SPATIO-TEMPORAL ANALYSIS AND MODELING OF LANDUSE LAND COVER CHANGE: THE CASE OF BISHOFTU TOWN

Getu Insermu Tedla

A Thesis Submitted to the Department of Geomatics Engineering,

School ofCivil Engineering and Architecture

Presented in Partial Fulfillment of the Requirements for the Degree of

Master's in Geo-Informatics Engineering

Office of Graduate Studies

Adama Science and Technology University

Adama,Oromiya Ethiopia
June, 2022

Spatio-Temporal Analysis and Modeling of Landuse Land Cover Change : The Case study of Bishoftu Town

By

Getu Insermu Tedla

Advisor:RobaGemechu (PhD)

A Thesis Submitted to the Department of Geomatics Engineering, School of Civil Engineering and Architecture

Presented in Partial Fulfillment of the Requirements for the Degree of Master's in Geo-Informatics Engineering

Office of Graduate Studies

Adama Science and Technology University

Adama, Ethiopia

June, 2022

APPROVAL OF BOARD OF EXAMINERS

We, the undersigned, members of the Board of Examiners of the final open defense by Getu Insermu Tedla have read and evaluated his thesis entitled "Spatio-Temporal Analysis and Modeling of Land use Land Cover Change : The Case of Bishoftu Town" and examined the candidate. This is, therefore, to certify that the thesis has been accepted in partial fulfillment of the requirement of the Degree of Masters in Geo-Informatics Engineering.

Roba Gemechu (PhD)	____________________	________________
External Examiner	Signature	Date
________________________	____________________	________________
Internal Examiner	Signature	Date
________________________	____________________	________________
Chairperson	Signature	Date
________________________	____________________	________________
Head of Department	Signature	Date
________________________	____________________	________________
School Dean	Signature	Date
________________________	____________________	________________
Post-graduate Dean	Signature	Date

CANDIDATE'S DECLARATION

I hereby declare that this MSc Thesis is my original work and has not been presented for a degree in any other university, and all sources of material used for this thesis have been duly acknowledged.

Name: Getu Insermu Tedla

Signature: ________________________

This MSc Thesis has been submitted for examination with my approval as thesis advisor.

Advisor

Name: Roba Gemechu (PhD.)

Signature: ________________________

Date of submission:________________

ADVISOR’S APPROVAL SHEET

To: Geomatics Engineering Department

Subject: Thesis Submission

This is to certify that the thesis entitled “Spatio-Temporal Analysis and Modeling of Landuse Land Cover Change : The Case study of Bishoftu Town” submitted in partial fulfillment of the requirements for the degree of Master’s in Geo-Informatics Engineering, the Graduate program of the department of Geomatics Engineering, and has been carried out by Getu Insermu Tedla.

ID. No. PGE/21427/12, under under my supervision. Therefore, we recommend that the student has fulfilled the requirements and hence hereby he can submit the thesis to the department.

Advisor

Name: Roba Gemechu (Ph.D.)

Signature: ________________________

ACKNOWLEDGMENT

My sincere thanks go to my dedicated supervisor Dr. Roba Gemechu for his commitment and guidance in all stages of this research . His patience and efforts during our discussions were remarkable. May God bless you.

Thanks to all my family for their assistance and the kindly atmosphere they offered during my study.I particularly thank the Manager, Survey Section of Bishoftu Land Adminstration office for giving me ample time to concentrate on my ressarch work.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS

CA	Cellular Automata
ERDAS	Earth Resources Data Analysis System
ETM+	Enhanced Thematic Mapper Plus
FAO	Food and Agricultural Organization
GIS	Geographic Information System
GPS	Global Positioning System
LRM	Logistic regression model
LULC	Land Use Land Cover
MLC	Maximum Likelihood Classification
OLI	Operational Land Imager
RS	Remote Sensing
USGS	United States Geological Survey

ABSTRACT

Land Use Land cover data is highly acknowledged for land resources management. The total areal change due to massive migration from rural to urban has legitimated various land deforming issues for the land managers and planners (i.e. unplanned growth, poor environment).Image classification was using support vector machine algorism and the simulation of built-up area based on the past trend using land change modeler. Subsequently, the urban growth extent of the area was forecasted for the years 2050 on the land change modeler using the Markov chain method, together with drivers representing proximity, biophysical, and socioeconomic variables and finally the relationship between population growth and peredicted LULC were analyzed.Accordingly, the result showed that, during the entire study period (2000 –2021), built-up area was increased by 38.08% with its' total area coverage 7235.34 ha and cropland also little increased by 4.63% (880.01 ha). However, Water bodies ,bare soil, forest land and grassland were declined by 0.35 % and 23.14 %,11.87 % and 7.36 % with a total coverage area of 67.27, 4396.33, 2254.71and 1397.04 hectares respectively .More over,the result showed that, the overall accuracy of the land use and land cover change maps during the the periods(2000 – 2021) was 86.59 %, which is greater than an acceptable standard (85%). The study has also resulted, MARKOV chain modeling techniques was employed for land use and land cover prediction by 2050. Accordingly, built-up area has shown increased by 2348 ha (12.36%) but, nun built up area has decreased with values 2000.97ha,368.74ha and 79.31 ha for bare soil, grassland and crop land for the period (2021-2050) respectively The avareage Annual rate of urban area expansion of the town for the entire periods was 0.17%. whereas the average annual land consumption rate of the town was 0.4%. The study found that, the land use and land cover of the town has resulted anegative and positive effects on the built-up area. Generally, the study was revealed that, an integrated geospatial tool is vital for evaluating urban growth effects on the built-up area. Therefore, the town administrative of Bishoftu should utilize an integrated geospatial tool to overcome the negative impacts of urban land use and land cover in the built environment.

***Key words*: LULC, Geospatial tools,Bishoftu,MARKOV**

INTRODUCTION (CHAPTER ONE)

1.1 Background to the Study

Land cover refers to the physical and biological cover over the land surface, including; vegetation, bare soil, water, and artificial structures. Land use is defined as any physical and biological or chemical change to the physical and biological attributes of land which may be attributed to management (29). Land use and land cover change are major concerns regarding the change in the global environment. Land cover is a fundamental variable that impacts and links many parts of the human and physical environment. It is well established that land cover change has significant effects on basic processes, including biogeochemical cycling and thereby on global warming, the erosion of soils, and thereby sustainable land use. For the next 100 years; it is likely to be the most important variable impacting biodiversity (28).

Worldwide land use and land cover (LULC) change in a vast area along with rapid urbanization and population growth have become an issue of major concern, particularly in developing countries (23). Recently, the 2018 Revision of World Urbanization Prospects prepared by the Population Division of the UN Department of Economic and Social Affairs has predicted an addition of another 2.5 billion people to urban areas by 2050, and this report also states that Asia and Africa will contribute 90 % of this addition.

Studies have shown that only few landscapes on the Earth remain still in their natural state. Due to anthropogenic activities, the Earth's surface is being significantly altered in some manner, and man's presence on the Earth and his use of land have had a profound effect on the natural environment, thus resulting in an observable pattern in the land use/land cover over time. Land use and land cover change is the conversion of different land-use types resulting from complex interactions between humans and the physical environment (26). Land use and land cover change have become a central component in current strategies for managing natural resources and monitoring environmental changes.

Ethiopia is one of the most populous countries in Sub Saharan Africa and urban population growth is estimated at about 4.8 per cent, a higher figure compared to other Sub Sahara African countries. The country is one of the least urbanized in the third world and its economy almost entirely depends on smallholder agriculture. Like most developing countries, Ethiopia experiences high rural to urban migration in search of better employment and different opportunities. The need for housing is not integrated with the need to prevent horizontal expansion and hence saving land. Formal and informal settlements are stretching out horizontally from the central capital in all directions. Land is ineffectively used, and new developments are planned on virgin land usually leapfrogging from cores. (36) has put the lists of problems linked to sprawl such as the loss of open space, urban decay, unsightly strip mall developments, the loss of a sense of community, patchwork housing developments in the midst of agricultural land, increasing reliance on the automobile, the separation of residential and work locations, and the spreading of urbanized developments across the landscape. Generally, urban sprawl in Ethiopia is a result of population pressure both from natural increase and migration (15).

Bishoftu town is one of the emerging towns of Ethiopia located in the outskirts of Addis Ababa is rapidly growing Oromia took place. The town is under the influence of population spillover from the Addis Ababa city which caused fast land use land cover dynamics within the past few years. Hence, due to competition over the land for various developments, the town is sprawling to the surrounding rural areas where in many circumstances the land use is not efficiently utilized. Therefore, such spontaneous developments require identification of the extent and patterns of sprawling of the town for guiding and monitoring its urban development. Given such rapid development characteristics and land use land cover dynamics of the town, there is little/no study conducted on analyzing the extent and pattern of urban sprawl of Bishoftu town. A study conducted by (37) on urban sprawl mapping and land use detection of the city of Addis Ababa and its surroundings assessed the wider sprawling.

Results of various studies have demonstrated that improving knowledge on urban growth will have a high impact on the design of appropriate management strategies. Specifically, it will guide urban planners and decision makers in what approaches would be appropriate to tackle land cover changes anduncontrolled urban growth (38).

Earlier research on LULC changes based on ground surveys or statistics encountered diculties with capturing and monitoring speedy urbanization. Accurate, consistent, and timely data on trends in urban growth are needed for assessing current and future needs (43). With the advent and development of geospatial techniques that integrate the use of remote sensing (RS) and a geographic information system (GIS), the detection of spatio-temporal LULC dynamics has become easy, quick, and cost-efective (39).

Remote Sensing (RS) and Geographic Information Systems (GIS) are now providing new tools for advanced ecosystem management. Remote sensing images have been used as one of the most important datasets for studying spatial and temporal LULC changes (12). In this context, remote sensing represents a major, though still under-used, source of urban information by providing spatially consistent coverage of large areas with both high spatial detail and temporal frequency, including historical time series (17). During the last two decades, we have made important strides toward developing remote sensing methods that allow for the accurate characterization of LULC change (36), including land use land cove. With increased availability and improved resolutions of remote sensing images, it is now possible to monitor and analyze urban expansion and -use change in a timely and cost-effective way (35).

Bishoftu Town accommodates many activities and multiple functionalities, and any changes in suchpatterns are obvious. In the last 30 years, the spatial organization of Bishoftu and its original structure has changed dramatically, and involving a particular activity. Bishoftu's population has grown rapidly over the past three decades. The population increased by more than 95% between 2000 and 202021 (20). It is undergoing both a very high rate of urbanization and human-induced changes in land use land cover . Using Landsat images, the objective of this study is to assess, monitor, and map urban expansion over the past three decades in Bishoftu in order to provide the required input data for urban modeling.

There is no information on the extent and patterns of changes that occurred in Bishoftu Town over time. Besides, there are no extensive studies conducted related to urban growth and its impacts. Urban planners and decision-makers should consider the potential of geospatial tools to detect, monitor, and evaluate urban land cover changes.Therefore, this study was Spatio-Temporal Analysis and Modeling of Land use Land Cover Change.

1.2 Statement of the Problem

Land as a finite and a potentially productive natural resource represents our basic food production facility. However, the diversity of residents and intensive use of the resources through the increasing of population coupled with economic activities and global market drive unprecedented land use and land cover changes (39). These changes lead to transformations in the hydrological, ecological, geomorphologic and socioeconomic systems and which are often neglected by both rural and urban administrations.Thus, special attention and continuous assessment are required for monitoring and planning urban development and decision making.

Bishoftu is one of the worth note towns in the history of early urbanization process of the country in general and Oromia in particular. It has witnessed remarkable expansion, growth, and developmental activities such as building, road construction, deforestation and many other anthropogenic activities. During the last three decades, growth in population, industry, and economic activities has been strongly concentrated. Out of many, one key problem for developing twon like Bishoftu is the disorganized urban development, mostly without proper planning strategies. Examples of drive factors include high unemployment. Secondly, rural to urban migration from the nearby Bishoftu town surrounding rural kebeles, which the town is near to the country's capital city or close to Addis Ababa and since the town is very attractive to live there. However, a farmer in rural area whose land has become unproductive because of drought may decide to move to a nearby city where he perceives more job opportunities and possibilities for a better because of this, it is difficult to improve one’s standard of living beyond basic sustenance. Farm living is dependent on unpredictable environmental conditions, and during of drought, flood or pestilence, survival becomes extremely problematic.This increase has undoubtedly reflected the demand for land due to the increased population and has led to numerous challenges arising from land-use change (25).

towns are usually the result of factors or combination of factors which is also true of urbanization processes of our country. Favorable ecological and climate conditions, relative advance of technology and a well-established power structure enhanced urban settlement. As such a combination of factors has contributed to the emergence of Bishoftu city. The fact that there is abundant water resources existing in the area, favorable climate for settlement and an area situated in a grain producing area etc.

According to (40) state that modifications that can occur to different landuses in the study area include: forest clearance, rapid expansion of agricultural land, road and other infrastructural development, grazing lands replacing grasslands or other natural terrestrial ecosystems, urbanization , wetlands removal or reduction, stream cut off that spills the lake, and mining in quarries etc are the causes of rapid urbanisation is accountable for many environmental and social changes in the urban environment and its effects are strongly related to global change issues. The rapid growth of twon pressures their capacity to provide services such as energy, education, health care, transportation, sanitation and physical security. However, direct implication of urbanisation is attributed to spatial growth of towns and cities or in other words growth in urban areas. This increase has undoubtedly reflected the demand for land due to the increased population and has led to numerous challenges arising from land-use change. In light of the environmental challenges of rapid population growth and land use land cover in Bishoftu town,

Unmanaged population growth, increasing social inequality, economic disparities, and poverty all increase the potential of conflict. Poor urban planning and housing development lead to the construction of informal settlements that lack access to basic infrastructure and provide poor living conditions because of massive growth in urban population may force to cause uncontrolled urban growth resulting in spread(6).

In accumulation to low level of geo-information to figure out the range and configuration of the change in the study area, there is also still severe lack of geospatial facts to forecast the future growth and dynamics of the city. This is an opportunity can adversely mark the judgment making process of urban, regional and environmental planners. So, the purpose of the study was to identify, analyze and compare the relative Land Use Land Cover Changes On The Urban Environment of Bishoftu Town

1.3 Research Questions

1. What are the major driving forces of LULC changes in the in the study area 2000_2021?
2. What is the magnitude,extent and rate of LULC changes for the period 2000 to 2021 G.?
3. What is the Landuse Land Cover changes on the Urban Environment of Bishoftu Town?
4. How to predict the extent and distribution of LULC Change urban Enviroment in 2050 using Markov methods in the study area?

1.4 Objectives

1.4.1 General Objectives

The objective of this study is to Spatio-Temporal Analysis and Modeling of Land use Land Cover Change : The Case of Bishoftu Town

1.4.2 Specific Objectives

The specific objectives are to:

1. Identify the land use land cover change at different spatial and temporal scales from 2000-2021;

2.To generate change detection Maps of from 2000,2010 and 2010 to 2021 G.C

3. To analyizing Land Use Land Cover Changes on the Built-up area.

4. To Predict the extent of urban environment in 2050 using MARKOV Chain methods in the study area.

1.5 Significance of the study

This study tried to quantify and analyze the changes between 2000 and 2021 to contribute in the urban land, environmental management and monitoring plan of theareas. The study also helps the government take actions on the plan of the city to protect from Disorder developments such as fragmentation of natural resources, environmental pollution,residential crowding, and traffic congestion. Further, society will be bnefit if the government takes policy plan action on areas of the city most probably affected by the spatial expansion. This enables them to preserve their social life and protect their families and economy from damage. Saving the number of people that are in hazard has great importance for society by protecting everyone from disturbance.

In general,the finding will provide scientific and technological facts for all the following responsible bodies such as societies, researchers/scholars, town planers, municipalities.

•**Societies**: The output will benefit society by providing job opportunities and ensuring land tenure.

•**Town planers**: will be profite from the result by providing it as a guideline for future analysis

• **Municipalities:** may not be tackled more difficulties during solving problems related land use land cover on land use land cover in the case study area. .

•**Researchers/scholars:** may be used the output as baseline information for further investigations related to the study.

1.6 Scope of the Study

This study is limited to Bishoftu town, Orormia regional state, Ethiopia, for the periods 2000, 2010, and 2021 and prediction of the future urban growth modeling at (2050) using Geospatial technologies and giving hints about the importance of developing land use land cover change map for urban planning in Bishofttown.

1.7. Limitation of the study

To perform this type of spatiotemporal analysis, satellite images from the same time interval is used. The spatial resolution of the images is essential once again. Landsat satellite images were used for this study since they are only commercially available but can be accessible in the public domain for free. The main concern in working with Landsat images is its low resolution. Landsat Image has a spatial resolution of 30 meters (U.S. Geological Survey). Higher quality satellite photos from IKONOS, Quick Bird, SPOT, or other sources may be a better option, although they are more expensive. As a result of resource constraints, only free public-domain data were employed for this study.

Some other consideration when choosing satellite imagery is seasonal variation. Seasonal changes in urban land, forest land, crop land, bare land, and other land cover types are visible. In an ideal world, satellite images from the same season would be chosen for this type of research.

2 .LITERATURE REVIEW (CHAPTER TWO)

Studies of Land Cover changes are fundamental for better understanding of interactions between human and the natural environment. Remote sensing technology has played a key role in the studies of land use land cover changes. Availability of Multi-temporal satellite datasets provides the capability for mapping and monitoring of Land cover/use changes. (41).
Definition of basic terms:

Urbanization: is the process of urban expansion but, Different researchers define urbanization in various ways, some researcher defines, urbanization process is mainly linked to economic growth, commercialization, and industrialization, as well as rural-urban migration and globalization, while other researchers define urbanization is the link of population growth and urban built-up area expansion.

Urban environment :is constantly under transition with new constructions being put up now and then.

Urban growth: is a spatial and demographic process that refers to the increased importance of towns and cities as a concentration of people within a particular economy and society.

Land use: The purpose for which land is used by humans.

Land cover: The physical surface of the earth including natural and artificial features.

GIS: is a tool used to capture, store analyze and display both spatial and non-spatial data.

2.1 Forms of urban expansion

Urban expansion takes place in different forms. The major forms are the positive effects (orderly) form of urban expansion properly laid out in simple geometric forms, of urban expansion such as the center of the market area, center for production and distribution of goods and services, an opportunity for access to employment, economic development, full facilities, and technology development. The other forms are negative effects (disorderly) of urban expansion are loss of prime agricultural farmland, displacement of farm communities, solid waste disposal and land degradation, enclosing surrounding rural land to urban territory, overexploitation of natural resources, and conflict.

2.2 Consequences of urban expansion

The rapid rate of urban growth leads to rapid changes in 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 in a massive cost to the environment (32). The negative effects (disorderly) urban expansion highly increase the land use and land cover changes and becomes many problems such as uncontrolled development, deteriorating environmental quality, loss of prime agricultural lands, destruction of important wetlands, and loss of fish and wildlife habitat, loss of prime agricultural farmland, displacement of farm communities, solid waste disposal and land degradation, enclosing surrounding rural land to urban territory, overexploitation of natural resources and conflict.

2.3 Land use land cover

Land cover of any area is directly related to factors like terrain, lithology, soil type, rainfall , socio-cultural practices, and relative location. Thus land use planning is function of multiple elements as mentioned above. Thus abstraction of feature and arranging in appropriate class is another vital aspect of land use planning. Sokal stated that "the ordering or arrangement of objects into groups or sets on the basis of their relationships‖. Classification is systematic approach of distinguishing classes and adding in appropriate clusters and assigning relationship between associated classes. (17) stated that classification requires definition of classes boundary must be clear, precise quantitative and based on objective criteria. Concepts concerning land cover and land use activity are closely related and in many cases have been used interchangeably. The purposes for which lands are being used commonly have associated types of cover, whether they are forest, agricultural, residential, or industrial. Remote sensing image-forming devices do not record activity directly. The remote sensor acquires a response which is based on many characteristics of the land surface, including natural or artificial cover.

2.4 Factors of land use land cover

Economic development, technological innovation, the industrial revolution, the emergence of huge manufacturing factors, job possibilities, infrastructure availability, and migration are all factors in land use land cover In general, the reasons of urbanization and urban expansion are classified into three broad categories.

2.4.1. Demographic factors

Several studies showed that, Demographic effects such as rural to urban migration and natural population growth in the city, the level of urbanization, and the rank of the city/town in the country‘s urban hierarchy. According to (44) stated that, population growth is a major element in urban growth for all countries, and migration of rural to urban contributes fast growth of urban population in many developing countries.

2.4.2. Economic factors

Economic effects include the level of economic development, the difference in household incomes, exposure to globalization, the level of foreign9 direct investment, the degree of employment, the level of financial markets, the level and effectiveness of property taxation, and the presence of high inflation and acute shortage of housing (45).

2.4.3. Natural/environment factors

Natural /environmental effects include those of climate, slope, mountain barriers, and the existence of drillable water aquifers. In addition, the minor causes such as Redevelopment and rebuilt up of inner cities again cause displacement of citizens (46).

2.5. Land Use Land Cover (LULCC)

The 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 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 (5).

Although the terms 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 a feature of the land surface, which may be natural, semi-natural, managed, or man-made. They are directly observable by remote sensors. 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 (5).

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 LULCC is a basic precondition of regional LUCC monitoring, driving factor analysis, and even 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 have wide coverage (32).

2.6. Urban Land Use The Land Cover Image Classification

Image classification refers to the extraction of differentiated classes or themes, usually, land cover and land use categories, from raw remotely sensed digital satellite data(19)Image classification using remote sensing techniques has attracted the attention of the research community as the results of classification are the backbone of environmental, social, and economic applications (19). Because image classification is generated using remotely sensed data, many factors cause difficulty to achieve a more accurate result. Some of the factors are the characteristics of a study area, availability of high resolution remotely sensed data, ancillary and ground reference data, Suitable classification algorithms and the analyst‘s experience, time constraints. Image classification refers to grouping image pixels into categories or classes to produce a thematic representation. Classification is the most important aspect of image processing to GIS. Image classification operations that include image restoration, image pre-processing, enhancement, compression, spatial filtering, and pattern recognition are applied to image data. Various image classification methods can be applied to extract land cover information from remotely sensed images (19)However, their application depends on the methodology and type of data to be used. Some of these methods are artificial neural networks, support vector machines, fuzzy sets, and expert systems. In a more specified way, image classification approaches can be categorized as supervised and unsupervised, or parametric and nonparametric, or hard and soft (fuzzy) classification, or per-pixel, sub-pixel, and per-field.

2.6..1. Supervised Image Classification Methods

Supervised image Classification methods such as Parallelepiped Classification, Minimum Distance Classification ,Maximum Likelihood Classification, Mahalanobis Distance Classification, Binary Encoding Classification, Artificial Neural Network (ANN) Classifier and Support Vector Machine (SVM) Classification.

Parallelepiped Classification:- Parallelepiped classification, sometimes also known as box decision rule, or level-slice procedures, are based on the ranges of values within the training data to define regions within a multidimensional data space. The spectral values of unclassified pixels are projected into data space; those that fall within the regions defined by the training data are assigned to the appropriate categories. As pixels of unknown identity are considered for classification, those that fall within these regions are assigned to the category associated with each polygon, as derived from the training data. The procedure can be extended to as many bands, or as many categories, as necessary. In addition, the decision boundaries can be defined by the standard deviations of the values within the training areas rather than by their ranges. This kind of strategy is useful because fewer pixels will be placed in an "unclassified" category (a special problem for parallelepiped classification), but it also increases the opportunity for classes to overlap in spectral data space (8).

Minimum Distance Classification:- According to (8) suggested that, This approach to classification uses the central values of the spectral data that form the training data as a means of assigning pixels to informational categories. The spectral data from training fields can be plotted in multidimensional data space in the same manner for unsupervised classification. Values in several bands determine the positions of each pixel within the clusters that are formed by training data for each category. These clusters may appear to be the same as those defined earlier for unsupervised classification. However, in unsupervised classification, these clusters of pixels were defined according to the "natural" structure of the data. Now, for supervised classification, these groups are formed by values of pixels within the training fields defined by the analyst. Each cluster can be represented by its centroid, often defined as its mean value. As unassigned pixels are considered for assignment to one of the several classes, the multidimensional distance to each cluster centroid is calculated, and the pixel is then assigned to the closest cluster. Thus, the classification proceeds by always using the “minimum distance” from a given pixel to a cluster centroid defined by the training data as the spectral manifestation of an informational class.

Maximum Likelihood Classification:- according to (31) explained that, the Maximum Likelihood Classification uses the training data by means of estimating means and variances of the classes, which are used to estimate probabilities and also consider the variability of brightness values in each class. This classifier is based on Bayesian probability theory. It is the most powerful classification methods when accurate training data is provided and one of the most widely used algorithm.Therefore, in this study, the researcher employed the maximum likelihood classification techniques to come up with a solution.

Mahalanobis Distance Classification:- The Mahalanobis distance classification is a direction-sensitive distance classifier that uses statistics for each class. It is similar to the maximum likelihood classification but assumes all class covariances are equal and therefore is a faster method. All pixels are classified to the closest training sample class unless you specify a distance threshold, in which case some pixels may be unclassified if they do not meet the threshold (20).

Binary Encoding Classification:- The binary encoding classification technique encodes the data and endmember spectra into zeros and ones, based on whether a band falls below or above the spectrum mean, respectively. An exclusive OR function compares each encoded reference spectrum with the encoded data spectra and produces a classification image. All pixels are classified to the endmember with the greatest number of bands that match, unless you specify a minimum match threshold, in which case some pixels may be unclassified if they do not meet the criteria.

Artificial Neural Network (ANN) Classifier:- A multi-layered feed-forward ANN is used to perform a non-linear classification. This model consists of one input layer, at least one hidden layer and one output layer and uses standard back propagation for supervised learning. Learning occurs by adjusting the weights in the node to minimize the difference between the output node activation and the output. The error is back propagated through the network and weight adjustment is made using a recursive method (34).

Support Vector Machine (SVM) Classification:- SVM is a classification system derived from statistical learning theory. It separates the classes with a decision surface that maximizes the margin between the classes. The surface is often called the optimal hyperplane, and the data points closest to the hyperplane are called support vectors. The support vectors are the critical elements of the training set. The SVM can be adapted to become a nonlinear classifier through the use of nonlinear kernels. While SVM is a binary classifier in its simplest form, it can function as a multiclass classifier by combining several binary SVM classifiers (creating a binary classifier for each possible pair of classes). SVM classification output is the decision values of each pixel for each class, which are used for probability estimates. This algorithm performs classification by selecting the highest probability. An optional threshold allows reporting pixels with all probability values less than the threshold as unclassified(34).

2.6.2.Unsupervised image classification methods

This classification algorithm is derived by modeling observed data as a mixture of several mutually exclusive classes that are each described by linear combinations of independent, non-Gaussian densities. The algorithm estimates the data density in each class by using parametric nonlinear functions that fit to the non-Gaussian structure of the data. This improves classification accuracy compared with standard Gaussian mixture models. When applied to images, the algorithm can learn efficient codes (basis functions) for images that capture the statistically significant structure intrinsic in the images. this classification method, is apply to the problem of unsupervised classification, segmentation, and denoising of images. Moreover, the method is effective in classifying complex image textures such as natural scenes and text. It is also useful for denoising and filling in missing pixels in images with complex structures. The advantage of this model is that image codes can be learned with increasing numbers of classes thus providing greater flexibility in modeling structure and in finding more image features than in either Gaussian mixture models or standard independent component analysis (ICA) algorithms. Index Terms Blind source separation, denoising, fill-in missing data, Gaussian mixture model, image coding, independent component analysis, maximum likelihood, segmentation, unsupervised classification.

2.7. Land use land cover change detection

According to [32] explained change detection that, it is the process of identifying differences in the state of objects or phenomena by observing them at different times by using remote sensing techniques. Change detection has a wide range of applications in different disciplines such as change analysis, forest management, vegetation phonology, and seasonal changes in pastureproduction, risk assessment, urban expansion, and other environmental changes. A change detection research to be good, it should provide the following vital information: area change and rate of changes, the spatial distribution of changed types change trajectories of land-cover types, and accuracy assessment of change detection results. Several studies clearly sattaed that, remote sensing and GIS technique, are a powerfull the tools which analyse the change detection of different land use/land cover (LULC) images .Supervised classification method with maximum likelihood algorithm is the most commen methods of the LULC map classifications.

2.8. LULC change prediction modeling techniques

Land Use Land Cover Change (LU/LCC) modeling is a rapidly growing scientific field because land-use change is one of the most important ways that humans influence the environment [32].Modeling means the process of creating a representation of reality; it could be a map, graph,picture, or mathematical representation. Land use land cover change modeling is defined asthe process of creating maps based on the history of land use land cover, existinginformation, and assumptions of the future. Modeling urban growth plays a significant roleto understand the impacts of the changes that occur through time. The Commonly used models are the modeling techniques embedded in IDRISI are Land Change Modeler(LCM), Earth trend, Cellular Automata (CA), Markov Chain, CA-Markov, GEOMOD, and STCHOICE (47). It is difficult to compare the performance of the numerous models because LU/LCC models can be fundamentally different in a variety of ways. For example, some models, such as GEOMOD, simulate change between two land categories (48) while others, such as CA_MARKOV, can simulate change among several categories (32). However, it is difficult to compare which one gives a more accurate representation(34)

2.9 Land Change Modeler (LCM)

Land Change Modeler (LCM) for Ecological Sustainability is an integrated software environment within IDRISI SELVA that is used to the pressing problem of accelerated land conversion and the very specific analytical needs of biodiversity conservation (Eastman, 2012). Land Change Models are important tools for environmental and geomatics research concerning LUCC (27). Monitoring and analysis of changes in LULC are needed to provide information on existing land use patterns and changes for decision-makers to support sustainable development (11).. In LCM, tools for the assessment and prediction of land cover change and its implications are organized around major task areas: change analysis, change prediction,habitat and biodiversity impact assessment, and planning interventions (10).In IRDRISI Run Transition Sub-Model panel is where the actual modeling of transition submodels is implemented. Three methodologies are provided for modeling: a Multi-Layer Perceptron (MLP), Similarity-Weighted Instance-based Machine Learning (SimWeight), and Logistic Regression. Multi-Layer Perceptron and SimWeight procedures perform best in modeling transitions (10). The MLP option can run multiple transitions, up to 9, per sub-model. But SimWeight and Logistic Regression can only run one transition per sub-model. Both MLP and SimWeight use half of the samples (change pixels) for training and the other half for validation. MLP generates predicted class memberships for each of the validation pixels at each iteration and reports the aggregate accuracy as well as a skill score. The skill score represents the difference between the calculated accuracy using the validation data and expected accuracy if one were to randomly guess at the class memberships of the validation pixels. SimWeight calculates the mean transition potential among validation pixels that changed (i.e., went through the transition) and the mean transition potential among pixels that did not change (persisted). These express the hit rate and false alarm rate respectively. The difference between them yields the Peirce Skill Score a value between 0 and1 Logistic Regression.This model undertakes binomial Logistic Regression and prediction using the Maximum Likelihood method.

2.9.1. Cellular Automata (CA)

Cellular Automata is, in general, a collection of cells, of an arbitrary shape, arranged in a grid-like structure. These cells can "hold" different values from time to time - binary being the simplest of the forms. All the cells change their states simultaneously, i.e., at the same time according to some rule - which may be fixed at the beginning or may vary from time to time. These rules are applied to the system at a regular discrete time interval (10). The cellular Automata (CA) model explains Change in urban areas over time using the variables such as extent of urban areas, elevation, slope, and roads.

2.9.2. Markov chain model

A Markov chain is a random process having a property characterized by memoryless transition from one state to another on a state space take place such that it depends only on the present state and not on the past states that the process went through. A random process could be termed as a Markov chain when in a series of events, any event that is about to occur depends only on the present state and eventually forms a kind of a chain. A Markov chain model is a stochastic process that analyses the probability that one state will change to another one – i.e., the state of a system at time t2 is predicted from the state the system is in at time t1. Future prediction using Markov chain modeling is generally done by analyzing two qualitative land cover images taken on different dates (25).

2.9.3. CA-Markov Model

The Markov model can quantitatively predict the dynamic changes of landscape patterns, while it is not good at dealing with the spatial pattern of landscape change. On the other hand, Cellular Automata (CA) has the ability to predict any transition among any number of categories.Combining the advantages of Cellular Automata theory and the space layout forecast of Markov theory, the CA- Markov model performs better in modeling land cover change in both time and spatial dimensions.

CA-MARKOV Used to explain Spatio-Temporal dynamic modeling and Predicts land use/cover in the future using Multi-Temporal Land Use land cover maps and Suitability maps. The strength of CA-MARKOV is creating the data is easy, CA add a spatial dimension to the model, and can simulate change among several categories. Its weakness is Socioeconomic factors are not considered and calibrating the model with MCE is too timeconsuming compared to other methods.

2.10. Geospatial technologies useful for urban LULC change analysis

Remote Sensing, GIS, and IDRISI are now providing new tools for advanced ecosystem management. With the advancement of technology, reduction in data cost, availability of historic spatiotemporal data and high-resolution satellite images used for urban planning, geography, earth science, transportation planning, environmental planning, disaster management, urban expansion change analysis, and modeling.

2.10.1. Remote Sensing

Remote Sensing According to Lambin (18), the definition of Remote Sensing (RS) is as follows: Remote sensing is the science and art of obtaining information about the Earth's surface through the analysis of data acquired by a device which is at a distance from the surface‖. Remote sensing is an essential tool of land change science because itfacilitates observations across larger extents of Earth‘s surface than is possible by ground-based observations by using of cameras, multispectral scanners.

2.10.2.Geographical Information System

Geographic Information System (GIS) GIS integrates hardware, software, and data for capturing, managing, analyzing, and displaying all forms of geographically referenced information (Maguire, 1991). GIS also allows the integration of these data sets for deriving meaningful information and outputting the information derivatives in map format or tabular format. GIS support any operation on geographic information: acquisition, editing, manipulation, analysis, modeling, visualization, publication, and storage. GIS has four basic subsystems: input, storage, analysis, and output.

2.10.3. IDRISI Selva

is the industry leader in raster, covering the full spectrum of GIS and remote sensing needs from a database query, to spatial modeling, to image enhancement and classification. Special facilities are included for environmental monitoring and natural resource management, including land change modeling and time series analysis, multi-criteria and multi-objective decision support, uncertainty and risk analysis, simulation modeling, surface interpolation, and statistical characterization (IDRISI). One advantage of using IDRISI for land-use change modeling is that in one software package you have: 1) the data, 2) the simulation model, and 3) the statistical techniques of goodness-of-fit (Pontius, 2002).

2.11 Emperical Literature Review Summary

Now a days the use of Remote Sensing and Geographic Information Systems techniques has become important for quantifying the degree of monitoring, and managing urban land-use/land cover changes. Mapping urban growth provides a picture of where this type of growth is occurring, and helps to identify the environmental and natural resources threatened by such sprawls, and it also suggests the likely future directions and patterns of expansive growth. There are limited number of studies conducted on quantifying the extent and detecting the pattern of Spatio-Temporal Analysis and Modeling of LULC in Ethiopia using GIS and Remote Sensing. Contrary to this there are quite significant number of studies conducted on the impact of LULCC in altering land uses especially the impact it has on consumption of agricultural land on the outer skirts of cities. Notable contribution on quantifying the rate of urban sprawl and mapping was done by [37] for the city of Addis Ababa and its surroundings. Recently similar study was conducted in Ethiopia by (42) on the major drivers of urban sprawl and its impacts on land use conversion in the peri-urban kebeles of the Dukem town, one of the towns in the Oromia Special Zone surrounding Addis Ababa city, using GIS. In this study expansion of residential and industrial developments over agricultural land were mapped using GIS instead of detecting spatio-temporal land use land cover dynamics in the study area. In the study, only a single period data was used and land uses are mapped. In such cases it is in fact difficult to analyze the extent and pattern of urban sprawl. LULC change maps.

The author attempted to demonstrate Understanding and quantifying the spatiotemporal dynamics of urban land use and land cover changes and its driving factors over space and time is essential to put forward the right policies and monitoring mechanisms on urban growth for decision making. Thus, the objective of this study was to analyze the Spatio-temporal dynamics of urban areas in Ambo town by applying geospatial and land-use change modeler tools. Insufficient comparison of study findings to existing literature.

The Research title”Analysis of spatio-temporal dynamics of urban sprawl and growth pattern using geospatial technologies and landscape metrics in Bahir Dar, Northwest Ethiopia” worked by Getu, Kenu And Bhat, H Gangadhara.The author tried to assess and monitor the spatiotemporal dynamics of urban sprawl and its growth pattern in Bahir Dar, Northwest Ethiopia for the last three and half decades (1984 – 2019). Supervised maximum likelihood technique has been used to map the land use land cover of Bahir Dar from 1984 to 2019 using Landsat TM and OLI datasets. Post classification comparison, spatial landscape metrics, and Shannon’s entropy index were used to detect changes in land use land cover, investigate the complex spatiotemporal dynamics and degree of urban sprawl.On this paper, I obsereved lack of synthesis and critical analysis in literature review and Inappropriate level of detail provided in the methods section.

According to Gemech Alemu(2019) state Researches on land use and land cover change in Ethiopia involved different regions and disciplines depending on the availability of data and tools to perform analysis (15) However, most of the studies have focused on deforestation, the expansion of cultivated land to land degradation, river catchments and watersheds, natural ecosystems, and forests as well as the associated consequences.

Another study of Landuse Landcover change in Ethiopia was conducted in Debre Berhan town which is located north-east of Addis Ababa (42). This study focused on assessing urban sprawl of Debreberhan town using satellite imageries. The findings of the study showed that rapid population pressure has resulted in unplanned growth in the area which in turn led to urban sprawl. Urban sprawl has resulted in loss of productive agricultural lands. In this study, too major emphasis was given to how land use/land cover particularly the built-up area has been increasing between 1986-2009 than detecting the extent and pattern of sprawling of the town. (42) on his part studied the rate and effect of sprawling of Addis Ababa city. The study indicated that the rate of urban sprawl along the Mojo (south of Addis Ababa on the way to Adama city) and Jimma outlets, compared to other outlets, is high causing both positive and negative effects to the areas and the people. Similar to other studies, this study did not explicitly show the pattern of sprawl and emphasis was given to land use/land cover change due to urban growth.

In conclusion, survey of few similar studies conducted on Spatio- Temporal Analysis and Modeling of LULC in Ethiopia showed that there is a confusion between urban expansion, urban growth and urban sprawl. It is a natural and expected process that cities grow. However, the rate and pattern of conversion of other land uses land cover into the built-up area is all about how land is utilized economically or uneconomically. In this regard, urban sprawl studies conducted in Ethiopia largely concentrate on the extent of land use land over has been changing than how and what pattern of developments have been occurring.

In this research the most prominent aim is to enumerate and calculate the change in percentage table. The spatial reflectance, radiometric sense ability & spectral resolution feed the temporal analysis and helps to measure and detect & quantify the change. For each land class spectral reflectance calculated what Satellite capture and stores (the remotely sensed data) and then the result interpreted and evaluation of analysis with the help GIS and its geospatial techniques made possible. Moreover, the Maximum likelihood is human interactive to interpret the coarse spectral signal so unsupervised is less accepted compare to ML technique as the user interaction involved the human interactive techniques utilize human familiarity with the zone.

MATERIALS AND METHODS (CHAPTER THREE)

3.1. Location

The locality of Bishoftu is a land of abundant cultural and natural heritages of high values, astonishing natural attraction and beautiful landscape scenery. Its scenery, natural beauty and terrain are ascribable to mountains massifs, peaks, crater lakes with the endemic animals. It is also one of the fertile zones of the county's highlands.The city is located at 47 kilometers south East of the capital, Finfinne. It is the center of lakes and one of the best breath taking towns. All this makes it an easily accessible popular recreation and resort town for overnight visitors and weekend excursionists throughout the year Informants 1,2,3,4,5;O C T B, 2006).The Bishoftu Town administration is located in Oromia regional state, between 8º45'- 8º47' North latitudes and 38º56'-39ºEast longitudes. It is situated at a distance of 47 km South East of Addis Ababa and 52 km from Adama.

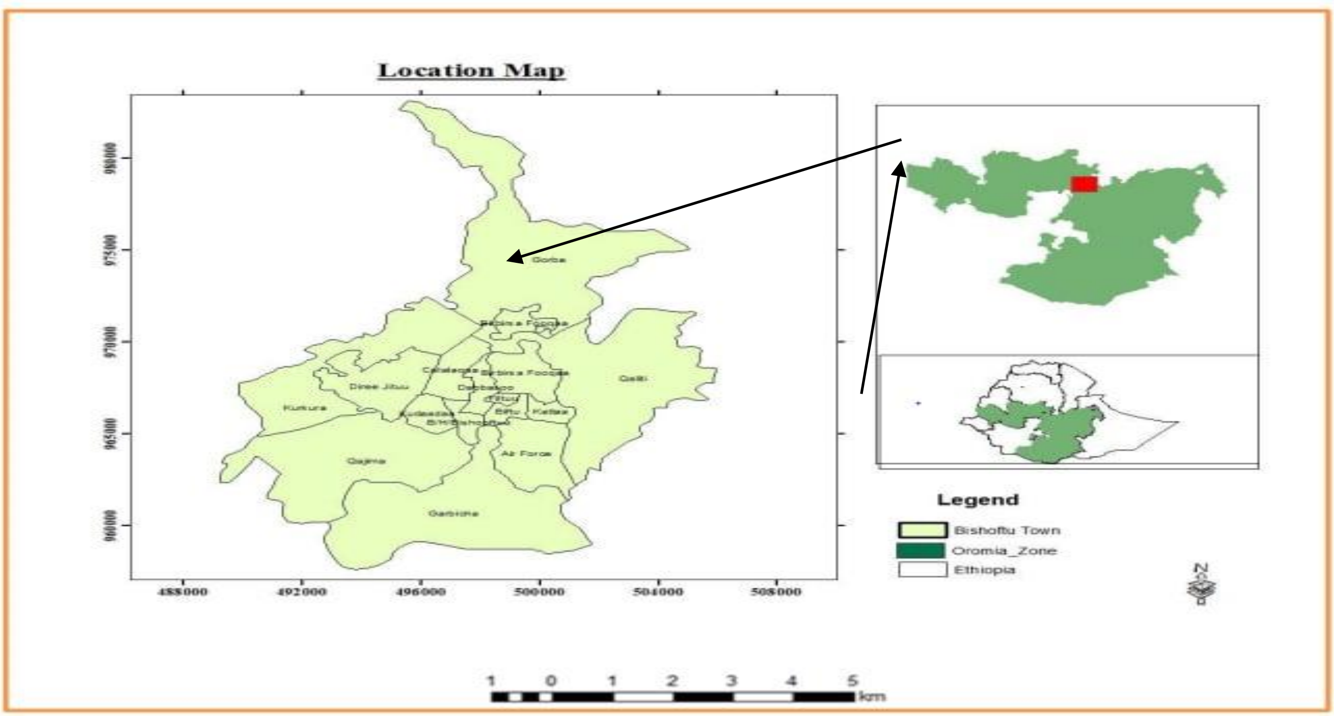


Figure 3.1: Location Map of the Study area

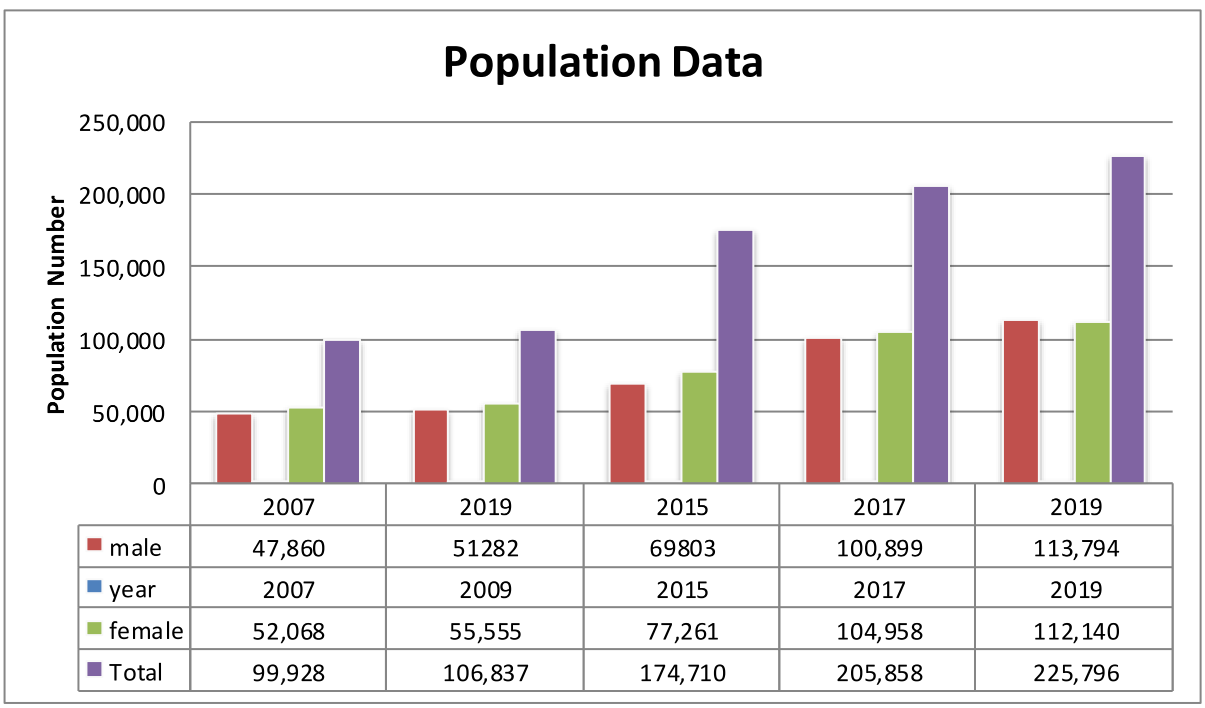
3.1.1.Population

The 2007 national census reported a total population for Bishoftu of 99,928, of whom 47,860 were men and 52,068 were women. The majority of the inhabitants said they practiced Ethiopian Orthodox Christianity, with 79.75% of the population reporting they observed this belief, while 13.82% of the populations were Protestant, and 4.98% of the populations were Muslim.The 1994 census reported that Bishoftu had a total population of 73,372 of whom 35,058 were men and 38,314 were women.

City	Year	Male	Female	Total
Bishoftu	2007	47,860	52,068	99,928
	2009	51282	55,555	106,837
	2015	69803	77,261	174,710
	2017	100,899	104,958	205,858
	2019	113,794	112,140	225,796

Source: CSA and projected population

Table: 3.1. The projected population size of Bishoftu City year 2007-2019.



3.1.2. Topography

Its topography is undulating, with flat territory to the north and east of the city, which is surrounded by multiple lakes, and hills to the south. The city has a geographical area of around 15,273 acres and is located between 1900 and 1995 meters above sea level. The town's height extends from 1893 to 1930 meters, almost completely covering the town's western, northern, and southern areas (40)

3.1.3. Climate Condition

Climate is one of the prominent factors that influence the activities of people either directly or indirectly. The elements of climate include temperature, rainfall, and wind. It is mainly the altitude that makes the climate to vary from place to place. The climate of the city, in general, belongs to Woina Dega (Agro-climatic zone). The Maximum annual temperature is 26.25 ^{0}C and the Minimum is 11.18^{0}C. The annual average rainfall of the city is 762 mm. April is the hottest month of the year (31.1^{0}C), while December is the coldest month (7.6^{0}C). December is the driest months, while August is the rainy month (209.9mm) of the year. The highest wind speed is registered in March (2.24m/s) and the most common wind direction seen in the city is easterlies the data was obtained from the NMA.

3.1.4. Soil

The physical and chemical analysis made in the Bishoftu Agricultural Research Center shows that the soil type in Bishoftu area is dark clay and very dark gray clay with high organic content and hence, good agricultural potential. It is very suitable for fruits and edible vegetation. The black clay soil has expansive nature that swells when wet and shrinks when dry hence, is not good for engineering construction activities.

3.2. Materials Used and soft ware

In this study, different materials were employed to achieve the objectives of the study as shown

in table 3.3. Differntial GPS has been used to collect data for validation.Moreover, Erdas Imagine 2015 software was also applied for overall data processing and change detection purposes and GIS 10.5 software also has been utilized for computing the study area using the city boundary of the period 2000,2010 and 2021.

Table 3.2: Hardware's and Software's, their specifications and purposes

Hardware/Software	Purpose for
DGPS	Collect Ground Controls Points (GCPs)
Arc GIS 10.5	Preparation of geospatial data
Edas Imagine 2015	Simulating and making Accuracy assessments
IDRISIS32 selva 17.0	Predicting or modeling the expansion of the town
Google Earth pro	for taking reference information

3.3 Data Collection

Landsat imageries were in bands in zipped files which were obtained from United States Geological Survey (USGS) online data portal.. Images of three epochs were obtained i.e. 2000, 2010, and 2021, the selection was done ensuring that the imageries were free of clouds. Basically, the satellite images were selected based on the availability of data and quality. For this reason, this study uses Landsat 30m resolution and sentinel image 10m. Several ancillary data were also collected for this research. Digital Elevation Model was obtained from the geospatial institution bureau. Vector data of roads, administrative boundaries, and population data were also obtained from the Ambo land administration office. All of the datasets used in the study were geometrically calibrated using WGS 1984_UTM zone 37 North projections.

Table 3.3:Data types and their sources

Item	Data type	Purpose	Source
Primary Data	GCP points	For ground truth	Ground Survey using DGPS
	Landsat Imageries (Spatial Resolution: 30m)	Generation of LULC maps	USGS (https://earthexplorer.usgs.gov/)
secondary data	Population Data	Projected Numbers	Statics office
	Structural Plan of the Town Aerial Photos	Checking ground truth	Administration Town
	DEM(Digital Elevation Model)	Model Prediction	Administration Town

3.4 Methodology

The land cover categories are integrated in a Geospatial Technologies and several spatial analysis procedures to quantify the urban growth and to detect changes in built-up comparing satellite images of Landsat TM of 2000,2010 and 2021 and analyse Landuse Landcover changes Urban Environment (Fig.3.4).

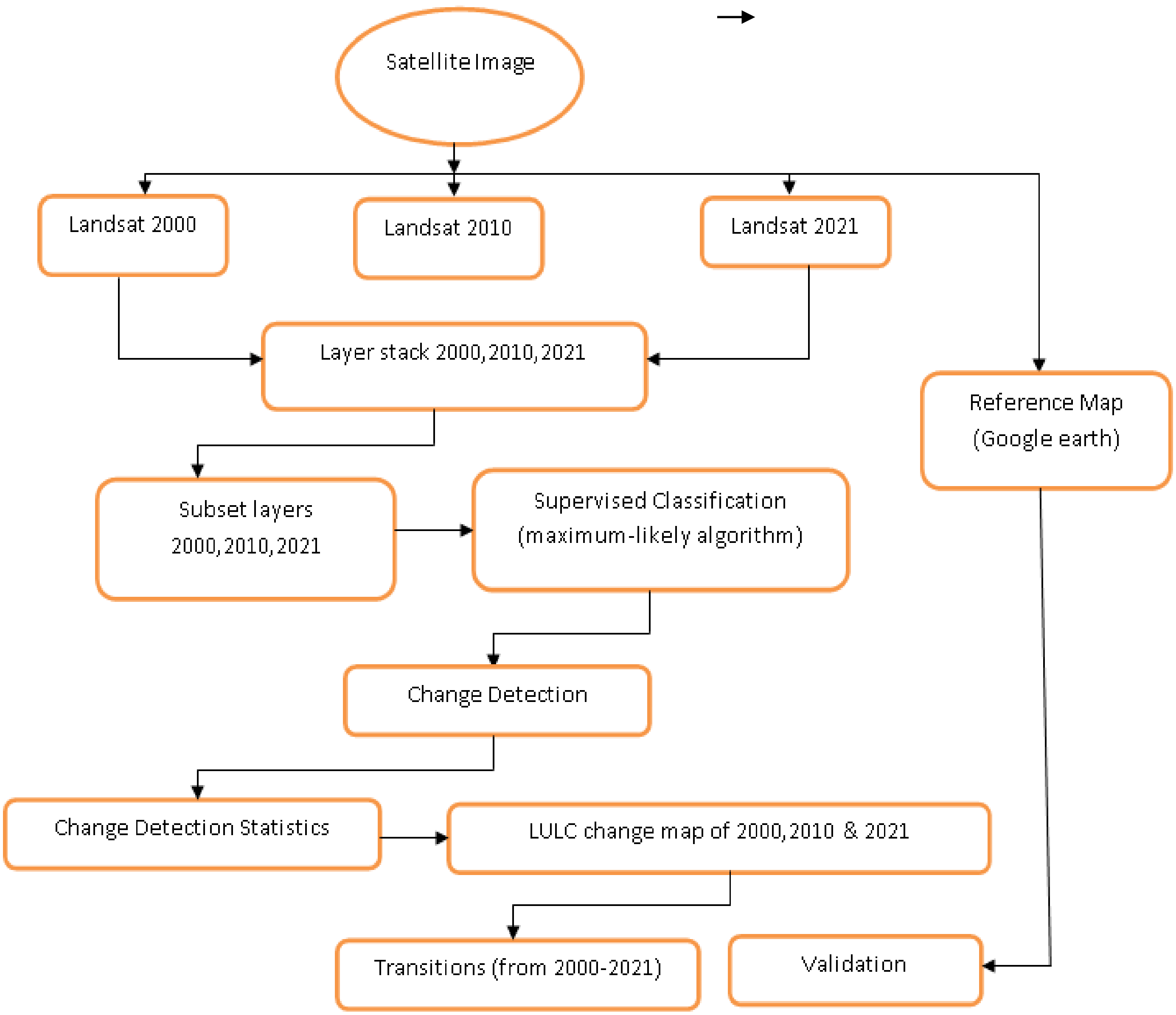


Figure 3.3:Technological schemes of study

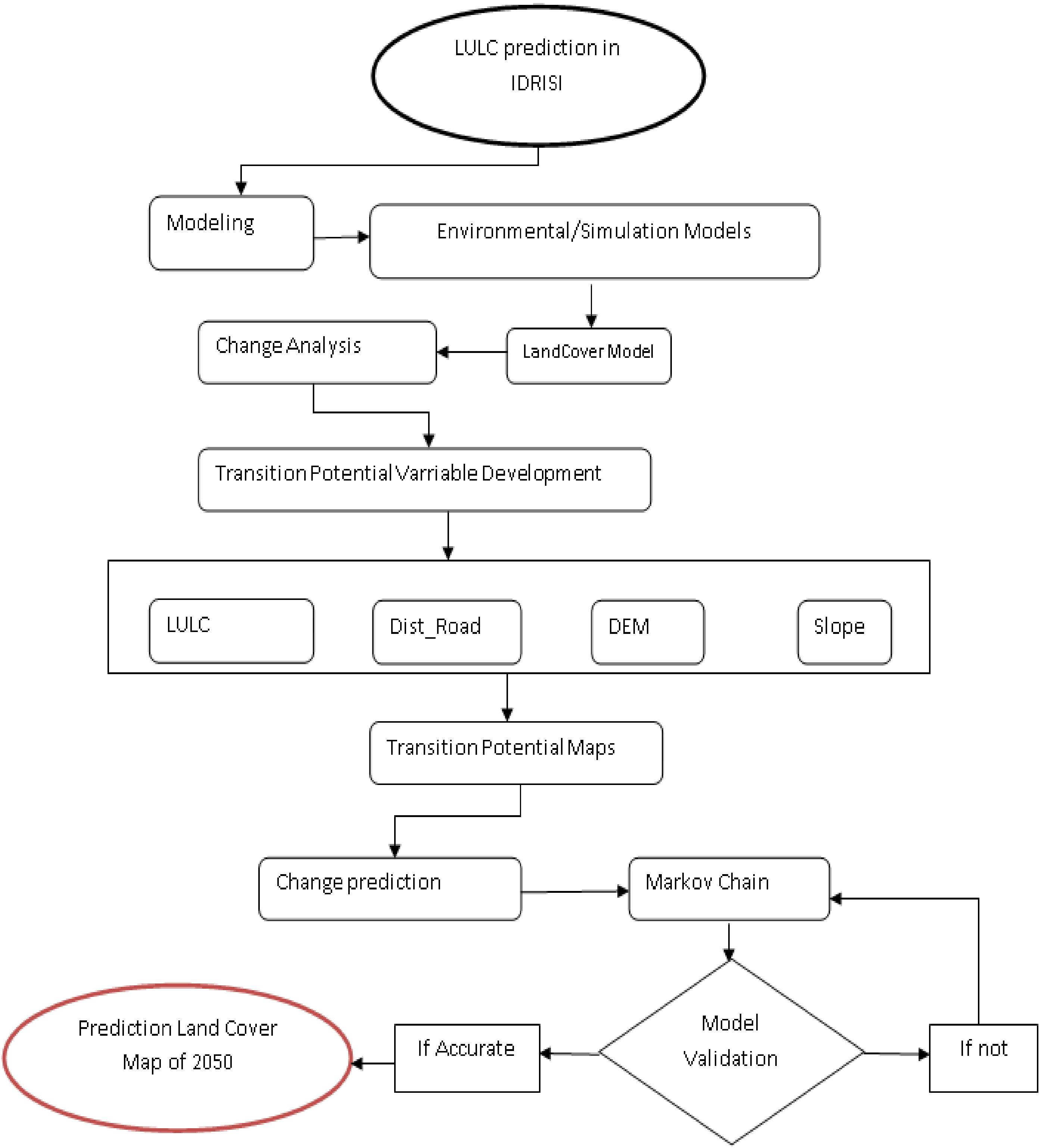


Figure 3.3: Technological schemes of LULC prediction of the study area

3.5 Image Pre-Processing

The first procedure was to layer stack the bands, which is a process of merging two or more registered bands together in order to enhance details contained across multiple exposures of the same scene. Since Landsat satellite images are acquired through bands with each sensor containing several bands, these bands need to be merged to form a scene image. Layer stacking brings all bands together for multi-layer or band operations. It was including mosaic construction, sub-setting of the image based on the boundary of the study area, and projection was performed for all images to be ready for use. Radiometric correction includes the process of haze reduction, removal of atmospheric noise, brightness inversion, and histogram equalization to make more representatives of the ground truth conditions based on the sensors.

3.6 Data Analysis Techniques

The acquired data were analyzed quantitatively as well as qualitatively. This study used quantitative research methods to raster data formats with a resolution of 30m*30m, such as land use land cover data. Using this cell value (900m2), the researcher would determine the area of each feature in the classified image by multiplying each counted cell. However, vector data (i.e.,ground truth data and digitizing for extracting boundaries) were analyzed qualitatively. Geospatial technology tools were used to come up with a solution. As a result, the extent and directions of the town's expansion for the years 2000, 2010, and 2021 were evaluated by superimposing the various time-series maps and computing the corresponding areas in a GIS environment. Finally, forecasting (or modeling) the town's growth 2050 using the CA-Markov model in the Idrisi selva environment. Another analysis was the population figures for Bishoftu town for the period under investigation and investigated the relationship between built-up areas and population change for the period under investigation. The methodologies are described in detail in the methods (figure 3.3).

3.6.1 Land Cover Nomenclatures

In order to make sample collection and classification easy, land cover nomenclatures are required to create and define the possible land cover classes first. Although the focus of the paper is on built-up areas, the land cover map of the study areas was first generated using land cover classes presented in table3.3.The land cover classes applied in this paper were adapted from the classification used by European Environment Agency (EEA), Co-ordination of Information on the Environment (CORINE) , which describes land cover (and partly land use) according to a nomenclature of 44 classes organized hierarchically in different levels .Moreover, due to the geographical location of the study area in Tropics, the CORINE land classes adopted were not entirely applied. It is a land cover class that is more applicable for Temperate and cold Polar Regions. In order to solve this challenge, AFRICOVER land cover classification system which is widely applied in East African Countries (1) was integrated. For the sake of simplicity, the researcher modified the descriptions of some of the land cover classes considering the land cover diversity of the study area. Six major land cover nomenclatures (forest land, grass land, bare land, crop land, Built-up areas and Water body) were used to produce the final land cover map of the study area

Table 3.4: Nomenclature of land use land covers classes

Land classes	Land cover types	Description
C1	Forest land	Natural and manmade forests, Woodland shrubs, sparsely planted trees.
C2	Grass land	Grasses, shrubs, bushes
C3	Bare land	Open spaces with little or no vegetation, beaches, dunes sands, bare rocks, sparsely vegetated areas
C4	Crop land	crop land with permanent crops, farming and fallow fields
C5	Built-up Area	Permanent residential areas of varied patterns and scale occupied by backyards, compounds, and individual buildings
C6	Water Body	Lakes and rivers road and other associated lands.

3.6.2 Training Site Collection

Once the classification scheme and segmentation are adopted, the image analyst selects training sites in the image that are represente of the land-cover or land-use of interest. The analyst would locate sites that have similar characteristics to the known land-cover types. These areas are known as training sites because the known characteristics of these sites are used to train the classification algorithm for the eventual land-cover mapping of the remainder of the image. To see which features show up better in which band, examine the Landsat images shown in the following table3.8. The individual band images appear as gray scale images - like old-fashioned black-and-white photographs. However, they can be combined to form composite images, with each gray scale image each adding a different color (typically a red-green-blue, or RGB combination). Three different and often used composites are summarized below. In this study, firstly, the optimal band mixing; secondly, image objects with appropriate segmentation algorithm (that is multiresolution) was done and finally, the training sites were selected based on the map obtained from the data collected during the field work, personal experience familiarity of the study area, interpretation of high resolution images and Google Earth.

Table 3.5: Appearance of various surface features in different composite images

Features	True Color RGB321	False Color RGB432	SWIR (GeoCover) RGB742
Trees and bushes	Olive Green Red	Olive Green Red	Shades of green
Crops	Medium to light green	Pink to red	Shades of green
Wetland Vegetation	Dark green to black	Dark red	Shades of green
Water	Shades of blue and green	Shades of blue	Black to dark blue
Urban areas	White to light blue	Blue to gray	Lavender
Bare soil	White to light gray	Blue to gray	Magenta, Lavender, or pale pink
Clouds	White	White	White-pink-lavender
Snow/Ice	White	Light green-blue	Medium blue

3.6.3 Image Classification

Image classification is defined as the extraction of differentiated classes or themes, land use and land cover categories, from raw remotely sensed digital satellite data. It is a technique to identify different features such as urban land cover, vegetation types, anthropogenic structures, mineral resources, or changes in any of these properties from the satellite image. Image classification is a complex and time-consuming process. In order to improve the classification accuracy, the selection of appropriate classification method is required. This would also enable the analyst to detect changes successfully (10). There are different types of image classification techniques. However, in most cases the researchers categorized them in to 3 major modes: Supervised, unsupervised and hybrid. For this study, the Supervised Classification type was applied. It is a type of classification based on the researcher the prior knowledge of to the study area. It requires the manual identification of Point of Interest areas as reference (Ground truth) within the images, to determine the spectral signature of identified features. It is one of the most common types of classification techniques in which all pixels with similar spectral value are automatically categorized into land cover classes or themes. In this work, Pixel based-supervised classification approach was used and passed through the steps such as: selecting training samples which are typical representative for the land cover classes; perform classification using the Maximum Likelihood Algorithm and finally assess the accuracy of the classified image through randomly generated training samples and analysis of a Confusion Matrix. The overall classification process was carried out in software "Arc GIS version 10.5. It can import images from different data format, generate training samples, classify and mapping. It also supports different methods to train the algorithm and build up resources and pixel-based image classification. Classification and post-classification overlay were carried out and thematic land-cover maps for the years 2000, 2010 and 2021 were produced for the study area by supervised classifications. five major land cover classes such as forest land, agricultural lands, bare lands, urban areas and water bodies were performed to detect possible details, the change trajectory of post classification comparison was used to map the patterns and extents of land use and land cover in the study area as well as to determine the magnitude of changes between the years of interest 2000, 2010, 2021.

3.6.3 Classification algorithm

The maximum likelihood classifier is one of the most popular methods of classification in remote sensing, in which a pixel with the maximum likelihood is classified into the corresponding class. The method is used in this project because it has some advantages in that: The classifier quantitatively evaluates both the variance and covariance of the category spectral response patterns when classifying an unknown pixel. This is done by assuming that the distribution of the cloud of points forming the category training data is normallydistirubted .Because highly heterogeneous land covers data (e.g., Urban areas) are unlikely normally distributed, the distribution of land cover surfaces is associated with various uncertainties which prevent their description based on data distribution (Lu and Weng, 2007).

3.7 Classification Accuracy Assessment

Accuracy assessment is an important step in the process of analyzing remote sensing data. It determines the value of the resulting data to a particular user. Users with a variety of applications should be able to evaluate whether the accuracy of the map suits their objectives or not. There are different ways of accuracy assessment; confusion matrix or error matrix is the most common means of expressing classification accuracy. It compares, on a category bycategory basis, the relationship between known reference data and the corresponding results of an automated classification. Ground truthing points were collected using a handheld GPS which were used to assess the accuracy of classified images.

3.8 Urban growth on Built-up area Analysis

Change detection involves the use of multi-temporal datasets to discriminate areas of Land cover/use change between dates of Imaging. In this resarch post classification change detection method was used to analyse change in different landuses to Built-up areas. Reclassification of data entailed aggregating the different classes of land cover/use into those classes that represent urban or built up area.

3.9 Change detection techniques

For detecting and analyzing the change on the earth's surface, various techniques are employed. Before studying about various change detection techniques, it is necessary to know about the procedure of change detection. To detect the changes of the surface of the earth, six main steps are important as mentioned by Jensen which are as follows:

1. Nature of change detection problems.
2. Selection of remotely sensed data.
3. Image preprocessing.
4. Image processing or classification.
5. Selection of change detection algorithm.
6. Evaluation of change detection results.

The goal of change detection is to discern those areas on digital images that depict change in the feature of interest between two or more image dates. The reliability of the change detection process may be strongly influenced by various environmental factors that might change between image dates.

3.10 CA-Markov Model Validation Approach

The use of kappa indexes for the calculation determines the overall achievement rate, and it delivers an understanding of the real factors in the strength or weakness of the results. When 75% ≤Kappa <100, the result maps are in a high level of agreement; if 50% ≤Kappa ≤75%, the result maps are in a medium level of agreement; and if Kappa ≤50, the result maps are in a poor agreement (27). Therefore, to know the accuracy of the CA-Markov model in simulating future LULC conditions, the model was confirmed (43) after simulating the 2021 LULC situations using the 2000 and 2010 classified images.

RESULT AND DICUSSION (CHAPTER FOUR)

4.1 RESULT

Three classification maps for the three scenes under investigation are produced as shown below. The Maps below shows the classified images for 2000,2010 and 2021.

4.1.1.LULC classification- Changes On The Urban Environment in 2000

As per the table below, 6929.63ha (36.47 %), 3459.60ha (18.21%), 3292.77ha (17.33%), 3067.94ha (16.15%), 1811.78ha (9.54%) and 436.98ha (2.30%) were classified as Bare soil,crop land ,forest land,grass land, Built-up area and water body respectively for the period 2000.

Table 4.1: Area coverage in hectares and percentage

LULC Types	Area (ha)	Area (%)
Water body	436.98	2.30
Built up Area	1811.78	9.54
Bare Soil	6929.63	36.47
Crop Land	3459.60	18.21
Forest Land	3292.77	17.33
Grass Land	3067.94	16.15
Total	18998.70	100.00

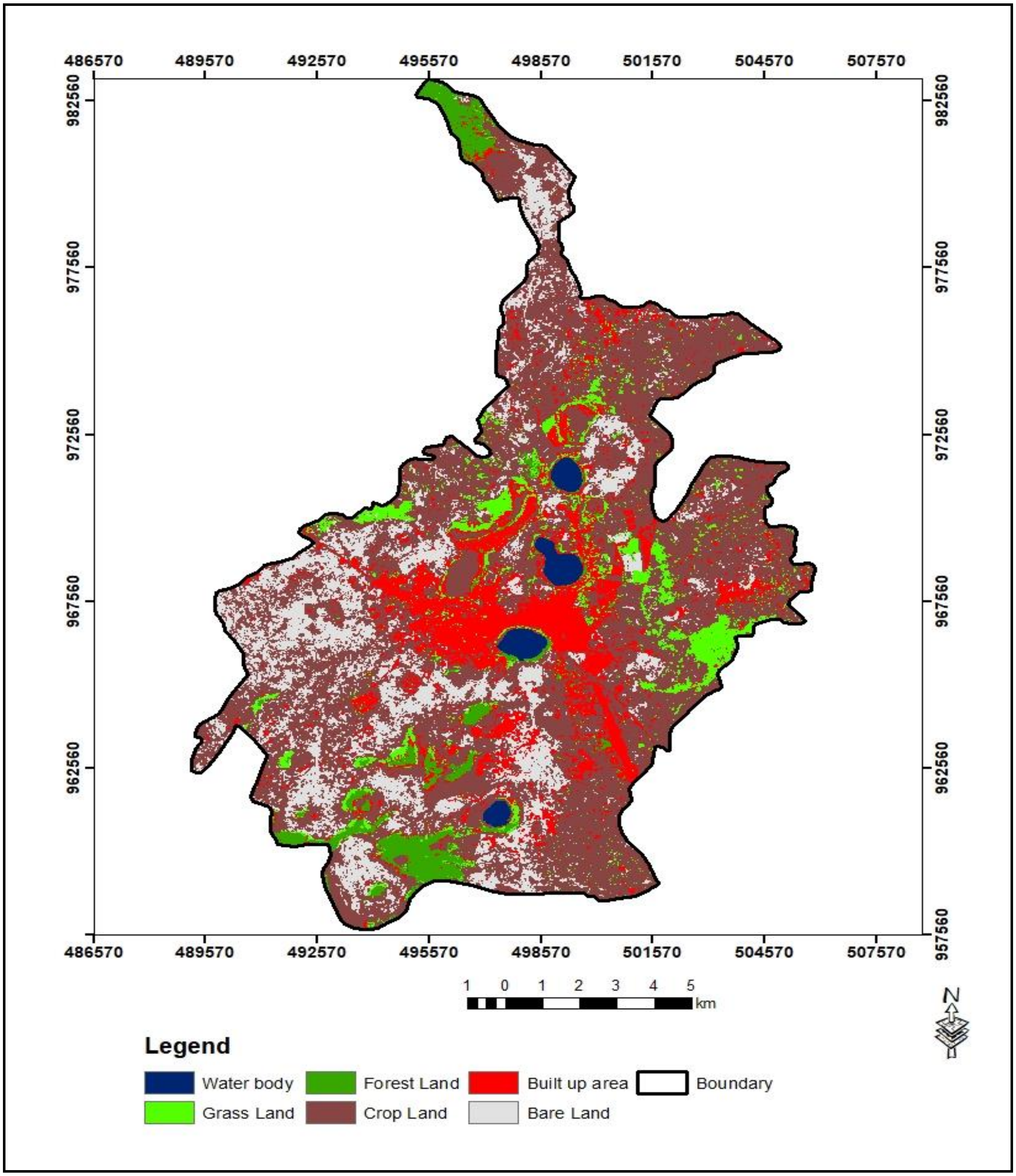


Figure 4.1: LULC classification map of the study area in 2000

Figure 4.1 above shows the different categories of land cover/use found in the study area in tabular form. The total area under consideration was 18998.70 hectares approximately. Six information classes were produced as shown above.

4.1.2.LULC classification- Changes On The Urban Environment in 2010

In this classification, crop land was classified as the highest coverage which accounts for a total area of 9572.63ha with a value of 50.39% and the lowest coverage during this period (i.e.,2010), was grass land which has a total area of 485.70 ha (2.56%). Built-up area,bare soil , Forest land and water body account a total coverage area of 3501.98 ha, 3154.23ha,1797.85 and 486.31 ha with the value of 18.43% , 16.60%, 9.46% and 2.56% respectively.

Table 4.2: Area coverage in hectares and percentage in 2010

LULC Types	Area (ha)	Area (%)
Water body	486.31	2.56
Built up Area	3501.98	18.43
Bare Soil	3154.23	16.60
Crop Land	9572.63	50.39
Forest Land	1797.85	9.46
Grass Land	485.70	2.56
Total	18998.70	100.00

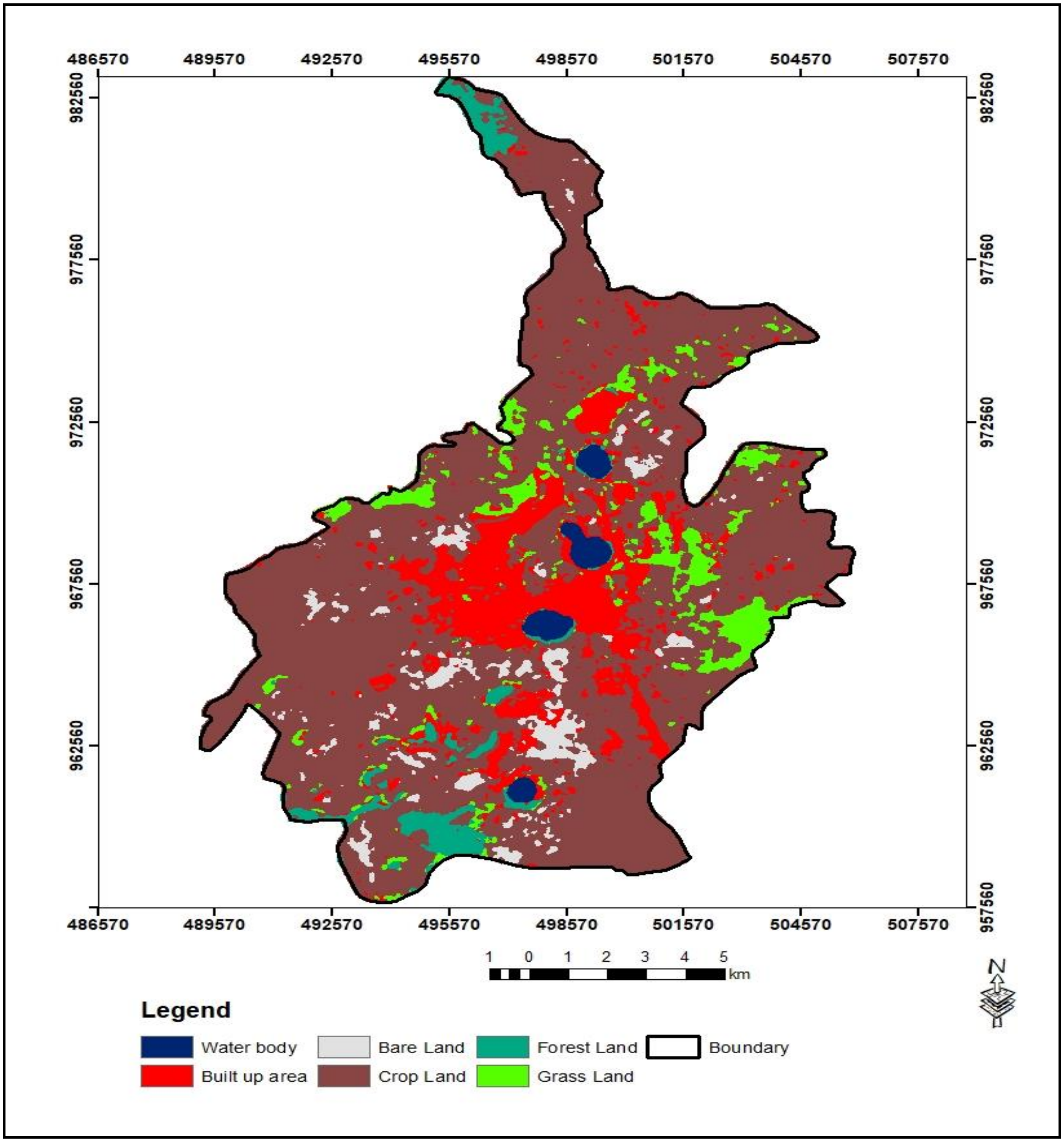


Figure 4.2: LULC classification map of the study area in 2010

In Figure above shows the different categories of land cover/use found in the study area in tabular form. The total area under consideration was 18998.70 hectares approximately. Six information classes were produced as shown above.

4.1.3. LULC Classification- Changes On The Urban Environment in 2021

As indicated in table 5.4 below, the water body has become low with a total coverage area of 369.71 ha (1.95%) and Built-up Area was classified 47.62% with total coverage area of 9047.12 ha which is high. The result also showed that, crop land,Bare soil,Grass land and forest land had were classified with values 4339.61 ha, 2533.30ha, 1670.90ha,and1038.06ha respectively.

Table 4.3: Area coverage in hectares and percentage

LULC Types	Area (ha)	Area (%)
Water body	369.71	1.95
Built up Area	9047.12	47.62
Bare Soil	2533.30	13.33
Crop Land	4339.61	22.84
Forest Land	1038.06	5.46
Grass Land	1670.90	8.79
Total	18998.70	100.00

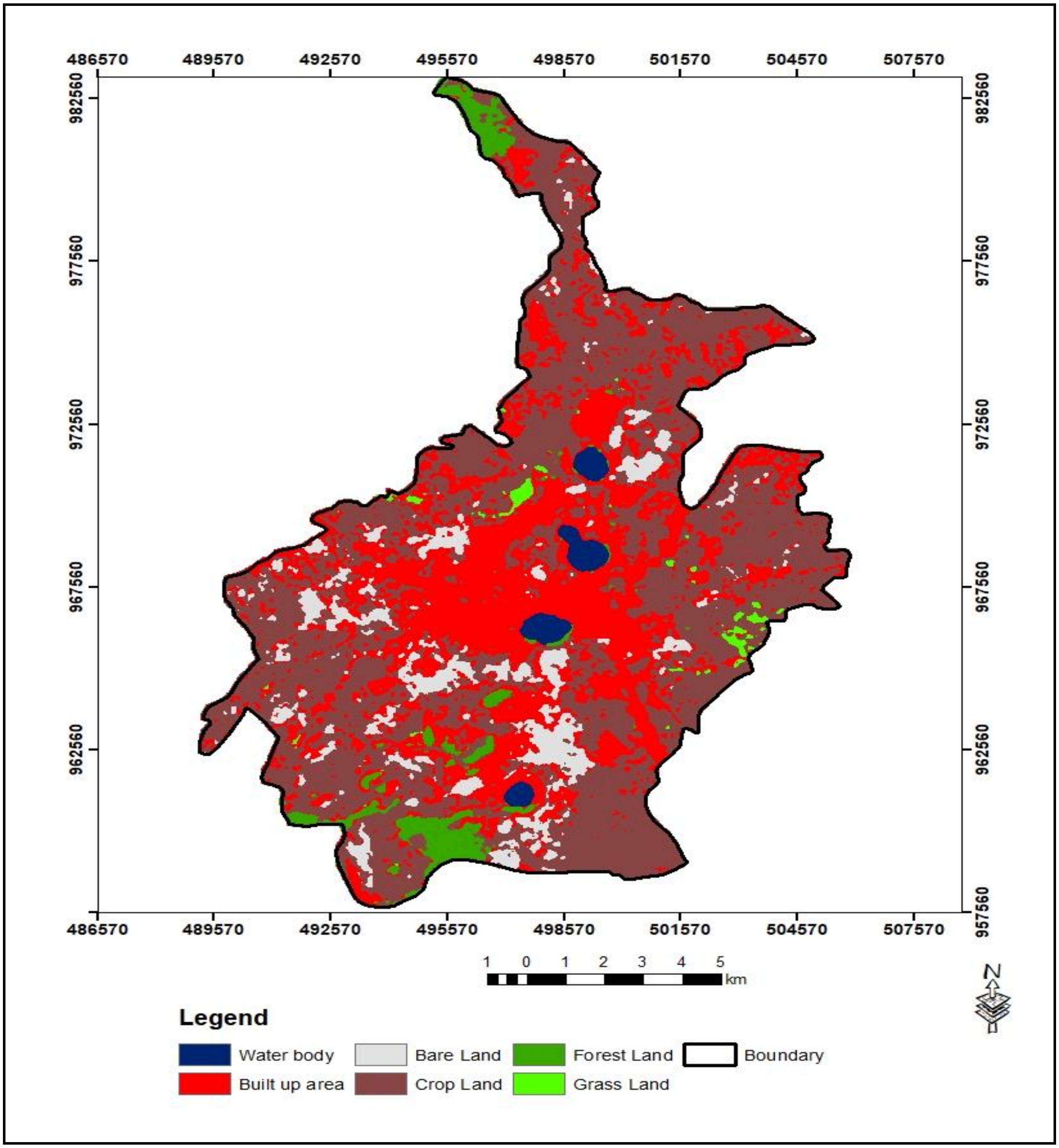


Figure 4.3: LULC classification map of the study area in 2021

In Figure above shows the different categories of land cover/use found in the study area. The total area under consideration was 18998.70 hectares approximately. Six information classes were produced as shown above.

4.2.Change Detection

4.2.1. LULC change on Changes On The Urban Environment for the period 2000-2010

Land-use/land-cover change detection was done by involving images of 2000 and. Using GIS techniques thematic image was compared. The cross operation process of mapping LU/LCC over time began with mapping the recent satellite imagery, then looking back in time to map the 2000 imagery. Post classification is among the most widely used approach for change detection purpose (Chen, 2000). The analysis of LU/LCC maps involved technical procedures of integration using the ArcGIS software techniques. The six LULC classes such as water body, Built-up area,bare soil, crop land, forest land and grass land were identified for the years 2000,2010 and 2021. In table 4.4 shows that, land use land cover changes for the period 2000-2010 and its total area coverage.

Table 4.4: land use and Area coverage changes for the period 2000- 2021

LULC Types	**2000**		**2010**		**Change(2000-2010)**	
	Ha.	%	Ha.	%	Ha.	%
Water body	436.98	2.30	486.31	2.56	49.33	0.26
Built-up Area	1811.78	9.54	3501.98	18.43	1690.2	8.89
Bare Soil	6929.63	36.47	3154.23	16.60	-3775.4	-19.87
Crop Land	3459.60	18.21	9572.63	50.39	6113.03	32.18
Forest Land	3292.77	17.33	1797.85	9.46	-1494.92	-7.87
Grass Land	3067.94	16.15	485.70	2.56	-2582.24	-13.59
Total	**18998.70**	**100**	**18998.70**	**100**	**0**	**0**

.

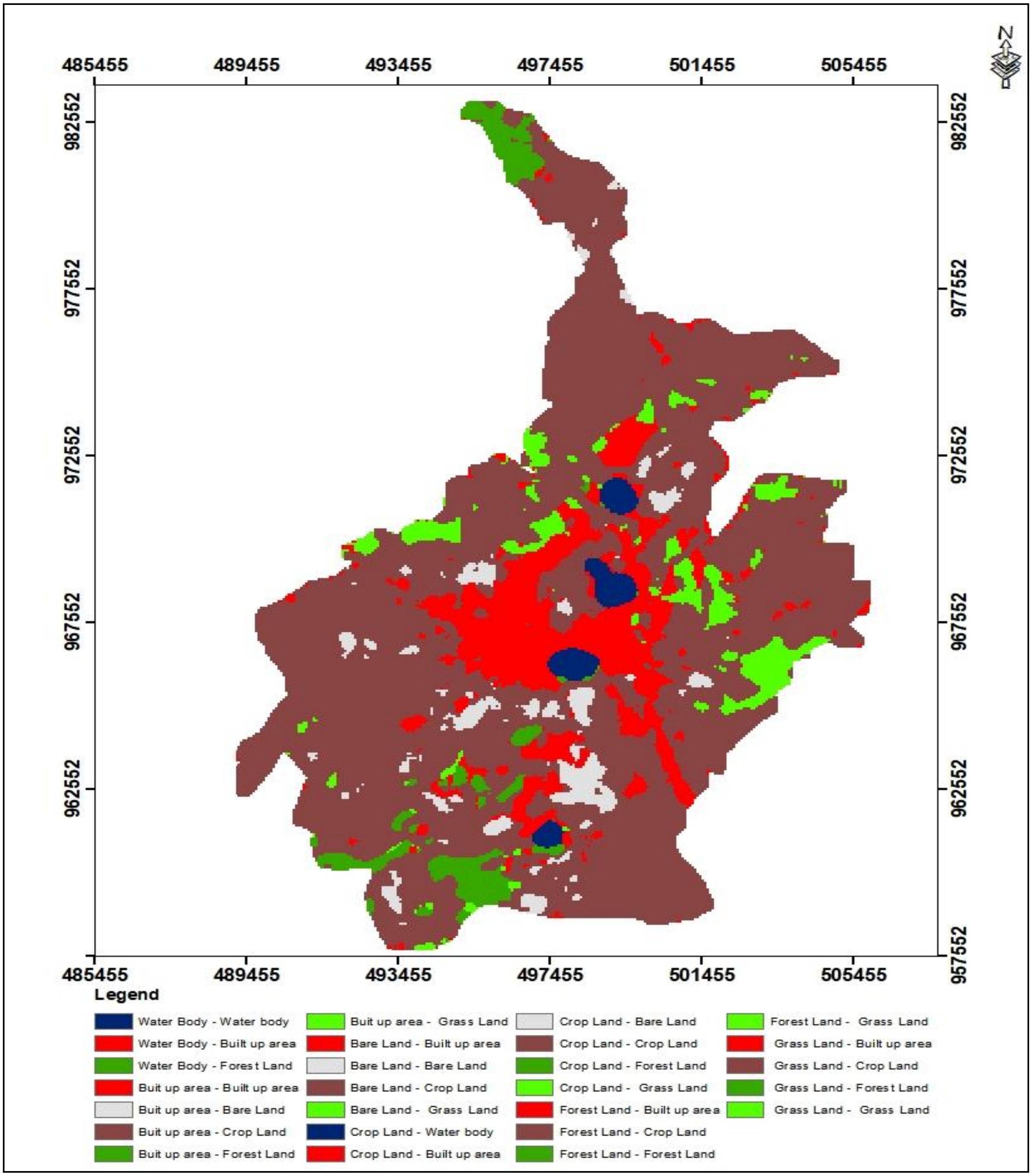


Figure 4.4: LULC change map of the study area (2000-2010)

Accordingly from the above data, crop land features, built-up areas and water bodies (in some extent) have increased.

4.2.2. LULC change Changes On The Urban Environment for the period 2010-2021

The post classification technique was used based on supervised classification based on the Maximum Likelihood Classifier (MLC) and introduction of human-knowledge from field experience to determine the amount of change over the study period. LULC maps for 2010-2021 were derived (Figure 4.5).

Table 4.5: land use and Area coverage changes for the period 2010- 2021

LULC Types	**2010**		**2021**		**Change(2010-2021)**	
	Ha.	%	Ha.	%	Ha.	%
Water body	486.31	2.56	369.71	1.95	-116.6	-0.61
Built-up Area	3501.98	18.43	9047.12	47.62	5545.14	29.19
Bare Soil	3154.23	16.60	2533.30	13.33	-620.93	-3.27
Crop Land	9572.63	50.39	4339.61	22.84	-5233.02	-27.55
Forest Land	1797.85	9.46	1038.06	5.46	-759.79	-4
Grass Land	485.70	2.56	1670.90	8.79	1185.2	6.23
Total	**18998.70**	**100**	**18998.70**	**100**	**0**	**0**

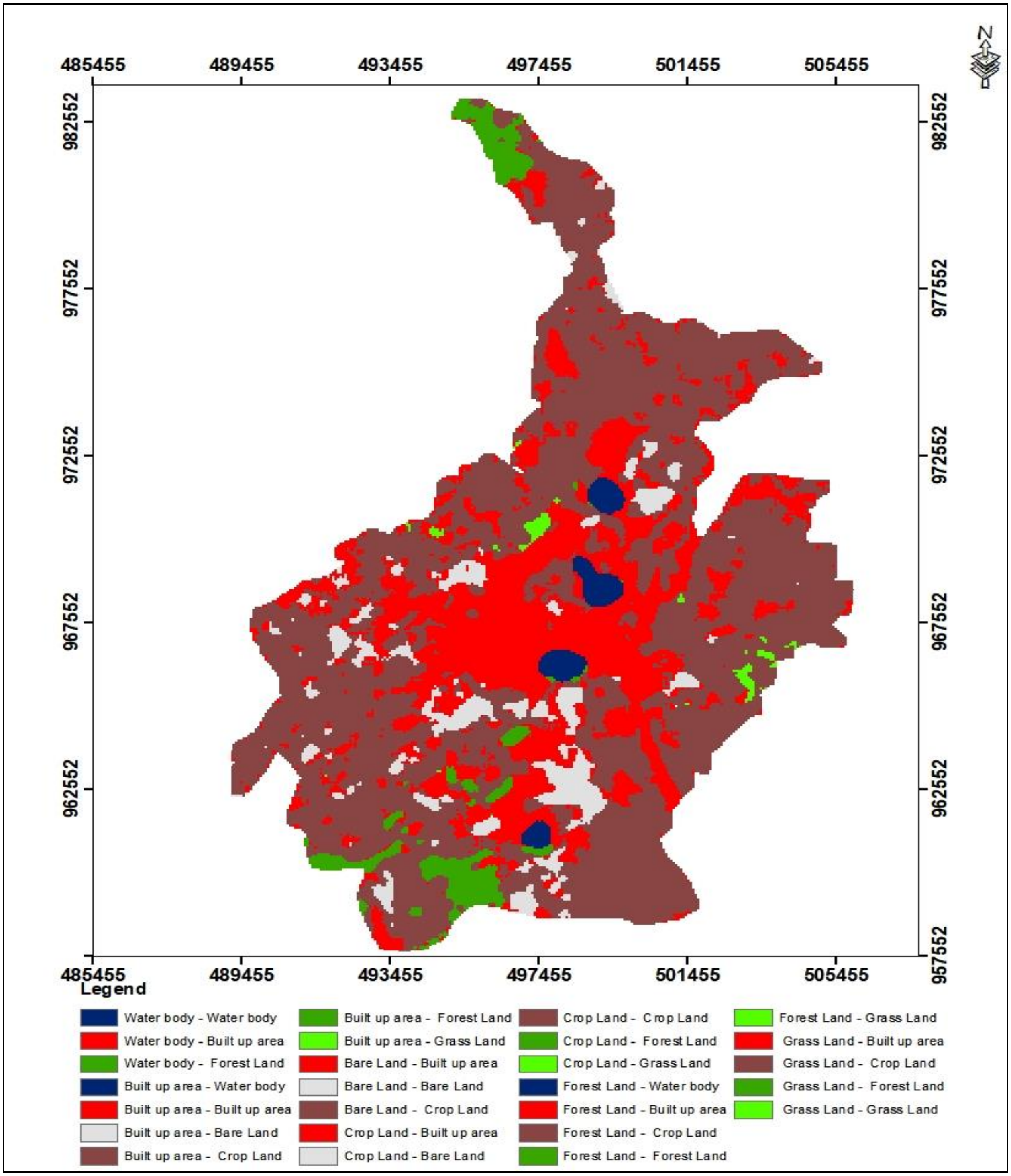


Figure 4.5: LULC change map of the study area (2010-2021)

Based on the above result;the magnitude of water body, bare soil, crop land, and forest land was decreased in the classification process, 4.2.3. LULC change on Changes On The Urban Environment for the period 2000 -2021

Table 4.6 showed, the net-area changes of the six LULC classes during the periods 2000–2010, 2010–2021, and 2000–2021. Accordingly, the magnitude of Water bodies ,bare soil, forest land and grassland declined by 0.35 percent and 23.14 percent,11.87 percent and 7.36 percent respectively, whereas built-up areas and croplands were increased by 38.08 percent and 4.63 percent, respectively.

Table 4.6: Land use and Area coverage changes for the period 2000- 2021

LU/LC types	2000		2010		2021		Change					
							2000-2010		2010-2021		2000-2021	
	Ha.	%	Ha.	%	Ha.	%	Ha.	%	Ha.	%	Ha.	%
Water body	436.98	2.30	486.31	2.56	369.71	1.95	49.33	0.26	-116.6	-0.61	-67.27	-0.35
Built-up	1811.78	9.54	3501.98	18.43	9047.12	47.62	1690.2	8.89	5545.14	29.19	7235.34	38.08
Bare soil	6929.63	36.47	3154.23	16.60	2533.30	13.33	-3775.4	-19.87	-620.93	-3.27	-4396.33	-23.14
Crop land	3459.60	18.21	9572.63	50.39	4339.61	22.84	6113.03	32.18	-5233.02	-27.55	880.01	4.63
Forest land	3292.77	17.33	1797.85	9.46	1038.06	5.46	-1494.92	-7.87	-759.79	-4.00	-2254.71	-11.87
Grass land	3067.94	16.15	485.70	2.56	1670.90	8.79	-2582.24	-13.59	1185.2	6.23	-1397.04	-7.36
Total	18998.7	**100**	18998.7	**100**	18998.7	**100**	**0**	**0**	**0**	**0**	**0**	**0**

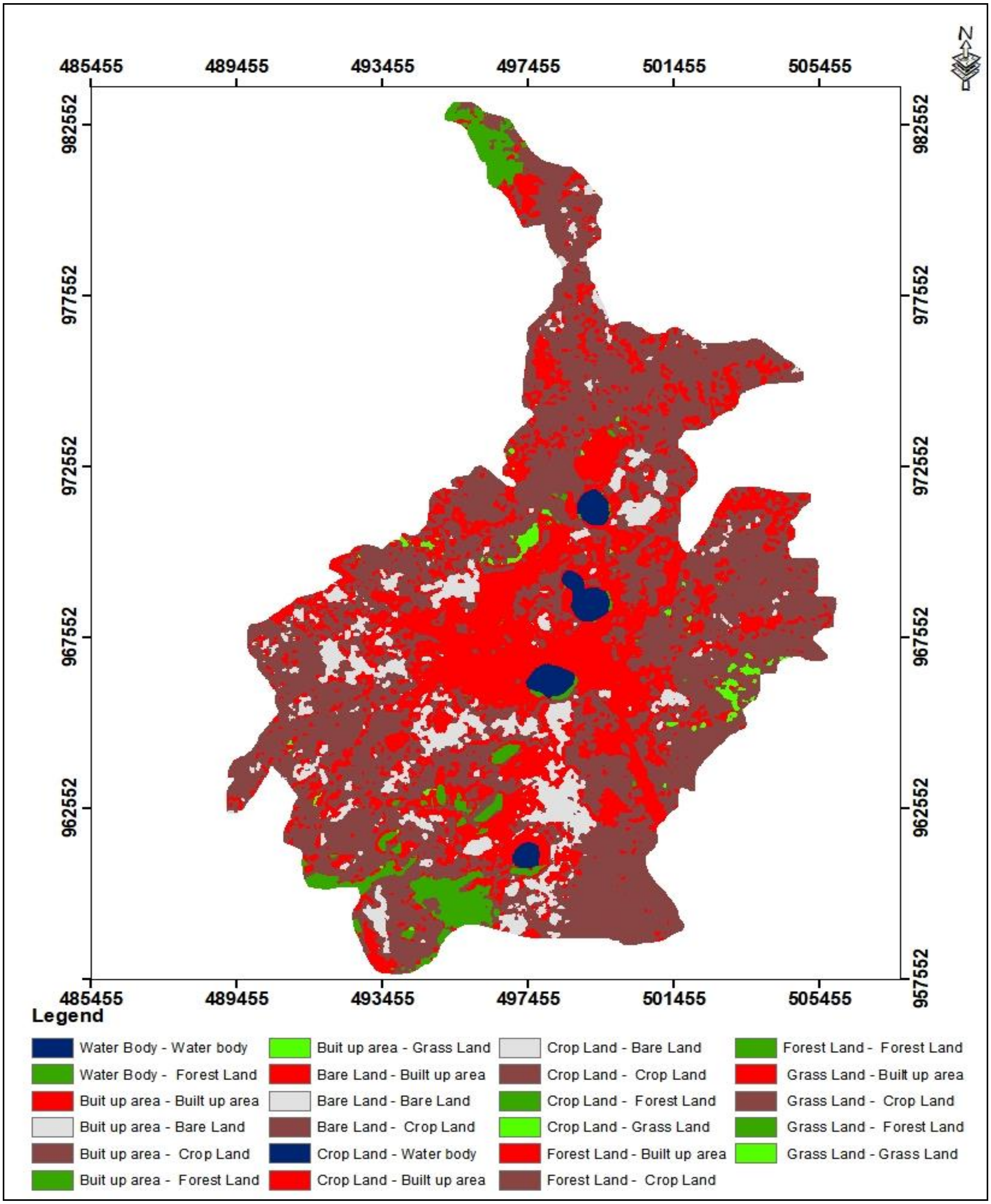
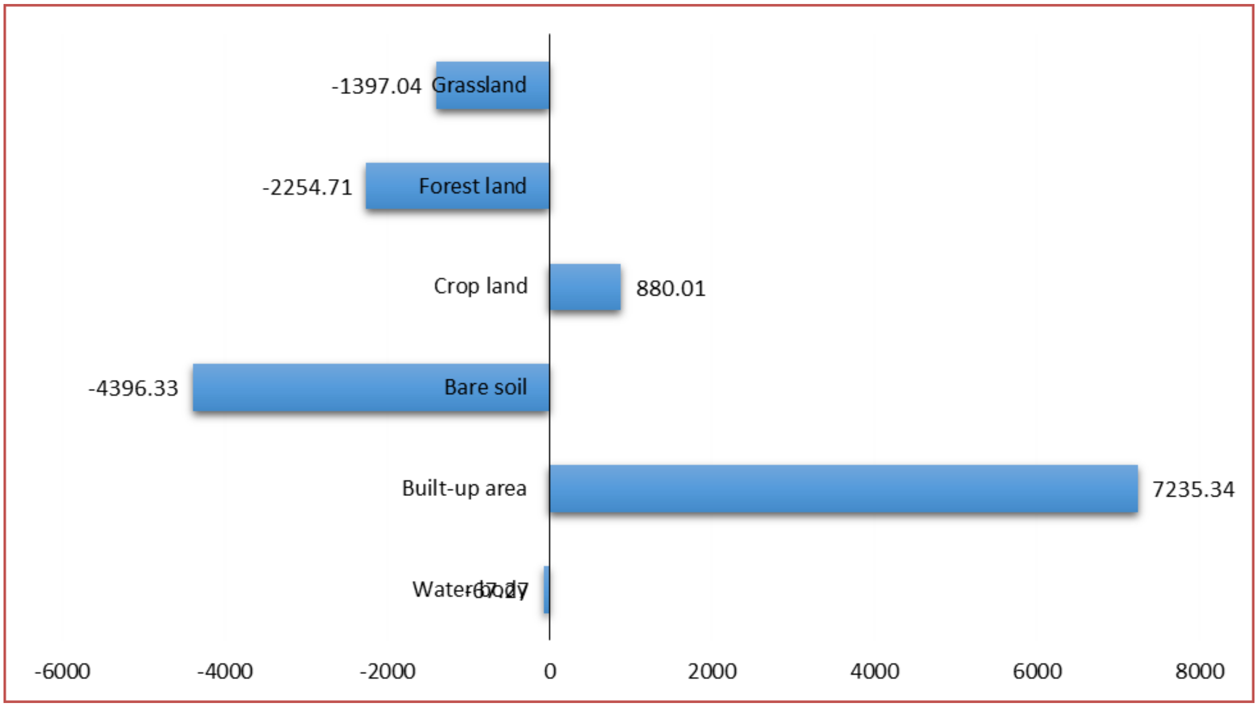


Figure 4.6: LULC change map of the study area (2000-2021)



Generally, from 2000 to 2021, urban area increased approximately 38.08 %, while agriculture decreased 12%. Achieved LULC change maps showed that urban land area increased 38.08% due to urbanization that resulted from high speed economic development, especially in period from 2010 to 2021, built-up area increased mainly due to the construction. Consequently, forest area decreased 11% from 2000 to 2021.

4.3. Accuracy Assessement

4.3.1. User's Accuracy

Users accuracy refers to the number of correctly classified pixels in each class (category) divided by the total number of pixels that were classified in that category of the classified image (row total). Results of user's accuracy in this study showed that, the maximum and minimum class accuracy were 94.45% and 77.78% were correctly classified as crop land and bare soil.However, 88.00%, 84.62%,84.62% and 84.21% were classified as built-up area,water body,forest land and grass land.

4.3.2. Producer’s Accuracy

Producer's accuracy refers to the number of correctly classified pixels in each class (category) divided by the total number of pixels in the reference data to be of that category (column total). This value represents how well classified reference pixels of the ground cover type . As shown in the table below the highest values was built-up areas with a value of 95.65% and the lowest values were classified as bare soil which accounts **77.78**%.

4.3.3. Over all accuracy

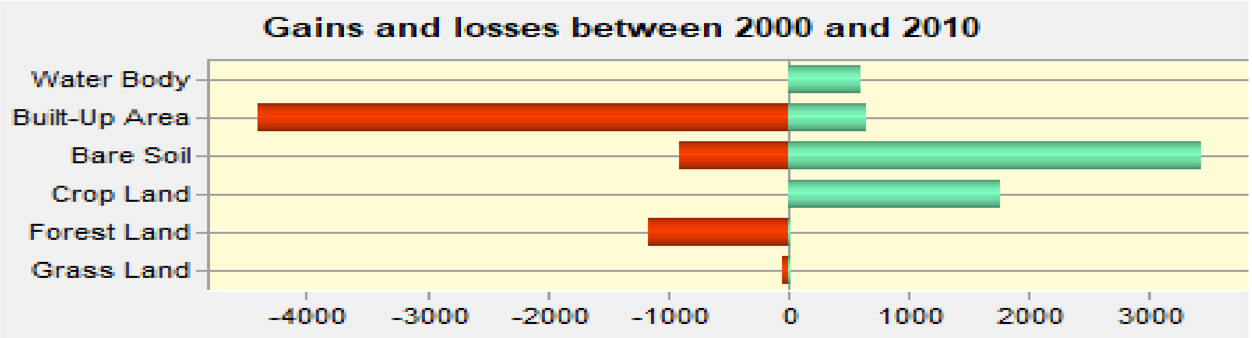
It is computed by dividing the total number of correctly classified pixels (i.e., the sum of the elements along the major diagonal) by the total number of reference pixels. According to (Anderson, 1976) stated that, for a reliable land cover classification, the minimum overall accuracy value computed from an error matrix should be 85%. Accordingly, the overall accuracy of this study for the period 2000 - 2021 was 86.59% as shown the table below.

Table 4.7: Overall Accuracy

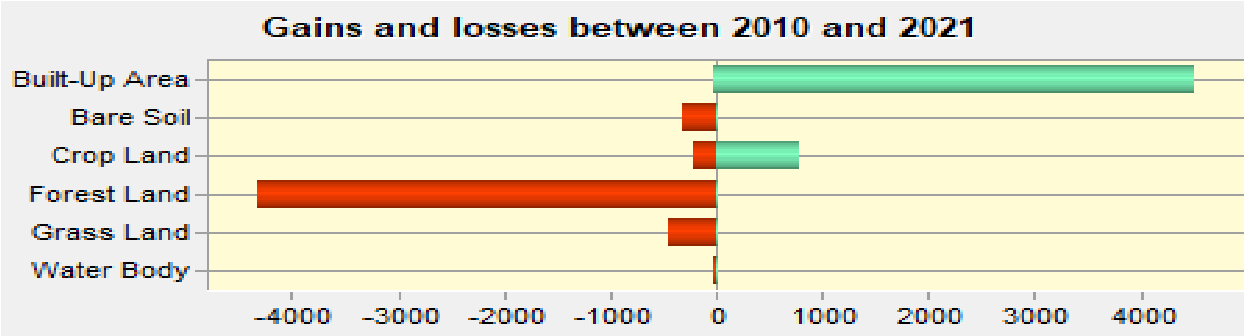
	LULC class	**Referenced map**							
		Water body	Built-up area	Bare soil	Crop land	Forest land	Grass land	User's total	User's Accuracy in %
Classified map	Water body	11	1	1	0	**0**	**0**	**13**	**84.62**
	Built-up area	0	22	1	1	0	1	**25**	88.00
	Bare soil	0	0	7	1	**1**	**0**	**9**	**77.78**
	Crop land	0	0	0	17	**0**	**1**	**18**	**94.45**
	Forest Land	1	0	0	0	11	1	**13**	84.62
	Grass Land	0	0	0	2	1	16	**19**	84.21
	Producer's total	**12**	**23**	**9**	**21**	**14**	**19**	**97**	
	Producer's Accuracy in %	**91.67**	**95.65**	**77.78**	**80.95**	**78.57**	**84.21**		
	Overall accuracy							**86.59%**	

4.4.Landuse modeler

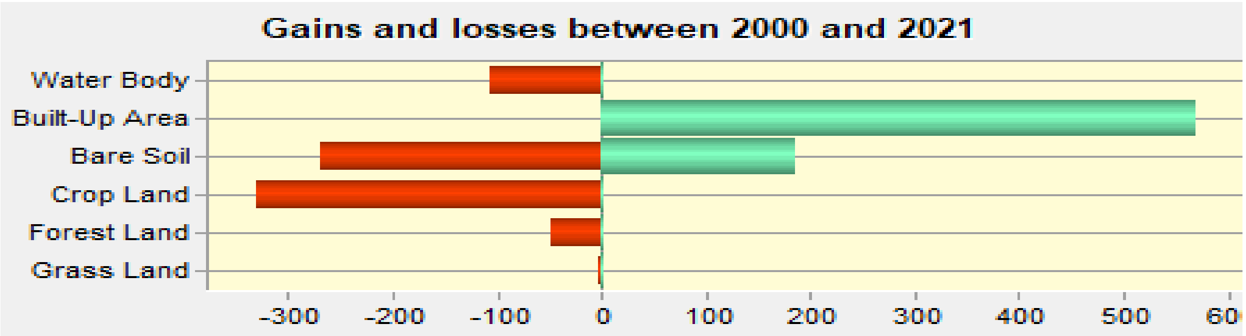
4.5. LULC change Analysis by Gains and losses (2000-2021)



(a)



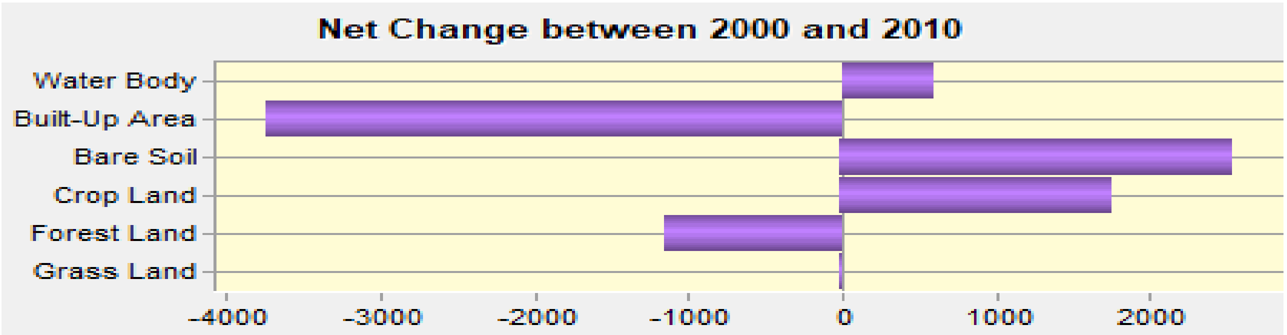
(b)



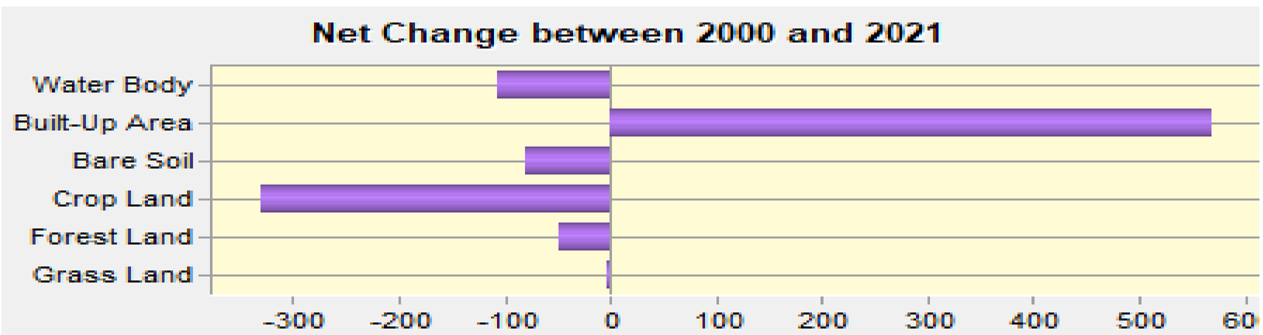
(c)

Figure 4.7: Gains and losses between 2000 and 2021

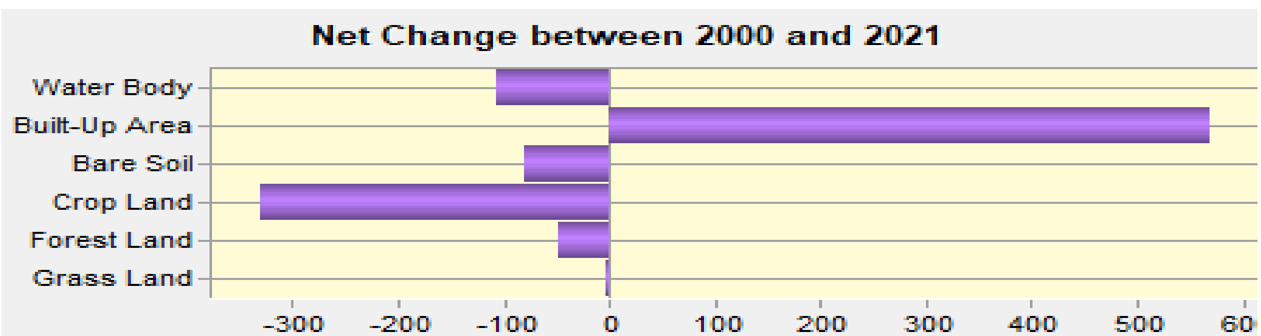
4.6. LULC Analysis by Net Changes (2000-2021)



(a)



(b)

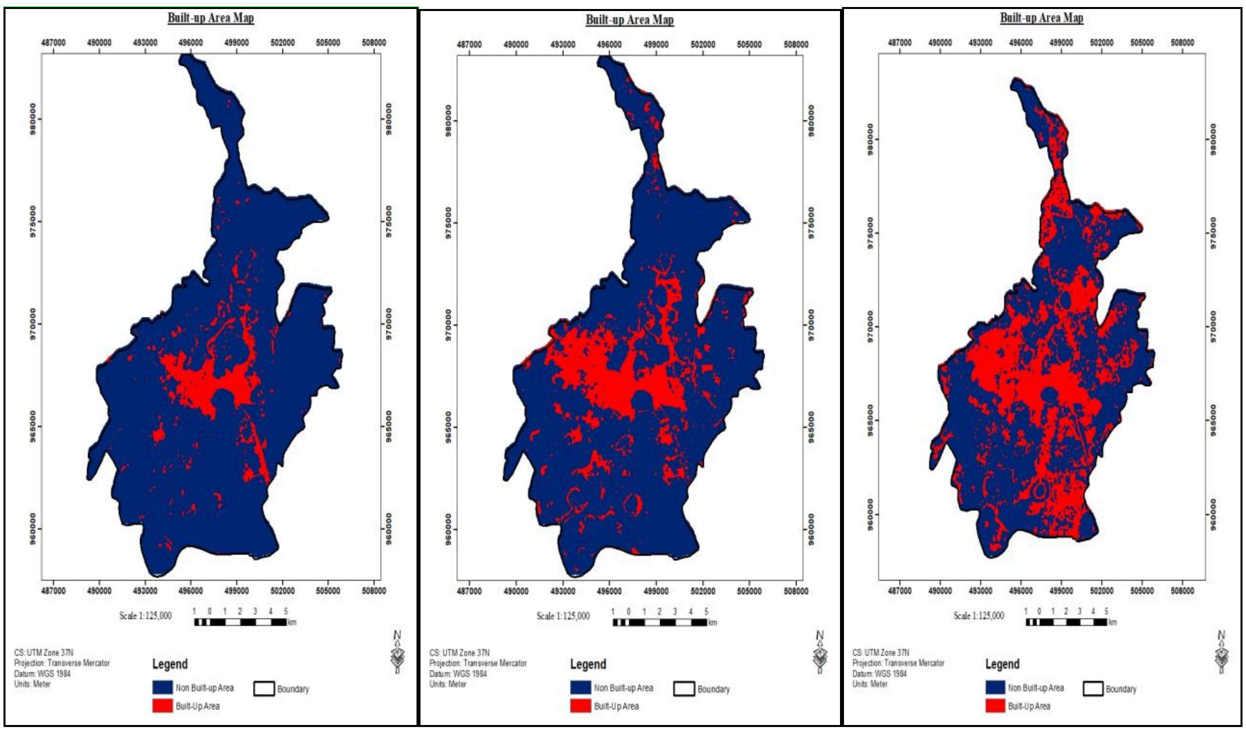


(c)

Figure 4.8:Net change beteween 2000 and 2021

4.7. LULC Changes to Urban Environment

The increment in infrastructure development of Bishoftu from time to time has played a major influence for the expansion of built up areas. The main focus of this study was assessing the spatial extents of built up areas within the three study periods. To achieve this, a reclassification was made to generate land use and land cover maps of built up and non built up areas as shown in figure below.



(a) (b) (C)

Figure 4.9: Built up and Non built Landcover Map of Bishoftu town (2000) -(a)

Figure 4.10: Built up and Non built Landcover Map of Bishoftu town (2010) –(b)

Figure 4.11: Built up and Non built Landcover Map of Bishoftu town (2021)-(c)

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.

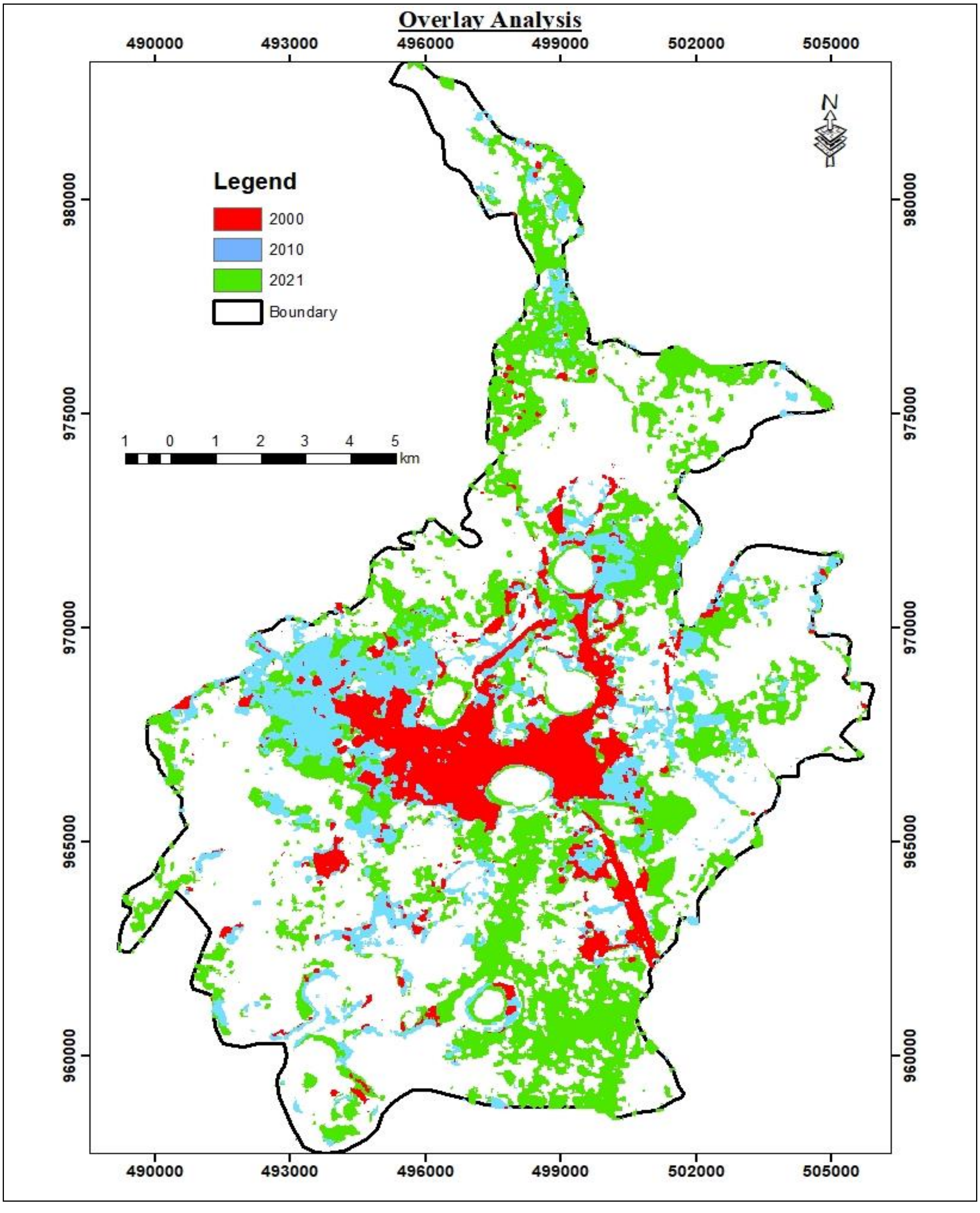

Overlay Analysis
490000
493000
496000
499000
502000
505000
980000
975000
970000
965000
960000
Legend
2000
2010
2021
Boundary
1 0 1 2 3 4 5
km
N

Figure 4.12: Buildup area overlay analysis 2000, 2010 and 2021

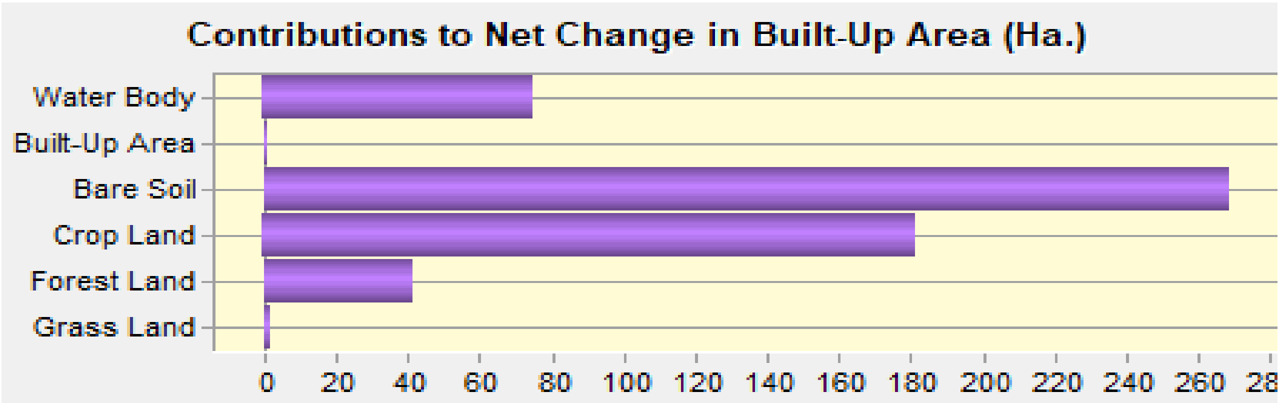


Figure 5.15: Contribution of LULC to Builtup area (2000 - 2021)

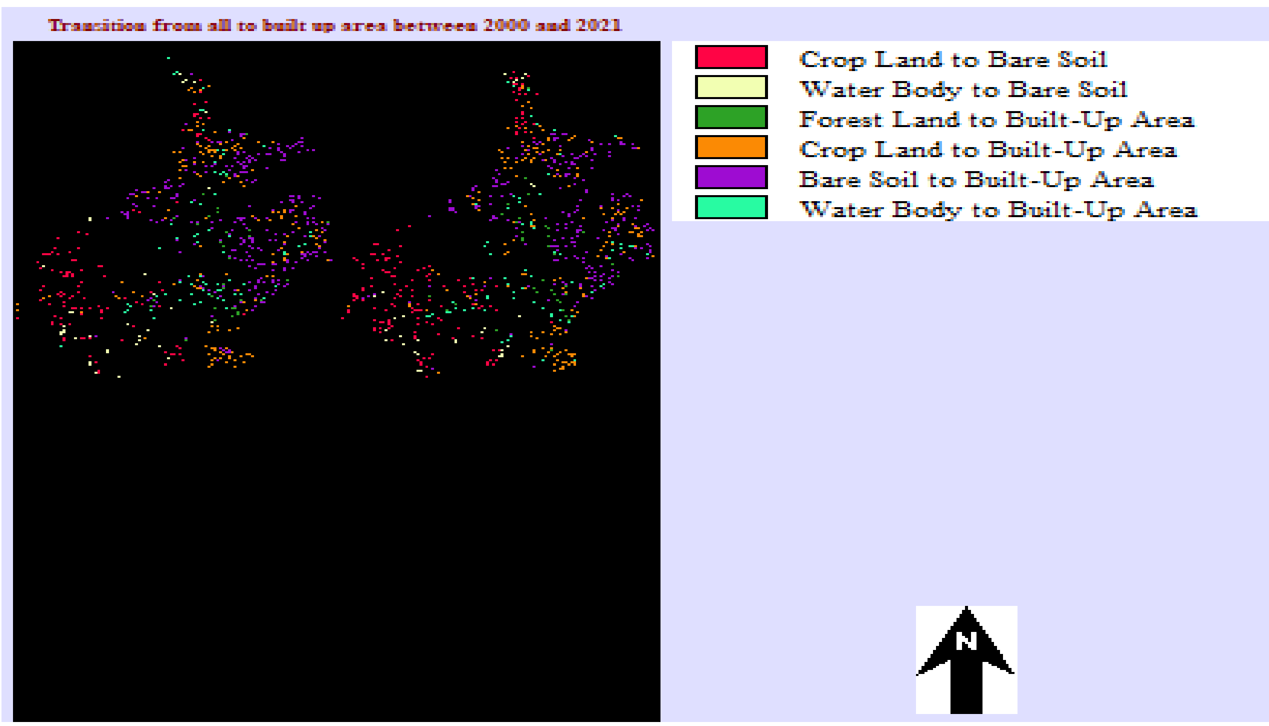
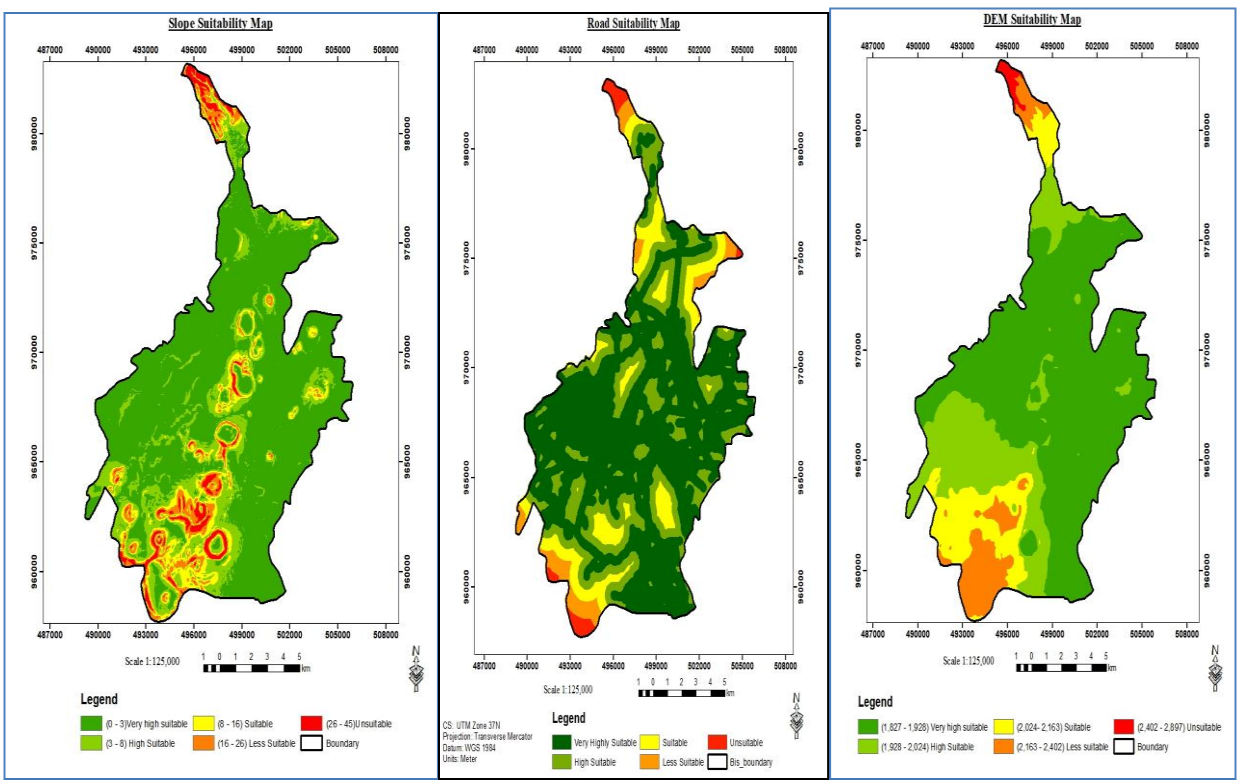


Figure 4.13: All LULC changed to buildup area 2000 - 2021

4.8. Future Prediction and Modeling Land Use/Land Cover

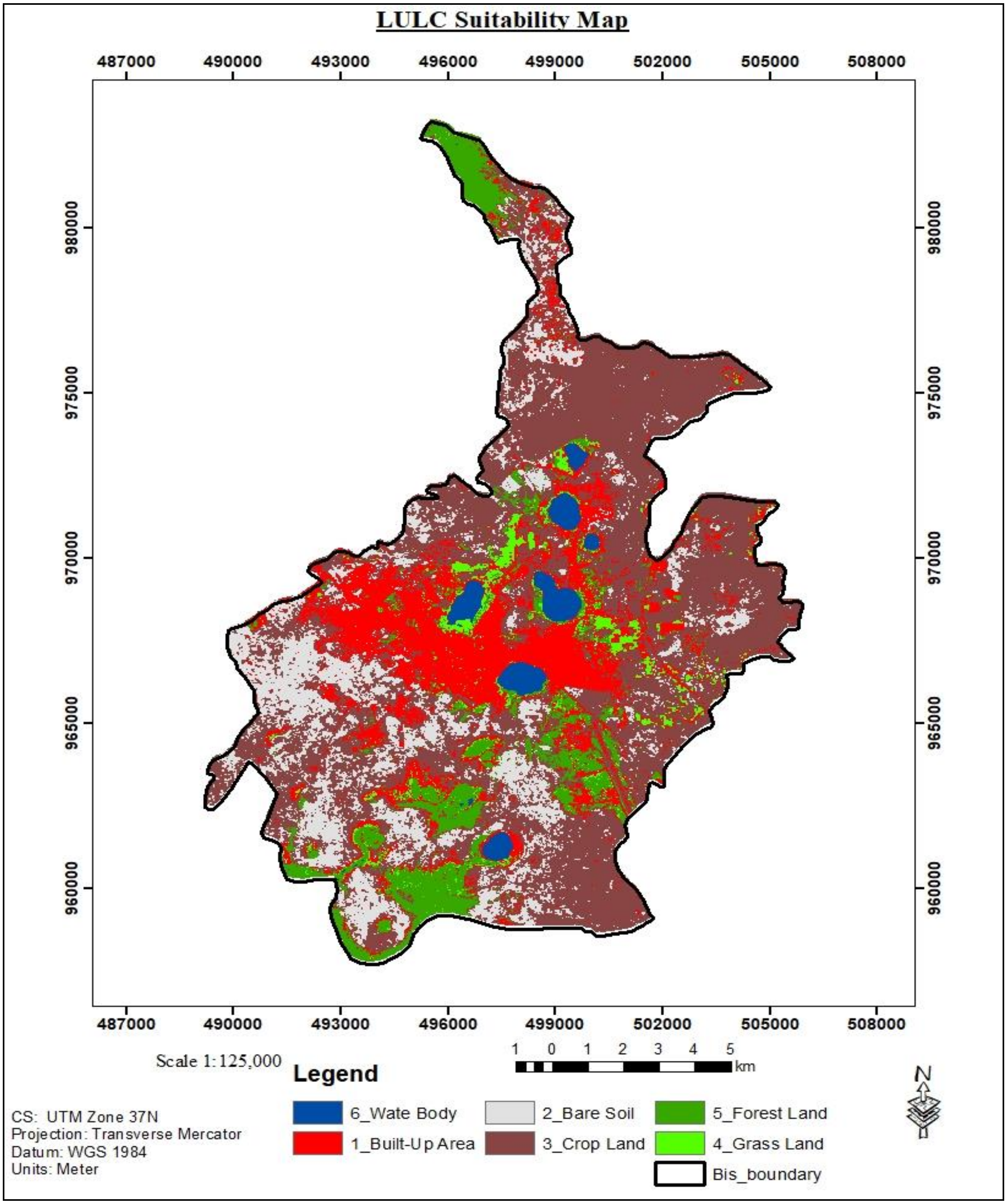
4.8.1. Transition Potential factor Development

Multi Layer Perceptron (MLP), an effective method for solving complex systems, was utilized to compute and map these potentials. The simulation outcome, as shown in the figures below, is more or less similar to the current situation, but this needs to be validated by accuracy assessment. The digital elevation model (DEM) was also obtained from the create spatial maps, such as slope. The data for transportation and road networks was from structural plan of the study area. ArcGIS was employed to find the distance from major roads using the Euclidean distance method. Figure shows the spatial parameters used for predicting theland use changes.



(a) (b) (c)

Figure 14:Spatial parameter map of Bishoftu. (a) Slope, (b) distance from road and (c) DEM



(d) Figure 4.15: Driver variables used for future prediction

4.8.2. Transition potential modeling

Potential for Transition Modeling demonstrates the potential for land to transform (Eastman, 2012). The transition potential maps are grouped within an empirically evaluated transition sub-model with the same underlying driver variables. For each transition, a transition potential map is created, which is an expression of the time-specific potential for change. Variables can be inserted as static or dynamic components to the model. Static variables represent fundamental features of fit for the transition under consideration and remain constant over time. Dynamic variables are time-dependent drivers, such as proximity to existing development or infrastructure, that are recalculated throughout the prediction process. Under data analysis, the Drivers/Factors evaluated are outlined in depth. Transform Potential Modeling is used to determine the ability of land to transition. A transition sub-model might be a single land cover transition or a series of transitions with the same underlying driver variables. The historical change process is modeled using these driver variables. Transitions A multilayer perceptron (MLP) neural network, logistic regression, or a similarity-weighted instance-based machine learning tool (SimWeight) are employed to model the submodel, however MLP was used in this study. However, because of its capability to transit multiple layers simultaneously, the researchers used a multilayer perceptron (MLP) neural network.

4.8.3. Influence of driver variable on urban growth

The sensitivity analysis found that, very high influential driver factor was distance from road.

DEM,Slope andLULC 2021 were classified as high, low and very low on the model respectively.

Table 4.8: relative importance of driving factors derived by forcing independent VC

Model	**Accuracy (%)**	**Skill measure**	**Influence order**
With all variables	100	1	N/A
Dist.from road	88	0.29	1 (most influential)
DEM	75	0.16	2
Slope	100	1	3
LULC_2021	57	0.19	4 (least influential)

*VC-Varriable Constatnt

4.9. Model prediction and validation

4.9.1.Markovian conditional probability land cover changes

Table 4.9 below illustrates the transition probabilities of features for being change.

Table 4.9: Markov probability of changing among land cover types

LULC Classes	Water body	Built-up area	Bare soil	Crop land	Forest land	Grass land
Water body	0.2000	0.2000	0.2000	0.2000	0.2000	0.0000
Built-up area	0.0013	0.1000	0.0954	0.0500	0.0030	0.9046
Bare soil	0.0070	0.0030	0.6276	0.0010	0.0006	0.3724
Crop land	0.2000	0.2010	0.2400	0.2000	0.2000	0.2000
Forest Land	0.0600	0.0203	0.1197	0.0000	0.0100	0.8803
Grass Land	0.0083	0.0190	0.0000	0.0000	0.2000	0.0021

4.9.1.1 Model validation

The accuracy assessment of image classification and simulation results is slightly different because in the latter case the accuracy is assessed by using the maps, not the specific points which are indicating the real category information (Rossiter, 2004). In many studies, kappa statistical measurements have been used for the accuracy assessment Pontius & Millones (2011). The aim was to observe the main changes between 2021classified and then comparing the results with the predicted map, to understand if the overall changes have been predicted correctly or not. The method used for the accuracy assessment, calculating kappa values related to the location and the quantity to observe the accuracy in each class.

The statistics given in the validation output allow the user to separate quantification error versus location error. Quantification error occurs when the quantity of cells of a category in one map is different than the quantity of cells of that category in the other map. Location error occurs where the location of a category in one map is different than the location of that category in the other map. Both the percent correct and the standard Kappa index of agreement confound these two types of errors. Thus, in addition to calculating the conventional standard Kappa index of agreement (KIA, also denoted Kstandard, in crosstab), Validate offers more statistics: Kappa for no information (Kno), Kappa for location (Klocation), Kappa for quantity (Kquantity), Value of perfect information of location (VPIL), and Value of perfect information of quantity (VPIQ). All of these statistics are linear functions of the nine points given in the validate output (Pontius, 2000). Based on the above proposed suggestions, a cross-tabulation matrix and validation was computed by comparing the actual and simulated land use map of 2021 as shown below.

Table 5.14: Cross tabulation of actual land cover and simulated land cover map of 2010

Caagories	KIA(When Actual land cover map was reference)	KIA(when simulated map was reference)
Water body	0.8527	0.8731
Built up Area	0.9951	0.9975
Bare Soil	0.4193	0.4583
Crop Land	0.5304	0.5274
Forest Land	0.6409	0.5851
Grass Land	0.4981	0.4883
Over all kappa 0.8887		

Kappa value < 0.2 is poor, 0.21-0.4 is fair, 0.41-0.6 is moderate, 0.61-0.8 is good and 0.81-1 is very good (Landis and Koch, 1977).Accordingly, the result of KIA was very good for overall kappa for built-up area and water body; good for forest; moderate for crop land, grass land and baresoil. This variation occurs due to the temporal variations of satellite data. The kappa coefficients of per category are showing high values from above results. This proves that the agreement between the two maps is almost perfect or perfect agreement (0.81-1).

K indicators	
K no	0.8889
K location	0.8974
K quantity	0.8895
K standard	0.8789

Moreover, in comparing the map of reality to the alternative map: Kno indicates the overall agreement; Klocation indicates the extent to which the two maps agree in terms of location of each category given the specified quantities; Kquantity indicates the extent to which the two maps agree in terms of quantity of each category given the specified locations. Accordingly, the overall kappa is 88.87%, Strength of Agreement for Kappa Statistic is almost perfect (Landis, 1977); so the model is acceptable and it can be used for the future simulation (2050).

Land Use Land Cover classes	Actual Map of 2021		simulated Map of 2021		Change	Change (%)
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Water body	369.71	1.95	413.61	2.18	43.9	0.23
Built up Area	9047.12	47.62	9623.7	50.65	576.58	3.03
Bare Soil	2533.30	13.33	2329.59	12.26	-203.71	-1.07
Crop Land	4339.61	22.84	4130.3	21.74	4108.56	-1.10
Forest Land	1038.06	5.46	1076.95	5.67	38.89	0.21
Grass Land	1670.90	8.79	1424.55	7.50	-246.35	-1.29
Total	18998.70	100.00	18998.70	100	0	0

4.9.2.Model prediction

The weights of the transitions that will be included in the Markov Chain matrix of probabilities for future prediction can be determined using CA-Markov chain analysis. The input images are land cover maps from 2010and 2021, with a time period of 11-year and 30-year time difference to project forward from the second image.

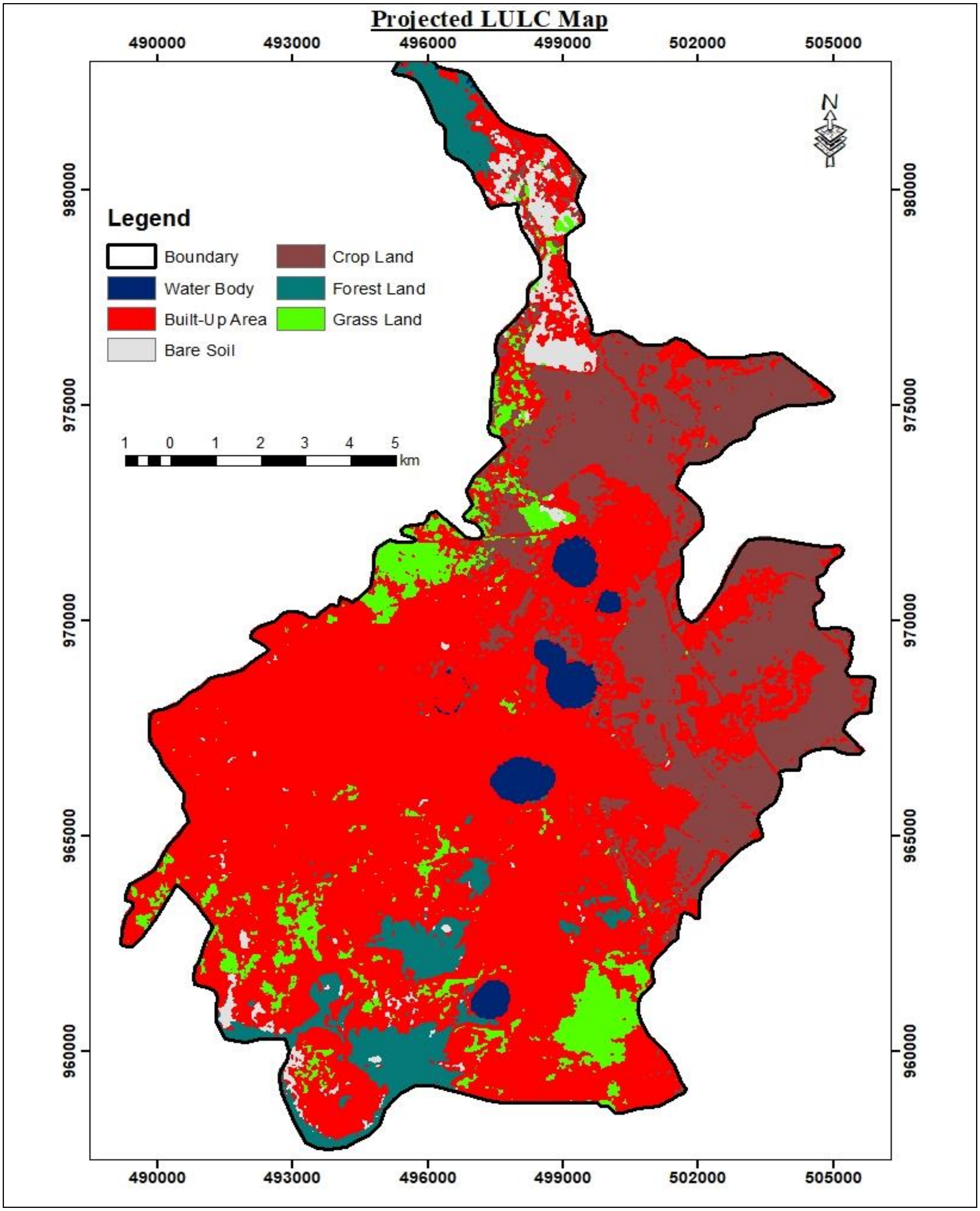


Figure 4.18: Predicted LULC Map of Bishoftu town (2050)

Table 4.10: Area percentages of actual and predicted map

Land Use Land Cover classes	Actual Map of 2021		Predicted Map of 2050		Change	Change (%)
	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Water body	369.71	1.95	431.83	2.27	62.12	0.32
Built up Area	9047.12	47.62	11395.12	59.98	2348.00	12.36
Bare Soil	2533.30	13.33	532.33	2.80	-2000.97	-10.53
Crop Land	4339.61	22.84	4260.30	22.42	-79.31	-0.42
Forest Land	1038.06	5.46	1076.95	5.67	38.89	0.21
Grass Land	1670.90	8.79	1302.16	6.85	-368.74	-1.94
Total	18998.70	100.00	18998.70	100	0	0

Table 4.12 shows the per category change in area between the two maps(actual and predicted map). In the most ideal case, the change in area should be 0. The more the deviation, the less sophisticated is the model. In terms of area, it is clear that, built-up area has increased 2348 ha which accounts 12.36% and water body in some extent shows 62.12ha (0.32%).Conversely,Bare soil, grassland and crop land shows a decremental trends for the period (2021-2050); 2000.97ha,368.74ha and 79.31 ha with value 10.53%,1.94% and 0.42% respectively. This occurs because of time variations, especially in case of land use applications this is difficult to manage due to uneven temporal availability of satellite data. So in this study there was a 29 year gap between the last actual image and the predicted one 2050.

4.10. Horizontal Urban Expansion

The extent and direction of the town expansion on the built-up area for the years 2000, 2010 and 2021 were analysed by superimposing the different time-series maps and by calculating the corresponding areas in a GIS environment. Accordingly, the horizontal expansion of the town was increased from 1811.78 ha in 2000,3501.98 ha in 2010 to 9047.12ha in 2021 which accounts

9.54%,18.43% and 47.62% respectively.moreover,the extent of the predicted map (2050) has also showed a horizontal expansion with value 11395.12ha (59.98%).Annual rate of urban area expansion (ARUE) for the periods 2000-2010, 2010-2021, 2000-2021 and 2021-2050 was calculated using the following (Mohan, 2011).

$$ARUE = \frac{UA_{i+n} - UA_i}{n * UA_i} * 100$$

where UA_{i+n} and UA_i are the urban area in ha at time i + n and i, respectively, and n is the interval of the calculating period (in years).

Therefore, the average annual rate of urban area expansion of Bishoftu town is 0.17% as illustrated in table 5.13 below.

Table 4.13: Annual rate of urban area expansion in Bishoftu town

Year	Area (ha.)	Annual Rate of Urban area Expansion			
		(2000-2010)	(2010-2021)	(2000-2021)	(2021-2050)
2000	1811.78	0.09			
2010	3501.98		0.16		
2021	9047.12			0.40	
2050	11395.12				0.03
				Average ARUE	0.17

*ARUE-Annual Rate of Urban area Expansion

5.11. Land Consumption Rate

According to (Fanan et al., 2011) suggested that, the land consumption rate (LCR), which was used as an index to evaluate the progressive spatial expansion of the study area, was determined using the following relationship.

$LCR = \frac{UA}{P}$ Where,UA is Urban Area in (ha) and P is the population of the town

Upon the computation,the average land consumption rate of the town is 4% as illustrated in table 4.14.

Table 4.14: Land Consumption Rate in Bishoftu town

Year	Area (ha.)	Population	Land consumption Rate			
			2000	2010	2021	2050
2000	1811.78	85624	0.021			
2010	3501.98	108329		0.032		
2021	9047.12	140309			0.064	
2050	11395.12	264766				0.043
					Average LCR	**0.040**

4.12. The impact of Urban expansion

The importance of the urban environment cannot be over emphasized because communities must develop and make progress irrespective of the fact that the impacts of settlement growth may be positive or negative on the urban environment.

4.12.1. The positive impact

The growth of the urban area has numerous benefits for the inhabitants of Bishoftu town and the outlying areas. These benefits include the emergence of new jobs, the expansion of infrastructure such as education, transportation, health, and power, and the improvement of communication services.

4.12.2.The negative impact

According to (Narimah, 2014) stated that, theimpact of urban urban expansion causes cities to be spreading into the countryside, transforms non built-up areas into built-up areas and creates remarkable changes on the physical landscape as well as on the socio-economic condition of the local community.

Similarly, in the ccase study area, the built-up area expansion has a number of detrimental effects on the surrounding physical and human ecosystems. Loss of agricultural land, relocation of people from their native land, environmental contamination, and an increase in crime and social problems are among the negative consequences of urban expansion in the study area.

From the Data analysis and LULC classification it was observed that growth of built-up area is radially outward from zero point. During the period of 2000 to 2021, growth seemed to be concentrated within existing built-up areas. There was vast expansion of new built-up area. Mostly in the period of 2000 to 2021, there were developments of new built-up areas in center and west area .

Urbanization in Bishoftu seems to have occurred in horizontal dimension. Factor behind development of built-up areas in urban fringes, suburbs and rural areas are low slope, land price and construction of new highway.

According to 2019 census population of Bishoftu City was 225,796, during the year 2021 population was expected to reach up to more than 300,000, with this increase in population, there is necessity of development of new built-up areas, commercial areas, service center and other infrastructure facilities. These newly developed built-up areas outside of core areas served attractive facilities for business opportunity and possess high commercial values. Whereas, residential areas within the nearest proximity of core cities, major roads changed from residential facilities to commercial or business facilities.

Land value played major role in urban sprawl development. Area near to zero point and major roads has highest land price. Thus cultivation and bare land in these areas were unevenly converted to built-up areas. Also, rapid population growths in the city, residential area were shifted towards outer reach of ring roads, due to land values for development of built-up areas, resulting in multi-directional development of urban growth.

4.13. Discussion

The aim of this study was to Spatio-Temporal Analysis and Modeling of Landuse Land Cover Change that have taken place in Bishoftu Town over a period of 29 years using Landsat Satellite Imagery and GIS based technique. The key findings of this study are as follows:

- The relationship between the LULC classes was identified and investigated and three thematic maps for year 2000, 2010 and 2021 were developed. Bishoftu.In the study periods covered, the major land use land cover classes of Bishoftu Town identified includes Crop, forest, barren land, built up areas and water.
- Significant buildings construction, construction of the construction of a highway were major drives of land use landcover changes over the study period from 2000 to 2021.This study showed a continuous decrease in agricultural lands in BishoftuTown.Consequently, the built-up area is increased.
- The remarkable changes of land use classes have occurred from 2010 to 2021, but the changes were not so significant during 2021 to 2050.
- The remote sensing and classifications of the Landsat satellite imagery can be used as economical and accurate way to produce accurate land use land cover change maps in the Međimurje County that can be used as inputs for regional analyses, formulating effective environmental policies and resource management decisions as useful up-to date information.

Among the most important driving forces that led to expand the town are population, biophysical and socio-economic determinants.Several related studies showed that,the magnitude of built-up areas has increased through time due to the above mentioned factors (Ilinca-Valentina et.al., 2020). This study also analyzed the effect of urban growth on the built up area that has resulted air pollution, environmental, social and cultural disturbance in the study area. This would have significant impact on the surrounding ecosystem such as loss of crop land, destruction of forestland, grassland and on the benefits generated from the land.according to (Wei Dai and Wenzhan Dai, 2019) stated that, the effect of LULCbrings about profound nature environmental impacts such as heated island, flooding, soil erosion, air pollution and biodiversity loss. Bishoftu town has shown rapid horizontal expansion at an average annual growth rate of 1.7% as shown clearly in table 5.13. Therfore, the annual rate of LULC in the town is 0.9%, 1.6%, 4% and 0.3% from 2000-2010, 2010-2021,2000-2021 and 2021-2050 respectively.The land consumption rate of the town is computed as the ratio of urban area in ha to the number of population.Accordingly,0.21%, 0.32%, 0.64% and 0.43% was computed for the periods 2000,2010,2021 and 2050 respectively. A total of six LULC feature class types were employed during the study periods and has also been comprehensively discussed to come up with a solution. To this end, Water bodies, bare soil, forest land, and grassland declined by 0.35 percent, 23.14 percent, 11.87 percent, and 7.36 percent, respectively, throughout the study period (2000–2021), however built-up areas and croplands increased by 38.08 percent and 4.63 percent, respectively. This is possibly due to agricultural expansion as a result of human population increment in the study site.

The finding of this research is consistent with other studies carried out in different parts of the country, for instance, Zeleke and Humi (38) in Dembecha area of northwest Ethiopia stated that 99% of the forest cover was transformed into farmland between 1957 and 1995. Similarly, Kindu et al. (39) in Munessa-Shashemene landscape of the Ethiopian highlands stated that almost 66.2% of woodland is converted to farmland. Many other local LULC studies also indicated similar trends 40]. Also, a study in Baro river basin in southwestern Ethiopia showed the conversion of forest land to nonforestland between 1984 and 2010 mainly by the expansion of farmland and settlement (38).

CONCLUSION AND RECOMMENDATION

Conclusions

Urbanization and population concentration in cities are rising exponentially, particularly in the developing countries. Changes in urban land use and land cover have a wide range of effects throughout all spatial and temporal aspects. As a result of these impacts and consequences, it has evolved as one of the most pressing concerns in terms of environmental change and natural resource management. To predict future developments, design decision-making processes, and build alternative scenarios, it is vital to understand the complex interaction of changes and their causes across space and time.

This research was carried out by integrating GIS, remote sensing, and spatial modeling technologies. Such approaches were used to detect and assess changes in land cover classes. In this study, satellite data from 2000, 2010, and 2021 were used, as well as remote sensing techniques, to generate land use land cover maps using a supervised classification algorithm. The accuracyasssesment and change detection processes have also been used.

Accordingly, the analysis for the period 2000 –2010 revealed that, crop land class, built-up areas and water body (in some extent) has been increased with values 32.18%, 8.89% and 0.26% respectively whereas classes such as bare soil,Grass Land and forest land were decreased by 19.87%, 13.59% and 7.87% respectively.

A similar analysis for the period 2010 –2021 conclude that, in the classification process, the magnitude of water bodies, bare soil, crop land, and forest land were declined by 0.61 %, 3.27 %, 27.55 %, and 4.00 % respectively. Conversely, the built-up area and grassland area have expanded by 29.19% and 6.23%, separately.

During the entire study period (2000–2021), Water bodies, bare soil, forest land, and grassland decreased by 0.35 %, 23.14 %, 11.87 %, and 7.36 %, respectively, however, built-up areas and croplands increased by 38.08 % and 4.63 %, respectively.

The study also discovered that accuracy assessment was also used to evaluate classification results in order to eliminate errors caused by satellite data capture and classification techniques.

Accordingly, the overall accuracy of the land use and land cover maps produced in this study was 86.59 %, which is greater than an acceptable standard (85%).

The study also revealed that, MARKOV chain modeling techniques was employed for LULC prediction by 2050. Accordingly, built-up area has shown increased by 2348 ha (12.36%) but, nun built up area has decreased with values 2000.97ha,368.74ha and 79.31 ha for Bare soil, grassland and crop land for the period (2021-2050) respectively.

The study conclude that, the average Annual rate of urban area expansion of the town for the entire periods was 1.7%.In addition to this, the average annual land consumption rate of the town was 0.4%. The study found that, the expansion of the town has resulted a negative and positive effects on the built-up area.

In general, the study found that, an integrated geospatial tool is critical for evaluating the effcts of long-term urban growth on the built up area.

Recommendations

The results of this specific study have shown that, geospatial tools are important for land use and land cover change studies. Therefore, based on the findings of this study, the following are recommended as future research directions:

- The use of high-resolution imagery, such as IKONOS and Quick Bird, is critical in producing high-quality landuse land cover maps. Because urban areas have complex and heterogeneous characteristics in nature. Moreover, including ancillary data as ground truth improves image classification accuracy.
- Incorporating socio-economic data, land policy, biophysical and human factors (population density, technology, political) could improve the performance of land use models for future predictions. Hence, it is important to the planners, decision makers and stakeholders for efficient utilization of land. It is high time for planner and policy makers to develop urbanization not only in horizontal dimension but in vertical dimension as well. Furthermore, implementation of building by laws and land use plans is highly recommended.
- Bishoftu City is facing major traffic congestion, sewerage disposal problem and many other environmental and socio economic problems, which cannot be solved without taking consideration of problems associated with urban growth.
- The town administrative of Bishoftu shuld utilize the integrated geospatial tools for the betterment of urban expansion management and sustainable development.

REFERENCE

1. AFRICOVER, 2002.AFRI Cover Land Cover Classification And Mapping Project
2. A. K. Tilahun, “Land use land cover change and its implication on surface runoff: a case study of Baro river basin in south western Ethiopia,” Journal of Environmental Earth Science
3. Anderson, J.R. (1976) A Land Use and Land Cover Classification System for Use with Remote Sensor Data. Vol. 964, US Government Printing Office, Washington DC.
4. Angel et al,2005The Dynamics of Global Urban Expansion.
5. Atalel Getu Sahalu .2014.ANALYSIS OF URBAN LAND USE AND LAND COVER CHANGES A Case Study in Bahir Dar, Ethiopia
6. Basudeb, 2011 Urban Growth Analysis and Remote Sensing
7. Bekalo, M. T. (2009). Spatial metrics and Landsat data for urban land use change detection: the case of Addis Ababa, Ethiopia
8. Bekalo, M. T. (2009). Spatial metrics and Landsat data for urban land use change detection: the case of Addis Ababa, Ethiopia.
9. B. Tegene, “Land-cover/land-use changes in the derekolli catchment of the South Welo zone of Amhara region, Ethiopia,” Eastern Africa Social Science Research
10. Campbell, J.B. and Wynne, R.H. (2011) Introduction to Remote Sensing Fifth Edition. The Guilford Press, New York.
11. Cernea, 1995The risks and reconstruction model for resettling displaced populationsDayong N. (2004). Several Acute Issues in China’s Urban Planning:
12. Diriba D., Hossein A. , Feyera S., Ketema A., Fatemeh T., Till S. “Urban sprawl and its impacts on land use change in Central Ethiopia.” Urban forestry and Urban Greening 16(C), 132-141, 2016.
13. Eastman, J.R. (2012). Assessing and Predicting Changes in the Status of Gambari Forest Reserve, Nigeria Using Remote Sensing and GIS Techniques
14. Fanan et al., 2011.Urban expansion and vegetal cover loss in and around Nigeria's Federal Capital City

15. Fekadu K. “The Rates and Effects of Urban Sprawl in Developing Countries: The Case of Addis Ababa, Ethiopia.” International Journal of Area Studies, 9(2), 2014.9758,iig,suitability,Bahirdar

16. Fichera R.C., Modica G., Pollino M. (2012) - Land Cover classification and change-detection analysis using multi-temporal remote sensed imagery and landscape metrics. European Journal of Remote Sensing, 45: 1-18. doi:

17. Getu, Kenu & Bhat, H Gangadhara, 2021.Analysis of spatio-temporal dynamics of urban sprawl and growth pattern using geospatial technologies and landscape metrics in Bahir Dar, Northwest Ethiopia

18. Gugler, 1996.The Urban-Rural Connection:Changing Issues Belong and Identification.

19. Haregeweyn, N., Fikadu, G., Tsunekawa, A., Tsubo, M., & Meshesha, D. T. (2012). The dynamics of urban expansion and its impacts on land use/land cover change and small-scale farmers living near the urban fringe: A case study of Bahir Dar, Ethiopia. Landscape and urban planning

20. Ilinca-Valentina Stoica , Marina Vîrghileanu , Daniela Zamfir , Bogdan-Andrei Mihai and Ionuț Săvulescu, (2020). Comparative Assessment of the Built-Up Area Expansion Based on Corine Land Cover and Landsat Datasets: A Case Study of a Post-Socialist City.

21. Jensen J.R., Cowen D.C. (2003) - Remote sensing of urban/suburban infrastructure and socio-economic attributes. Photogrammetric Engineering and Remote Sensing.

22. Lambin, E. F. (2004). Dynamic Causal Patterns of Desertification. Bioscience

23. Lu, D. and Weng, Q. (2007) A Survey of Image Classification Methods and Techniques for Improving Classification Performance. International journal of Remote Sensing

24. Lv, Z. W. (2011). Monitoring of the urban sprawl using geoprocessing tools in the Shenzhen Municipality, China. Environmental Earth Sciences, 62, 1131–1141.

25. Maguire, D.J. (1991) An Overview and Definition of GIS. In: Maguire, D.J., Goodchild, M.F. and Rhind, D.W., Eds., Geographical Information Systems: Principles and Applications, Wiley, Hoboken

26. M. Kindu, T. Schneider, D. Teketay, and T. Knoke, “Land use/land cover change analysis using object-based classification approach in Munessa-Shashemene landscape of the Ethiopian highlands.

27. Narimah Samat, (2014). Urban expansion and its impact on local communities: A case study of Seberang Perai, Penang, Malaysia.

28. Newbold, K.B., and Scott, D. (2013). Migration, commuting distance, and urban

29. Nugusa Duressa Geleta [2020]Modeling Spatial and Temporal Urban Growth Patterns and trends by using Geospatial technologies: The Case of Modjo Town

30. Oromia Urban Planning Institute History of Bishoftu City Report

31. Pielke RA, Sr., Pitman A, Niyogi D, Mahmood R, McAlpine C, Hossain F, et al. Land use/land coverchanges and climate: modeling analysis and observational evidence. Wires Clim Change.2011

32. Pontius, R.G. (2002) Statistical Methods to Partition Effects of Quantity and Location during Comparison of Categorical Maps at Multiple Resolutions. Photogrammetric Engineering & Remote Sensing

33. Qian J, Zhou Q, Hou Q. Comparison of pixel-based and object-oriented classification methods for extracting built-up areas in arid zone. InISPRS workshop on updating Geo-spatial databases with imagery & the 5th ISPRS workshop on DMGISs. 2007;

34. Quentin FB, Jim C, Julia C, Carole H, Andrew S. Drivers of land use change, Final report: Matching opportunities to motivations, ESAI project 05116, Department of Sustainability and Environment and primary industries, Royal Melbourne Institute of Technology.2006

35. Regassa, B., Kassaw, M., & Bagyaraj, M. (2020). Analysis of Urban Expansion and Modeling of LULC Changes Using Geospatial Techniques: The Case of Adama City.

36. Rogan J., Chen D. (2004) - Remote sensing technology for mapping and monitoring land-cover and land-use change. Progress in Planning, 61 (4): 301-325. Doi

37. Sankhala et al., 2014 Evaluation of Urban Sprawl and Land use Land cover Change using Remote Sensing and GIS Techniques : A

38. T. Gashaw, T. Tulu, M. Argaw, and A. W. Worqlul, “Evaluation and prediction of land use/land cover changes in the Andassa watershed, Blue Nile Basin, Ethiopia,” Environmental Systems Research.

39. UN. 2005. The Millenium Development Goals Report,United Nations. New York

40. Wu and Webster 2000; Chang, 2006Cellular Automata Modeling for Urban and Regional Planning Urban Informatics .

41. Yang L., Xian G., Klaver J.M., Deal B. (2003) - Urban land-cover change detection through sub-pixel imperviousness mapping using remotely sensed data.

42. Zewdu A. “Analysis of Urban Growth and Sprawl mapping using Remote Sensing and Geographic Information System: A Case study of Debre Birhan town, Ethiopia.” Master thesis, Addis Ababa University, 2011.

43. Nguyen T.A 2019.Geotechnics for Sustainable Infrastructure Development edited

44. Gugler, 1996. Introduction: The Urban-Rural Connection: Changing Issues of Belonging and Identification

45. Angel et al,2005. The Dynamics of Global Urban Expansion

46. Cernea, 1995. The risks and reconstruction model for resettling displaced population

47. Eastman, 2006. IDRISI Andes Guide to GIS and Image Processing, Worcester, Clark Labs.

48. Silva and Clarke 2002. Calibration of the SLEUTH urban growth model for Lisbon and Porto, Portugal

APPENDEX

Appendex_1: Bishoftu city population growth history (1967-2019 G.C)

S/N	Year	Number of People			Av. Annual Growth Rate	
		Male	Female	Total	Duration	Percent
1	1967	9,090	12,130	21,220	1967-70	8.9
2	1970(Oct.)	12,730	15,017	27,747	1970-84	5
3	1984(May)	25,764	29,891	55,655	1984-94	2.8
4	1994(Oct.)	35,058	38,314	73,372	1994-2007	2.4
5	2007(may)	47,860	52,068	99,928	2007-2009	3.3
6	2009(OUPI)	51,282	55,555	106,837	2009-2015	8.2
7	2015*	69803	77261	174,710	2015-2017	8.2
8	2017	100,899	104,958	205,858	2017-2019	5.5 average
9	2019 (March)	113,794	112,140	225,796	1967-2019	
Source:CSA reports, OUPI, Bishoftu city profile, 2019						

Appendex_2: Bishoftu Town Population Growth Projection for the year 2050

The population growth rate is indicated by using the following formula:

$$PG_{rate} = \frac{a_2 - a_1}{a_1} * 100\%$$

Where, PG rate =percentage of population growth rate per annum

a_1= Base year population

a_2 = Latest year population

Therefore, Population growth trend in Bishoftu town is 2.38%

Based on the growth rate, one can compute the population number of each year. For example, to calculate the number of population for year three (3), simply apply the following equation.

$$P_f = P_0 \left(1 + \frac{R}{100}\right)$$

year	Projected population	Rate =0.0238* projected population
2000	**85624**	**2042**
2001	87666	2086
2002	89752	2136
2003	91888	2186
2004	94074	2238
2005	96312	2292
2006	98604	2346
2007	100950	2402
2008	103352	2459
2009	105811	2518

2010	**108329**	**2578**
2011	110907	2639
2012	113546	2702
2013	116248	2766
2014	119014	2832
2015	121846	2899
2016	124745	2968
2017	127713	3039
2018	130752	3111
2019	133863	3185
2020	137048	3261
2021	**140309**	**3339**
2022	143648	3418
2023	147066	3500
2024	150566	3583
2025	154149	3668
2026	157817	3756
2027	161573	3845
2028	165418	3936
2029	169354	4030
2030	173384	4126
2031	177510	4224

2032	181734	4325
2033	186059	4428
2035	190487	4533
2036	195020	4641
2037	199661	4751
2038	204412	4865
2039	209277	4980
2040	214257	5099
2041	219356	5220
2042	224576	5344
2043	229920	5472
2044	235392	5602
2045	240994	5735
2046	246729	5872
2047	252601	6011
2049	258612	6154
2050	**264766**	**6301**

Appendex_3: Sample of GCP collected by Diferential GPS.

NO	X	Y
1	496067	969118
2	495060	968933
3	493852	969076
4	492251	969025
5	492948	968087
6	493687	968215
7	494858	968088
8	495838	968099
9	494832	967088
10	493851	966745
11	495695	967173
12	494753	968643
13	483454	969064
14	495497	967797
15	495200	967169

Appendex_3: Bishoftu Town Structural Plan