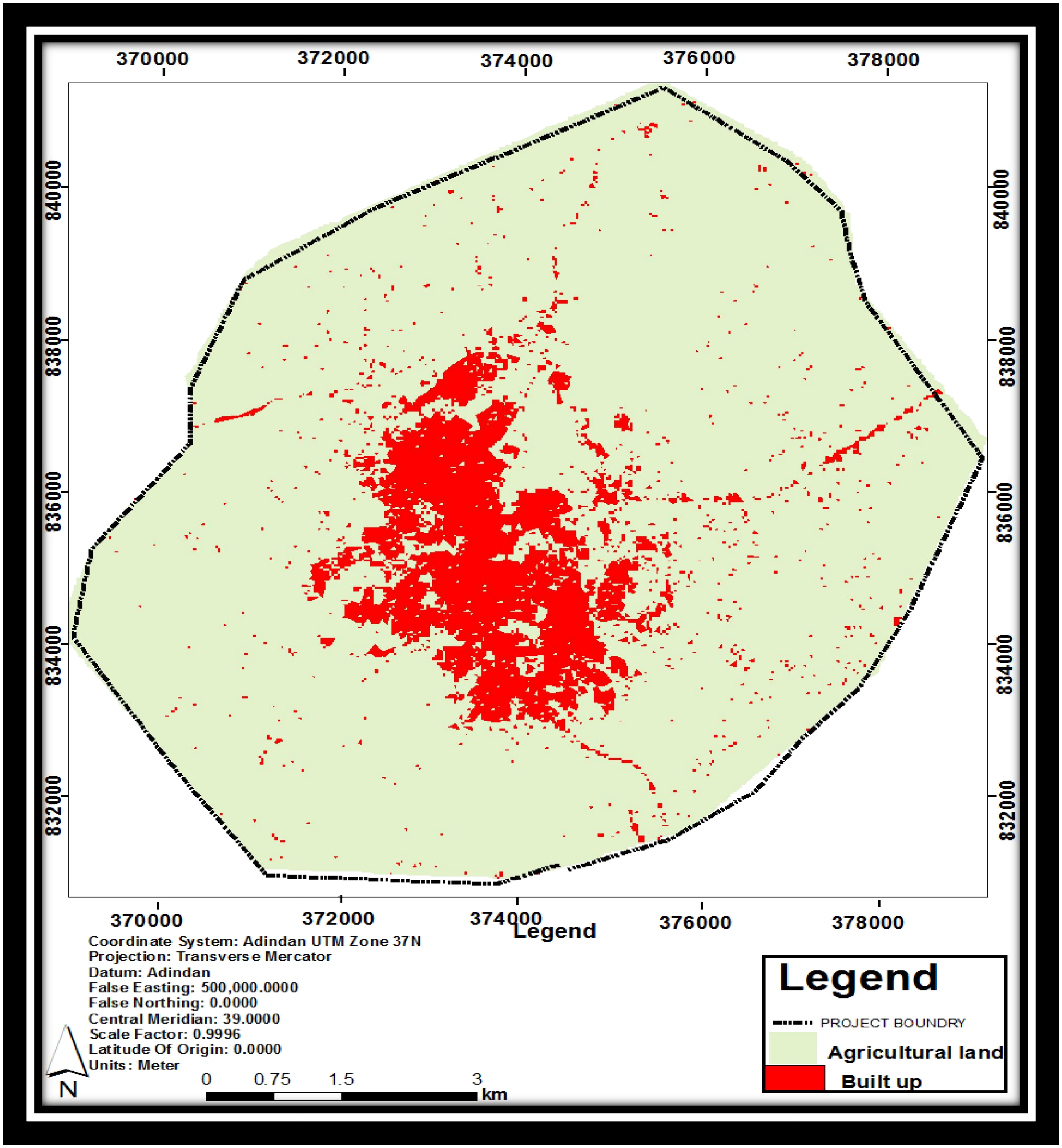


Figure 4.5.2 Built up and Non Built up areas for 2010

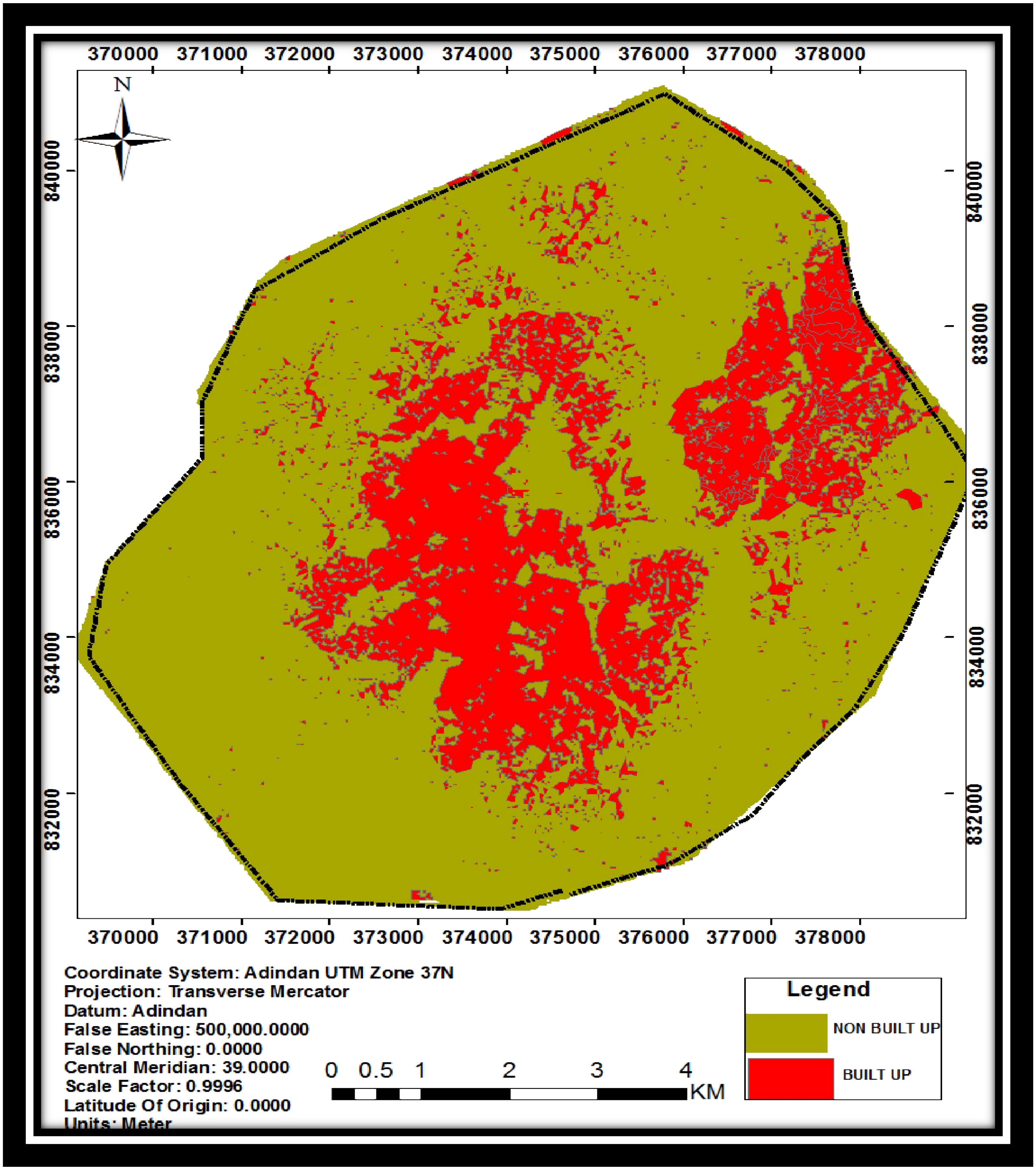


Figure 4.5.3 Built up and Non built up areas for 2018

4.6 Analysis of Land covers maps

In this study the classified land cover maps of 2000, 2010 and 2018 were used as input Parameters and was use to identify the locations and magnitude of the major land use and land cover changes and unchanged.

Moreover, the spatial trends of major Transitions between land use and land cover classes of special interest in the study area has been quantified.

4.6.1. Change Analysis Results

The results of the cross-tabulation comparison of both land use and land cover maps was shown in figure 4.6.1and4.6.2 below. Accordingly there have been remarkable changes in all land use and land cover classes between 2000, 2010 and 2018.

The increase in vegetation cover is related to awareness of farmers for maintaining the drainage and tree is becoming a good source of income compared to farming crops and construction input in the area. This has encouraged farmers to plant more trees in their surroundings and farm plots.

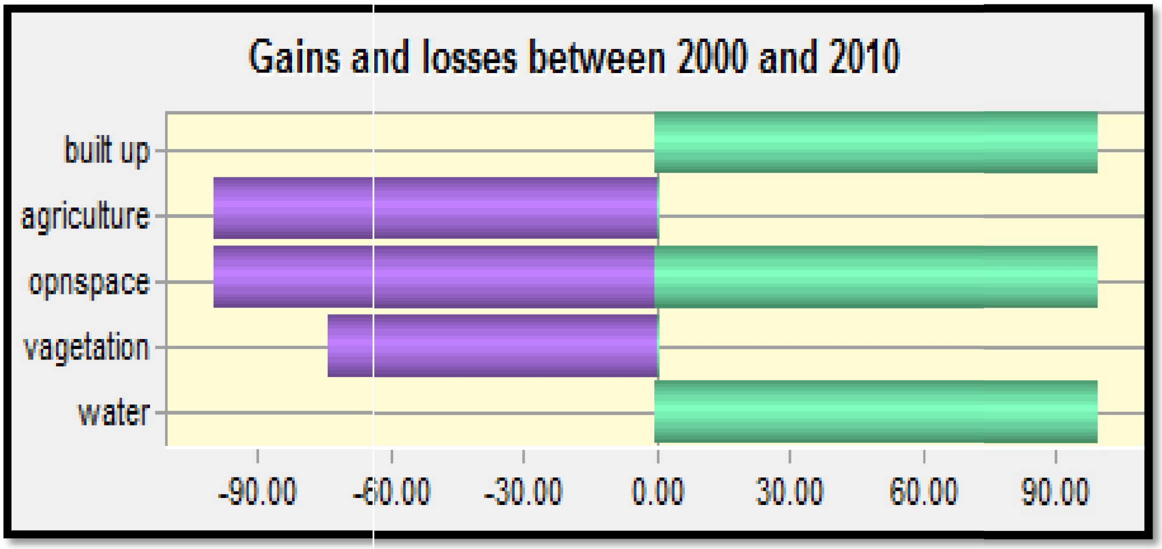


Figure .4.6.1 Gains and losses of land cover classes 2000-2010

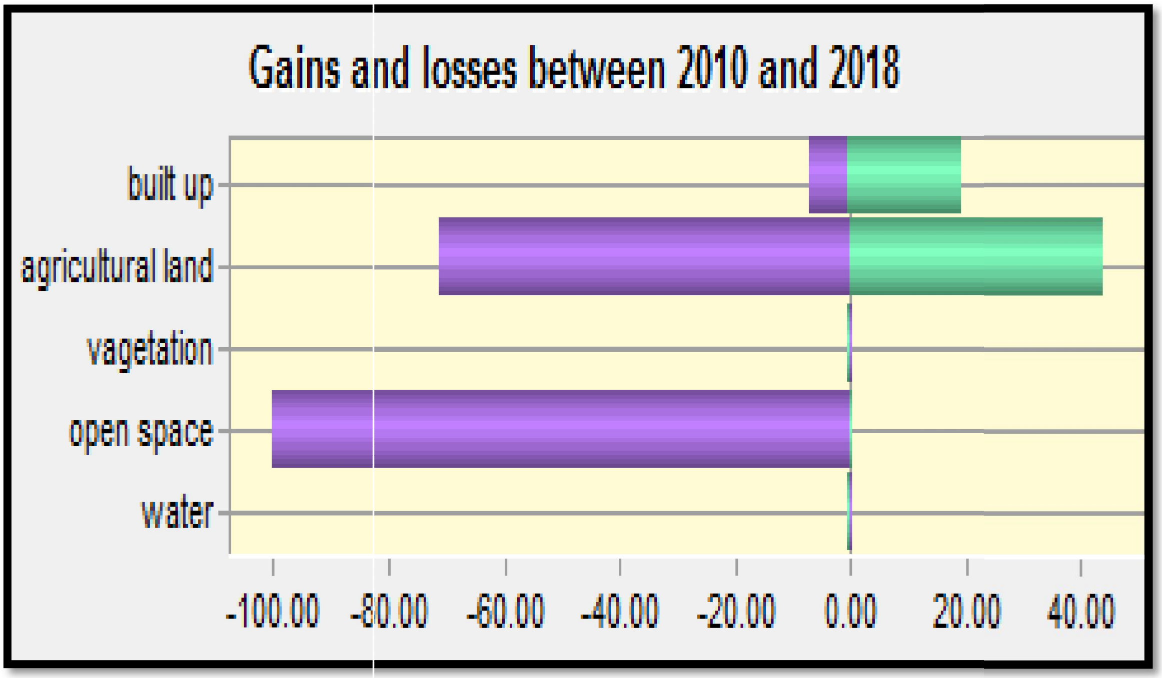


Figure 4.6.2 Gains and losses of land cover classes 2010-2018

Table 4.6.1: Comparison of changes in land cover classes, 2000-2018

Land cover classes	2000-2010		2010-2018		2000-2018	
	Area in Hectare	%	Area in Hectare	%	Area in Hectare	%
Built up Land	606.44	8.43	571	7.84	1178	16.34
Water Bodies	5.35	0.075	39.41	0.54	44.78	0.6
Forest/vegetation	401.40	5.58	253.12	3.51	654.52	9.09
Grazing Land	-106.27	-1.48	-42.49	-0.58	-148.75	-2.06
Agricultural land	-907.44	-12.59	-822.21	-11.41	-1729.6	-24.01

Built up lands (606.44 ha), which represents about 29% of gain area, water bodies (5.35 ha) or 0.27% and vegetation cover or forest (401.40 ha) or19.81 %, of the total percentage of the class gain from 2000-2010. On other hand Agricultural land (907.44ha) or 44.77%, Grazing lands (106.27) or 5.25% of the total percentage of the class loss (2000-2010) as indicated in the table 4.6.1 above. Similarly Built up area increased from 2010-2018 (571 ha), which represents about 33%, water bodies (39 ha) or 2.28%, vegetation cover (253.12ha) or14.64%, of the total percentage of the class gain however Agricultural land losses (-822.21ha) or 47.58%, Grazing land (-42.49) or 2.45% of the total percentage of the class loss (2010-2018).

Generally in the study period Built up areas gain (1178ha), which represents about 31.36%, and vegetation cover or forest (654.52ha) or17.43%, on the other hand Agricultural land (-1729.6 ha) or 46.05%, grazing land (-148.75 ha) or 3.96% contributed for the total percentage of the class loss between(2010 -2018)

4.7 DISCUSION

Change detection studies were showed that urban expansion was influenced by the constructions. Urban expansion and land use changes in the cities were converting Agricultural land in the alarming ways. Hawassa, Addis Ababa and other cities confirmed that remote sensing and Geographic information system applications were significant in urban expansion and land use land cover change detection and identification processes. For instance Sahelu 2014 land *use land cover change analysis in Bahir Dar,* kidane(2017) modeling urban growth in mekele. Both studies were explains Remote sensing application advantages urban growth analysis. Landsat images particularly cellsize30*30 some sort of difficulties in identifying micro level land use land cover changes in detail and misclassification of one land use on the other as (Genemo2015, kidane,2017) were common. Landsat imageries were used for preparing land-use/land-cover maps but difficult to used for predicating future urban land use land cover (kidane, 2017). In order to minimize such problems using high resolution images and frequent field verification were recommended by the many researchers. Uncontrolled urban Population growth is factors for the spontaneous development of urban fringes as (Ergando, 2011). Because of the lack of appropriate land use planning and the measures for sustainable development, uncontrolled urban growth has been creating severe environmental consequences. Similar studies by different researcher have been explained by different title of urban expansion. First, the study did by (Fekadu, 2015) Urban Expansion and Its Effects on Peripheral Farming Communities. My research can show the trends of growth of the expansion of urban in the town of Hosaena. Clearly shows that there is an increase in urban expansion and highly dispersed expansion of horizontal sprawling. Urban land-use agriculture and grazing land has been converted in to built-up areas due to the increase in urban activities. Currently, ongoing urban sprawl and strong population growth, the city of Hoseana needs to consider smart growth policies to encourage the effective and efficient use of newly developed urban land-use of established land. The urban expansion particularly built-up expansion area in Hoseana is the displacement of farmers, excessive use of natural resources and unfair farmland compensation system. Besides, these impacts of urban land-use stress on the farm households affected their livelihood sources of incomes (fekadu 2015).This study noted that, the expansion of the built-up areas is predominantly at the expense of Agricultural and Grazing land).

CHAPTER FIVE

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

Land use land cover changes are the cumulative effect of social and biophysical factors. As the result environmental change as well as natural resource management challenges facing human beings in the last decades. The complex interaction between changes and its drivers over space and time is important to predict future developments, set administrative mechanisms and construct alternative scenarios. This study has been conducted by integrating GIS, remote sensing tools for detect and analyze changes in land cover classes.

satellite data acquired for the study periods of 2000, 2010 and 2018 and remote sensing techniques were applied to generate land cover maps through a maximum likelihood supervised image classification algorithm. The classified and field data were used to accuracy check and change detection processes have also been completed. The information extraction from image classification accuracy became important. In the last section, land use analysis was applied to analyze dynamic changes in built up areas

The image classification output showed that the proportion of Built up areas was increased. There was a rapid change in built up areas from 5.4% in 2000 to 13.52% in 2010 and 21.46% in 2018 respectively. Agricultural areas contributed major component for this much conversion to Built up areas. It showed a continuous decreasing from 77.55% in 2000 to 64.95% in 2010 and finally 53.54% in 2018. The conversion of Agricultural land to built-up could be related to an increment in population and faster economic transformation in the town. Accuracy assessments of classified images show better results with an overall accuracy of 81.2% in 2000, 82.3% in 2010 and 94% in 2018. The change analysis results showed that Built up areas gained 523.65ha between 2000-2010 where as Agricultural areas lost with a total of 907.43 ha in the year 2000-2010….. The contribution of land cover classes to the increase of Built-up areas also showed that Agricultural areas contributed the greater part of the total increase or 1180.44ha. The spatial trend of changes in Built up areas between 2000-2018 were assessed through transition from all categories to Built up areas and particularly transition from Agriculture to Built up in year2010-2018 showed in figure 4.6.1 And it indicated that there was a growing pattern to the Eastern and North West part of the study area with a small trend towards South West relative to other directions because of the landscape of the town. The trend and extent of changes in built up area are likely to continue with the rapid development of infrastructure and increasing of population as discussed in the result section.

5.2. Recommendations

The results of this specific study have shown that remote sensing; GIS were important tools to studies land use and land cover change. Therefore, based on the findings of this study, the following recommendations are recommended for the next researchers in the area.

The use of course imagery does not fit for high level of accuracy of urban features as they are complex and heterogonous. Hence, identification of detailed features using course satellite image is impossible and there is a need to adopt high resolution imageries such as IKONOS and Quick Bird for generating quality land cover maps.

Moreover, the use of ancillary data as ground truth helps for better accuracy of an image classification. Consistent multi-temporal Landsat satellite data for each year provides detail comparison of images. Hence, the output of detailed maps is important to the planners, decision makers and stakeholders for efficient utilization of land.

BIBLIOGRAPHY

Abinete Ergando (2011) The Role of Remittance and Return Migrants Impact on Rural Urban Linkage (AAU, 2011) in hadiya hosaena.(unpublished paper).

- Al-Shalabi, M. A., Bin Mansor, S., Bin Ahmed, N and Shiriff, R. (2006). GIS based multi-criteria approaches to housing site suitability assessment. In XXIII FIG Congress, Shaping the Change, Munich, Germany, October (pp. 8–13).
- Atalel Getu Sahalu *ANALYSIS OF URBAN LAND USE AND LAND COVER CHANGES: A Case Study in Bahir Dar, Ethiopia (2014)*
- Barros, J. X. (2004). Urban growth in Latin American cities: exploring urban dynamics through agent-based simulation (Doctoral), University of London.
- Bekalo, M. T. (2009). Spatial metrics and Landsat data for urban land use change detection: case of Addis Ababa, Ethiopia.
- Berhane Kidane 2017 Cellular Automat Model Based Urban Sprawl Mapping: A Case of MEKELLE CITY, ETHIOPIA
- Bhatta, B. (2010). Causes and Consequences of Urban Growth and Sprawl. In Analysis of Urban Growth and Sprawl from Remote Sensing Data (pp. 17–36). Springer.
- Brown, D. G., Walker, R., Manson, S and Seto, K. (2004). Modeling land use and land cover change. In Land Change Science (pp. 395–409). Springer.
- Brothers and Fish, 1978). To detect land cover change, a comparison of two or more satellite images acquired at different times.
- BAYSAL (2013) Urban Land Use and Land cover change analysis and modeling a case study of Malatya Turkey.
- Cabral, P. and Zamyatin, A. (2009). Markov Processes in Modeling Land Use and LandCover Changes in Sintra-Cascais, Portugal. Dyna, 76(158), 191–198.
- Cao, M., Tang, G., Zhang, F and Yang, J. (2013). A cellular automata model for simulating the evolution of positive–negative terrains in a small loess watershed. International Journal of Geographical Information Science, (ahead-of-print), 1–15.
- CSA (2007, 2015). Summary and statistical report of the population and housing census. Federal Democratic Republic of Ethiopia.

- Foody, G. M. (2002).Status of land covers classification accuracy assessment. Remote Sensing of Environment, 80(1), 185–201.
- Gao, Y and Mas, J. F. (2008). A Comparison of the Performance of Pixel Based and Object Based Classifications over Images with Various Spatial Resolutions. Online Journal of Earth Sciences, 2(1), 27–35.
- Gong and Howarth, 1990). Data selected for this study consisted of SPOT High Resolution. Visible (HRV) imagery recorded on 4 June, 1987
- Haregeweyn, N., Poesen, J., Nyssen, J., De Wit, J., Haile, M., Govers, G and Deckers, S. (2006). Reservoirs in Tigray (Northern Ethiopia): characteristics and sediment deposition problems. Land Degradation & Development, 17(2), 211–230.
- John A. Richards · Xiuping Jia Remote Sensing Digital Image Analysis(fourth edition Canberra, Australia,2005).
- Iacono, M., Levinson, D., El-Geneidy, A and Wasfi, R. (2012). A Markov Chain Model of Land Use Change in the Twin Cities, 1958-2005..
- Jensen, J. R. (2009). Remote Sensing of the Environment: An Earth Resource Perspective Pearson Education India.
- John A. Richards · Xiuping Jia Remote Sensing Digital Image Analysis(fourth edition Canberra, Australia,2005
- Lambin, E. F., Turner, B. L., Geist, H. J., Agbola, S. B., Angelsen, A., Bruce, J. WFolke, C. (2001). The causes of land-use and land-cover change: moving beyond the myths. Global Environmental Change, 11(4), 261–269.
- Land Change Modeling inIDRISI.(2014).http://www.clarklabs.org/products/Land-ChangeModeling-IDRISI.cfm, accessed date 3, 2018.
- Levinson, D and Chen, W. (2005). Paving new ground. Access to Destinations, 243–266.
- Lu, D and Weng, Q. (2010). A survey of image classification methods and techniques for improving classification performance. International Journal of Remote Sensing, 28(5), 823–870.

- MacLean, M. G and Congalton, R. G. (2012). Map accuracy assessment issues when using an object-oriented approach. In Proceedings of the American Society for Photogrammetric and Remote Sensing 2012 Annual Conference.
- Matthews, R. B., Gilbert, N. G., Roach, A., Polhill, J. G and Gotts, N. M. (2007). Agent-based land-use models: a review of applications. Landscape Ecology, 22(10), 1447–1459.
- Margo1992 Steering the Metropolis: Metropolitan Governance for Sustainable Urban.
- NIGUSIE DEJENE (2017) urban expansion and its implication on livelihood of communities in pre –urban area case of sebeta.
- Parker, D. C., Berger, T., Manson, S. M and Use, L. (2003). Agent-based models of land-use and land-cover change: report and review of an international workshop, October 4-7, 2001, Irvine, California, USA. LUCC Focus 1 Office.
- Pontius Jr, R. G and Millones, M. (2011). Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment. International Journal of Remote Sensing, 32(15), 4407–4429.
- Rimal, B. (2011). Application of remote sensing and GIS, land use/land cover change in kath mandu metropolitan city, Nepal. Journal of Theoretical & Applied Information Technology, 23(2).
- Schmidt, E and Kedir, K. (2011). Urbanization and spatial connectivity in Ethiopia: Urban growth analysis using GIS.
- Singh, A. (1989). Review Article Digital change detection techniques using remotely-sensed
- Solomon Tesfaye, the Problem of Housing in Hosanna Town (AAU, 2014).
- Teketel Fekadu (2015),Urban Expansion and Its Effects on Peripheral Farming Communities (Harmaya university 2015): in hadiya hosaena

- Tegene, B. (2011). Land-cover/land-use changes in the Dere kolli catchment of the South Welo zone of Amhara region, Ethiopia. Eastern Africa Social Science Research Review, 18(1), 1–20
- Thomas Lillesand and Kiefer, 2000 Remote sensing and image interpretation fifth edition
- Turner, B.L., Meyer, W.B. and Skole, D.L. (1994) Global Land-Use/Land-Cover Change: Towards an Integrated Study. AMBIO Stockholm, 23, 91-95.
- Weng, Q. (2010, 2012). Remote sensing of impervious surfaces in the urban areas: Requirements, methods, and trends. Remote Sensing of Environment, 117, 34–49.
- Liu, JG and Mason (2009): Essential image processing and GIS for Remote Sensing. Wiley Black.
- Worku Zewdie, Elmar Csaplovies(2015) :Spatiotemporal change analysis of semiarid regions is vital for understanding major threats to the ecosystem, European Journal of Remote Sensing(volum48).
- Zhou, Q and Robson, M. (2001). Automated rangeland vegetation cover and density estimation using ground digital images and a spectral-contextual classifier. International Journal of Remote Sensing, 22(17), 3457–3470.
- Zhou, W., Huang, G., Troy, A and Cadenasso, M. L. (2009). Object-based land cover classification of shaded areas in high spatial resolution imagery of urban areas: A comparison study. Remote Sensing of Environment, 113(8), 1769–1777.
- Zahra_Hassan, Rabia Shabbir, Sheikh Saeed Ahmad, Amir Haider Malik, Neelam Aziz, Amna Butt, and Summra Erum Dynamics of land use and land cover change (LULCC) using geospatial techniques: a case study of Islamabad Pakistan(2007)
- Yue Chang, Kang Hou, Xuxiang Li*, Yunwei Zhang, Pei Chen School of Human Settlements and Civil Engineering, Xi'an Jiao tong University, Xi’an, 710049, China Review of Land Use and Land Cover Change research progress.

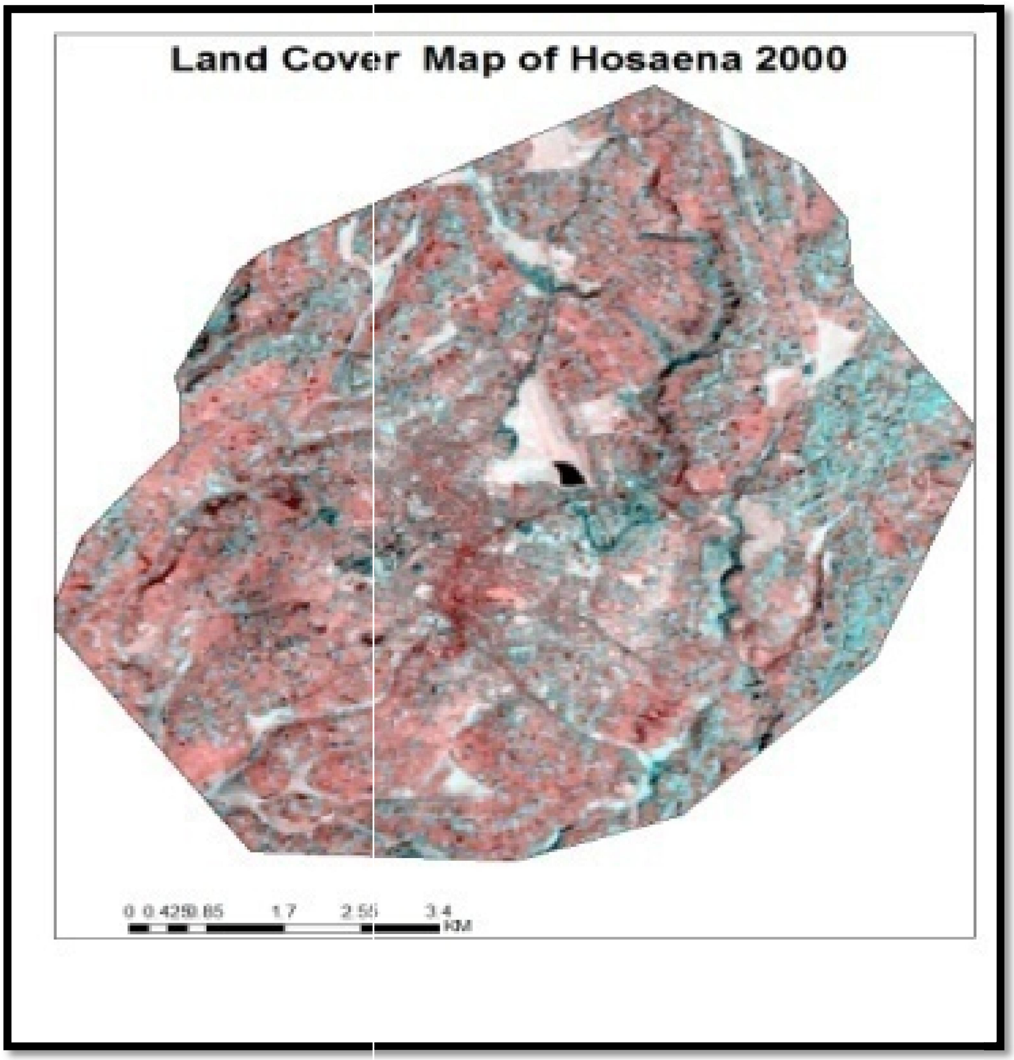
APPENDEX

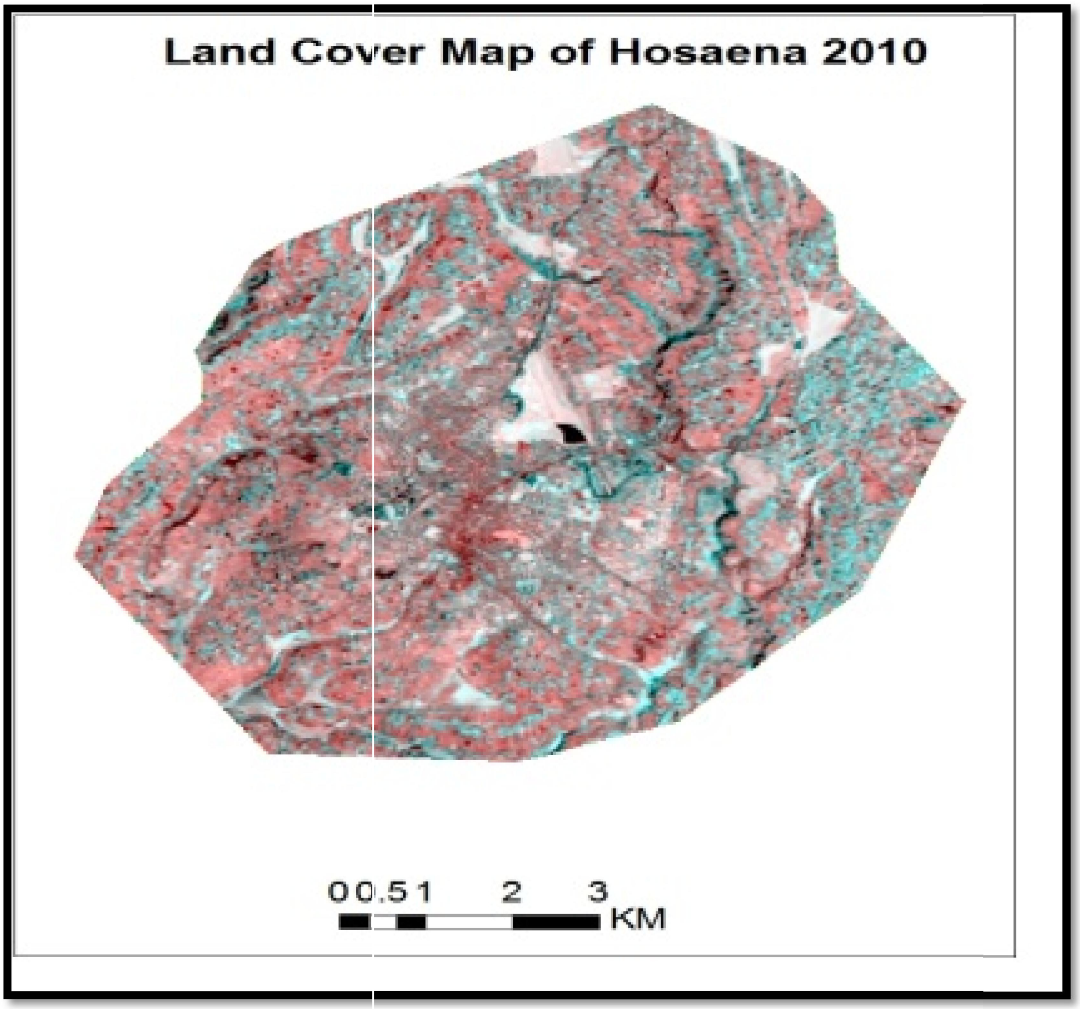
SAMPLE GPS 2018

POINT_X	POINT_Y
37.881388	7.576049
37.882557	7.579384
37.873699	7.587005
37.875479	7.582306
37.87116	7.581118
37.877801	7.59564
37.87446	7.596219
37.874054	7.601314
37.876607	7.601516
37.835988	7.585534
37.832466	7.580624
37.827194	7.568851
37.830156	7.563175
37.827217	7.560619
37.824279	7.557671
37.821527	7.558252
37.816438	7.55177
37.820179	7.548252
37.817444	7.543149
37.822942	7.543556
37.825875	7.548267
37.826675	7.543174
37.830018	7.541419
37.835715	7.540846

37.838085	7.536148
37.83416	7.534766
37.831221	7.532406
37.827669	7.538473
37.817459	7.537465
37.816469	7.540402
37.814487	7.547061
37.886801	7.532943
37.895592	7.551585
37.894994	7.555308
37.880806	7.573107
37.879836	7.568205
37.891808	7.572156
37.896123	7.574519
37.899097	7.56355
37.874721	7.571328
37.880129	7.53077
37.858171	7.515817
37.844988	7.525191
37.842051	7.521655
37.839687	7.524393
37.84557	7.52774
37.883741	7.577427
37.880596	7.578399
37.88037	7.589766
37.876631	7.592501
37.876222	7.598771

Appendix B CLIPED MAPS





Land Cover Map of Hosaena 2010