ADDIS ABABA UNIVERSITY

ADDIS ABABA INSTITUTE OF TECHNOLOGY

SCHOOL OF CIVIL AND ENVIRONMENTAL ENGINEERING

MODELING SPATIO-TEMPORAL URBAN LAND USE CHANGES: A CASE OF BURAYU TOWN USING REMOTE SENSING AND GIS TECHNIQUES.

A THESIS SUBMITTED TO GRADUATE STUDIES OF ADDIS ABABA INSTITUTE OF TECHNOLOGY IN PARTIAL FULFILMENT OF THE REQUIREMENT FOR THE DEGREE OF MASTERS OF SCIENCE IN GEODESY AND GEOMATICS ENGINEERING (SPECIALIZATION IN GEOMATICS ENGINEERING).

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BY

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CANDIDATE’S DECLARATION

I declare that the work which is being presented in the thesis entitled “Modeling Spatio-temporal Urban Land use Changes: a case of Burayu Town using Remote sensing and GIS Techniques ” Submitted to Addis Ababa Institute of Technology, School of Civil and Environmental Engineering in partial fulfillments of the requirements for the award of the degree of Master of Science in Geomatics Engineering is entirely my own work carried out from April to October,2019 under supervision of Dr. Dani’el Alemayehu (Advisor) from Adama Science and Technology university, school of civil and Architecture Engineering lecturer.

All references, including citation of published and unpublished sources have been appropriately acknowledged in the work. I further declare that the work has not been submitted for the purpose of academic examination, either in its original or similar form, anywhere else.

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As Master research advisors, we hereby certify that we have read and evaluated this MSc Research prepared under our guidance by me, entitled.

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ABSTRACT

Urbanization is the most powerful and visible force that has fundamental changes Land Use Land Cover around globe. High population increment leads to a quick expansion of urban growth, causing changes in Land use Land Cover in many urban areas especially in developing countries. Burayu Town population growth rapidly increased by 90 times within the past 35 (1984-2019) years and expansion of squatter houses is increased. The main objectives of this study is that integrating GIS, Remote sensing and Land use Land cover Modeling tools to Model Spatio temporal Urban Land use Changes of Burayu Town using Landsat of 1990,2000,2010 and 2019 year for the last three decades (1990-2019) and predict for future three decades (2050). For this study using supervised classification method, Maximum likely hood algorithm, the overall accuracy of Classified Burayu Town Land use for 1990,2000,2010 and 2019 is 88%, 92%, 93.6% and 97.6% and respectively and it is acceptable.

This study results show Urban land use land cover changes (urban expansion) of Burayu Town area highly increased from 100 Ha (1%) to 4600Ha (46%) in last three decades (1990-2019) and for future three decades 5800Ha (58%) in 2050 if Urban expansion is positive effect, and if negative effect urban expansion is greater than this value is expected. Land Change Modeler and Multi-Layer perceptron sub model used for modeling using Factors and constraints and validating kappa statistic is moderate and acceptable to predict for future (2050). Now a days Burayu Town Urban Planners and policy makers lacks accurate, timely and scientific method of urban land use land cover changes and no scientific site selection for Housing development, for monitoring and resolving the negative consequences, and make decision concerning Land Resource management for better Land use management and Environmental development.

Burayu Town Urban planner, Land Administration offices and Environmental protection offices use this basic information of urban Land use Land Cover changes and use scientifically site selected for Housing development to solve the society problems and avoid risks. Federal and Regional Government should give attention for the main problems of housing, infrastructure services and losses of Agriculture Land by modifying Land policy and giving Land for housing. Therefore modeling spatio temporal urban Land use Changes and predict for future is very important for Burayu Town.

KEY WORDS: urbanization, Burayu Town, Urban Land use Land cover Change, Land satellites, decades, hectare (Ha), Population.

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LIST OF ACRONYMS/ ABBREVIATION

CA-MARKOV-Cellular Automata Markov Model

CSA- Central Statistical Agency

DEM - Digital Elevation Model

ERDAS -Earth Resources Data Analysis System

ETM+ -Enhanced Thematic Mapper /plus

ETM-Earth Trends Modeler

FAO- Food and Agriculture Organization

GCP- Ground Control Points

GIS - Geographical Information System

GPS- Geographic Positioning System

KIA-kappa Index Agreement

LCM - Land Change Modeler

LPGS- Level Product System

LULCC- Land Use and Land Cover Change

LULC- Land Use and Land Cover

MCE - Multi Criteria Evaluation

MLP - Multi Layer Perceptron

MODIS-Moderate Resolution Imaging Spectrometer

MOSAIC -Multimodality Operational Site Analysis and Intelligent Change-detection.

MSS- Multi Spectral Scanner

MUDC- Ministry of Urban Development and Construction

NDVI -Normalized Difference Vegetation Index

ONRS- Oromiya National Regional State

OLI-Operational Land Imager

RMSE- Root Mean Square Error

ROC -Relative Operating Characteristic

SPOT- Système Pour l'Observation de la Terre (French)

TM -Thematic Mapper

TIRS- Thermal Infrared Sensor

UN- United Nations

UTM -Universal Trans Mercator

WGS -World Geodetic System

CHAPTER ONE: INTRODUCTION

1.1 Background

Urbanization is the most powerful and visible force that has fundamental impact on the Land Use Land Cover Change around the globe. High population increment leads to a quick expansion of urban growth, causing changes in land use land cover in many urban areas of developing countries (Barros, 2004). According to United Nation in 2011, 3.6 billion of the world's populations (52%) were urban dwellers. Universal level of Urbanization expected to rise 67% in 2050.

In Africa alone the urban population is expected to triple from 414 million in 2011 to 1.2 billion in 2050 (Barros, 2004). African urbanization characterized by rapid and uncontrolled urban growth. This has brought various socio-economic and environmental problems such as urban poverty, food insecurity, shortage of housing and basic services, unemployment, ethnic tensions and violence, substance abuse, crime and social disintegrations. The current urbanization process that is taking place in developing countries indicates that this process needs considerable attention not only as a bases for transformation of societies in the developing countries but also for sustainable development. Natural 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 (Gugler, 2004).

Ethiopia has one of the fastest growing urban populations and least urbanized countries in the world. (MUDC, 2011). Burayu Town is one of the first grade and the fastest growing Towns in Oromiya National Regional State established in August 2006 (MUDC, 2011). The population of Burayu Town was 4,138 in 1984 and has grown to 375,000 in 2019 (estimated), showing that the population of the Town has increased by more than 90 doublings within the past 35 years (Burayu Town Communication offices, 2019).

In this study area there is no research similar to this title but related paper that try to indicate urban land use changes (Urban expansion) of the Town such as Masresha Taye (2013) show the urban land use changes (urban expansion) in Burayu Town for four decades (1960-2000). Masresha use 372 households (sample data) interviewed with different sets of the community and experts at municipalities in all kebele of Towns and make statistical results. Based on these samples before 1960 there were 20 house (4.0%), to 26 House (7.4%) in 1960-1970 to 28 House (8.5%) in 1970-1980 to 102 House (27.4%) in 1980-1990 to 196 House (52.7%) in 1990-2000 years. He simply show Burayu Town urban was expanded because of House number are increased, but he doesn't use Remote sensing and GIS techniques to show the changes rates and area, no change result and map that show Burayu Town Land Use Land Cover Changes for last four decades and as well as no prediction for future. But this study use remote sensing and GIS techniques to model spatio temporal urban land use changes for the last three decades (1990-2019).

Degu Bekele paper (2014) urban environment and squatting a case of Burayu Town, from 424 Residential House 325 (58.1%) of House are located in sensitive areas. These environmentally sensitive areas usually include high tension electric lines, river sides, industrial areas, solid waste disposal site, flood and hilly areas, near water reservoirs, areas prone to landslides and flooding, protected forests and other susceptible areas. Burayu town also has most of these and other environmentally sensitive areas. 36.2 per cent of the sample squatter houses are located in the buffer areas of river, 16.7 per cent of the sample squatter houses are located in the buffer areas of high tension electric line and 21.5 per cent are located around different solid waste disposal sites. The squatter houses which are located in different industrial zones of the town, adjacent or around hilly and flood areas are 12.2 per cent, 9.8 per cent and 3.6 per cent respectively. The two related paper use sample data by interview techniques and not used GIS and Remote sensing techniques.

Remote Sensing, and GIS 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, transportation planning, environmental planning, urban expansion change analysis and modeling.

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 land, displacement of farm communities, solid waste disposal and land degradation, enclosing surrounding rural land to urban territory, over exploitation of natural resources and conflict (Alexander, 2015). Urban land use and land cover change has been recognized as an important driver of environmental change on all spatial and temporal scales as well as emerging as a key environmental issue and on a regional scale is one of the major research endeavors in global change studies. These changes encompass the greatest environmental concerns of human populations today, including climate change, biodiversity loss and the pollution of water, soils and air (Adepoju, 2015).

Rapid Urban land use land cover changes and High population increment in case of Migration from Rural to Urban are growing steadily specially in the developing countries especially in Burayu Town became the main problems that need great attention from government and socities. Urban Land use and land cover changes have wide range of consequences at all spatial and temporal scales. This study has been conducted by integrating GIS, remote sensing and Land use land cover modeling tools to Model Spatio temporal urban land use land cover changes of Burayu Town using Land satellites 1990, 2000, 2010, and 2019 Year and predict for future three decades (2050).

1.2 Problem Statement

Location is one of the most important aspects which determine Population growth and housing value. Burayu Town population growth rapidly increased by 90 times within 35 years from the population size of 4,138 in 1984 to more than 375,000 in 2019), and still many people want to have their residence in this Town this is due to its located close proximity to Finfinne (Addis Ababa), city. This kind of increasing and over population pressure is putting impacts like converting Agriculture Land, Forest Land and Shrub Land to urban Land (Built-up areas) through legal and illegal. Nowadays vast area of Burayu Town and Farmland occupied by many Industries which consume more Land and Squatter settlements. These problems became the main conflicts and influence societies to construct the House in sensitive areas and live in squatter settlement to survive. (Efa, 2017). According to the estimate of the Burayu Town administration (2012), the total number of residential houses in the Town are 23,043 of which 12,572 (54.6 per cent) are informally developed houses. To address the problems related to these, Burayu Town Administration has been taking curative actions including demolishing of squatter settlements and regularizing significant number of houses in different years. These efforts have achieved little in terms of addressing the problems. Now a days Burayu Town Urban Planners and policy makers lacks accurate, timely and scientific method of urban land use land cover changes and no scientific site selection for Housing development for monitoring and resolving the negative consequences, and make decision concerning Land resource management for better Land use management and Environmental development. Therefore, Modeling Spatio temporal urban land use land cover changes and predict for future is important for Burayu Town.

1.3 Objectives

The general objective of the study is to model urban land use land cover changes and identify suitable site for new housing development (expansion) using Remote sensing and GIS techniques.

Specific Objectives

1. To generate urban land use Maps of Burayu Town for 1990, 2000, 2010 and 2019 years.
2. To quantify Urban Land use land cover changes from 1990 to 2019.
3. To identify the factors and constraints for site suitability of new housing development.
4. To conduct site suitability analysis for Housing expansion in the Town.
5. To predict projected Land use land cover classes of Burayu Town in 2050.

1.4 Research Questions

1. What are the extents and rates of urban land use changes of Burayu Town from 1990 to 2019 year?
2. What are the factors and constraints that affect the site suitability of new housing development?
3. Which sites of Burayu Town are suitable for housing expansion?
4. What is the extents of Burayu Town Urban land use land cover classes in year 2050?

1.5 Significance

Modeling and prediction of future LULC is a latest research, growing rapidly in scientific field which is very much useful to the urban planning and Urban Land resources management in forecasting where and how urban land use land cover changes.

Monitoring and analysis of changes in LULC are needed in order to provide information on existing land use patterns and changes for decision makers to support sustainable development (Fan, 2007). LULCC models are used to improve and/or better understand of the alteration of land use that is induced by human activities (Brown, 2004).

Modeling accurate, timely and cost effective spatio temporal urban land use and land cover changes of the year 1990,2000,2010 and 2019 is highly required to Burayu Town urban planners and development office, land administration and management office, environmental protection office, and policy makers, to make decision concerning land resource management and conflict resolution related to land, for better land use management and environmental development, for monitoring the negative consequences and increases the benefits, and for estimating rates of deforestation, loss of agricultural land, and urbanization of the Town and predict for future in 2050 year using Remote Sensing and GIS.

1.6 Scope

This research conduct and model Spatio temporal urban land use land cover changes of Burayu Town for the last three decades (1990- 2019) and predict for three decades (2050) using Remote sensing, and GIS.

1.7 Limitations and Assumption

The study of Modeling Spatiotemporal Urban land use changes using Medium Resolution Landsat is used and the overall accuracy for classified images are above 85%, in my assumption using High Spatial resolution Satellite image such as Quick bird, IKONOS, Geo Eye, World view, SPOT, and Pleiades will provides better and detail information with good quality to map Land use land cover classes and overall accuracy may greater than the value obtained. For this study Landsat image of the same seasons that clearly seen in December and January select for this kind of research, but in my assumption it is best if all land satellites image are in one month with the same time. For Accuracy Assessment Validation of 1990, 2000 and 2010 it is not possible to visit the field to find out the actual Land use Land cover classes because of historical map, Ortho photo map and Aerial photo were not exist in study area, so the Google earth pro is used and the result of overall accuracy increase from 1990 to 2019 because of Google earth version and visualization increased.. The other limitation of this study is that while site of Housing selected five factors and constraints are used but more than this Factors and constraints including socio economic data and soil laboratory, the most accurate and the best places are selected.

1.8 Structure of the Thesis

The Thesis is structured into five different sections. The first chapters deals introductions, problem statement, objectives, research questions, significance, Scope and limitation of the study. The second chapter deals theoretical literature review of urban land use changes, land use change models, tools used for land use and land cover change, image classification, change detection methods and accuracy assessments of land cover maps generated. The third chapter deals description of study area, materials used, data sources and methods, data analysis, Transition potential modeling, suitability analysis and future prediction. The fourth chapter deals data analysis, results and discussions. The quantified results from image classification and land use change modeling, change detection and accuracy assessments, change analysis, spatial trends and Validation of the simulated land cover maps has been done for comparison of model performance. The Fifth chapter deals conclusions and recommendations i.e. Key findings and critical points that need further treatment has been forwarded as a recommendation for future work.

CHAPTER TWO: REVIEW LITERATURE

2.1 INTRODUCTION

The earth's surface has been changed considerably over the past decades by humans because of urbanization, deforestation and agriculture. Even though the conversion of land to agriculture and deforestation rates vary across the world, the number of people residing in cities has been increasing continuously. Expansion of settlements and burgeoning are among the challenges posed by rapid rate of urbanization especially in developing countries. Urban growth has increasingly significant socioeconomic and environmental impacts at local, regional and global scales (Meysam, 2002).

2.2 Theoretical frameworks of urban land use land cover change

2.2.1 Land use land cover (LULC)

The terms 'land use' and 'land cover' are sometimes used interchangeably, each has a distinct meaning. Land cover is the bio-physical layer covering the earth surface, while land use represents the human utilization of the land cover. Land cover includes earth's land surface distribution of vegetation, water, desert and ice as well as the biota, soil, topography. Land use is attributed to how humans exploit the land cover to serve their own purposes and includes features such as residential zones, agricultural farms, logging areas etc (Zubair, 2006; Oumer, 2009).

2.2.2 Land use land cover change (LULCC)

Land Use Land Cover change can be defined as the modification of surface features on earth's landscape which is realized by the difference in their surface appearance assessed at two different times (Ayele, 2011).

2.2.3 2.2.3 Drivers of Land use Land cover Change

LULC change involves a conversion from one LULC to another or intensification of the present or current LULC (Turner et al., 1994). LULC change can be modelled as a function of socio-economic and environmental factors. These factors are often referred to as ‘driving factors’. The driving factors of LULC change are categorized as proximate factors are direct modifications by individuals at a local scale such as individual farms and underlying factors, are indirect changes which occur at a regional scale (Lambin and Geist, 2007).

2.2.3.1 Proximate driving factors

The proximate driving factors are usually caused by human activities such as infrastructure (Transport, Market Infrastructure and Settlement (urban) Expansion) and agriculture expansion (Permanent Cultivation, Resettlement and Cattle Ranching). (Lambin et al., 2001).

2.2.3.2 Underlying factors

The underlying factors are caused by complex interactions between social, political, demographic and environmental variables. The underlying driving factors such as policy and institution factors includes: Formal Policies on land, taxation, economic development, population e.g. migration), Informal Policies (Corruption, mismanagement, Demographic factors includes: Natural Increment (Fertility, Mortality), Population Density

Population Growth, Population Distribution and Migration, Economic factors includes: Economic Structures (Poverty, unemployment, poor living conditions, Economic Crisis, Foreign Debts), Market Growth (Growth of demand for consumer goods),Technological factors include: Agro-technological change (Land use intensification, land use extensification), Agricultural Production Factors (land scarcity and labour shortages),and cultural factors such as Public attitudes values and beliefs (dominance of other public attitudes, modernization, unconcern about welfare of others), Individual and household behavior (Lambin et al. (2001).

2.2.4 Urbanization and classification of urban areas

The urbanization and urban growth have accelerated worldwide. Within two decades, the population of cities has doubled or even tripled. At the beginning of the nineteenth century, only about 3 percent of the world's population lived in urban places (Lug hood and Hay, 1977).

This continuous urban growth, particularly in developing country cities, is neither anticipated nor strategically planned for. Therefore, the cities face high risks and problems, which result in a conflict between their environmental resource base and development needs. Ultimately neither the human population nor the environmental resource base escapes the detrimental effects of unsustainable resource consumption and degradation. The current rates of urbanization in Africa, exceeding 4 to 5 % per annum in most countries, are close to those of western cities at the end of the nineteenth century (Cope, 1995). Rapid urbanization without economic growth, increase in slums and the lack of basic criteria amenities leading to adverse living condition and rapid urbanization call for decisive and effective planning, polices and large scale investments. Without investment in a region where only 13% of roads are paved and less than 3% of the populations have access to telephone or mobile phone, cities may just remain mega –villages offering no comparative advantage for private investment to pioneer and for production to increase and bring the promises of economic growth and development. Assertive pro-poor polices, sustained by effective and transport governance and involving the community should also be backbone structure for the development of sustainable urban center (Cope, 1995).

Thus, the current urbanization process that is taking place in developing countries indicates that this process needs considerable attention not only as a bases for transformation of societies in the developing countries but also for sustainable development. The expectation with the growth of cities and their expansion is to be followed by economic growth and development which acts as a deriving forces in the social transformation and improvement of not only in urban areas but the greater rural hinterland served by the urbanized region. However, experiences of developing countries show that rate of urbanization is not accompanied with expected socio-economic transformation. This also resulted in problems of urban infrastructure in cities of developing countries particularly the most vulnerable areas of recent urban expansion and settlement of the urban poor(Lwasa, 2004).

2.2.5 Factors of urbanization

Generally, the causes of urbanization are group into three major classes.

1. **Demographic effects** include 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. Natural 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 (Gugler, 1996).
2. **Economic effects** include the level of economic development, difference in household incomes, exposure to globalization, the level of foreign direct investment, the degree of employment, the level finance markets, the level and effectiveness of property taxation and the presence of high inflation and acute shortage of housing (Angel et al 2005).
3. **Natural /environment effect** 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 (Cernea, 1995).

2.2.6 Forms of Urban Expansion

Urban expansion takes place in different forms. The two major forms of urban expansion are:

1. **Positive effects (orderly)** form of urban expansion properly laid such as center of market area, center for production and distribution of goods and services, an opportunity for access to employment, economic development, full facilities, and technology development.
2. **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, over exploitation of natural resources and conflict.

2.2.7 Consequences of the negative effects of Urban Expansion

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 land, displacement of farm communities, solid waste disposal and land degradation, enclosing surrounding rural land to urban territory, over exploitation of natural resources and conflict (Alexander, 1995; Rosenfeld, 1994)

2.2.8 Digital Image Processing

The most of the common digital image processing categorized into the following four categories. Pre-processing operations, sometimes referred to as image restoration and rectification, are intended to correct for sensor Platform-specific radiometric and geometric distortions of data. Radiometric distortion due to variations in scene illumination and viewing geometry, atmospheric conditions, and sensor noise and response. The geometric distortions due to perspective of the sensor optics, the motion of the scanning system, the motion of the platform, the platform altitude, attitude, and velocity, the terrain relief and, the curvature and rotation of the Earth. Geometrically correcting the original distorted image, a procedure called resampling is used to determine the digital values to place in the new pixel locations of the corrected output image.

Image enhancement is the process of making an image more interpretable for a particular application. The most common are: Radiometric Enhancement used for adjusting the brightness values of image. Spatial enhancement used for adjusting the quality of image and deriving new information using spatial operation. Spectral enhancement used for image transformation techniques working with multispectral image. Pan sharpening (Resolution merge) used for increasing the resolution of colors image using higher resolution panchromatic image.

Image transformations one widely used image transform is the Normalized Difference Vegetation Index (NDVI) which has been used to monitor vegetation conditions on continental and global scales using the Advanced Very High Resolution Radiometer (AVHRR) sensor. Image transformation techniques used to reduce data redundancy and correlation between bands called principal components analysis

2.2.9 Image Classification Techniques

Pixel based classification is the traditional method of image classification and mainly based on the pixel reflectance values of the images (Wang, 2004). Mainly two kinds of pixel based classification supervised and unsupervised (Caetano, 2009).

2.2.10 Accuracy Assessment

Accuracy Assessment is a kind of process to compare the classification with ground truth or other data. Reference pixels are points on the classified image. Each point of reference pixels represents specific geographic coordinate of the image. These reference pixels are randomly selected (Congalton, R., 1991). The randomly selected points within the classified image list two sets of class. The first set of class values represents the actual land cover type. The second set of class values are known as reference values. An error matrix is a square assortment of numbers defined in rows and columns that represent the number of sample units assigned to a particular category relative to the actual category as confirmed on the ground. The rows in the matrix represent the remote sensing derived land use map, while the columns represent the reference data that will be collect from fieldwork. The error matrix tables produce many statistical measures of thematic accuracy including overall classification accuracy, percentage of omission and commission error and kappa coefficient that estimates in the influence of chance (Congalton and Green, 1999).

2.2.11 Change detection.

Change detection is the process of identifying differences in the state of object or phenomena by observing them at different times by using remote sensing techniques (Singh, 1989).

2.2.12 Change Detection Techniques

The change detection methods like; image differencing, image rationing, image regression, and vegetation index differencing. Techniques of change analysis are different depending upon whether pairwise (simple change) or multiple (time series) comparisons are being made.

2.2.13 Types of Modeling

Land Use Land Cover Change (LUCC) modeling is a rapidly growing scientific field because land use change is one of the most important ways that humans influence the environment (LUCC 2002). Modeling means the process of creating a representation of reality; it could be a map, graph, picture, or mathematical representation. Land use land cover changes modeling defined as the process of creating maps based on the history of Land use land cover, existing information and assumptions of the future. Modeling land use land cover plays a significant role to understand 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 (Eastman, 2006). It is difficult to compare the performance of the numerous models because LUCC models can be fundamentally different in a variety of ways. For example, some models, such as IDRISI's GEOMOD, simulate change between two land categories (Silva and Clarke 2002) while others, such as IDRISI's CA_MARKOV, can simulate change among several categories (Pontius and Malanson 2005). However, it is difficult to compare which one gives more accurate representation (Wu and Webster 2000; Chang, 2006).

2.2.13.1 Land change Modeler (LCM)

The Land Change Modeler (LCM) for Ecological Sustainability is an integrated software environment within IDRISI oriented 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 (Pontius, 2015). Monitoring and analysis of changes in LULC are needed in order to provide information on existing land use patterns and changes for decision makers to support sustainable development (Fan, 2007).

LULCC models are used to improve and/or better understand of the alteration of land use that is induced by human activities (Brown, 2004). 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 (Eastman, 2012).

In IDRSIS Run Transition Sub-Model panel is where the actual modeling of transition sub-models 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 (Eastman, 2012). 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 and 1. Logistic Regression. This model undertakes binomial Logistic Regression and prediction using the Maximum Likelihood method.

2.2.13.2 Earth Trend Modeler (ETM)

Earth observation image time series provide a critically important resource for understanding both the dynamics and evolution of environmental phenomena. As a consequence, Earth Trends Modeler (ETM) is focused on the analysis of trends and dynamic characteristics of these phenomena as evident in time series images. Further, the system is highly interactive, with the process of exploration largely being an active process. The trends and dynamics emphasized include: Inter-annual trends, Seasonal trends, Cyclical components, Irregular but recurrent patterns in space/time (recurrent patterns in space/time including a unique form of Wavelet analysis), Teleconnections (analysis of climate patterns of variation between widely separated areas of the globe), and variability such as the coupled ocean-atmosphere (Eastman, 2012).

2.2.13.3 GEOMOD

GEOMOD is the model that has been used frequently to analyze baseline scenarios of deforestation (Pontius and Chen, 2006). It is a grid-based land-use and land-cover change model, which simulates the spatial pattern of land change forwards or backwards in time. Simulates the change between exactly two land categories denoted as 1(non-developed and 2 (developed), but 1 and 2 could represent any two categories for any particular application (Pontius, 2006).

The minimum input requirements are: the beginning time, the ending time, an image of the beginning time for two land cover types that must be denoted by 1 and 2, and an estimate of the number of cells of each of the two categories at the ending time and Suitability map.

GEOMOD used to Predicts land selected land class in the future using land use/cover map. Its advantages need only one time land use map for calibration and its disadvantage can simulate change only in two category (Pontius & Chen, 2008). GEOMOD has been designed such that it can take maximum advantage of data that can vary highly in availability, completeness, precision, currency, and accuracy (Silva and Clarke 2002).

2.2.13.4 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 on the system at a regular discrete time interval (Eastman, 2012). Cellular Automata (CA) model explain Change in urban areas over time using the variables such as Extent of urban areas, Elevation, Slope, and Roads. Its advantage is allows each cell to act independently according to rules and its disadvantage is doesn't include human and biological factors (Agarwal et al., 2002).

2.2.13.5 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 which 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 (Thomas and Laurence, 2006). Future prediction using Markov chain modeling is generally done by analyzing two qualitative land cover images taken on different dates (Moghadam and Helbich, 2013). The transition probability matrix stores the probability that each state will change to every other state. The transition area matrix, produced from this transition probability matrix, stores the expected number of pixels that might change over a predetermined number of time units (Behera et al., 2012).

Markov Model used to explain Land use change using Multi Temporal Land Use/ cover Maps. Its strength is considers both spatial and temporal change and its weakness is no sense of Geography (Agarwal etal, 2002).

2.2.13.6 CA-Markov Model:

The Markov model can quantitatively predict the dynamic changes of landscape pattern, 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 (GIL et al., 2005). Combining the advantages of Cellular Automata theory and the space layout forecast of Markov theory, CA-Markov model performs better in modelling land cover change in both time and spatial dimension.

CA-MARKOV Used to explain Spatio-Temporal dynamic modeling and Predicts land use/cover in the future using Multi Temporal Land Use/ cover maps and Suitability maps. The strength of CA-MARKOV is creating the data is easy, CA add spatial dimension to the model, and can simulate change among several categories. Its weakness is Socio economic factors are not considered and calibrating the model with MCE is too much time consuming compared to other methods (Adhikari & Southworth, 2012).

2.2.14 Transition sub model

A transition sub-model can consist of a single land cover transition or a group of transitions that have the same underlying driver variables. These driver variables are used to model the historical change process. Transitions Sub model are modeled using either a multi-layer perceptron (MLP) neural network, logistic regression, or similarity-weighted instance-based machine learning tool (SimWeight). Multilayer Perceptron feed forward Artificial Neural Network (ANN) is a network of simple neurons called the perceptron (Multilayer Perceptron). It is composed of an input layer, output layer and hidden layers between input and output layer. It is a feed forward method which means data flows in one direction from input to output. Input Layer are the elements of a feature vector (wave bands/image) (Atkinson, P. M. et al, 1997). This can also be ancillary data like slope, elevation, soil type, zoning etc (Civco, D. L, 1993). Internal or hidden layer. It does not contain output units and used to multiply the value from each input neuron by a weight (Wji). Larger the number of nodes in the hidden layer, the better the neural network represents the training data (Atkinson, P. M. et al, 1997). Output layer presents the output data. For image classification, the number of nodes in the output layer equals to the classes in the classification.

2.2.15 Model Validation and Future Prediction

Model validation refers to comparing the simulated and reference maps. Sometimes the simulated maps can give misleading results. (Eastman, J. 2009)

Map comparison is vital in evaluating the analytical techniques for spatial data. It produces numerical expressions to compare two maps (Vliet, J. V., 2009).The best way to validate a model is to compare the predicted map of time *t2* with the reference map of time *t2 (*Pontius, G. R., e Chen, H., 2006). The validation was based on kappa statistic and multiple-resolution.

2.2.16 The role of remote sensing and GIS in urban planning.

The ability of GIS to store, manage and manipulate large amounts of spatial data provides urban managers with a powerful tool. GIS's ability to link tabular, non-spatial data to locational information is likewise a powerful analytic capability. Many different facets of government use GIS technology. GIS also provides ways of viewing and analyzing data that was previously impossible or impractical. With the aid of a GIS, a local planning and community development office can track zoning and site design plans that help form and shape a city (Zeng, 1999).

RS and Geographic Information system (GIS) is a novel technology widely used to survey the land use problem. The GIS adopts the numerical methods and spatial analysis tools to delineate the land use. The methods can yield the same results after repeatedly applying the same procedures. Moreover, they reduce the manpower and time consumption for the delineation of land use. In contrast with the manual methods, the GIS is the most economic and objective methods. They can be used separately or in combination for application in studies of urban sprawl. In the case of a combined application, an efficient, even though more complex approach is the integration of remote sensing data processing.

The applications of Remote Sensing and GIS in urban studies at present is giving more weight on the acquisition of urban land use information and the comparison on the urban sprawl spanning most recent several decades, giving an image that remote sensing and GIS applications are located in the dynamic monitoring of urban growth only, therefore only in a few cases, we see GIS technology are applied in empirical analysis on the urban spatial structure (Barnes et al., 2001).

Urban growth remains a major topic concerning GIS and remote sensing applications.

Remote sensing and GIS have proved to be effective means for extracting and processing varied resolutions of spatial information for monitoring urban growth (Epstein, 2002). Not only remote sensing and GIS but also IDRISI is the software in raster for spatial modeling, 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 Selva Manual version 17.01).

CHAPTER THREE: MATERIALS AND METHODS

3.1 INTRODUCTION

There are a different number of methods, strategies and techniques to process input data to generate the required output with desired accuracy/quality. The method integrate remote sensing, GIS and IDRISI.

3.2 Description of study area

3.2.1 Location

Burayu Town is located in Oromiya Regional State around the central part of Ethiopia. It is about 15 km from Finfinnee (Addis Ababa), the capital city of Ethiopia and Oromiya region towards the North West on the way to Ambo town. Located between {995810-1006310} m North and {454935-468135} m East, UTM Zone37 covering an area 9000Ha. Burayu Town name comes from tree name called Burayu this means in Afaan Oromo ''Muka Gurracha'' or black tree". Burayu established as one of kebeles in 1972 under Zone of West Shawa, Walmara district. Burayu called as Burayu Town Administration in 1996 under zone of West Shawa and Burayu Town with its own zone and administration established in 2006. Burayu Town has six kebeles; Burayu kata, Lakku Katta, Gafarsa Burayu, Gafarsa Guje, Gafarsa Noonno, and Malka Gafarsa.

Burayu Town located West of Finfinnee Town, East of Kolobo Town, and South of Sululta Town.

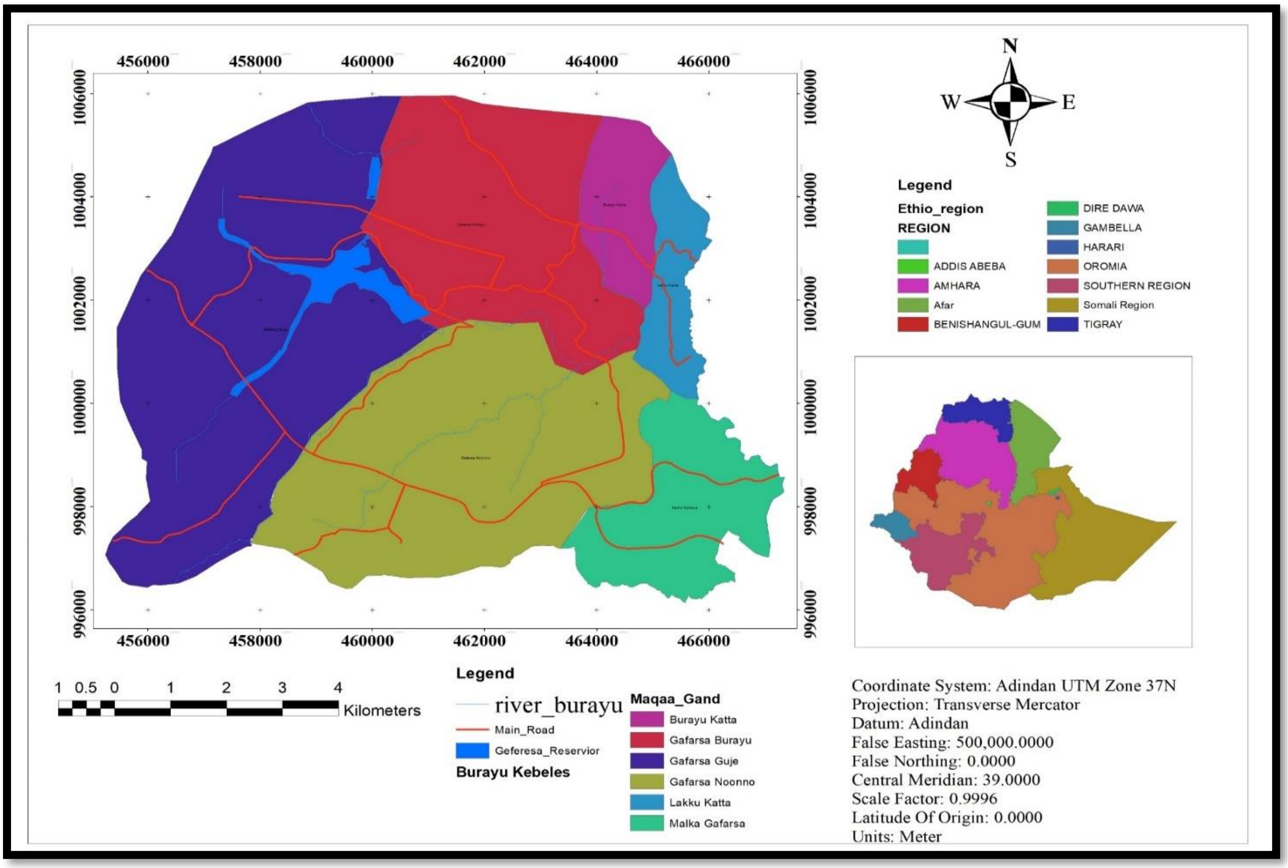

Figure 3-1 Map of study area.

3.2.2 Topography (Elevation Range and Slope)

The topography of the area varies from chains of mountains around Intoto ridge in the North east to plain lands in the south, south-west, and west. The average elevation in the town is 2619m (2909m - 2349m) above M.S.L. The study area mostly covered by flat and rolling terrain types.

3.2.3 Geology and Soils

The study area contains two subtypes of geological soils. Frist one is Tertiary Plateau Basalts are volcanic products consisting huge accumulation of basaltic rocks, and the second one is Quaternary Rift Volcanic and sediments comprise variety of rock units (both acidic and basic) associated to the formation of Main Rift System during the Quaternary Period (Ethiopian geological map 2011).

In the study area there are six major types of soil. Eutric Nitisols, chromic Vertisols, chromic Luvisols, Orthic solonchaks, Vertic Cambisols and calcic xerosols (Soil *Map of*, 1974).

3.2.4 Rainfall and Temperature

The mean annual rainfall of Burayu Town is 1067mm i.e. (1300mm -834mm).

The mean annual temperature is 16°C i.e. (26°C-6°C) and study area is Dega (Burayu Town Communication offices, 2019).

3.2.5 Socio-economic Aspects

Burayu town became following the trade route in search of jobs and livelihood and serving as a major focal point for trade and small-scale industries. The Town is an important center of distribution of goods that are manufactured locally by the various industries, full of travelers, many hotels, restaurants, bars and cafes in the town (Burayu Town Communication office, 2019).

3.3 Material used.

Table 3-1 Material used.

NO	SOFTWARE/MATERIAL	PURPOSE/ Used
1	ArcGIS (10.6)	Data acquisition, editing, manipulation, analysis, modeling, visualization, publication, and storage
2	ERDAS (2014)	Digital image preprocessing, Classification image, map land use/ land cover
3	IDRISI (17)	Land change modeling and time series analysis, multi criteria and multi-objective decision support, compare and predict for the future
4	Google Earth	Visualization,
5	Microsoft office (2016)	Writing, chart preparing, graphs and statistical analysis
7	GPS	Collect Ground Controls Points (GCPs)

3.4 Data Sources and Types

There are different types of data collected from both primary and secondary data sources to success a desired goal. Data from primary sources include GCP data. Secondary data such as Landsat images, population, soil, rainfall, shape files, published Research, journal, report etc are gathered from different organization and websites.

Landsat data types 1990, 2000, 2010 & 2019 acquired in the same season December and January, level of resolution (30m), Map projection = "UTM", Projection units = "meters", Datum and Ellipsoid= "WGS84" and UTM zone = 37.

The False Color Composite (FCC) images are useful to distinguish between different cover types or ground objects like buildings, roads, and vegetation. The FCC of RGB= bands 4, 3 and 2 has been chosen for this research. The urban areas appear blue, vegetation red, water bodies from dark blue to black, soils with no vegetation from white to brown (Eastman, 2009).

Table 3-2 Data sources and types

Types of data	Sources	Uses
Boundary of Burayu Town	Burayu municipality office	Subset/extract area of study
Landsat (5,7,8 sensor)	USGS earth explorer	For classification of LULC types.
DEM	USGS earth explorer	For knowing terrain types
Soil	FAO	For knowing soil types
River, Road, Gafarsa water	Burayu municipality office	For suitability analysis
Ground truth	Researcher	For accuracy assessment validation

3.5 Methodology

This section describe the method used in this study. The methods of the research composed of three phases first phase is Classification of LULC and Accuracy assessment the general methods/work flow shown in Fig 3-2. The second phase suitable site selection for Residential area, the general methods/work flow shown in Fig 3-3 and third phase is change detection and Modeling the general methods/work flow shown in Fig 3-4.

3.5.1 Digital Image Processing

The most of the common digital image processing categorized into the following four categories.

The first is Pre-processing operations, sometimes referred to as image restoration and rectification, and are intended to correct for sensor Platform-specific radiometric and geometric distortions of data. The second is Image enhancement is the process of making an image more interpretable for a particular application. The most common are: Radiometric Enhancement used for adjusting the brightness values of image. Spatial enhancement used for adjusting the quality of image and deriving new information using spatial operation. Spectral enhancement used for image transformation techniques working with multispectral image. The third is Pan sharpening (Resolution merge) used for increasing the resolution of colors image using higher resolution panchromatic image. Image transformation techniques used to reduce data redundancy and correlation between bands called principal components analysis

3.5.2 Data extraction

1. **Digitization** used to converts the structural plan of the area into digital map to use in GIS environment by encoding the spatial coordinates of the features on the map such as boundaries, roads and streams that exist in the study area from the structural plan. Burayu Town boundary, kebeles, Road and River are digitized (converts the structural plan of the area into digital map) from Burayu Town Structural plan 2006/2014 that exist in AUTOCAD form. (Burayu Town Municipality office 2014).
2. **Layer stack** used to stack multiple (usually single band) images as bands/layers into a single output multi-band image file. Since downloaded land sat has separately in multiple band selecting the bands. Landsat1990, 2000, 2010, and Landsat 2019 has 7, 9,7,11 separate band respectively, those separately exist band combined into single multiband for each land satellites.
3. **Clip/ Extract by mask** Used to cut out a piece of one feature class using one or more of the features in another feature class, creating a new feature class also called study area or area of interest (AOI) that contains a geographic subset of the features in another, larger feature class. Layer stack image cover large area 3,111,000 hectare (170km * 183km) but in case of this study area is 9000hectare. So using the boundary of Burayu Town Clip /extract by mask the area of study or windowing as rectangle. Landsat images were in GeoTIFF format GeoTIFF is a public domain metadata standard which allows georeferencing information to be embedded within a TIFF (image) file (GeoTIFF) (ERDAS field Guide, 2013).

3.5.3 Image classification and Accuracy Assessment

Mainly two kinds of pixel based classification supervised and unsupervised (Caetano, 2009).

“Supervised classification is a procedure for identifying spectrally similar areas on an image by identifying “training” sites of known targets and extrapolating those spectral signatures to other areas of unknown targets”. (Mather, 2011)

Supervised classification is usually appropriate when relatively few classes, when training sites verified with ground truth data, or when homogeneous regions that represent each class (Erdas Field guide, 2013). There are different algorithms for supervised classification; the classic classifiers are minimum distance, parallel pipelined and maximum likelihood methods.

The maximum likelihood algorithm uses a maximum likelihood procedure derived from Bayesian probability theory to determine the probability of the cell to be belonging to a particular class defined in training sites. The maximum likelihood classifier computes the class probabilities and classifies the cell where the probability is higher (Smith, 2011). Most accurate of the classifiers (if the input samples/clusters have a normal distribution). Maximum Likelihood is parametric, meaning that it relies heavily on a normal distribution of the data in each input band.

Burayu Town classified land use land cover change using supervised classification method, maximum likely hood algorithm, finally making accuracy assessment for each year classified land use land cover maps.

A. Errors of omission refer to reference sites that were left out (or omitted) from the correct class in the classified map. Omission errors are calculated by reviewing the reference sites for incorrect classifications in columns for each class and adding together the incorrect classifications and dividing them by the total number of reference sites for each class

Omission error$= (C_I/C_t)\ 100$ *(Eq-1)*

Where C_I = incorrectly classified sample locations of the reference data or column and C_t = total number of sample locations of the column.

B. Producer's Accuracy is the map accuracy from the point of view of the map maker (the producer). Producer's Accuracy = 100%-Omission Error.

Producer's Accuracy$= (C_i/C_t)\ 100$ *(Eq-2)*

Where C_i = correctly classified sample locations of the reference data or column and C_t = total number of sample locations of the column.

C. Commission errors are calculated by reviewing the classified sites for incorrect classifications by going across the rows for each class and adding together the incorrect classifications and dividing them by the total number of classified sites for each class.

Commission error$= (R_I/R_t)\ 100$ *(Eq-3)*

Where Ri = correctly classified samples in the row and Rt = total number of samples in the row.

D. User's Accuracy is the accuracy from the point of view of a map user, not the map maker. User's Accuracy = 100%-Commission Error.

User's Accuracy$= (R_i/R_t)\ 100$ *(Eq-4)*

Where Ri = correctly classified samples in the row and Rt = total number of samples in the row.

E. Overall Accuracy is essentially tells us out of all of the reference sites what proportion were mapped correctly. The overall accuracy is usually expressed as a percent, with 100% accuracy being a perfect classification where all reference site were classified correctly. The diagonal elements represent the areas that were correctly classified.

Overall Accuracy (PCC) = (S_d /n) 100 *(Eq-5)*

Where Sd = sum of values along diagonal and n = total number of sample

Overall Accuracy**:** also known as Percent Correctly Classified (PCC)

F. Kappa Coefficient is generated to evaluate the accuracy of a classification performed as compared to just randomly assigning values. The Kappa Coefficient can range from -1 to 1. A value of 0 indicated that the classification is no better than a random classification. A negative number indicates the classification is significantly worse than random. A value close to 1 indicates that the classification is significantly better than random. (Jennes etal (2007).

The Kappa statistic (K)

$$K = \frac{P\ (A) - P\ (E) RL}{1 - P(E) RL} \qquad \textit{(Eq-6)}$$

Where, P (A) = Percentage of cells in the map that are identical; P (E) RL = Random Location (RL) conditional to the observed distribution in both maps.

$$P\ (A) = \sum_{n=1}^{m} Pnn \qquad \textit{(Eq-7)}$$

$$P\ (E)_{RL} = \sum_{n=1}^{m} Pn * Pm \qquad \textit{(Eq-8)}$$

Where, Pnn. = the proportion of cells that is of category 'n' in row and 'm' in column. Pmn = the proportion of cells that is of category n in row and category m in column.

3.5.4 Suitable site selection for Housing (Residential area)

Land-use suitability is identifying the most appropriate spatial pattern of future land uses according to purpose (Hopkins, 1977). Suitability analysis has importance on LULC change modeling process for the future simulation can be grounded with the existing patterns and drivers (Factors and Constraints). Factors are generally continuous in nature (such as the slope, Soil types, Distance to Road, Types of LULC, distance from Built up area, Distance to water body); they indicate the relative suitability of certain areas. Constraints are the locations which are not allowed for urban development by law or existing occupied areas like existing built up area and Water body where the development is not possible (Eastman, J. R., 2009). Using the Factors and Constraints following steps are used to obtain suitable site selection for Housing.

1. **Proximity to Feature/Raster**

Proximity tools can be divided into two categories depending on the type of input the tool accepts: features or raster. Feature-based proximity tools used to discover proximity relationships using buffer features. Buffers are usually used to delineate protected zones around features.

Raster-based proximity tools used to discover proximity distance of each cell from a set of features or that allocate each cell to the closest feature using Euclidean distance function. Euclidean distance is straight-line distance gives distance from each cell in the raster to the closest source.

2. **Reclassification**

Reclassifying cells for Factors and constraints are used to simplify the data by grouping classifications or setting identified cell values to 'NoData', removing it from the analysis.

3. Multi Criteria Decision Making

Weight is used to a set of relative weights for a group of factors in a multi-criteria evaluation. These pairwise comparisons are then analyzed to produce a set of weights that sum to 1.

Analytical Hierarchy Process (AHP) is one of the multiple criteria decision-making method that used to provide measures of consistency. Consistency plays a vital role in AHP. Pair wise comparison matrix obtained by decision maker must satisfy Consistency Ratio condition (CR<0.1)**,** if not decision maker has to revise his decisions and improve the Consistency Ratio to acceptable range (i.e., < 10%).

$$CR = \frac{CI}{RI} ------------------------------ (Eq-9)$$

$$CI = \frac{\lambda max-1}{n-1} ------------------------------ (Eq\text{-}10)$$

RI is the average random index that depends on matrix order, λ_{max} is the highest Eigen value of matrix A, and n is the size of matrix A (Saaty, 1991).

4. Overlay analysis

There are two methods for performing overlay analysis i.e. feature overlay and raster overlay. Overlay analysis to find locations meeting certain criteria is often best done using raster overlay. There two types of raster overlay commonly used are Weight overlay and Boolean (Fuzzy) overlay. Weighted Overlay tools is one of the most used approaches for overlay analysis to solve multi criteria problems such as site selection and suitability models.

3.5.5 Change Analysis and Modeling

In Land Change Modeler (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 (Eastman, 2012).

In IDRSIS three methodologies of Transition Sub-Model panel is where the actual modeling of transition sub-models is implemented: 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 (Eastman, 2012).

The MLP option can run multiple transitions, up to 9, per sub-model. For this study Multi-Layer Perceptron (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.

1. Classification of LULC and Accuracy Assessment phase

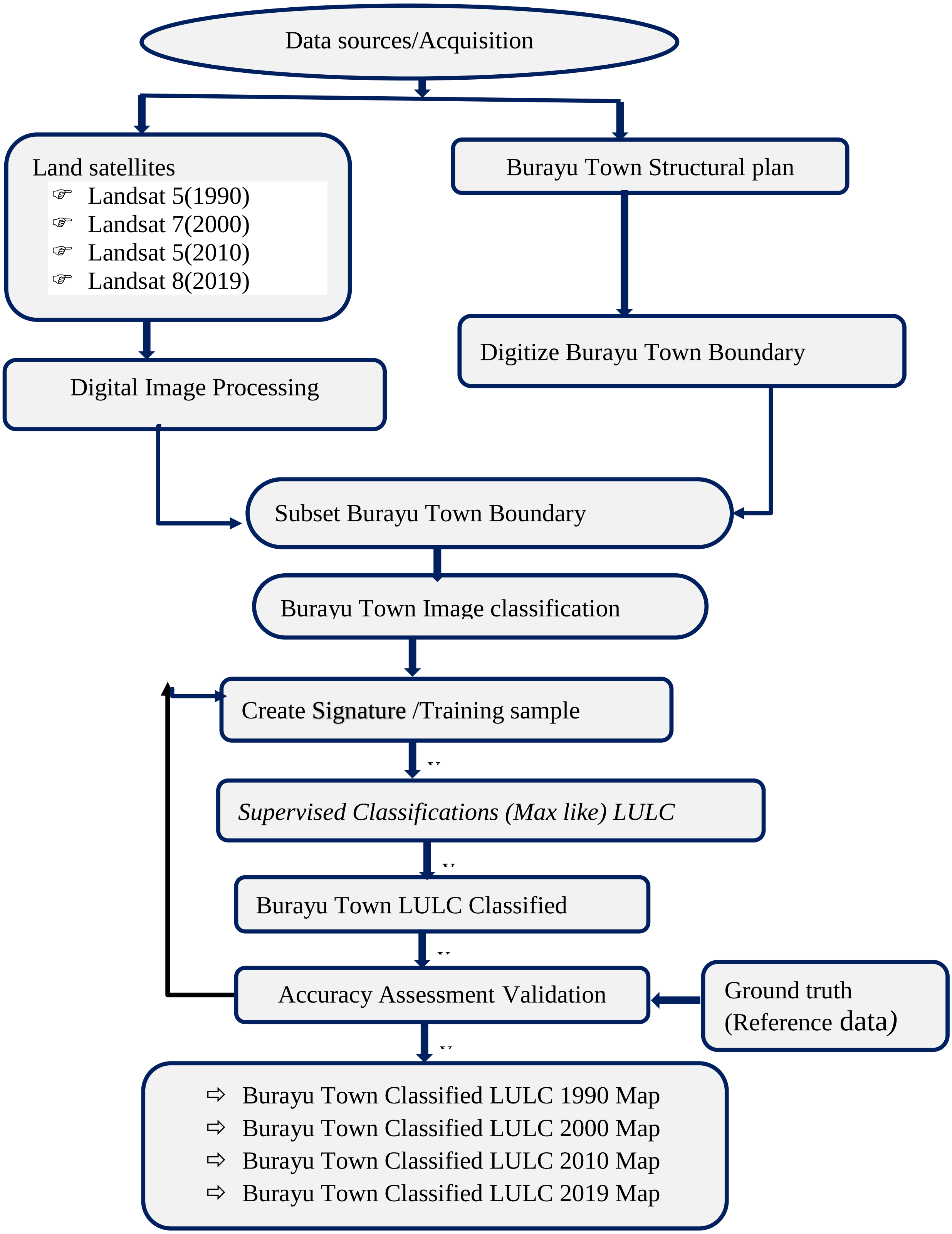

Figure 3-2 Classification and Accuracy Assessment phase.

2. Suitable Site selection for Housing development Phase

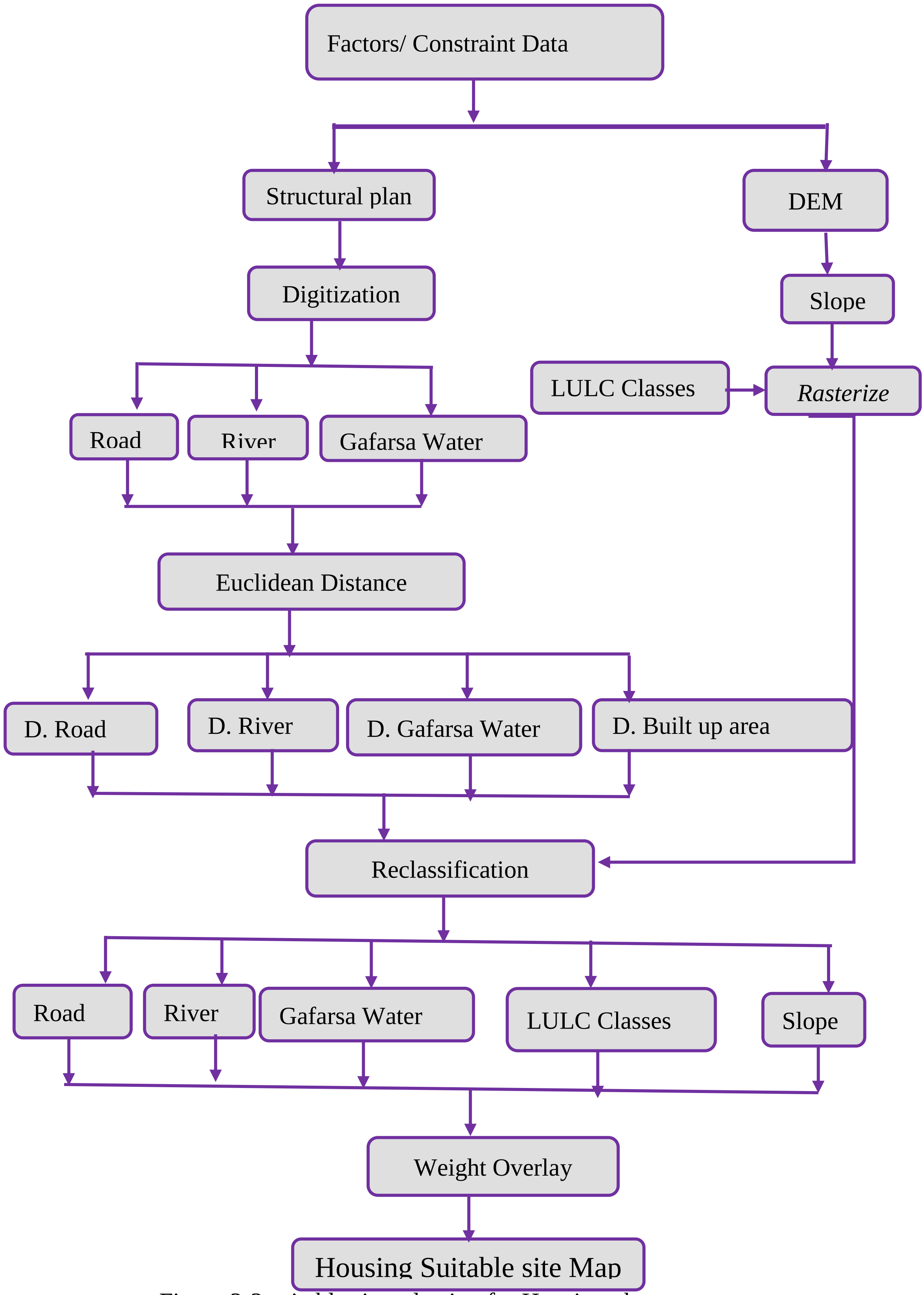

Figure 3-3 suitable site selection for Housing phase

3. *Change Analysis and Modeling phase*

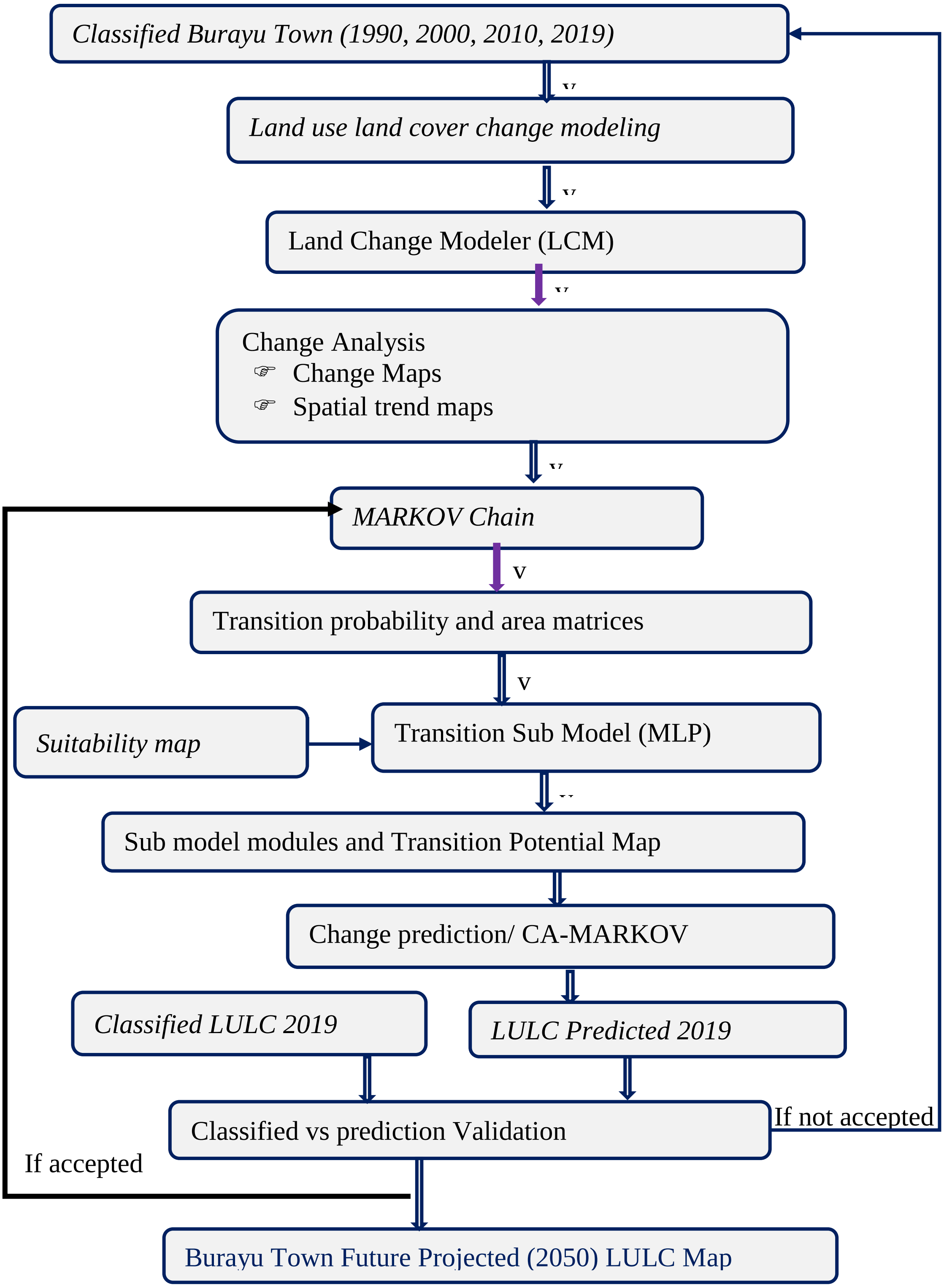

Figure 3-4 Change Analysis and Modeling Phase

CHAPTER FOUR: DATA ANALYSIS, RESULTS AND DISCUSSION

4.1 INTRODUCTION

This Chapter deals with explaining the detail procedures, results interpretation and discussion in Analysis of Burayu Town Urban Land use land cover changes and suitability for Housing using Landsat (1990, 2000, 2010 and 2019) and future prediction.

4.1.1 Land use land cover image classification

Training sites are the areas defined for each land cover type within the image and creating the spectral signature for each type of land use land cover. This is done by analyzing the pixels of the training sites (Eastman, J. R., 2009). This shown in appendix **B.**

The classification of these land sat image are pixel based classification category, supervised classification method with maximum likely hood algorithm for all Burayu Town Land use land cover classes of 1990,2000,2010 and 2019.

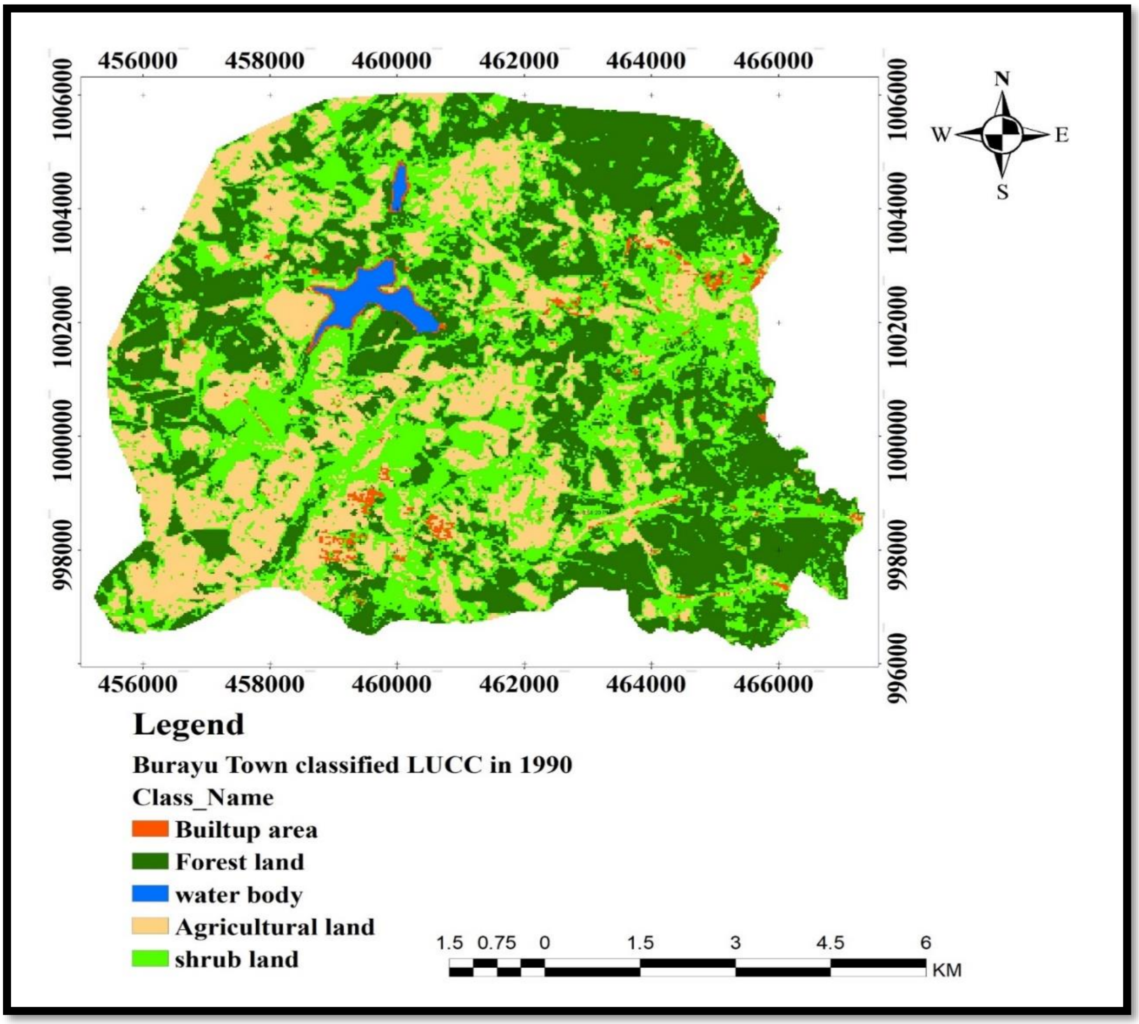

Figure 4-1 Burayu Town classified Land use land cover of 1990 year

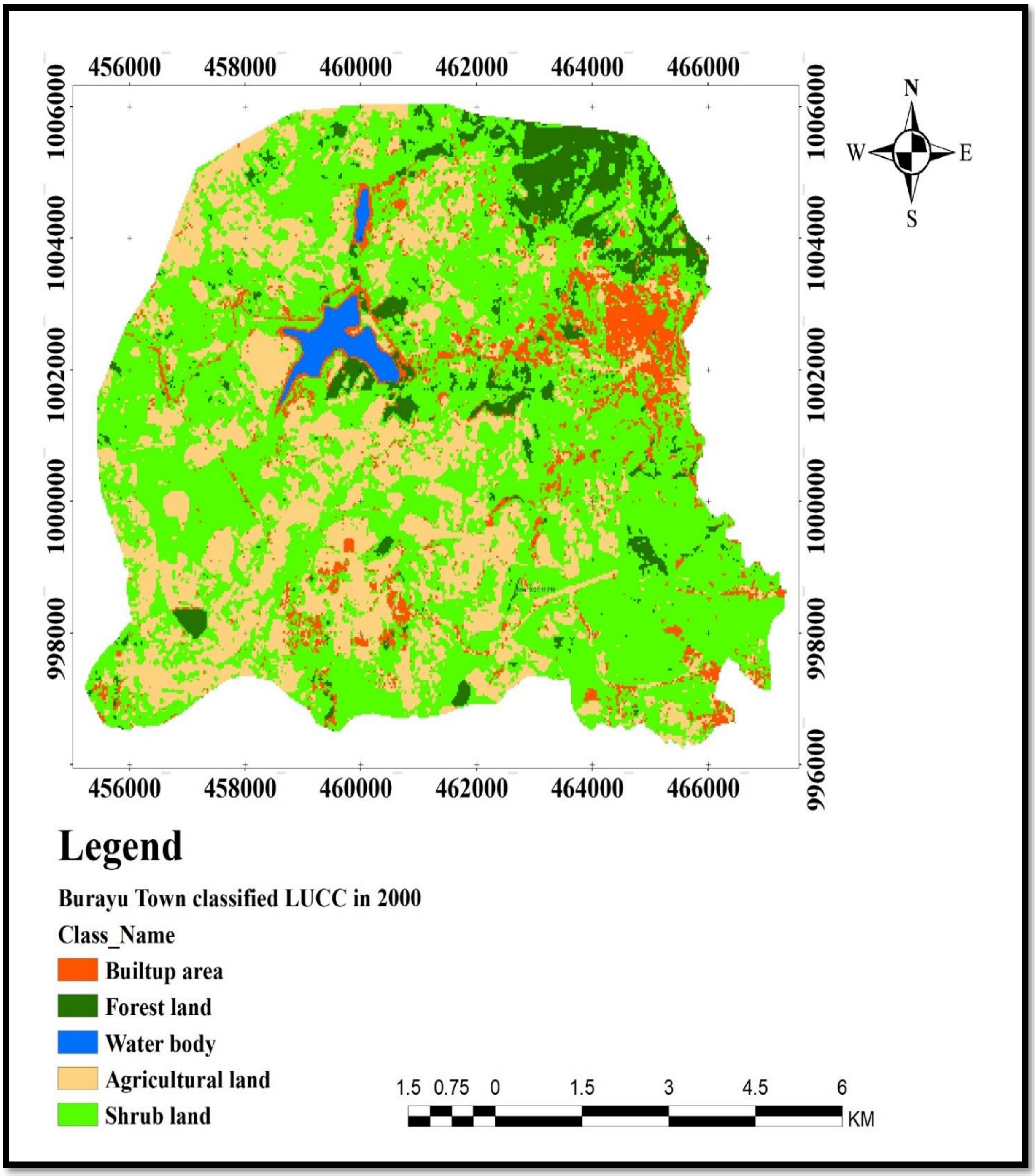

Figure 4-2 Burayu Town classified Land use land cover of 2000 year

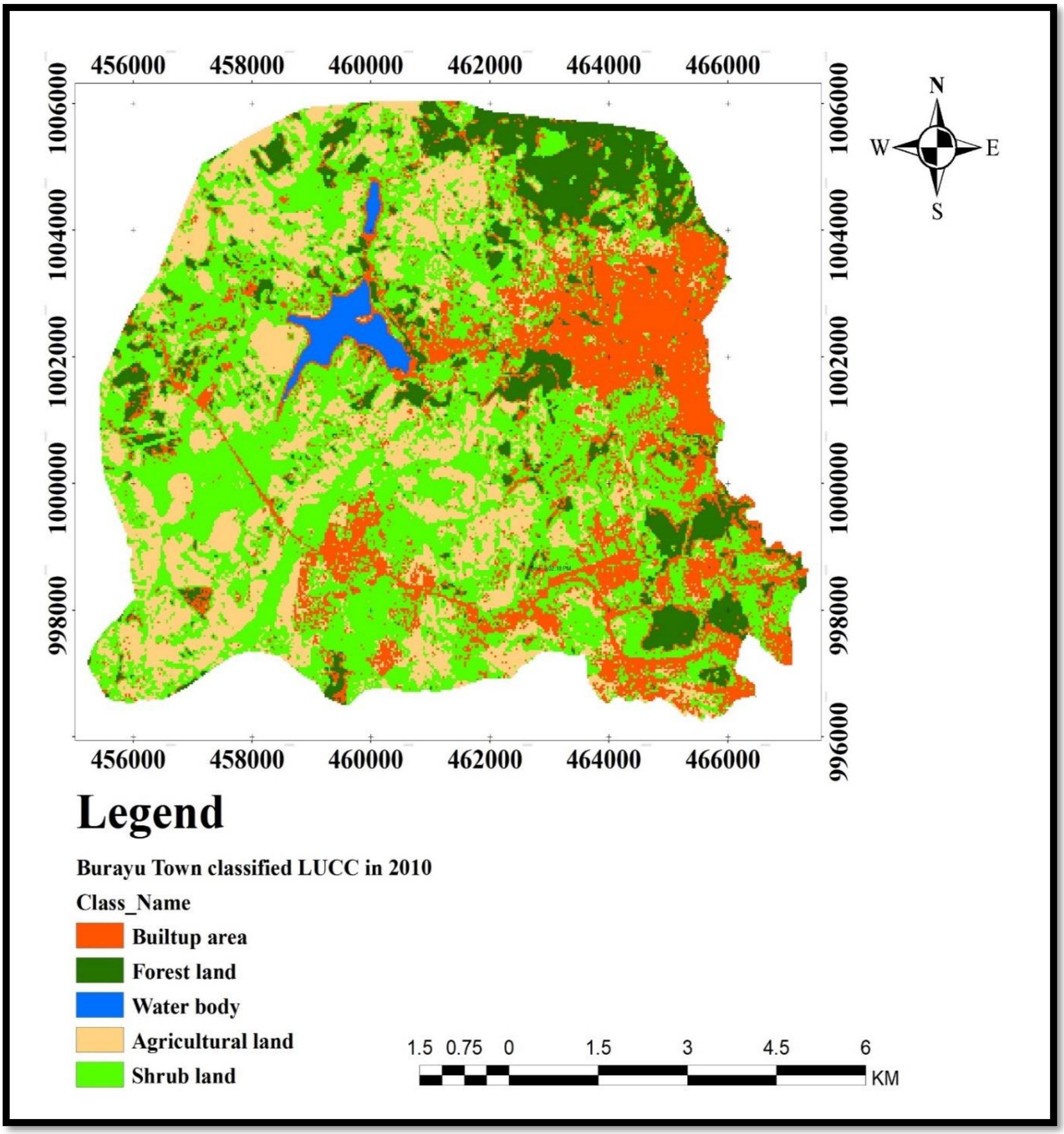

Figure 4-3 Burayu Town classified Land use land cover of 2010 year.

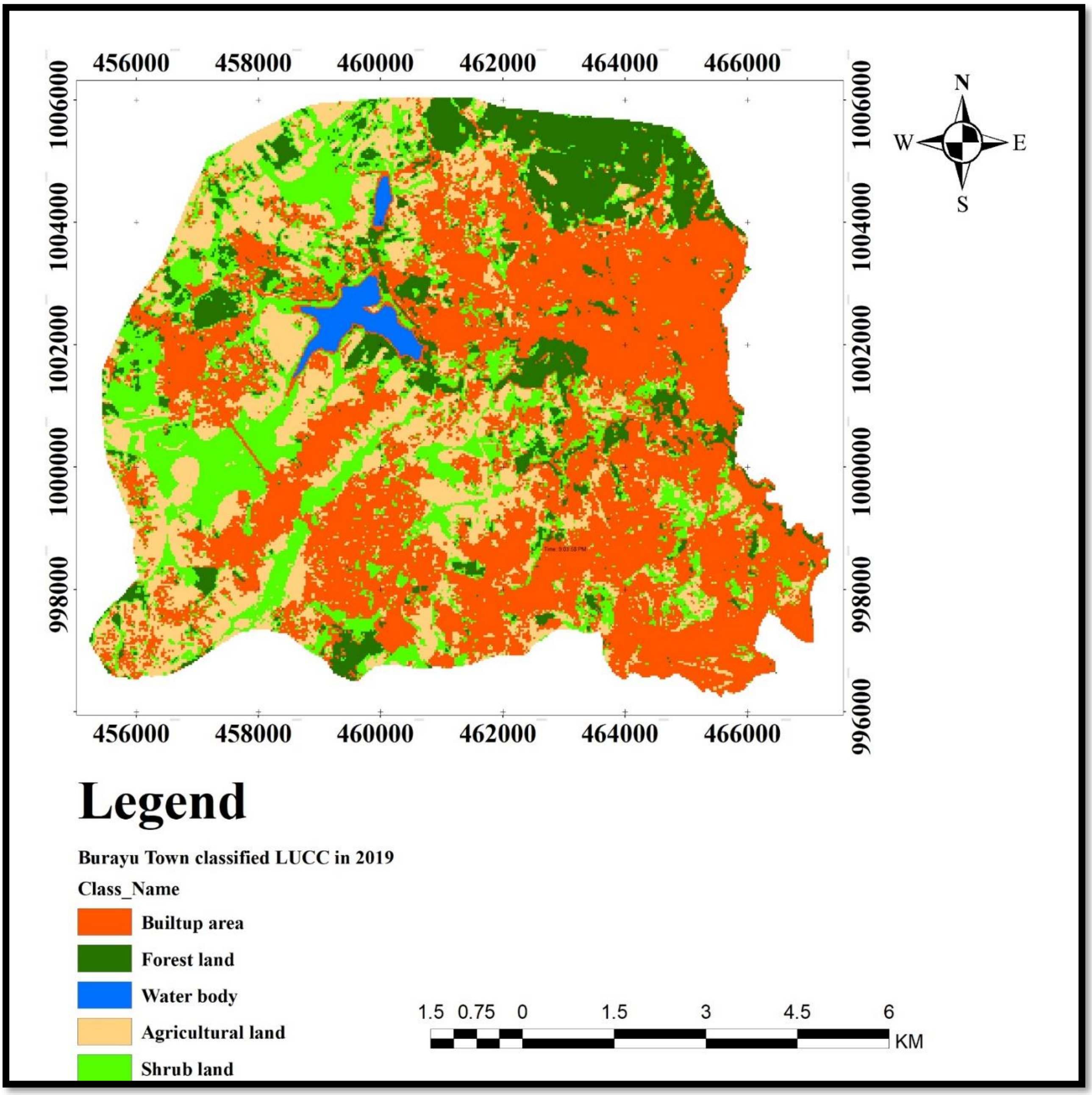

Figure 4-4 Burayu Town Classified LULC of 2019 Year

4.1.2 Accuracy Assessment of classified Land use land cover image

The Ground Control Points (GCPs) collected from known real study area, Ortho-photo and Google earth (2019). The Total number of reference points 250 are shown for each LULC Classified map of 1990, 2000, 2010 and 2019 shown in appendix **D.**

The Error matrix tables produce many statistical measures of thematic accuracy including overall classification accuracy, percentage of omission and commission error and kappa coefficient are shown in Table 4.1, Table 4.2, Table 4.3 and Table 4.4.

Based on this equation classified land use land cover map of Burayu Town in 1990 has 88 % overall accuracy and 0.85 kappa coefficient, similarly 2000 LULC map has 92% overall accuracy and 0.902

kappa coefficient, for 2010 LULC map has 93.6 % overall accuracy and 0.92 kappa coefficient , finally 2019 LULC Map has 97.6 % and 0.97 kappa coefficient. Based on Strength of Agreement for Kappa Statistic (Landis, J., 1977) all classified over all kappa and kappa statistics fall in almost perfectly classification.

Table 4-1 Error matrix of Burayu Town LULC Classes in 1990.

	REFERENCE DATA (1990)							
CLASSIFIED DATA (1990)		Built-up area	Forest Land	Water body	Agriculture Land	Shrub Land	**Total Points**	U. A (100%)
	Built-up area	42	0	2	0	5	**49**	85.714
	Forest Land	0	43	0	0	3	**46**	93.478
	Water body	0	0	45	2	0	**47**	95.745
	Agriculture Land	3	0	0	47	2	**52**	90.385
	Shrub Land	2	7	0	4	43	**56**	76.786
	Total points	**47**	**50**	**47**	**53**	**53**	**250**	
	P. A (100%)	89.362	86	95.745	88.679	81.132	89.362	
	Overall Accuracy =88%							
	Kappa Coefficient (K) =0.85							

Table 4-2 Error matrix of Burayu Town LULC Classes in 2000

	REFERENCE DATA (2000)							
CLASSIFIED DATA (2000)		Built-up area	Forest Land	Water body	Agriculture Land	Shrub Land	**Total Points**	U.A (100%)
	Built-up area	44	0	1	1	2	**50**	91.67
	Forest Land	0	48	0	2	3	**51**	90.57
	Water body	0	0	46	2	0	**48**	95.83
	Agriculture Land	1	2	0	47	2	**52**	90.38
	Shrub Land	1	2	0	1	45	**49**	91.84
	Total points	**46**	**52**	**47**	**53**	**52**	**250**	
	P. A (100%)	95.65	92.31	95.83	88.68	86.54		
	Overall Accuracy =92%							
	Kappa Coefficient (K) =0.902							

Table 4-3 Error matrix of Burayu Town LULC Classes in 2010.

	REFERENCE DATA (2010)							
		Built-up area	Forest Land	Water body	Agriculture Land	Shrub Land	**Total points**	U.A (100%)
CLASSIFIED DATA (2010)	Built-up area	48	0	0	0	1	**49**	97.96
	Forest Land	2	46	0	1	3	**52**	88.46
	Water body	0	0	47	1	0	**48**	97.92
	Agriculture Land	2	1	0	45	2	**50**	90
	Shrub Land	1	1	0	1	48	**51**	94.12
	Total points	**53**	**48**	**47**	**48**	**54**	**250**	
	P. A (100%)	90.57	95.83	100	93.75	88.89		
	Overall Accuracy =93.6%							
	Kappa Coefficient (K) =0.92							

Table 4-4 Error matrix of Burayu Town LULC Classes in 2019.

	REFERENCE DATA (2019)							
		Built-up area	Forest Land	Water body	Agriculture Land	Shrub Land	**Total Points**	U.A (100%)
CLASSIFIED DATA (2019)	Built-up area	49	0	0	0	1	**50**	98
	Forest Land	0	48	0	1	0	**49**	97.96
	Water body	0	0	50	0	0	**50**	100
	Agriculture Land	1	1	0	49	0	**51**	96.08
	Shrub Land	0	1	0	1	48	**50**	96
	Total points	**50**	**50**	**50**	**51**	**49**	**250**	
	P.A (100%)	98.00	96.00	100.00	96.07	97.96		
	Overall Accuracy =97.6%							
	Kappa Coefficient (K) =0.97							

4.1.3 CHANGE ANALYSIS AND PREDICTION MODELING

4.1.3.1 Change analysis

The Change Analysis used for the rapid assessment of changes such as gains and losses, net change, persistence and specific transitions both in map and graphical form.

The change between 1990-2000, 2000-2010, 2010-2019 and 1990-2019 are calculated using image difference (later- earlier) of classified LULC Burayu Town of four different years.

Table 4-5 Burayu Town Gain and losses of LULC Classes for three decades.

LULC Classes	1990	2000	2010	2019	Gain (+) /Losses (-) (1990-2019)
Built up area	200	700	2000	4100	+3900
Forest land	3400	600	1000	1200	-2200
Water body	100	100	100	100	0
Agriculture land	2300	2500	2100	1900	-400
Shrub land	3000	5100	3800	1700	-1300
Total (Ha)	9000	9000	9000	9000	0=3900-(2200+400+1300)

Burayu Town LULC classes changes in three decades (2019-1990) are: Built up area is increased by 3900 Ha(44%), Forest land is decreased by 2200 Ha(25%),Water body is neither increased nor decreased, Agriculture land is decreased by 400 Ha(5%) and Shrub land is decreased by 1300 Ha(14%). The area change less than 1km2 (100 Ha) for 10 year is ignored because of this Water body is neither increased nor decreased.

$$\text{Change in percent } (\%) = \left(\frac{\text{Area in T2} - \text{Area in T1}}{\text{Total area}}\right) 100 \qquad (\text{Eq} - 11)$$

$$\text{Anual Change } (\%) = \left(\frac{\text{Area in T2} - \text{Area in T1}}{\text{Total area}} * \frac{1}{\text{T2} - \text{T1}}\right) 100 \qquad (\text{Eq} - 12)$$

Where T1 is earlier image and T2 is later image.

Table 4-6 Burayu Town Net change by category of LULC Classes for three decades

LULC Classes		2000-1990	2010-2000	2019-2010	2019-1990
Built up area	Change in Area (Ha)	+500	+1300	+2100	+3900
	Change in (%)	6	14	24	+44
	Anual Change (%)	0.6	1.4	2.67	1.52
Forest land	Change in Area (Ha)	-2800	+400	+200	-2200
	Change in (%)	-31	4	2	-25
	Anual Change (%)	-3.1	0.4	0.22	-0.86
Agriculture land	Change in Area (Ha)	+200	-400	-200	-400
	Change in (%)	+2	-4	-3	-5
	Anual Change (%)	0.2	-0.4	-0.33	-0.17
Shrub land (Ha)	Change in Area (Ha)	+2100	-1300	-2100	-1300
	Change in (%)	+23	-14	-23	-14
	Anual Change (%)	2.3	-1.4	-2.56	-0.48

In Burayu Town for the last three decades, Built up area is increased by 3900Ha and the Forest land (-2200Ha), Agriculture land (-400Ha), and Shrub land (-1300Ha) are decreased. Totally the net change are zero i.e. the total summation of increased and decreased net change gives zero.

Table 4-7 Burayu Town LULC classes contributor to net change in Built up area.

	Changed to Built up area (Ha)			
LULC Classes	1990-2000	2000-2010	2010-2019	1990-2019
Forest land	100	100	200	1400
Agriculture land	200	300	700	1100
Shrub land	300	1100	1600	1500
Total	600	1500	2500	4000

Generally Burayu Town LULC Classes that contribute to Net change in Built up area for three decades (1990-2019),Shrub land more contribute (1500Ha),Forest land contribute 1400 (Ha) and Agriculture land is least contribute (1100Ha).

4.1.3.2 Markov Chain Model Analysis

Using Markov chain Analysis the following transition area and transition probability.

Table 4-8 Markov chain transition area of Burayu Town (2000-2010)

Markov chain Transition probability of Burayu Town LULC 2000-2010 (in cells)						
	Built-up area	Forest land	Water body	Agricultural land	Shrub land	Total probability
Built-up area	0.6644	0.0138	0.0203	0.0903	0.2112	1
Forest land	0.1558	0.6825	0.0005	0.0176	0.1436	1
Water body	0.0040	0.0000	0.9960	0.0000	0.0000	1
Agricultural land	0.1044	0.0000	0.0000	0.6587	0.2368	0.9999
Shrub land	0.2055	0.1123	0.0000	0.0874	0.5948	1
Total probability	1.1341	0.8086	1.0168	0.854	1.1864	4.9999

Table 4-9 Markov chain transition probability of Burayu Town (2000-2010).

Markov chain Transition area of Burayu Town 2000-2010 (in cells)						
	Built-up area	Forest land	Water body	Agricultural land	Shrub land	Total cells
Built-up area	14329	298	437	1947	4555	21566
Forest land	1761	7712	6	199	1623	11301
Water body	6	0	1514	0	0	1520
Agricultural land	2449	0	0	15448	5553	23450
Shrub land	8634	4719	0	3672	24992	42017
Total cell	27179	12729	1957	21266	36723	99854
Changing trends	5613	1428	437	-2184	-5294	

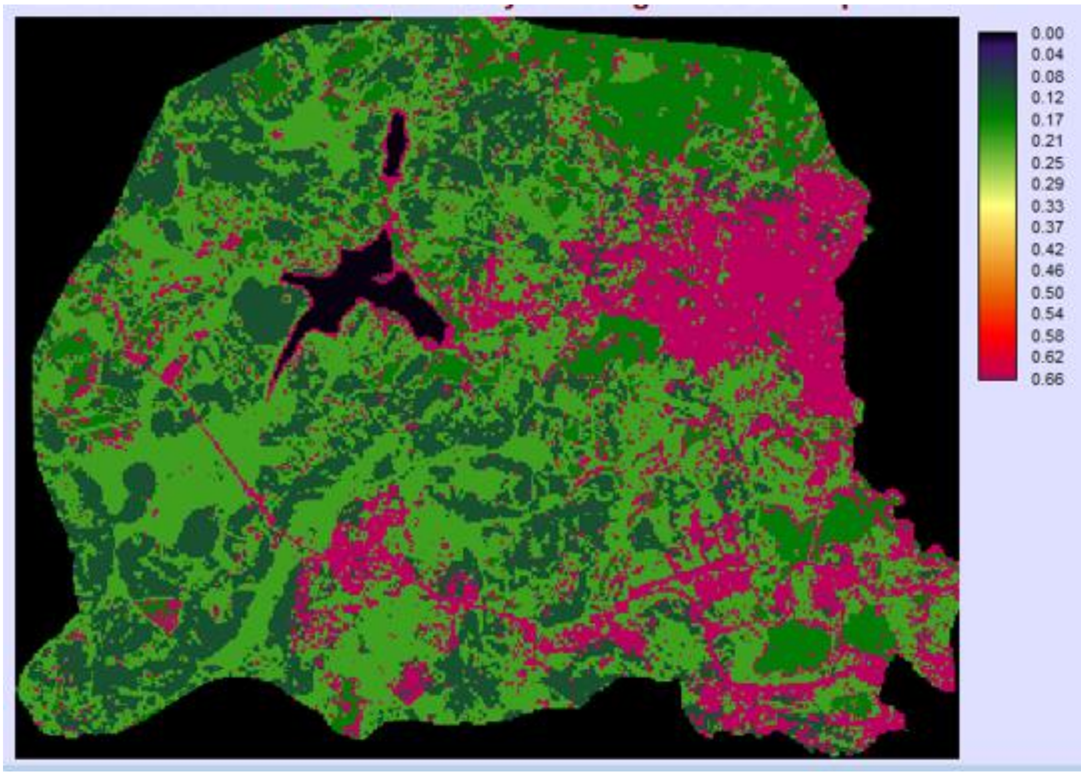

Figure 4-5 Markovian Conditional Probability of being class Built up area (predict 2019).

Markovian Conditional Probability of being class Built up area, Forest land, Water body, Agriculture land and Shrub land for predict 2019 maps area shown in Appendix **G.**

4.1.3.3 Transition Potential Modeling

Using MLP Sub model Burayu Town transition potential from all Land use land cover classes to Built up area for 1990, 2000, 2010 and 2019 are generated. Transition all LULC to Built-up area means change of Forest land, Water body, Agriculture land and Shrub land to Built up area within 1990-2000,2000-2010 and 2010- 2019. Transition from all LULC to all LULC means the change of all Built-up area, Forest land, Water body, Agriculture land and shrub land to Built-up area, Forest land, Water body, Agriculture land and Shrub land in cross correlation from 1990-2000, 2000-2010, and 2010-2019.

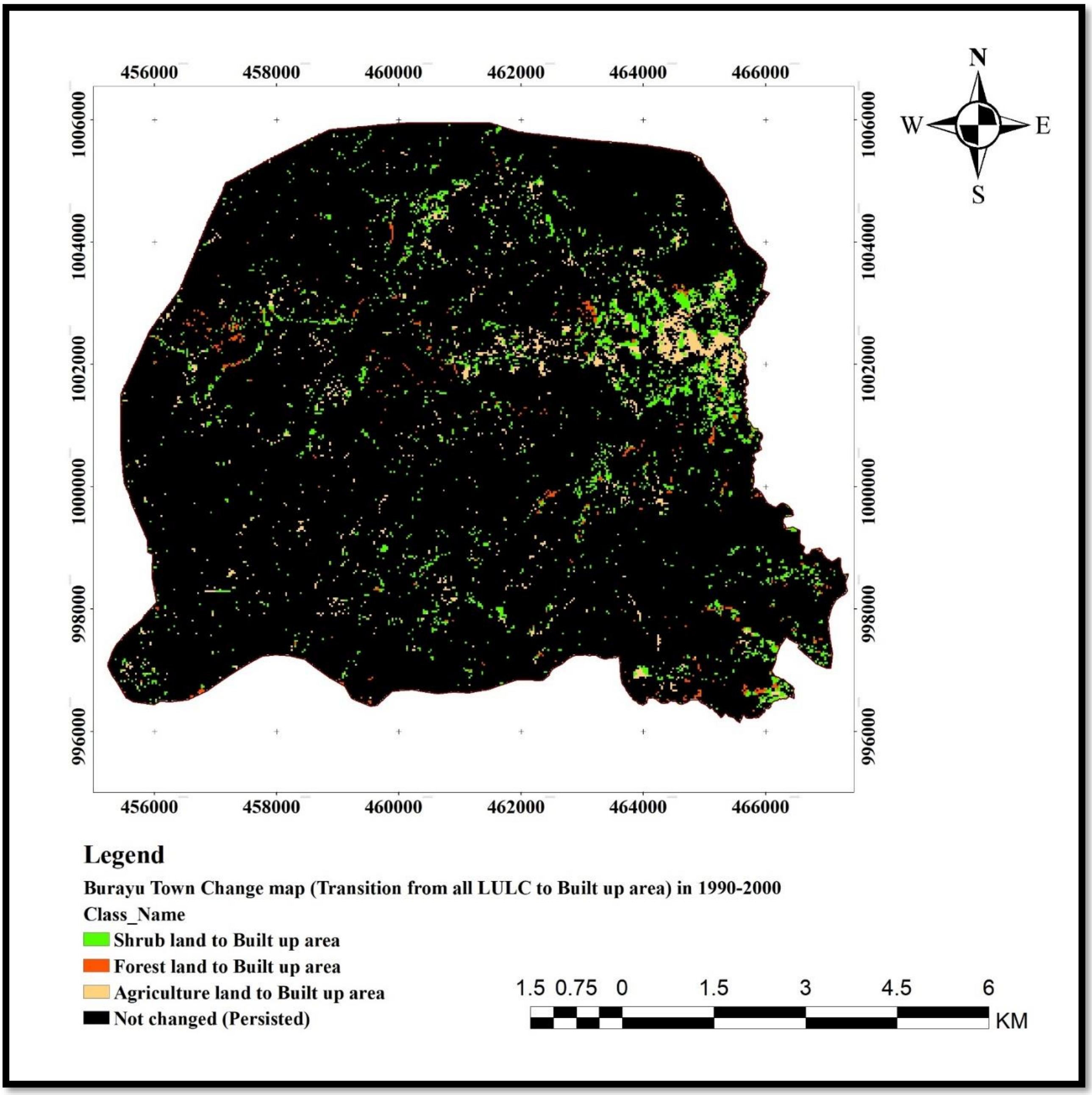

Figure 4-6 Burayu Town Transition from all LULC Classes to Built-up area (1990-2000).

Burayu Town Change Map (Transition from all LULC Classes to Built-up area) from 1990-2000 Shrub Land (300Ha), Agriculture land (200Ha), and Forest land is (100Ha).

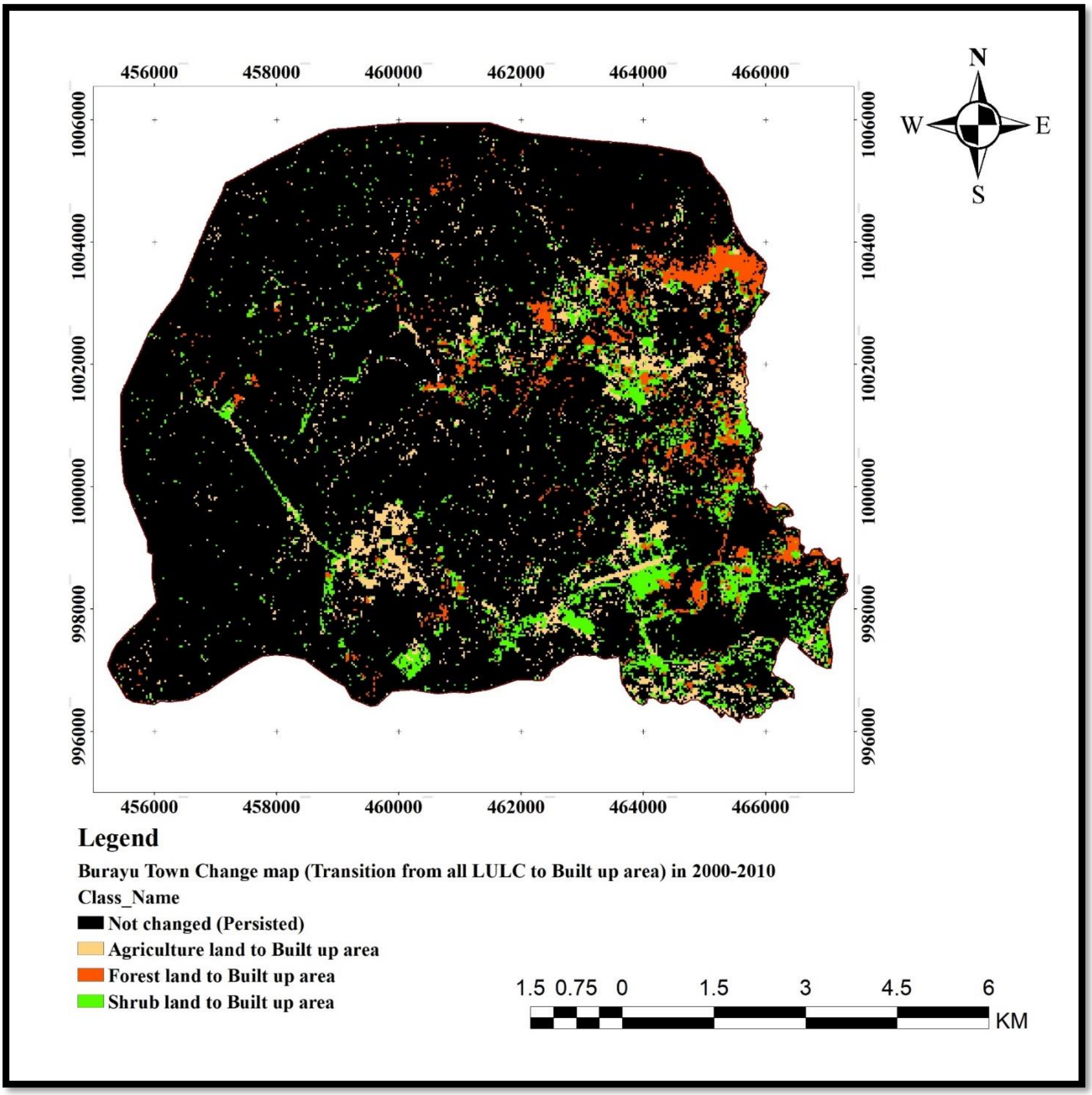

Figure 4-7 Burayu Town Transition from all LULC Classes to Built-up area (2000-2010).

Burayu Town Change Map (Transition from all LULC Classes to Built-up area) from 2000-2010 Shrub Land (1100Ha), Agriculture land (300Ha), and Forest land is (100Ha).

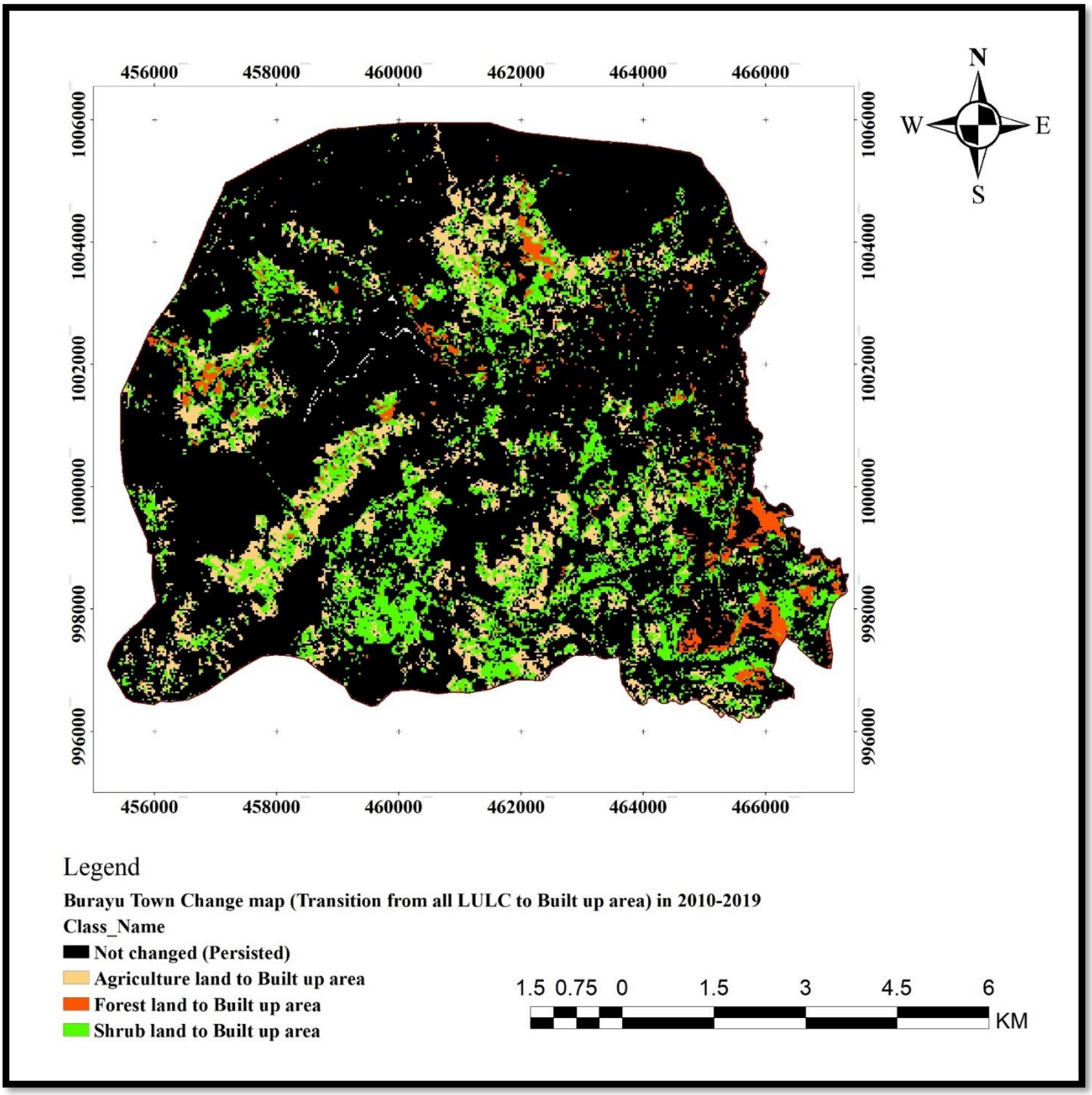

Figure 4-8 Burayu Town Transition from all LULC Classes to Built-up area (2010-2019)

Burayu Town Change Map (Transition from all LULC Classes to Built-up area) from 2010-2019 Shrub Land (1600Ha), Agriculture land (700Ha), and Forest land is (200Ha).

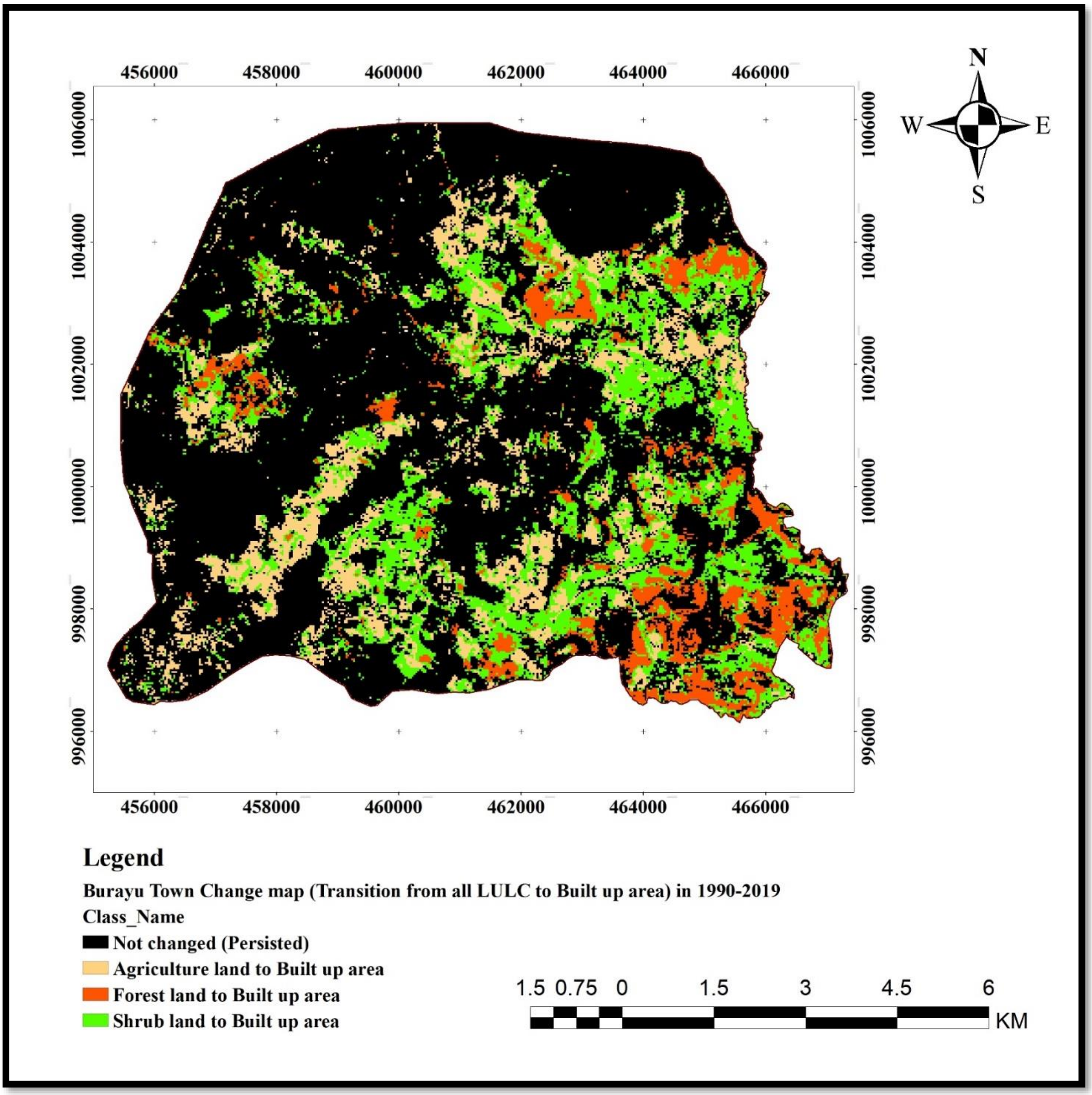

Figure 4-9 Burayu Town Transition from all LULC Classes to Built-up area (1990-2019).

Burayu Town Change Map (Transition from all LULC Classes to Built-up area) from 1990-2019 Shrub Land (1500Ha), Agriculture land (1100Ha), and Forest land is (1400Ha).

Burayu Town change maps of all to all LULC Classes means change of Built-up are Change to Built-up area, Forest land, Water body, Agriculture land and Shrub land, similarly Forest land to Built-up area, Forest land, Water body, Agriculture land, shrub land similar for Water body, agriculture and Shrub land. The detail map of transition from all LULC Classes to all LULC Classes are in Appendix G.

4.1.3.4 Spatial Trend of Change.

The spatial trend analysis tool used to compute maps of transition trends from all land cover categories to Built-up areas between change maps (1990-2000, 2000-2010, 2010-2019 and 1990-2019). It was created using a default 3rd order of polynomial, which is best fit to the pattern of change, in LCM. The numeric values produced don't have any special significances (Eastman, 2012). Thus, the result is interpreted as: the lower the value, the less changes and the higher the value, the more changes.

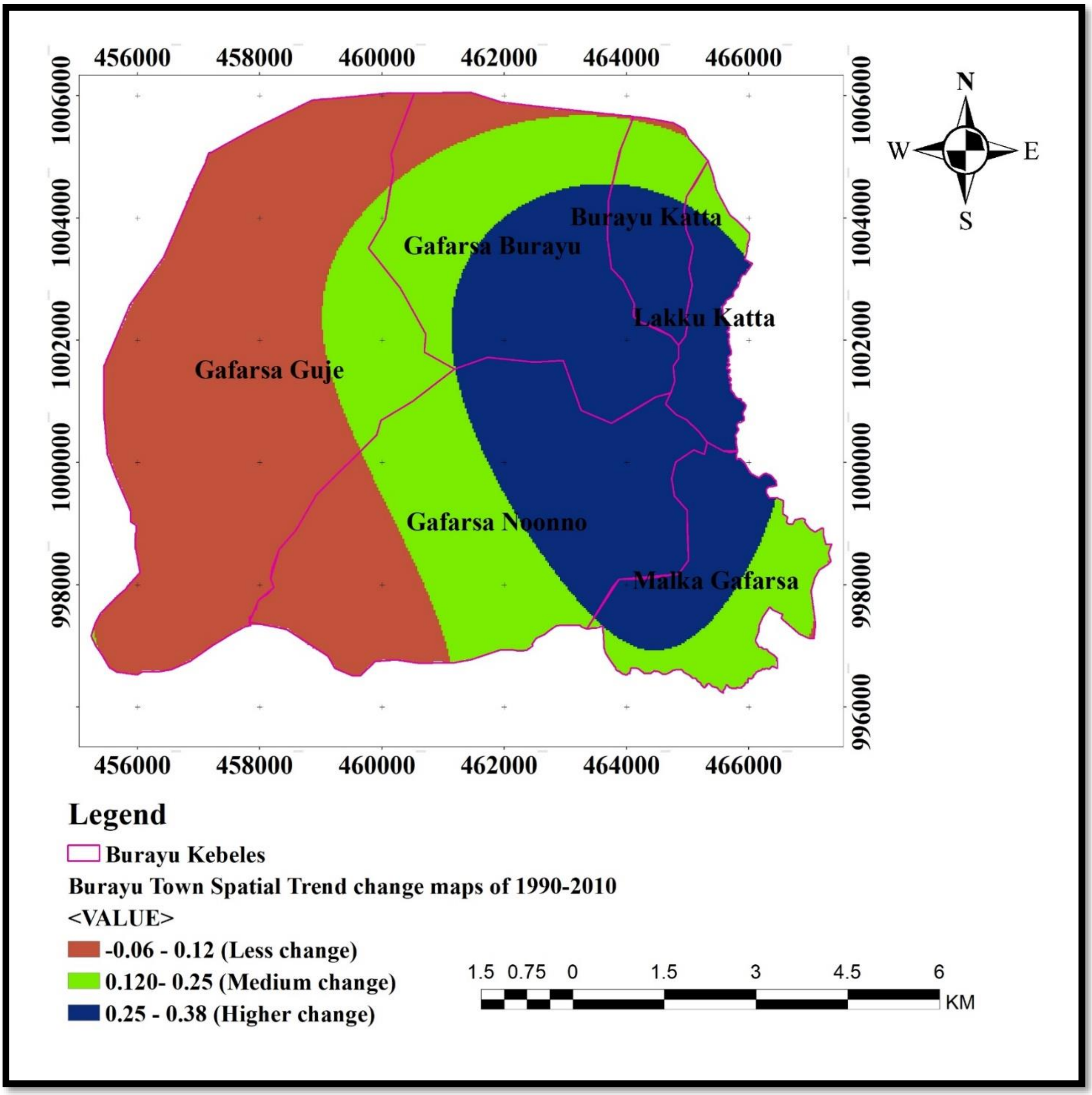

Figure 4-10 Burayu Town Spatial trend of change map (1990-2010).

Burayu Town spatial trend change map in each Kebeles (All LULC to Built-up area (1990-2010). Burayu katta, Gafarsa Burayu and Lakku Katta which indicated by Blue (higher the value) are more changes and Gafarsa Guje which indicated by Red (low value) are less changes, this is because Burayu Town kebeles nearest to Finfinnee until established of Burayu Town with its own zone and administration established in 2006G.C is more changed and kebeles which exist far from is less changed.

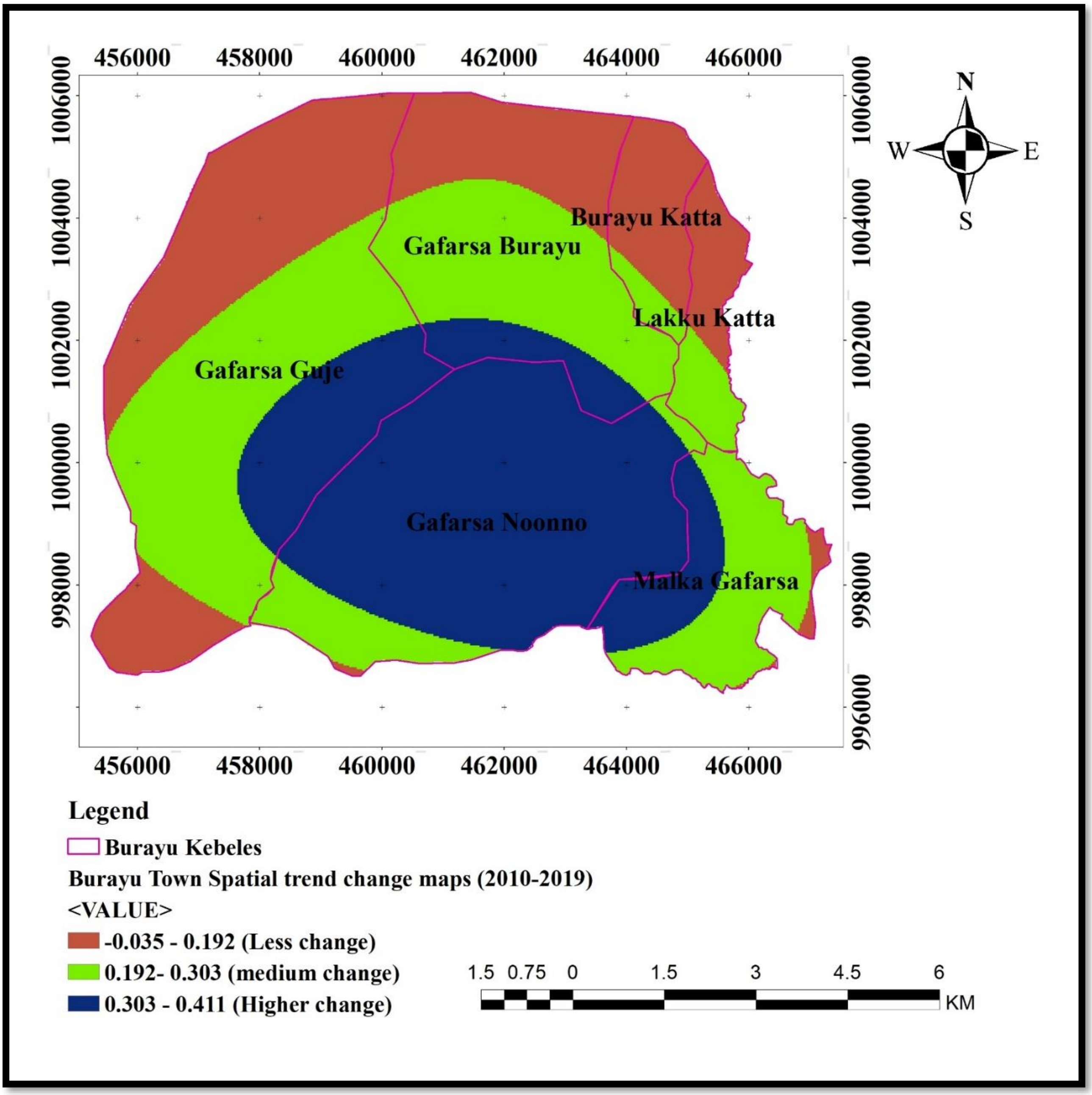

Figure 4-11 Burayu Town Spatial trend of change map (2010-2019).

urayu Town spatial trend change map in each kebeles (All LULC to Built-up area (2010-2019 and 1990-209). Gafarsa Burayu, Gafarsa Noonno, and Malka Gafarsa which indicated by Blue (higher the value) are more changes and Burayu Katta, Lakku Katta, and Gafarsa Guje which indicated by Red (low value) are less changes, this is because Burayu kebele nearest to Burayu Town Administration that exist in Burayu Gafarsa kebeles are mores change and kebeles far from it is less changed.

4.2 Suitability Analysis

The main steps for the suitability analysis are as follows:

4.2.1 Identifying the Factors and Constraints of study area.

For this study factors are: slope, distance to Road, types of LULC, distance from Built up area, distance to water body); they indicate the relative suitability of certain areas and Constraints are the locations which are not allowed for urban development by law or existing occupied areas like existing built up area and Gafarsa water reservoir where the development is not possible.

4.2.2 Proximity to Feature/Raster

The Raster-based proximity tools used to discover proximity distance of each cell from a set of features or that allocate each cell to the closest feature using Euclidean distance function.

4.2.3 Reclassification

Reclassifying the set values of a raster dataset allows the user to simplify the information in their raster by removing no data cell values.

There is no specific and standard number for suitable site selection, number and interval vary place to place and researcher to researcher so this table is not standard but using different theory of different factors this is used for study area. According to theory of overlay analysis higher value is very suitable, next higher value is suitable, medium value has moderate suitable ,less value but not least has less suitable and least value has unsuitable.

So based on this idea very suitable has 5 value, suitable has 4 value, moderate suitable has 3 value, less suitable has 2 value and unsuitable has 1 value.

Table 4-10 Reclassified Factors and Constraints

Factors Constraints	Very suitable	Suitable	Moderately suitable	Less suitable	Unsuitable
LULC	Shrub land	Agriculture land	----	Forest land	Built-up area, Water body
Road	0-1000m	1000-2000m	2000-3000m	3000-4000m	>4000m
River	>300m	200-300m	100m-200m	50-100m	0-50m
Gafarsa water. R	>400m	300m-400m	200m-300m	100-200m	0-100m
Slope	0-6^{o}	6^{o}-12^{o}	12-20^{o}	20-25^{o}	>25^{o}

The Euclidean distance and Reclassified factors and Constraints are shown in Fig 4-12 to 4-16.

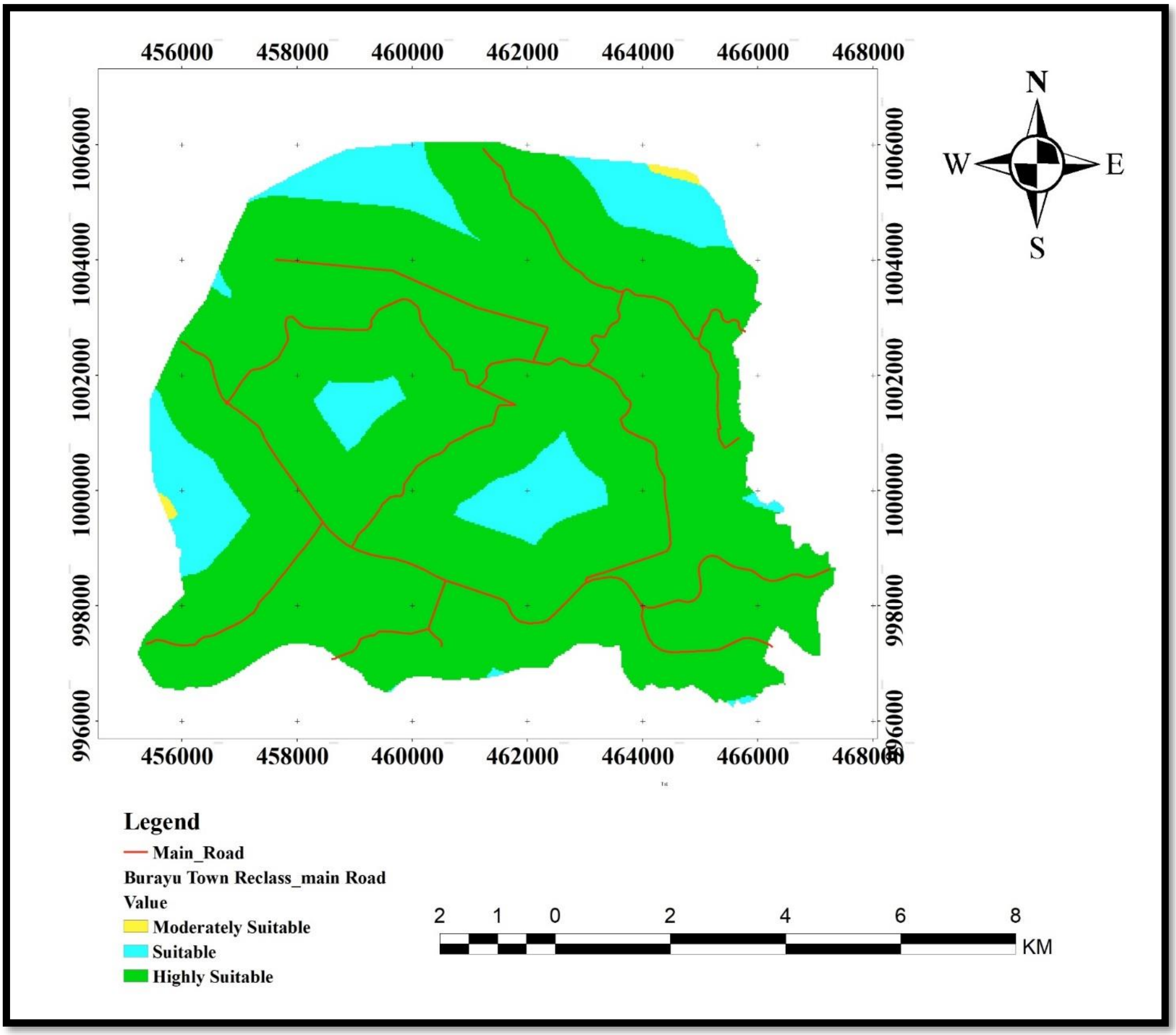

Figure 4-12 Burayu Town Reclassified Main Road distance map

For Road area/site up to 1000m distance is very suitable, area/site 1000m-2000m is suitable, area/site 2000-3000m moderately suitable, area/site 3000-4000m is less suitable and area/site greater than 4000m is unsuitable.

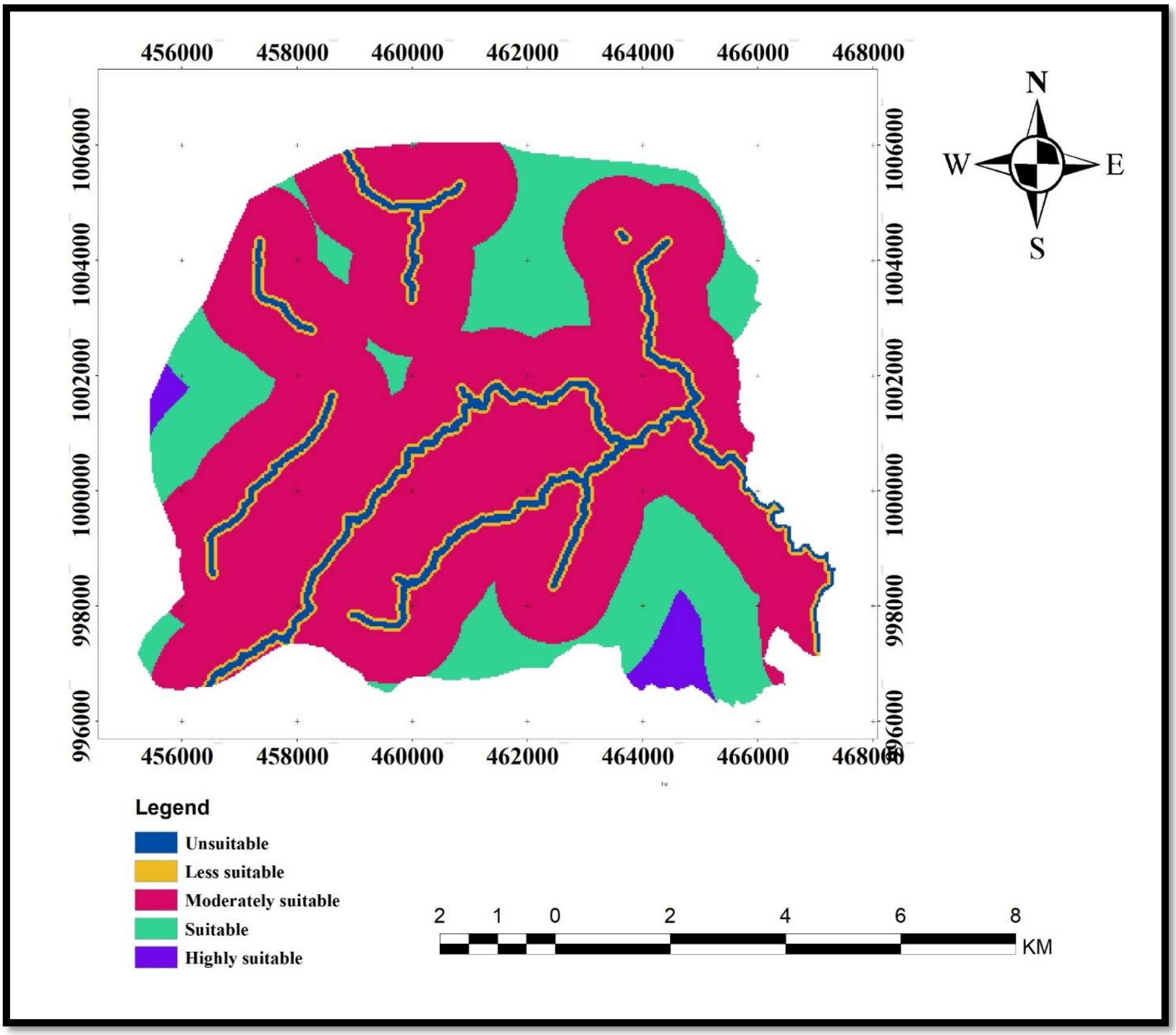

Figure 4-13 Burayu Town Reclassified River map.

For River area/site greater than 300m is very suitable, area/site 300-200m is suitable, area/site 200-100m is moderate suitable, area/site 100-50 is less suitable and area/site within 50m is unsuitable.

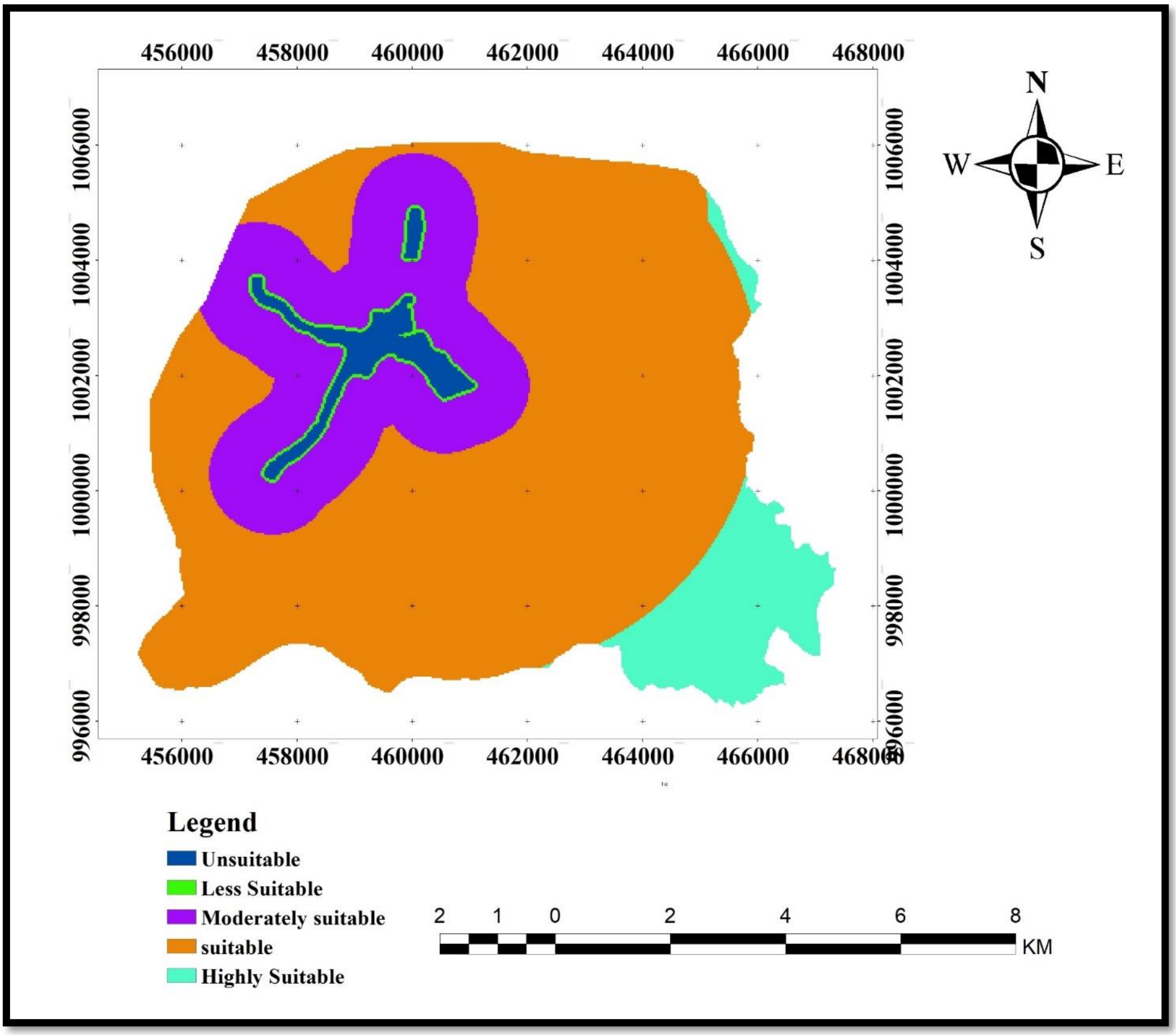

Figure 4-14 Burayu Town Reclassified Gafarsa water Reservoir map.

For Gafarsa water Reservoir area/site greater than 400m is very suitable, area/ site 400-300m is suitable, area/ site 300-200 moderately suitable, area/site 200-100 is less suitable and area/site within 100m is unsuitable.

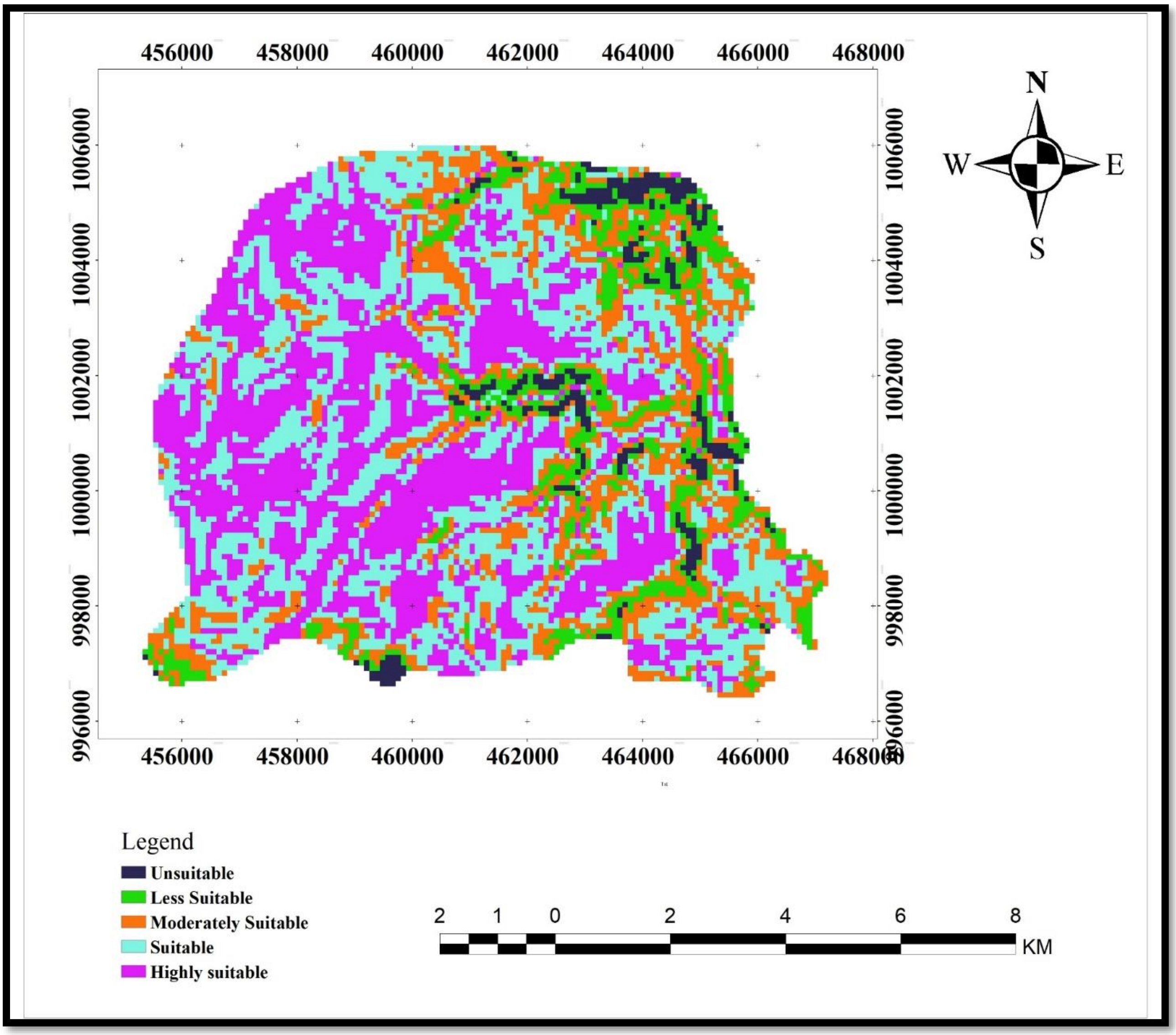

Figure 4-15 Burayu Town Reclassified Slope map.

For Slope area/ site 0-6 degree is very suitable, area/site 6-12 degree is suitable, area/site 12-20 degree is moderately suitable, area/site 20-25 degree is less suitable and area/site greater than 25 degree is unsuitable

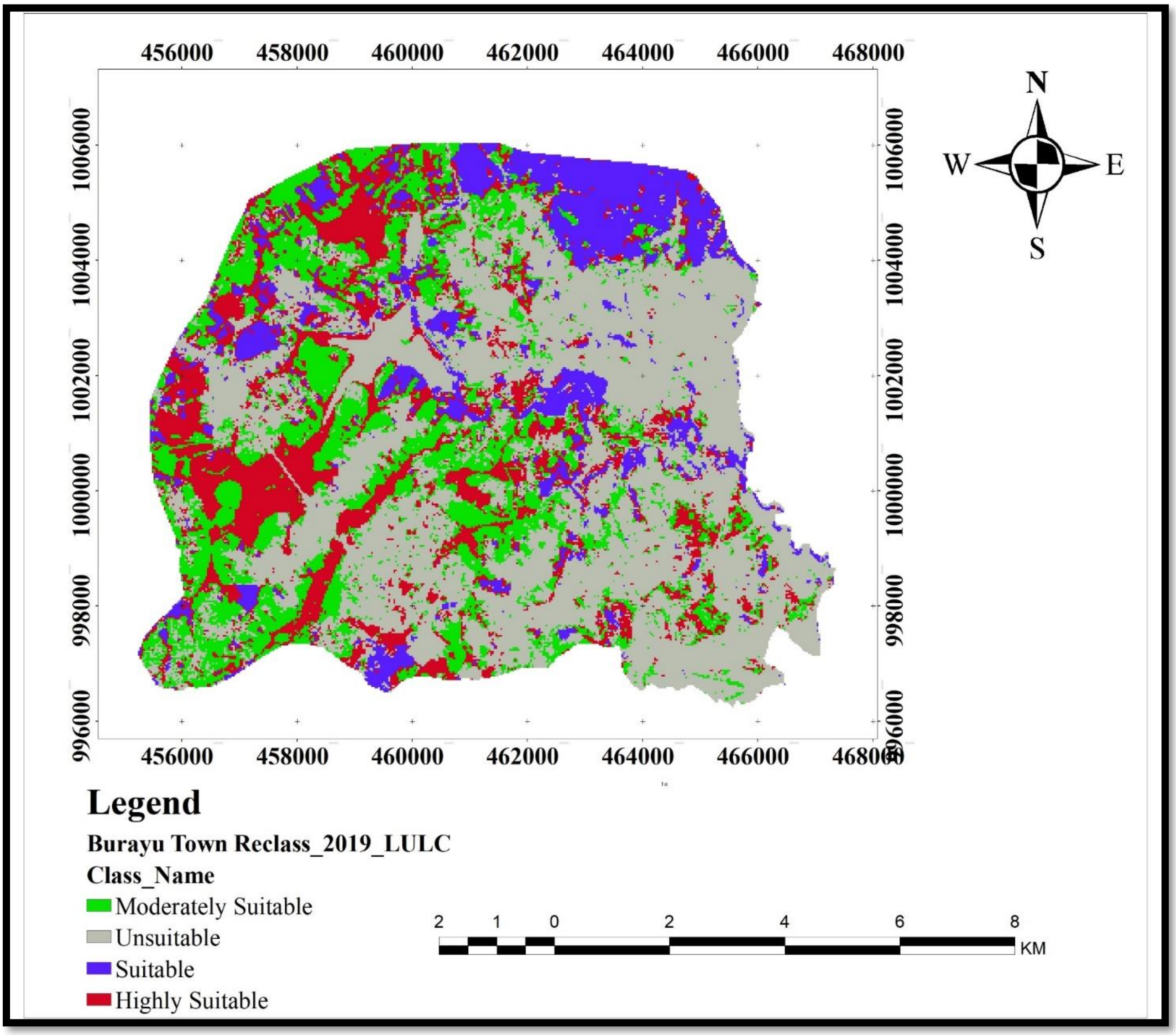

Figure 4-16 Burayu Town Reclassified LULC 2019 Map.

LULC type Shrub land is very suitable for Built-up area, Agriculture land is suitable, Forest land is less suitable and Built-up area and Water body is unsuitable.

4.2.4 Analytical Hierarchy Process (AHP)

The weights are developed by providing a series of pairwise comparisons of the relative importance of factors to the suitability of pixels for the activity being evaluated. Analytical Hierarchy Process (AHP) is one of the multiple criteria decision-making method that provides measures of consistency. Pair wise comparison matrix obtained by decision maker must satisfy Consistency Ratio condition (CR<0.1), if not decision maker has to revise his decisions and improve the Consistency Ratio to acceptable range (i.e., < 10%). Consistency Ratio (CR) is acceptable because is less than 0.1 CR=CI/RI<0.1.

Pairwise comparison

Table 4-11 Analytical Hierarchy Process (AHP) weight of Factors and Constraints.

Analytical Hierarchy Process (AHP) weight of each Factors and Constraints					
	Road	LULC (2010)	Built up (2010)	Gafarsa Water resevoir	River
Road	1				
LULC (2010)	1/3	1			
Built up (2010)	1/5	1/3	1		
Gafarsa water reservoir	1/7	1/5	1/3	1	
River	1/9	1/7	1/5	1/3	1

Table 4-12 Eigenvector of weights of constraints and factors.

The Eigenvector of weights of constraints and factors.	
Factors and Constraints	Factors and Constraints weights
Burayu Town Road	0.5128
Burayu Town LULC (2010)	0.2615
Burayu Town Built up area (2010)	0.1290
Burayu Town Gafarsa water	0.0634
Burayu Town Rivers	0.0333
Total weight=1.000	

4.2.5 Weighted Overlay

The Weighted Overlay tool applies one of the most used approaches for overlay analysis to solve multi criteria problems such as site selection and suitability models. In a weighted overlay analysis, each of the general overlay analysis steps is followed. The first steps Reclassifies values in the input raster into a common evaluation scale of suitability or similarly unifying scale , second Multiplies the cell values of each input raster by the raster's weight of importance and third Adds the resulting cell values together to produce the output raster. In Weighted Overlay tool was used for suitability modeling, higher values generally indicate that a location is more suitable. Using reclassified Road, River, Gafarsa water reservoir, Slope, and Burayu Town Land use land cover of 2019 doing weight overlay analysis the suitable site for Housing development result is shown in Fig 4-17.

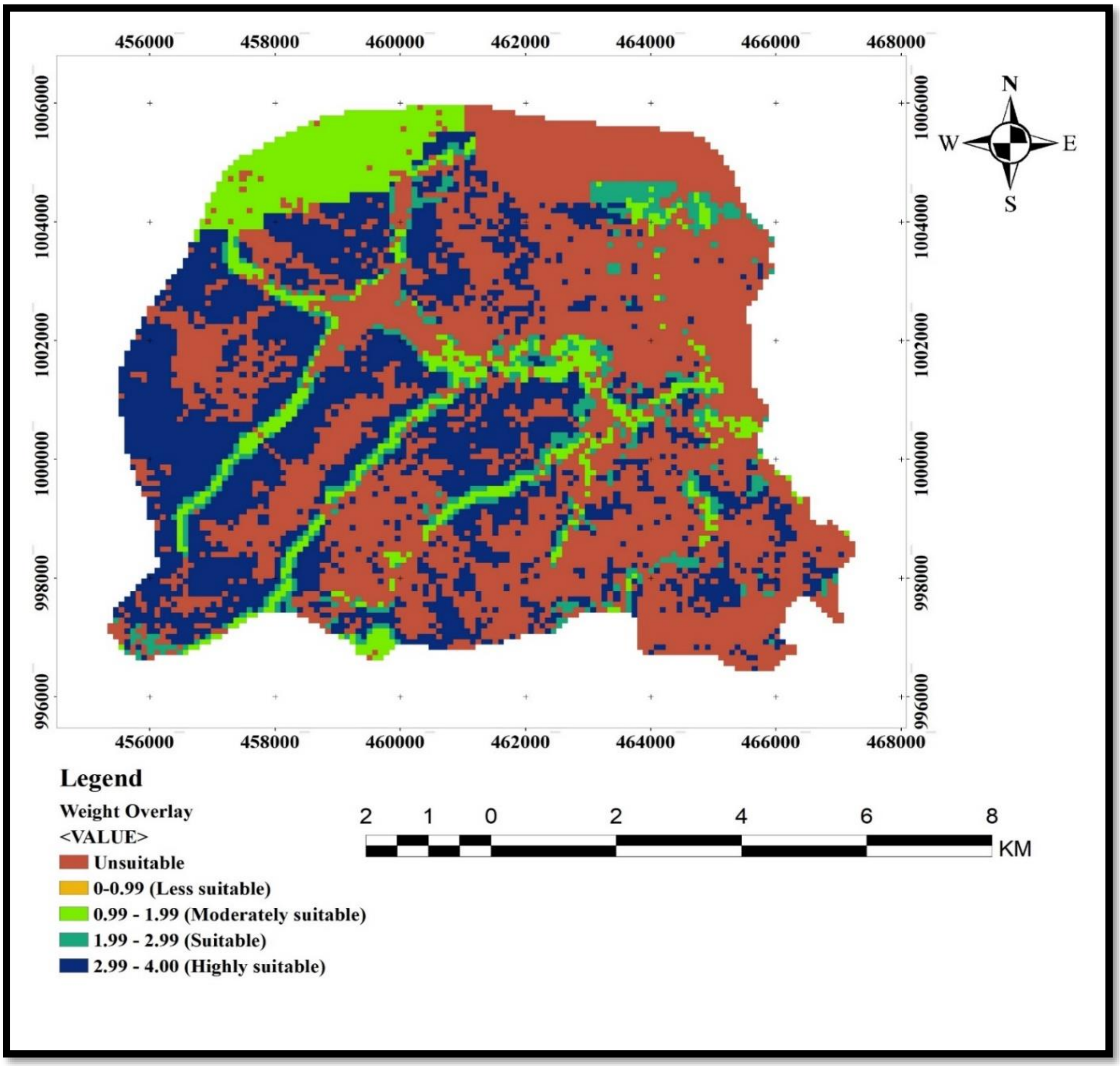

Figure 4-17 Burayu Town Suitable site for Housing Development.

Very suitable and suitable sites exist in Gafarsa Guje and Gafarsa Burayu Kebeles, and unsuitable sites are exist in Lakkku Katta, Burayu Katta and Malka Gafarsa.

The Pixel size of land sat used 30m by 30m=0.0009km2=0.09Ha. The Area obtained count times area of pixel size (0.09Ha).

Table 4-13 sites suitability for new Housing.

Level of Suitability	**Count**	**Area (Ha)**	**Percent (100%)**
Highly suitable	49779	300	3
Suitable	10512	2400	27
Moderately suitable	9025	800	9
Less Suitable	26672	1000	11
Unsuitable	2968	4500	50
Total	99956	9000	100

4.3 Transition Potential Modeling

Transition Potential Modeling, used to identify the potential of land to transition.

The Transition Potential for each LULC classes in between 2000-2010 is model, these model transition are many around 15 transition model. These model used to predict LULC of 2019 that used for validation in order to predict for 2050 LULC of Burayu Town. Transition potential from Forest land to Built-up area, water to Built-up area, Agriculture land to Built-up area, Shrub land to Built-up area using Multi-Layer Perceptron Transition potential. Transition Potential from all LULC to Built-up area from highest to lowest shrub land (0.36), Forest land (0.24), and Agriculture land (0.17) and water body (0.11) shown in figure 4-18 and the others are in Appendix K.

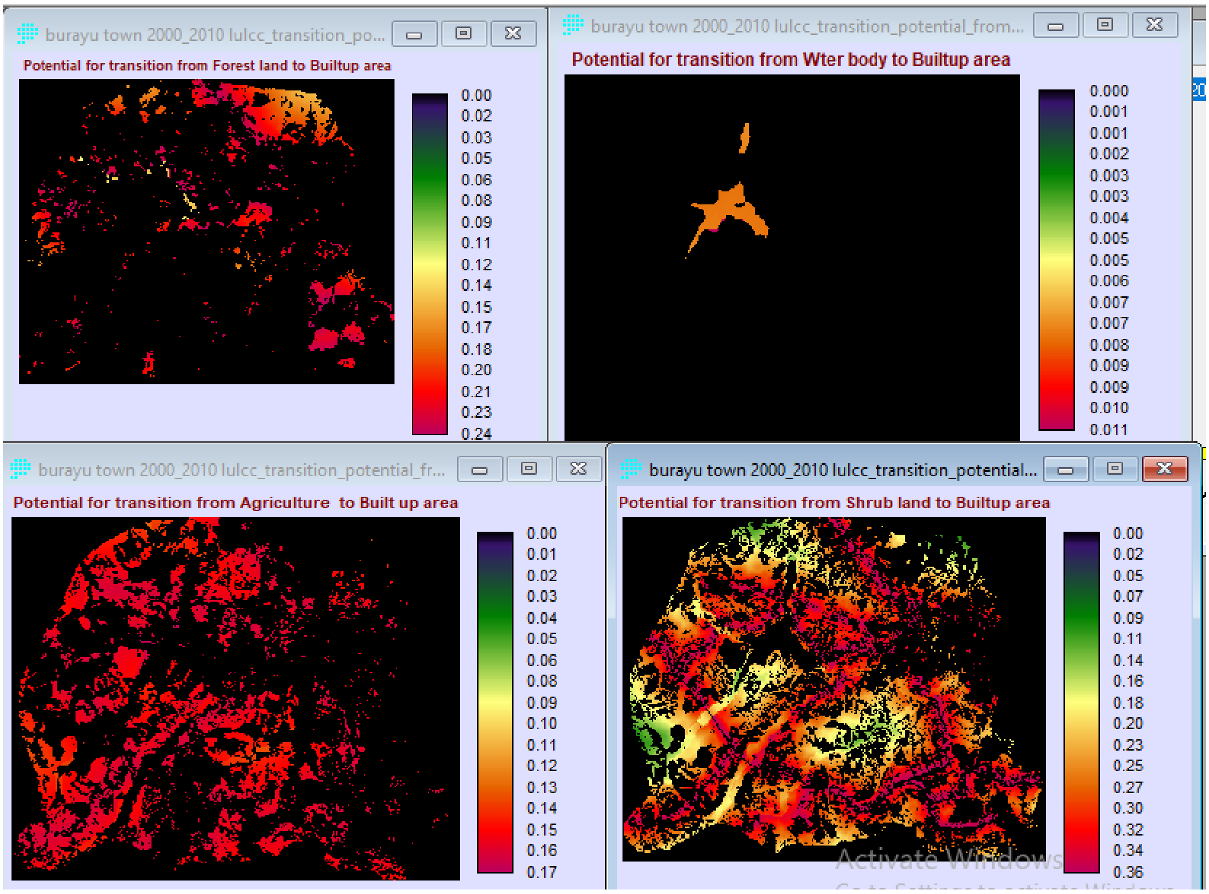

Figure 4-18 Burayu Town Transition Potential (2000-2010).

4.4 Future Prediction (Projected) and Modeling for 2019

MLP Markov model has been selected for simulating land cover map of Burayu Town for the year 2019 for validation and predict the final land use land cover map for 2050 year. Two basic models of change prediction are: Hard prediction model and a soft prediction model. The Hard classifiers make a definitive decision about the land cover class to which any pixel belongs. Soft classifiers do not make a definitive decision about the land cover class rather, they develop statements of the degree to which each pixel belongs to each of the land cover classes being considered.

For this study since the hard prediction model was used as the training area of each land use land cover classes to make a definitive decision to which any pixel belongs. There are two types of Map in Fig 4-19, the first on the left hand side is the predicted one and second on the right hand side is the classified Map of Buryu Town 2019 year that used for validation.

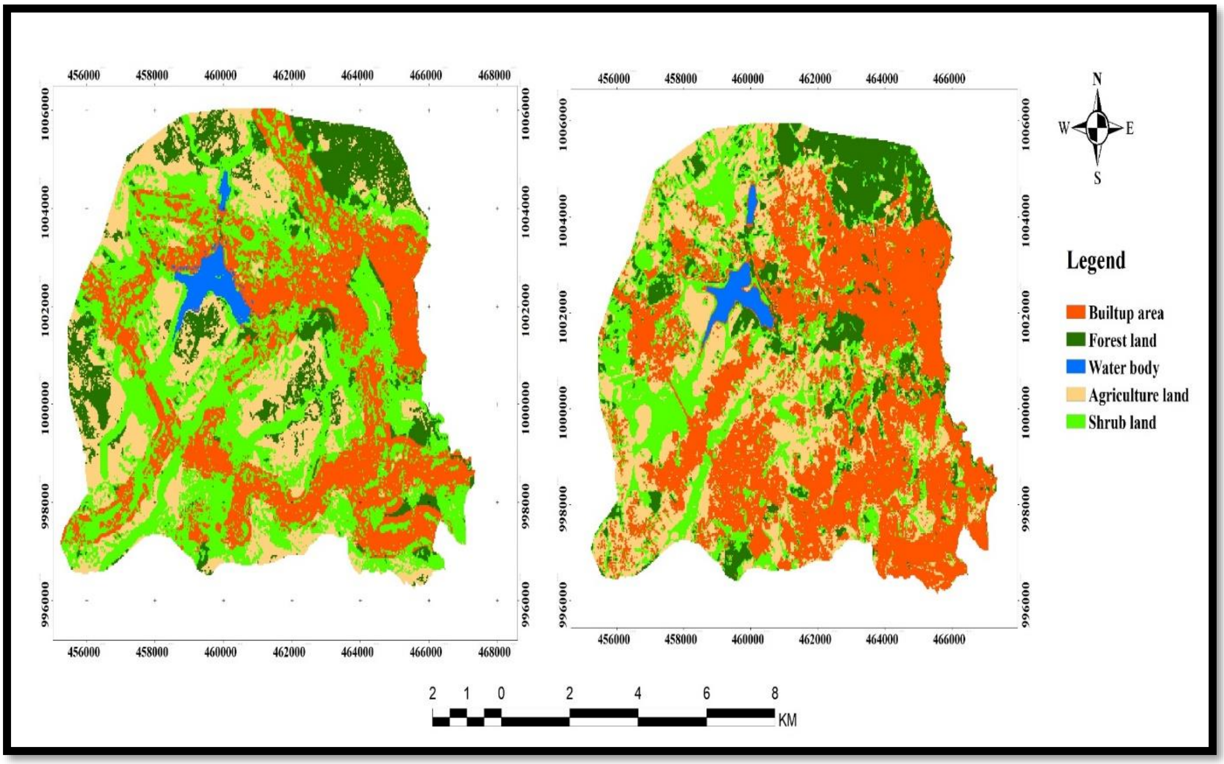

Figure 4-19 Burayu Town 2019 LULC predicted and classified.

Table 4-14 Burayu Town LULC classes area change between Predicted and Classified 2019

Burayu Town LULC Classes	Predicted Area 2019		Classified Area 2019		Area Difference	
	(Ha)	%	(Ha)	%	(Ha)	%
Built up area	2500	39	4100	46	1600	+7
Forest land	1200	13	1100	13	100	0
Water body	100	1	100	1	000	0
Agricultural land	1900	21	1900	21	000	0
Shrub land	3300	26	1800	19	500	-7
Total area	9000	100	9000	100		

Burayu Town Classified LULC Classes Built-up area of LULC 2019 is decreased from 4100Ha to 2500Ha predicted area using factors/variables that determine the suitability of Built up area. This shows (1600Ha) of illegal construction in sensitive areas. Finally Shrub land is increased from 1800Ha to 3300Ha.

4.5 Model Validation

In order to predict Burayu Town Urban Land use change for 2050 first predict for 2019 using the factors and constraints and validating the output of the predicted LULC map in 2019, with classified LULC map of 2019. From Validation bar Kstandard (overall kappa) is 0.5626 by Multiple Base Resolution (MBR) 100 x 100 and the strength of agreement is moderate based on strength of kappa statistics and continue to predict for 2050 urban land use changes.

4.6 Change Prediction (simulation) Modeling for 2050

The Change Prediction (simulation) modeling for 2050 was based on the Cellular Automata. The validation of the model accuracy is needed, in order to achieve acceptable accuracy, this study had employed an approach to simulate LULC of 2019 (time t3) from the historical LULCC process for time t1 (2000) and for time t2 (2010) and then the simulated result was compared the reference LULC map of 2019 (classified LULC map 2019). The simulated LULC in 2019 was successful and value was 56.26% that is a moderate agreement between the reference map and the Predicted (simulated) map. So using the historical LULCC process from 2000 to 2010 is accurate and reliable to predict LULC patterns in 2050. Generating the potential transition of all land use land cover classes of 2010 and 2019 with similar procedures and Predict Land use land cover classes of Burayu Town of 2050 year. Markov Chain Model Analysis that shown Transition area and transition Probability in Table 4-15 and 4-16.

Table 4-15 Markov chain transition area of Burayu Town (2010-2019)

Markov chain Transition area of Burayu Town 2010-2019 (1 cell=900sqm)						
	Built-up area	Forest land	Water body	Agriculture land	Shrub land	Total cells
Built-up area	28075	8315	163	4187	4718	45458
Forest land	5698	3737	0	1358	1699	12492
Water body	279	0	1153	0	0	1432
Agriculture land	12593	2166	0	4798	1759	21316
Shrub land	11430	2949	0	2632	2144	19156
Total cells	58075	17167	1316	12975	10321	99854

Table 4-16 Markov chain transition Probability of Burayu Town (2010-2019

Markov chain Transition probability of Burayu Town LULC 2010-2019 (in cells)						
	Built-up area	Forest land	Water body	Agricultural land	Shrub land	Total probability
Built-up area	0.6176	0.1829	0.0036	0.0921	0.1038	1
Forest land	0.4561	0.2982	0.0009	0.1087	0.1360	0.9999
Water body	0.1949	0.0246	0.7554	0.0104	0.0147	1
Agricultural land	0.5908	0.1016	0.0015	0.2236	0.0825	1
Shrub land	0.5968	0.1539	0.0017	0.1374	0.1102	1
Total probability	2.4562	0.7612	0.7631	0.5722	0.4472	4.9999

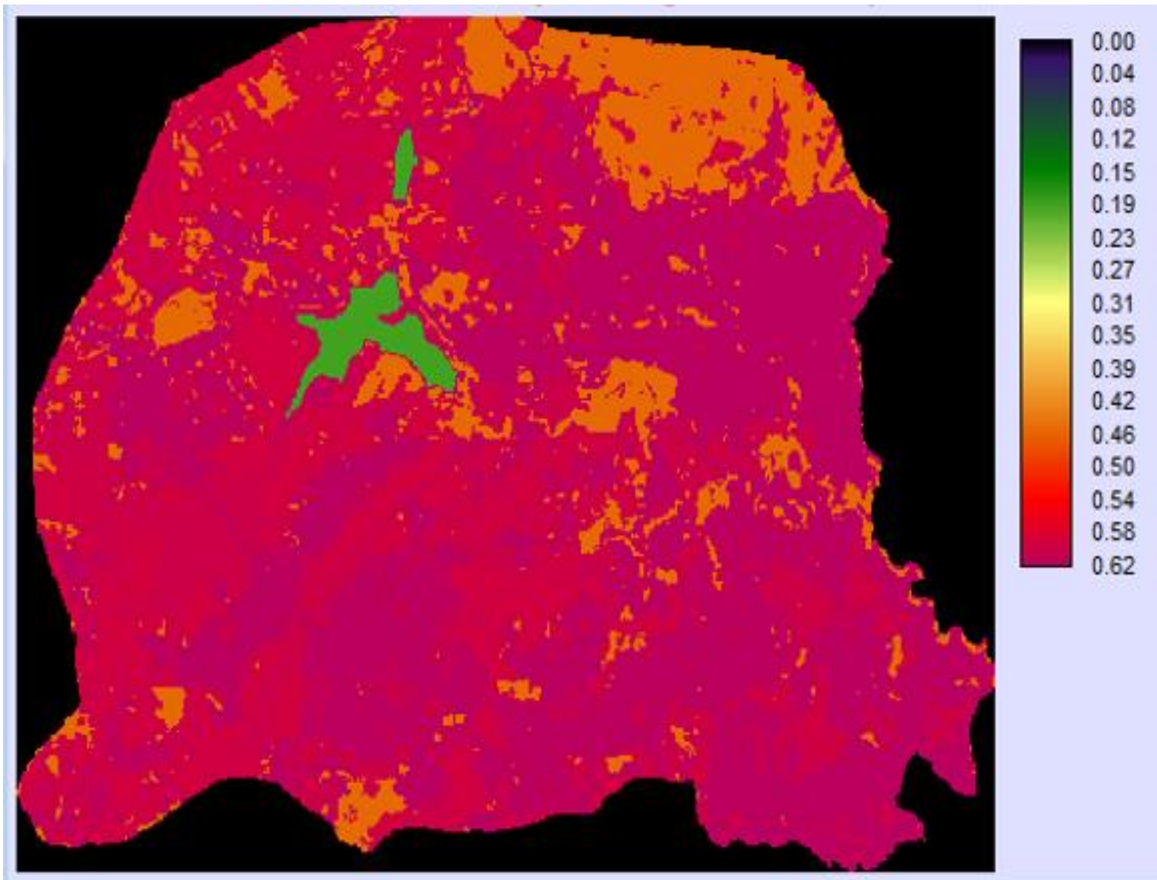

Figure 4-20 Markovian Conditional Probability of being class Built up area (predict 2050).

Markovian Conditional Probability of being class Built-up area, Forest land, Water body, Agriculture land and Shrub land for predict 2019 maps area shown in Appendix M**.**

*Burayu Town Simulated (Projected) LULC OF 2050 G.**C.***

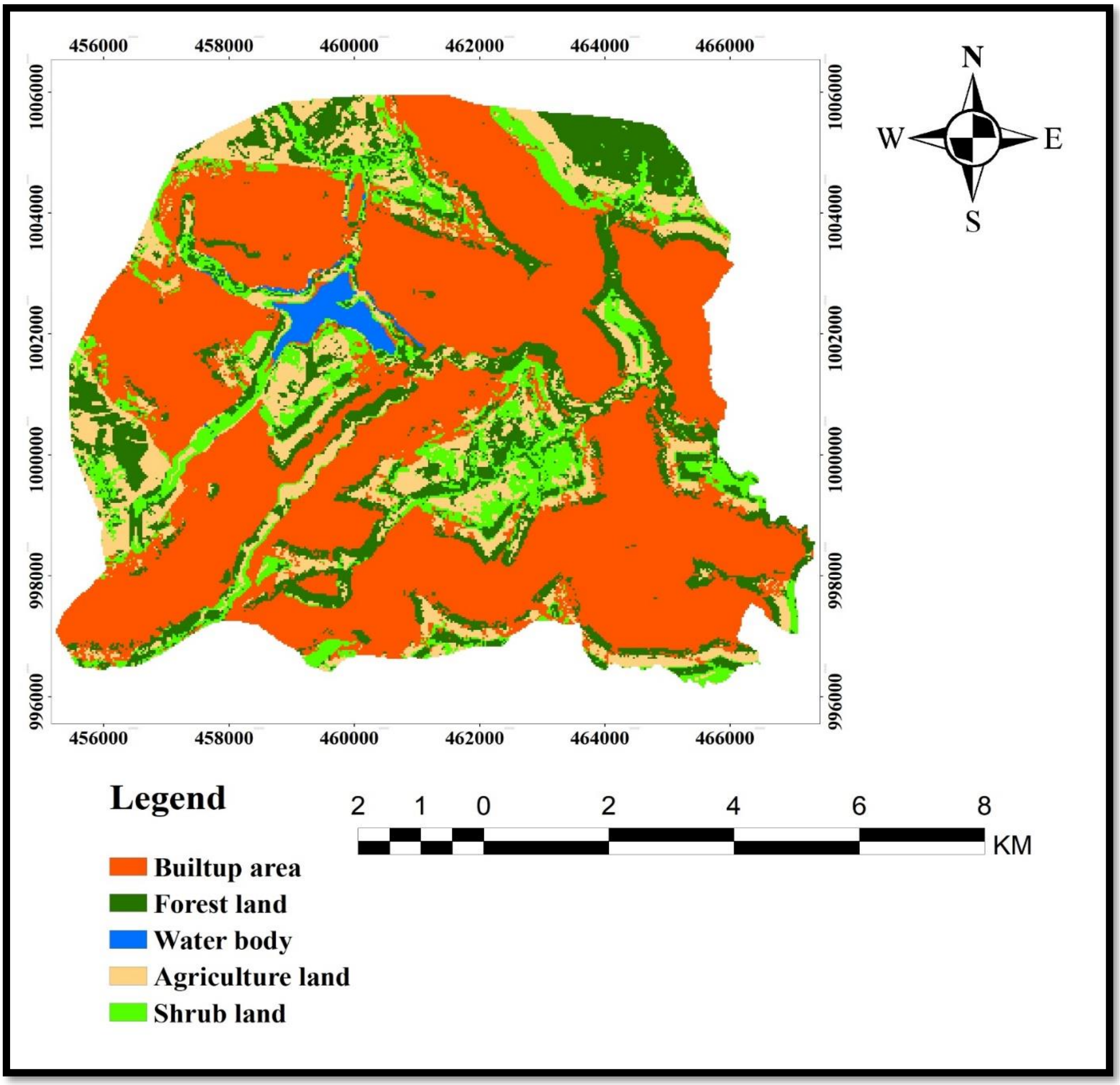

Figure 4-21 Burayu Town Simulated (Projected) LULC OF 2050 G.C

Using transition Potential of 2010-2019 future projected Burayu Town LULC in 2050 will contains 5200Ha (58%) of Built-up area, 1500Ha (17%) of Forest land, 100Ha (1%) of water body, 1200Ha (13%) of Agriculture land and 1000Ha (11%) of Shrub land. Based on this predicted result the Built-up area is increased from 4100Ha (46%) in 2019 to 5200Ha (58%) in 2050G.C this is predicted result by considering factors and constraints. Built-up area land use land cover type is increasing in an alarming rate over the years. While the major contributors are Shrub land and Forest land cover types.

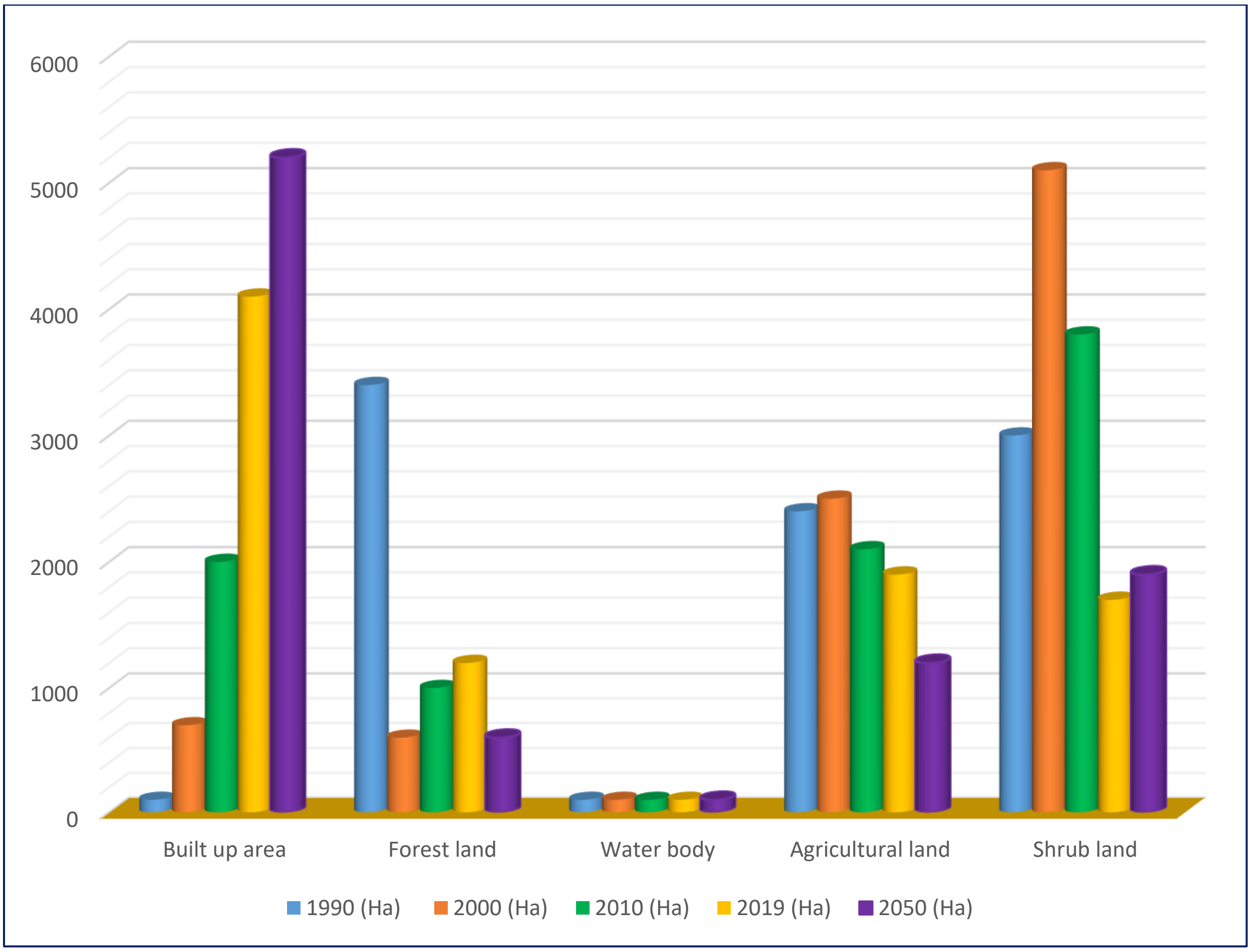

Figure 4-22 Burayu Town LULC Classes of three decades and predicted 2050.

Table 4-17 Burayu Town Land use land cover changes (1990-2019) and predicted (2050)

Burayu Town Land use land cover changes (1990-2019) and predicted (2050)					
Total area	1990 (Ha)	2000 (Ha)	2010 (Ha)	2019 (Ha)	2050 (Ha)
Built up area	100	700	2000	4100	5200
Forest land	3400	600	1000	1200	600
Water body	100	100	100	100	100
Agricultural land	2400	2500	2100	1900	1200
Shrub land	3000	5100	3800	1700	1900
Total	9000	9000	9000	9000	9000

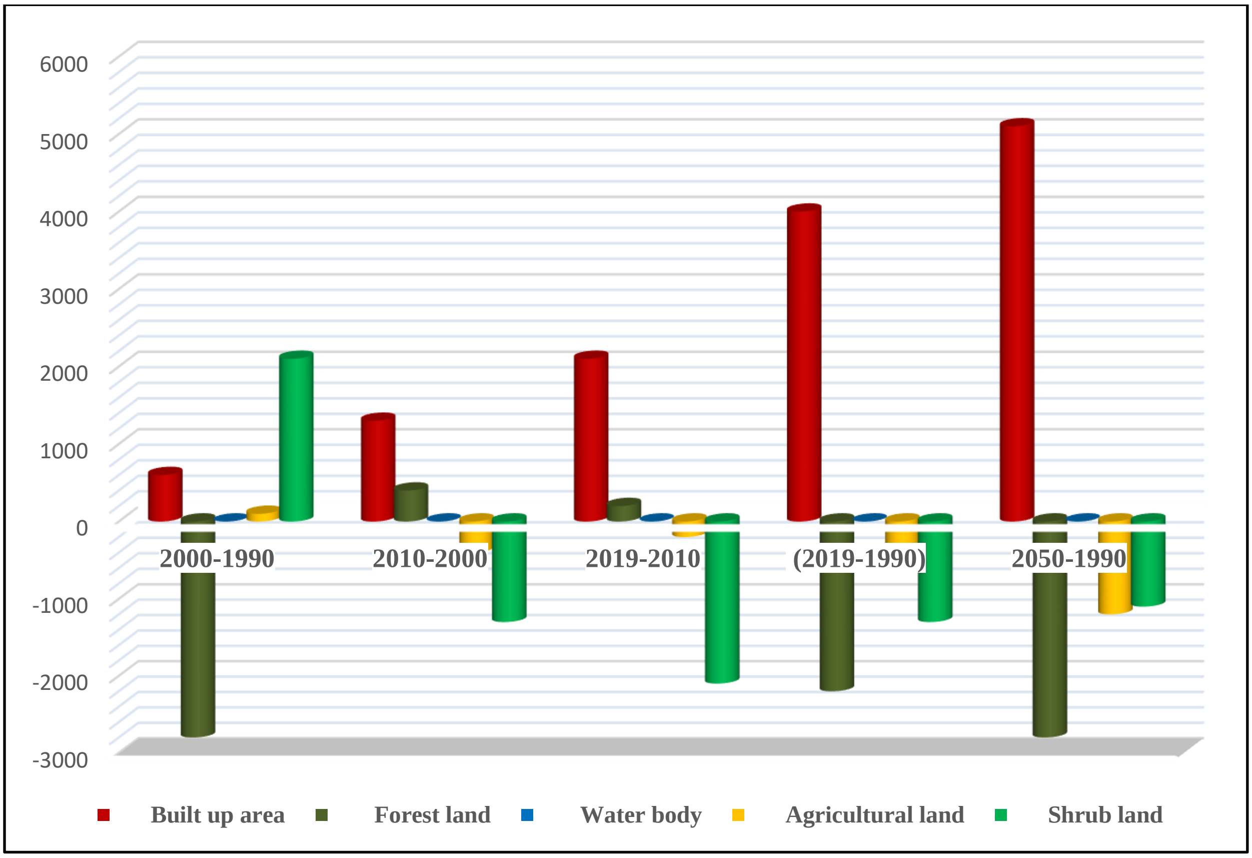

Figure 4-23 Burayu Town LULC Change (Ha).

In Burayu Town Urban land use land cover changes are double increased for last three decades and increase for Predicted year. The other such as Forest land, Agriculture land and Shrub land are decreased within 2050-1990.

Table 4-18 Burayu Town Land use land cover Net changes.

Burayu Town Land use land cover Net changes.					
	2000-1990	2010-2000	2019-2010	(2019-1990)	2050-1990
Built up area	600	1300	2100	4000	5100
Forest land	-2800	400	200	-2200	-2800
Water body	0	0	0	0	0
Agricultural land	100	-400	-200	-500	-1200
Shrub land	2100	-1300	-2100	-1300	-1100
Net change	0	0	0	0	0

4.7 Discussion

Land use and land cover changes have wide range of consequences at all spatial and temporal scales. Because of these effects and influences it has become one of the major problems for environmental change as well as natural resource management. Identifying the complex interaction between changes and its drivers over space and time is important to predict future developments, set decision making mechanisms and construct alternative scenarios.

Burayu Town urban land use changes (Urban expansion) is increased by 3900Ha (44%) within three decades (1990-2019) and increased 1100Ha (12%) for future three decades (2050). The rapid urban expansion over the past three decades, the spatiotemporal patterns of urban expansion varied among each decades. The extent, direction, and location of urban expansion in each decades have mainly been associated with variances in their physical setting, administrative conditions, demography, policies, and urban master plans. The physical growth of all the three cities showed clear footprints of topographic and physical limitations in the directions and shaping the growth of the town. The result is in harmony with the recent study in Ethiopia cities such as Addis Ababa, Adama and Hawasa city by (Berhanu K, et al, 2019), who reported that a city with higher administrative status is more likely to obtain a large area of land for development and subsequently acquire the high potential for urban expansion as well as economic growth. Other similar result by (Bayes. A, 2011) thesis quantify and investigate the characteristics of urban land cover changes (1989-2009) and predict the future urban growth of Dhaka City using the Landsat satellite images of 1989, 1999 and 2009. According to his research 58% of the total study area will be converted into Built-up area in 2019. (Bedassa R, 2014) Analyze urban expansion and modelling of land use/land cover changes in Adama city using Landsat 1973, 2000 and 2010. According to his results expansion of built up increase from 2%in 1973, 10% in 2000, 23% in2010 and 60.27% in predicted of 2040 after 30 years. (Atalel G, 2014) analyze of urban land use and land cover changes a case of Bahir dar city. His results shown that there was an increased expansion of built up areas in the last 25 years from 1.5% in 1986 to 4.1 % in 2001 and 9.4% in 2010.

The negative effects of urban expansion in Burayu Town highly increased, the land use and land cover changes and becomes many problems such as uncontrolled Housing development like increase of squatter settlements and expansion of slums, deteriorating environmental quality, loss of prime agricultural land, displacement of farm communities, enclosing surrounding rural land to urban territory and conflict related to land. According to Degu Bekele (2014) paper shows in Burayu Town out of 246 sample Houses, 58.1% of the squatter houses are located in environmentally sensitive areas. Similarly in this study Burayu Town 2019 Classified Land Use Land Cover classes of Built-up area is 4100Ha (46%) without Factors and constraints, but using factors and constraints that determine the suitability of Housing, Built-up area decreased to 2500Ha (39%) by Predicting for 2019. In Burayu Town the main Factors such as distance to Road, River, and slope, and constraints are Gafarsa water Reservoir and Built-up area. This shows around 7% (1600Ha) of Built up area is illegal construction in sensitive areas. So for future to solve the problems of social, environmental and economic problems of Societies, Burayu Town land administration and management select the suitable sites of Housing developments. By this study the sites of very suitable and suitable Housing development exist in Gafarsa Guje and Gafarsa Burayu Kebeles, and unsuitable sites exist in Lakkku Katta, Burayu Katta and Malka Gafarsa.

Burayu Town Urban land Change Map i.e. the Transition from all LULC Classes to Built-up area for three decades (1990-2019) from Shrub Land (1500Ha), Agriculture land (1100Ha), Forest land is (1400Ha) changed to Built-up area. Similar to this study results Efa Taddesse (2017) Paper shows the rapid Urban land use land cover changes in Oromiya special zone surrounding Finfinnee Towns especially in Burayu Town caused several prospects and challenges on the livelihood of nearby farming community by converting Agriculture land, Forest land and Bare land to urban built-up areas through legal and illegal.

This Predicted Burayu Town urban land use land cover change result are obtained by considering the Factors and Constraint as constant (not dynamic) and calculate changes within the Boundary of study. Built-up area is 5200Ha (58%), Forest land is 1500Ha (17%), water body is 100Ha (1%), Agriculture land is 1200Ha (13%) and shrub land is 1000Ha (11%). Based on this predicted result the Built-up area is increased from 4100Ha (46%) in 2019 to 5200Ha (58%) in 2050. Built-up area land use land cover type is increasing in an alarming rate over the years. While the major contributors are Shrub land, Agriculture land and Forest land cover types. The population of Burayu Town was rapidly increased from 135,670 in 2010 to 375,000 in 2019 showing that the population of the Town has increased by three times within the one decades and if population growth with this rate the total Population of Burayu Town became 3,375,000 Pop in 2050. Rapid Population growth, increase Urban Land use land cover Changes and the Predicted result may become less not only this, Burayu Town implement urban housing development program called Integrated Housing Development Program (IHDP) gives land for many Governmental worker such as Teachers, Police, and lawyer etc. to improve housing access to low and middle income residents of urban areas also increase Urban land use land cover. (Burayu Town Communication office 2019).

CHAPTER FIVE CONCLUSSIONS AND RECCOMMENDATIONS

5.1 Conclusions

Rapid Urban land use land cover changes and High population increment in case of Migration from Rural to Urban are growing steadily specially in the developing countries. Urban Land use and land cover changes have wide range of consequences at all spatial and temporal scales. The main reason Burayu Town selected for this study is that the issues of negative effects of urban land use and land cover changes such as: loss of prime agricultural lands and protected Forest lands, and expansion of slums lives in environmentally sensitive areas, rapidly population growth, deteriorating environmental quality, and this became great problems of social, economic and environmental. Monitoring and mediating the negative consequences of LULC while sustaining the production of essential resources has therefore become a major priority of researchers and policymakers around the world. This study has been conducted by integrating GIS, remote sensing and Land use land cover modeling tools to Model Spatio temporal urban land use land cover changes of Burayu Town using Landsat 1990, 2000, 2010, and 2019 Year and predict for future three decades (2050).

This study results show Urban land use land cover changes (urban expansion) of Burayu Town area highly increased from 100 Ha (1%) to 4600Ha (46%) in last three decades (1990-2019) and for future three decades 5800Ha (58%) in 2050 if Urban expansion is positive effect and if negative effect urban expansion is greater than this values. Since Burayu Town located nearest Finfinnee (Addis Ababa) city rapid population growth and expansion of squatter houses in Burayu Town is becoming beyond the capacity of the Local government. Squatter houses in the Town are built in catchment areas, along rivers and other environmentally sensitive areas. Even if Burayu Town Administration takes measurement such as demolishing of squatter settlements and regularizing significant number of houses in different years and implement urban housing development program called Integrated Housing Development Program (IHDP) to solve Housing Problems of Societies, these efforts have achieved little in terms of addressing the problems. Another problem is that while Housing land given for societies Site selection of Housing is very important to solve social, environmental and economic problems. According to this study, very suitable and suitable sites for Housing development exist in Gafarsa Guje and Gafarsa Burayu Kebeles, those are open and newly developed urban kebeles and unsuitable sites are exist in Lakku Katta, Burayu Katta and Malka Gafarsa, those are already occupied by Built up area. This study result shows Burayu Town Urban Land use Land cover change is increasing in an alarming rate over the years. While the major contributors such as Forest Land, Agriculture Land and Shrub land, decreased by 2200Ha, 1300Ha, and 500Ha respectively within the last three decades (1990-2019). Burayu Town loss Protected Forest Land, Shrub Land and Prime Agricultural Land, this result becomes deteriorating Environmental quality and Climate change, reduced Farmland.

5.2 Recommendations

Remote sensing, GIS and land use models are important tools in urban land use and land cover change studies. Based on the findings of this study, the following are recommended as future research directions.

- Utilization of high spatial resolution in future able to map finer level of details more accurately by improving the classification accuracy which allow the analysis of more changes in urban land use Changes and for accuracy assessment validation especially for the past year classified satellite images preparation of Ortho photo map or Aerial photo for each Town is better for researcher to do further detail analysis with high quality. Classification of recent images done by using ground truth data collection with the use of GPS technology, but for the past classification if historical images, and Aerial photo does not exist Google Earth is the only solution.
- Burayu Town Urban planner, Land administration offices and Environmental protection offices use this site selected for Housing development to solve the society problems and avoid risks. According to this research results around 40% of Built up area are not constructed in suitable site of residential area, thus consequently faced for many problems and high risk.
- 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.
- This study results can be used as a base information for Urban planner, Land administration and management office, environmental protection office, to investigate impacts of land use land cover change and urban expansion to natural resources and ecological service systems, as well as an effect to people's livelihood for natural and land resources management in the future.
- Federal and Regional Government should give attention for the main problems of housing, infrastructure services and losses of Agriculture land designing strategies for urban expansion based on the findings of the current study.

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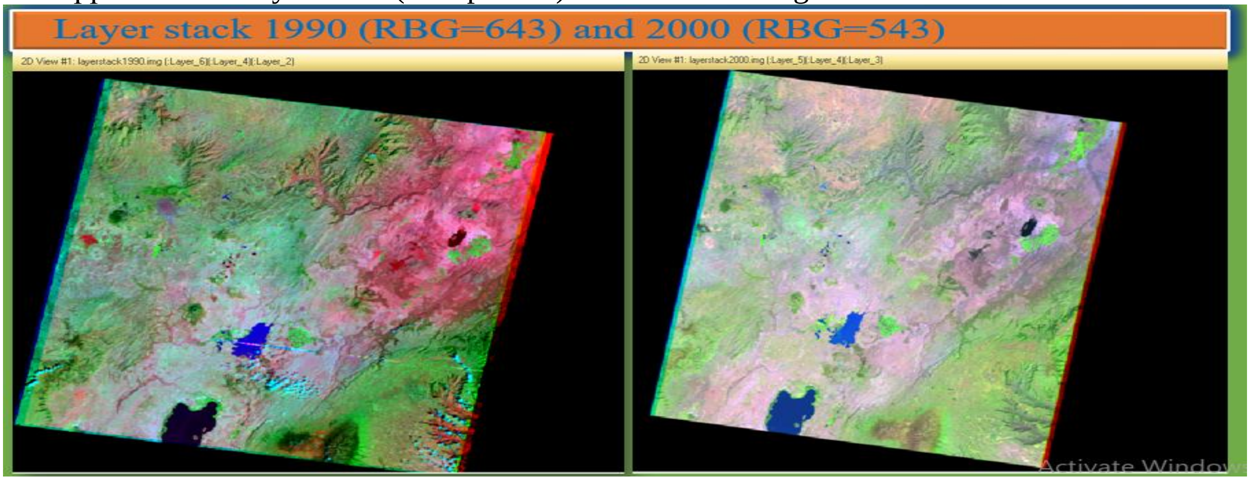
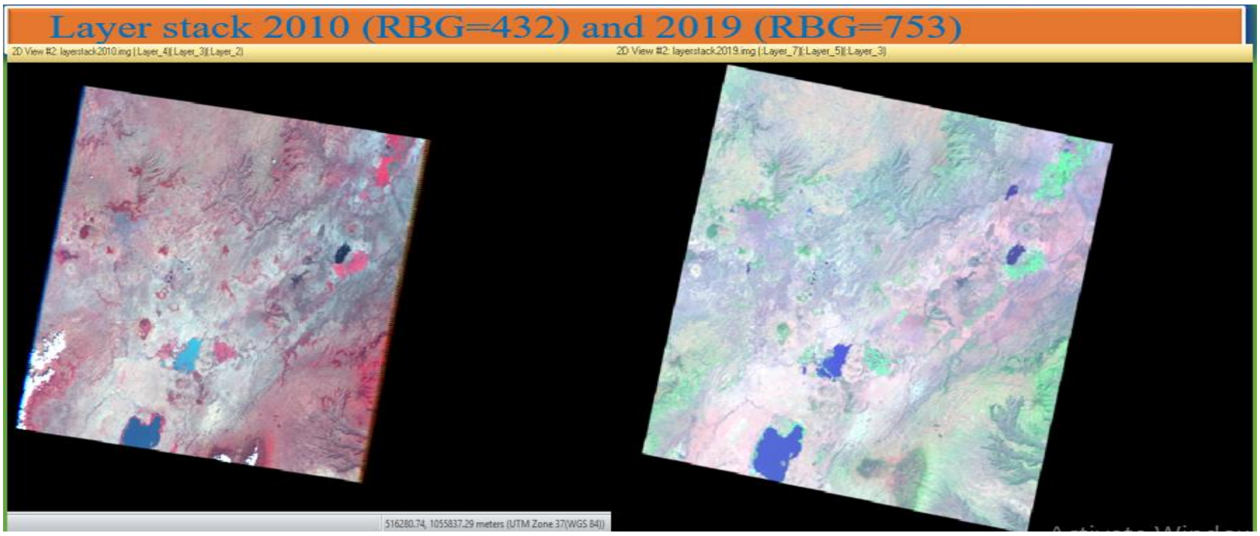
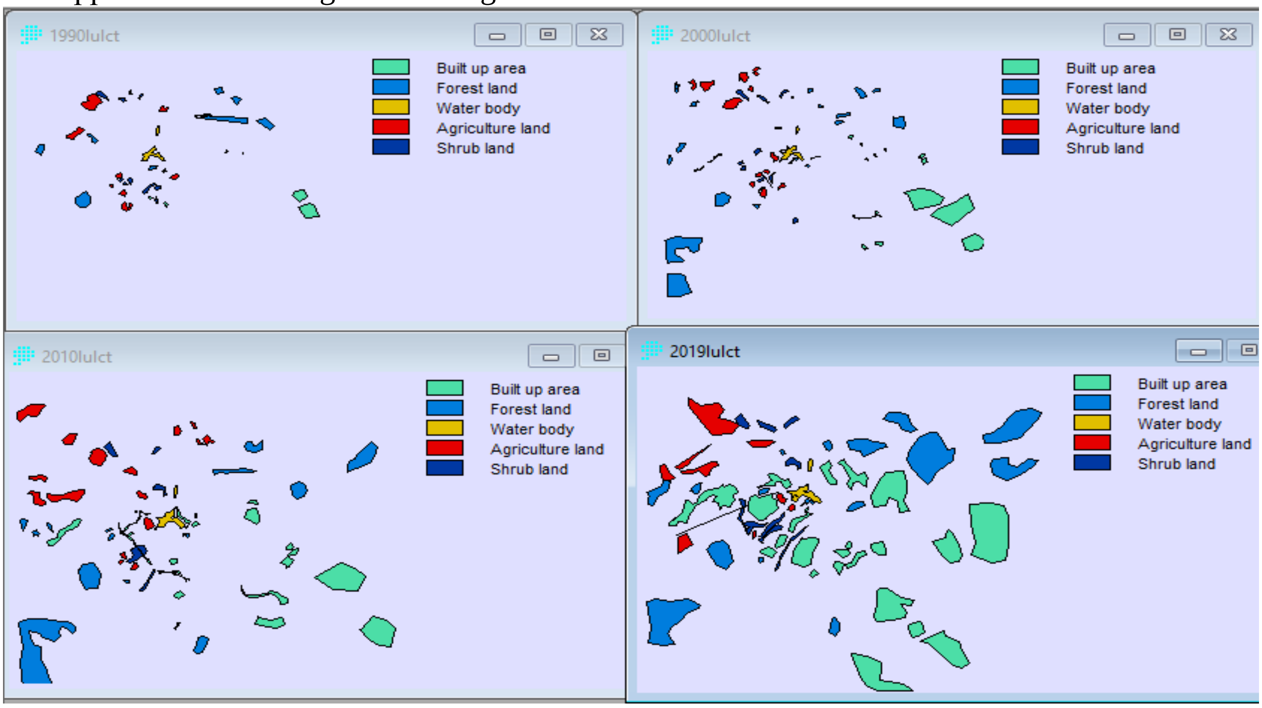
APPENDIX

1. Appendix 'A' Layer stack (Composites) land satellite images

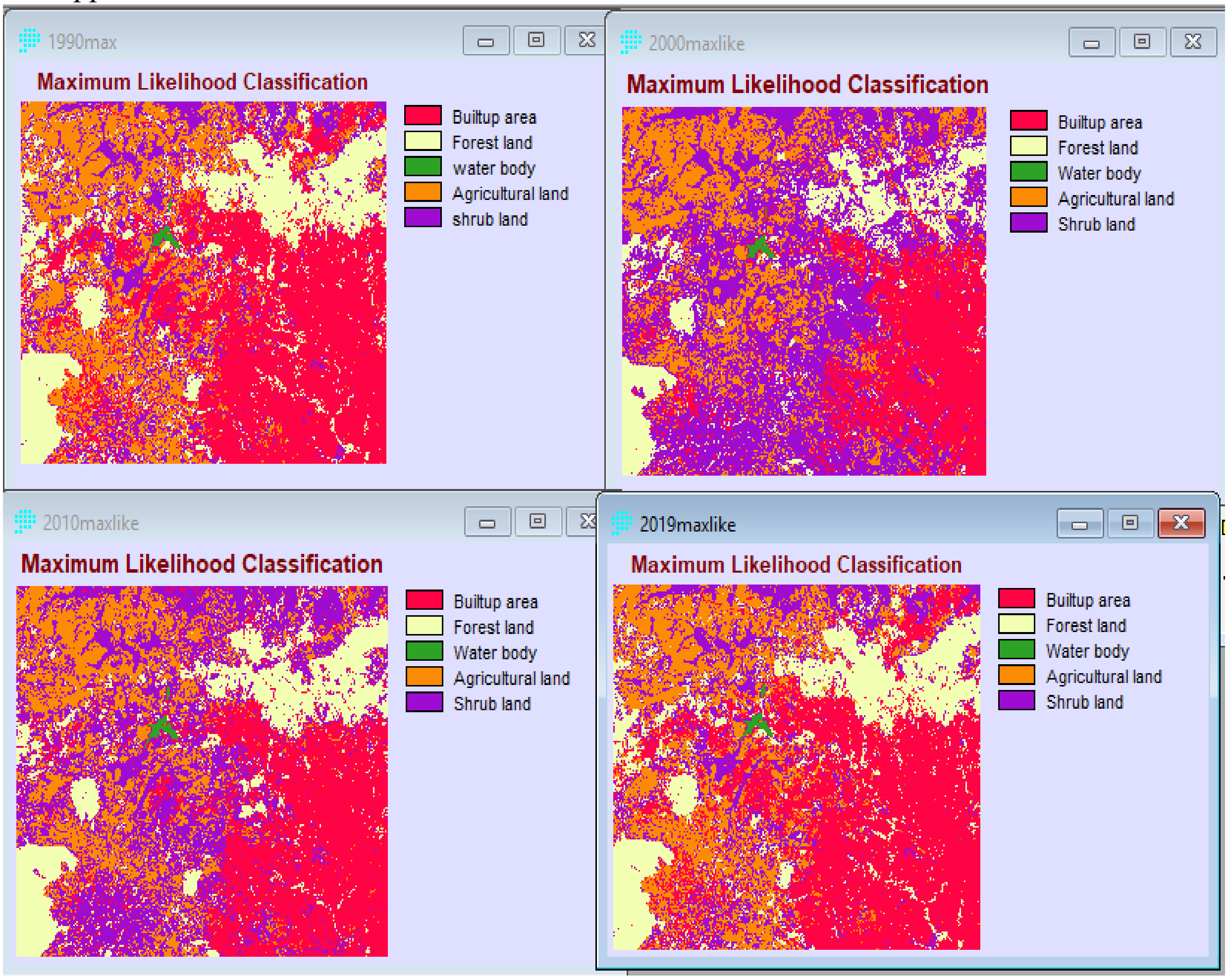




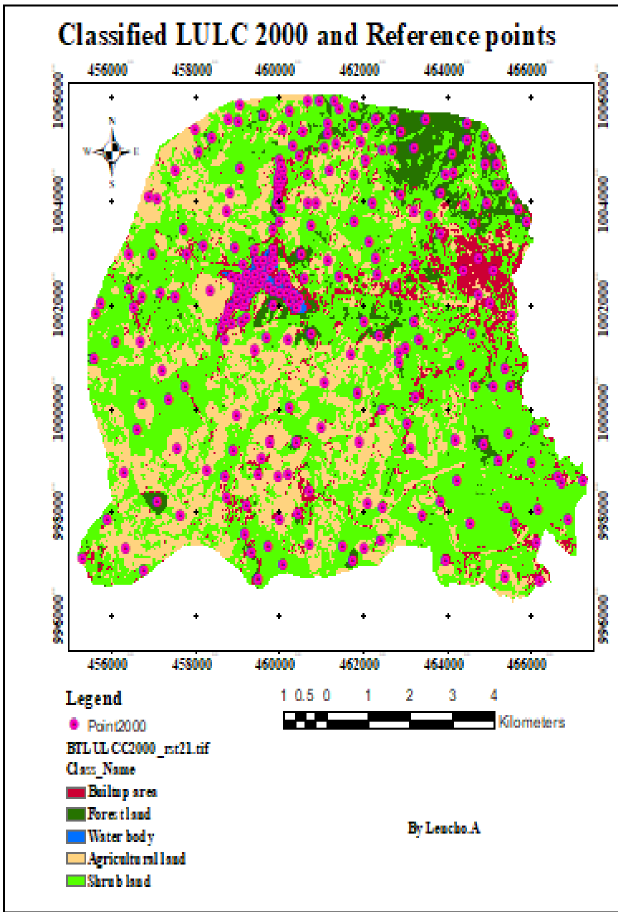
2. Appendix 'B Training area and signature



3. Appendix ‘C’ Maximum likelihood classification LULC Classes.



4. Appendix ‘D’ Reference/ GCP Points and classified image of 1990.2000,2010 and 2019



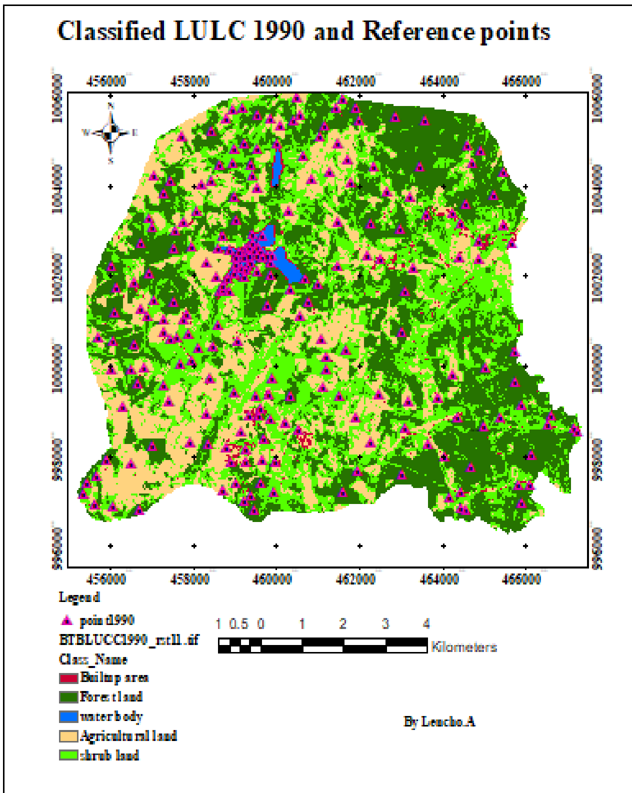
Table

Point2000

FID	Shape *	Id	Point_X	Point_Y	Classifie	Referen
0	Point	1	461773	1005446	1	1
1	Point	2	461085	1005025	1	1
2	Point	3	460698	1004523	1	1
3	Point	4	460506	1004857	1	1
4	Point	5	460572	1005339	1	1
5	Point	6	460028	1004794	1	1
6	Point	7	460052	1003894	1	1
7	Point	8	460702	1003945	1	1
8	Point	9	459141	1002789	1	1
9	Point	10	457799	1002976	1	1
10	Point	11	457539	1002166	1	1
11	Point	12	456448	1002309	1	1
12	Point	13	456561	1001951	1	1
13	Point	14	456888	1004083	1	1
14	Point	15	457789	1000396	1	1
15	Point	16	458869	1001622	1	1
16	Point	17	458707	1001330	1	1
17	Point	18	459136	1001655	1	1

2 (0 out of 249 Selected)

Point2000



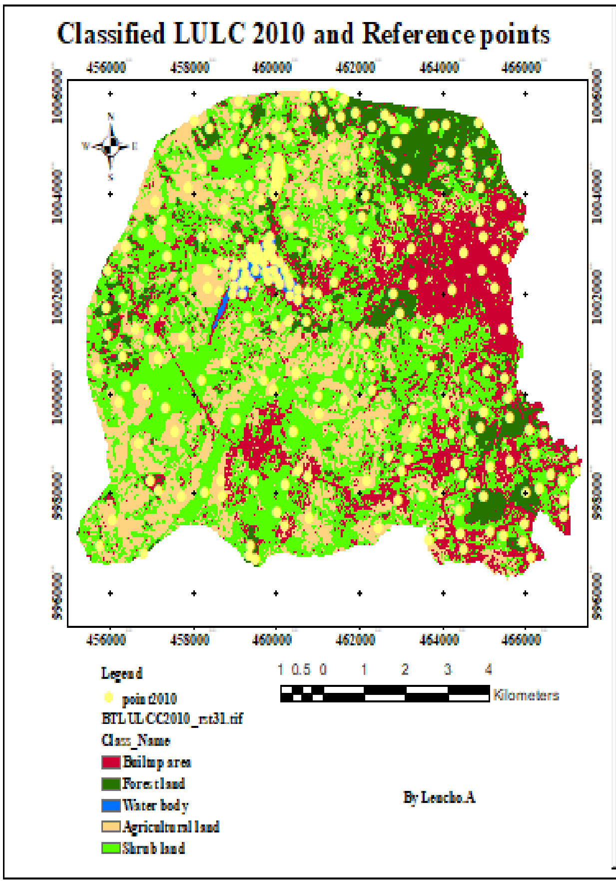
Table

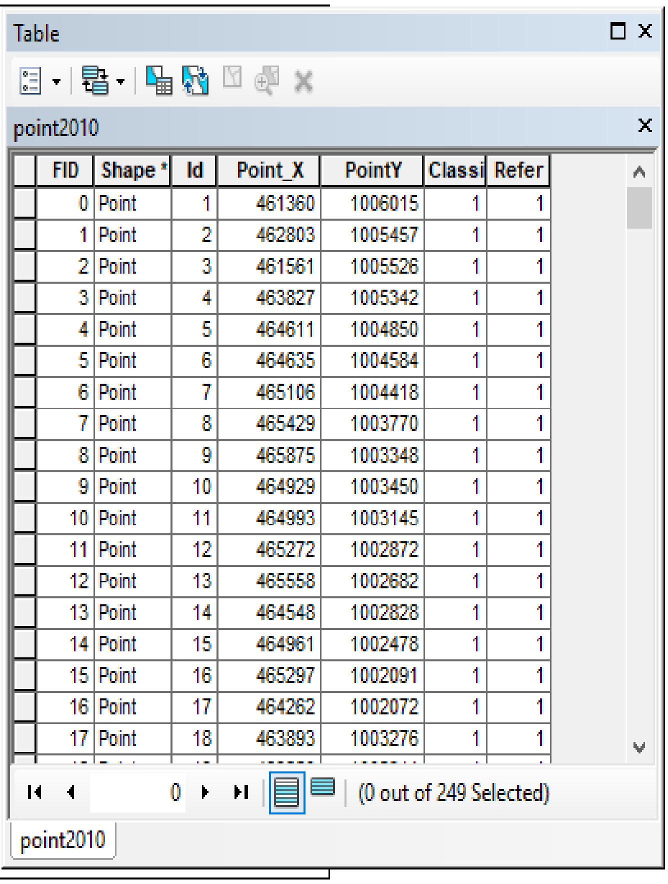
point1990

FID	Shape *	Id	Point_X	Point_Y	classi	Refere
0	Point	1	458703	1002893	1	1
1	Point	2	457591	1003013	1	1
2	Point	3	456579	1001868	1	1
3	Point	4	456089	1000534	1	1
4	Point	5	457295	1000734	1	3
5	Point	6	457778	1001012	1	1
6	Point	7	457869	1001139	1	1
7	Point	8	457615	1000620	1	1
8	Point	9	457979	1000119	1	1
9	Point	10	458401	999729	1	1
10	Point	11	458499	1000441	1	1
11	Point	12	459078	1000539	1	1
12	Point	13	459826	999356	1	1
13	Point	14	459618	999029	1	5
14	Point	15	459604	998880	1	1
15	Point	16	459356	998906	1	1
16	Point	17	460210	998721	1	1
17	Point	18	460550	998572	1	1

14 (0 out of 250 Selected)

point1990





Table

point2010

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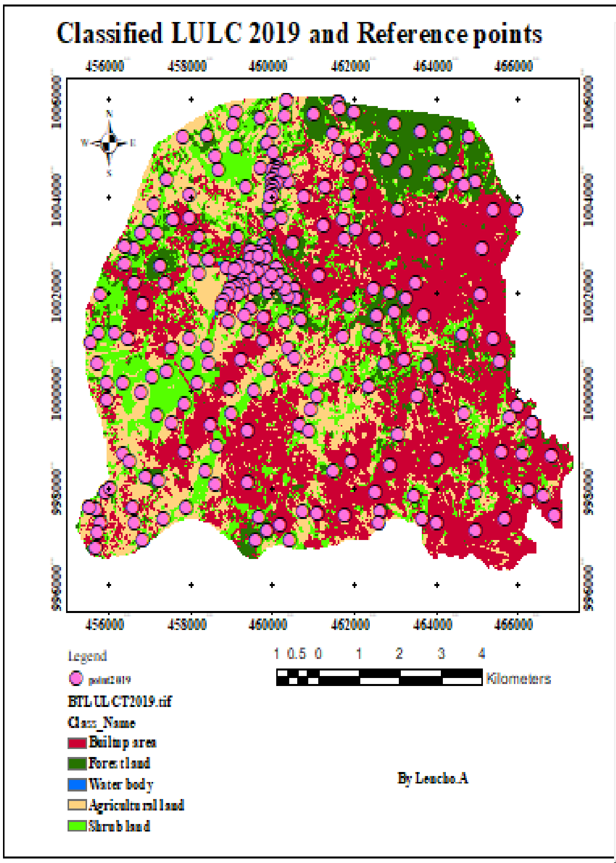
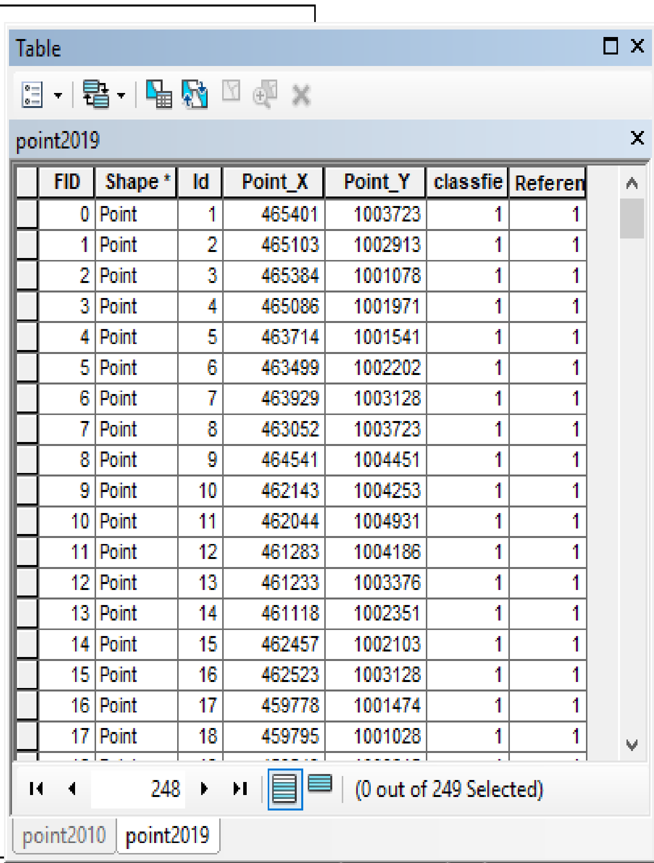
0	Point	1	461360	1006015	1	1
1	Point	2	462803	1005457	1	1
2	Point	3	461561	1005526	1	1
3	Point	4	463827	1005342	1	1
4	Point	5	464611	1004850	1	1
5	Point	6	464635	1004584	1	1
6	Point	7	465106	1004418	1	1
7	Point	8	465429	1003770	1	1
8	Point	9	465875	1003348	1	1
9	Point	10	464929	1003450	1	1
10	Point	11	464993	1003145	1	1
11	Point	12	465272	1002872	1	1
12	Point	13	465558	1002682	1	1
13	Point	14	464548	1002828	1	1
14	Point	15	464961	1002478	1	1
15	Point	16	465297	1002091	1	1
16	Point	17	464262	1002072	1	1
17	Point	18	463893	1003276	1	1

0 (0 out of 249 Selected)

point2010





Table

point2019

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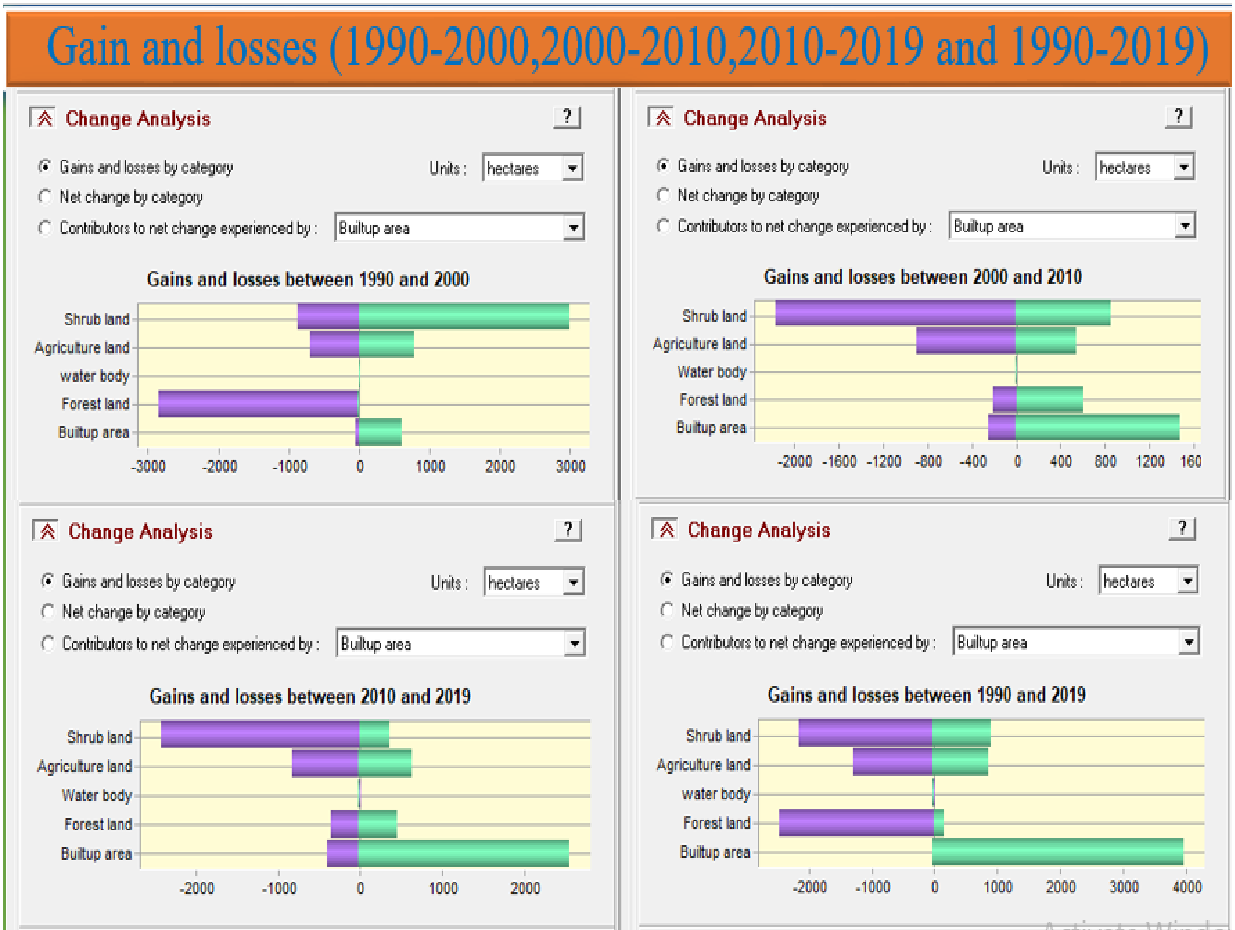
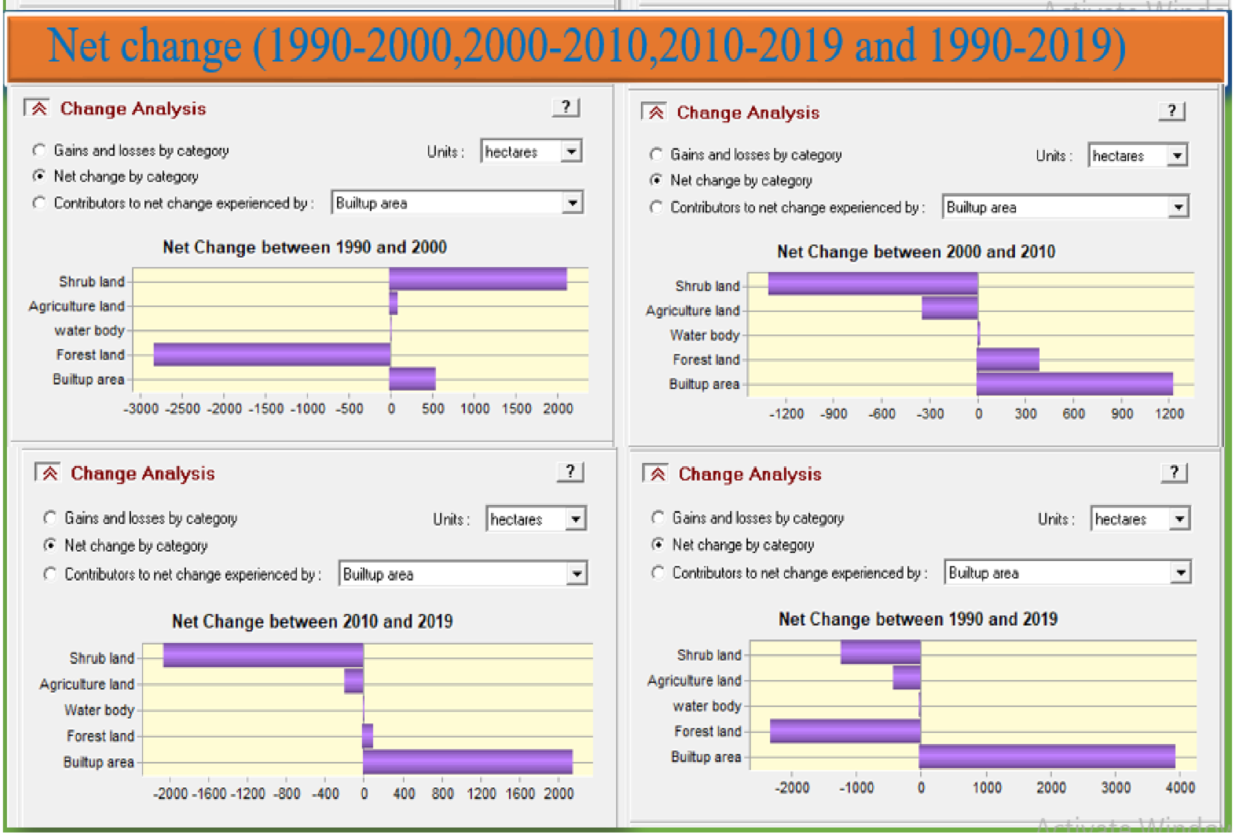
0	Point	1	465401	1003723	1	1
1	Point	2	465103	1002913	1	1
2	Point	3	465384	1001078	1	1
3	Point	4	465086	1001971	1	1
4	Point	5	463714	1001541	1	1
5	Point	6	463499	1002202	1	1
6	Point	7	463929	1003128	1	1
7	Point	8	463052	1003723	1	1
8	Point	9	464541	1004451	1	1
9	Point	10	462143	1004253	1	1
10	Point	11	462044	1004931	1	1
11	Point	12	461283	1004186	1	1
12	Point	13	461233	1003376	1	1
13	Point	14	461118	1002351	1	1
14	Point	15	462457	1002103	1	1
15	Point	16	462523	1003128	1	1
16	Point	17	459778	1001474	1	1
17	Point	18	459795	1001028	1	1

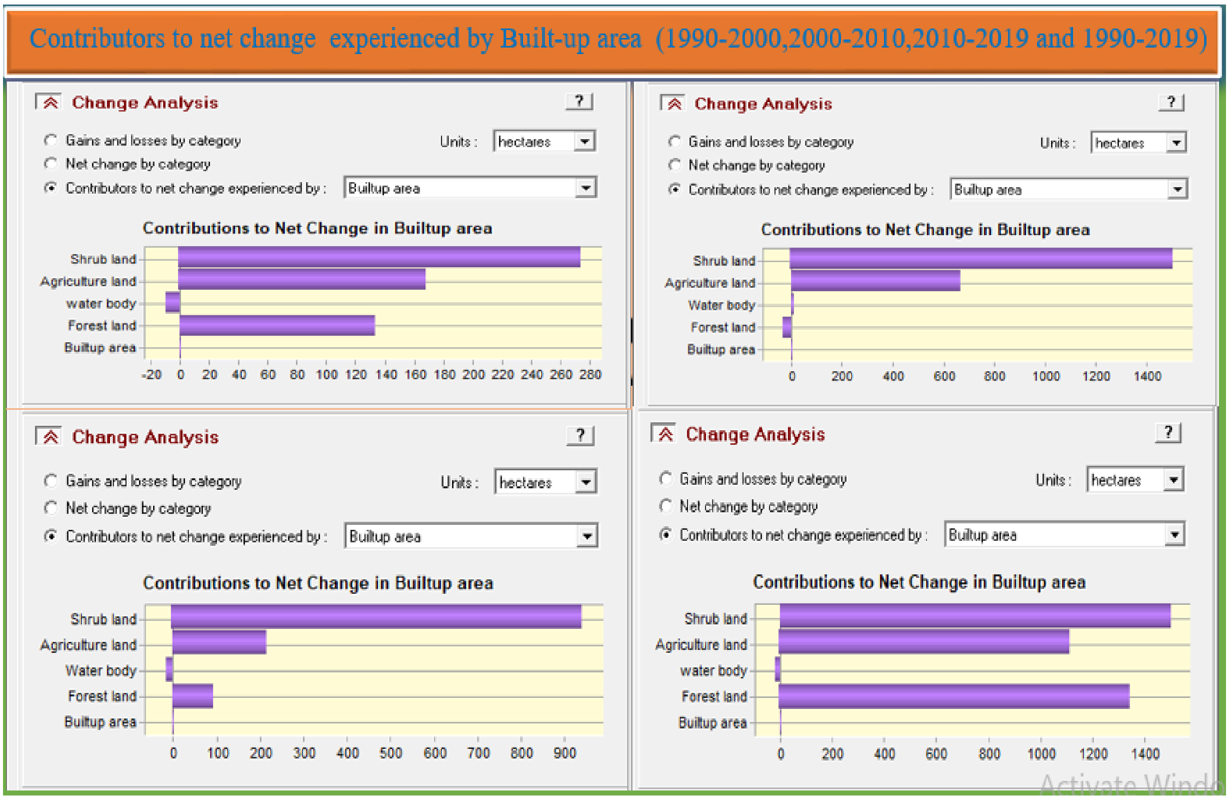
248 (0 out of 249 Selected)

point2010 point2019

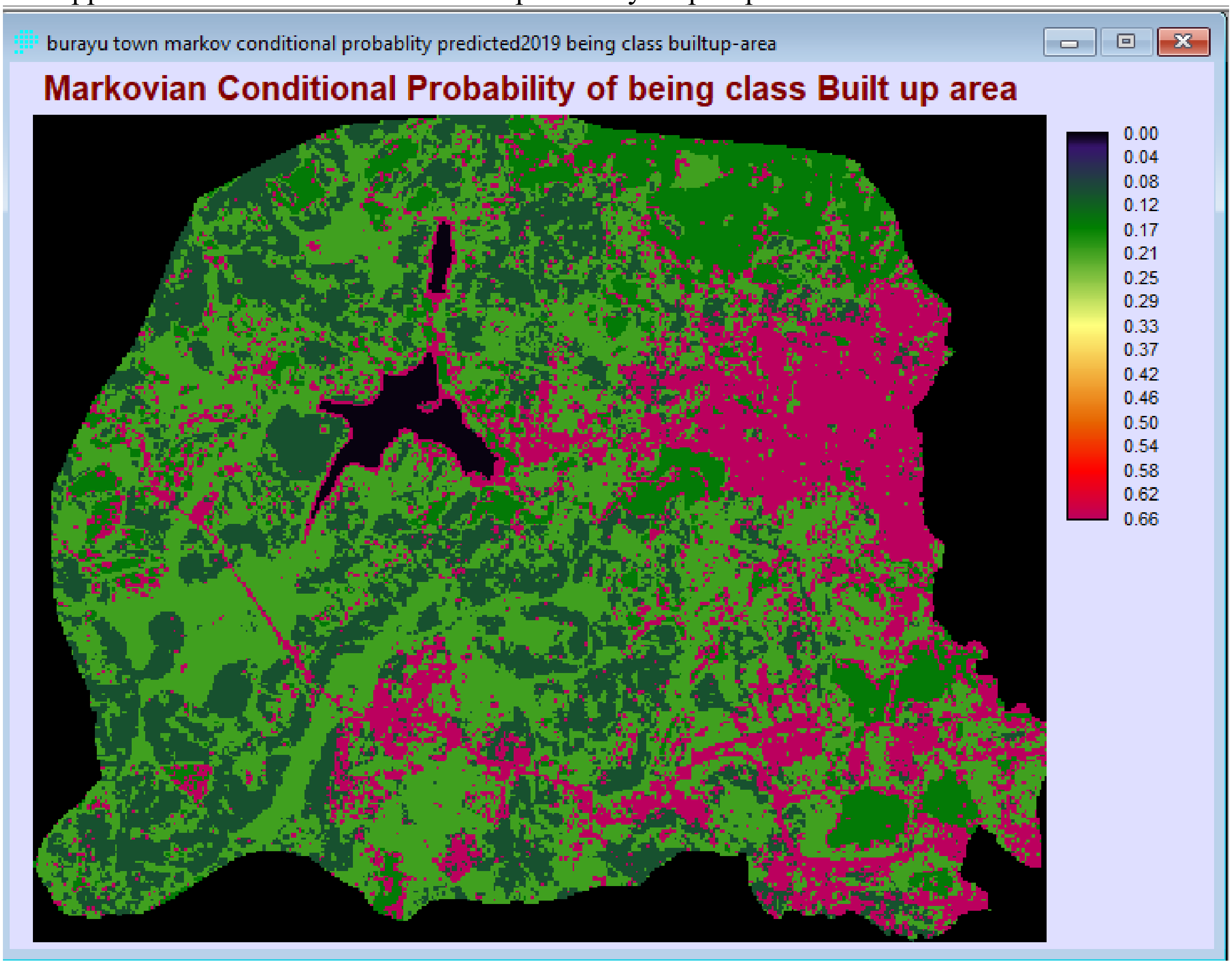
5. *Appendix "E" Change analysis (gain and losses, net change and contributor to net change)*

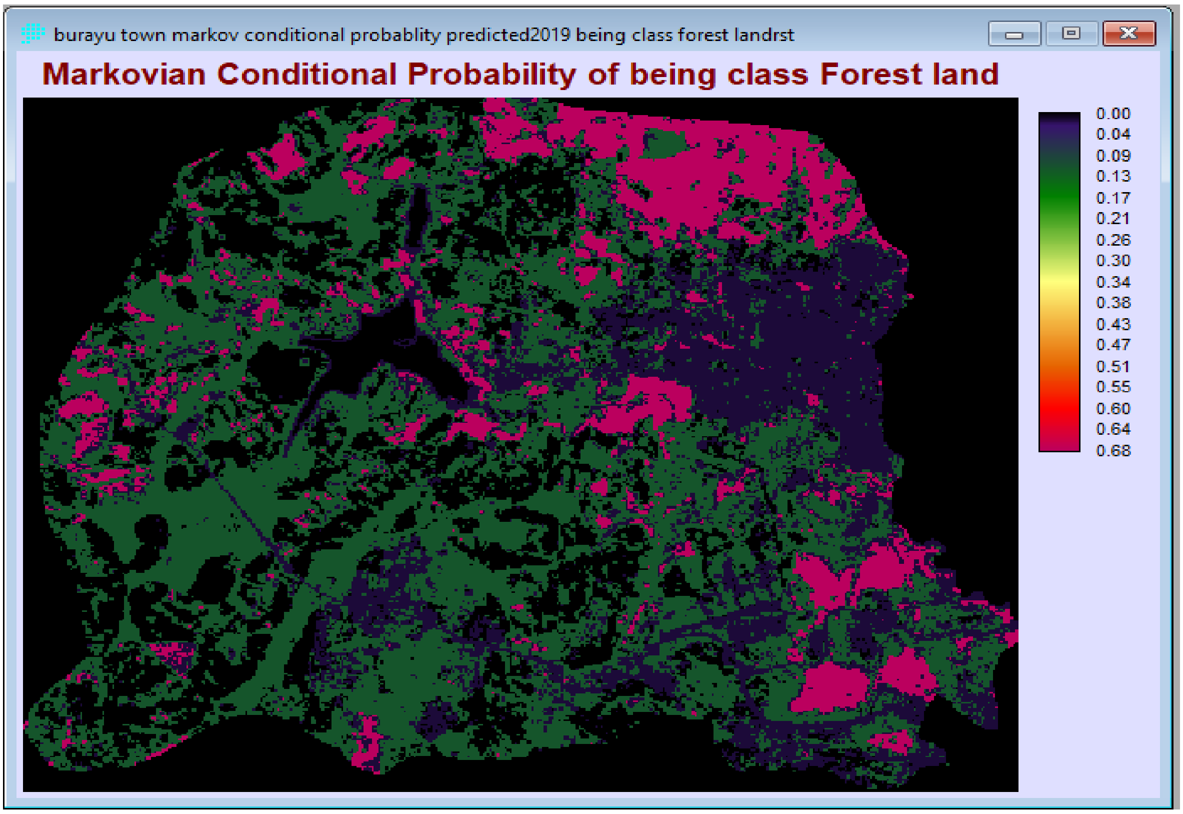


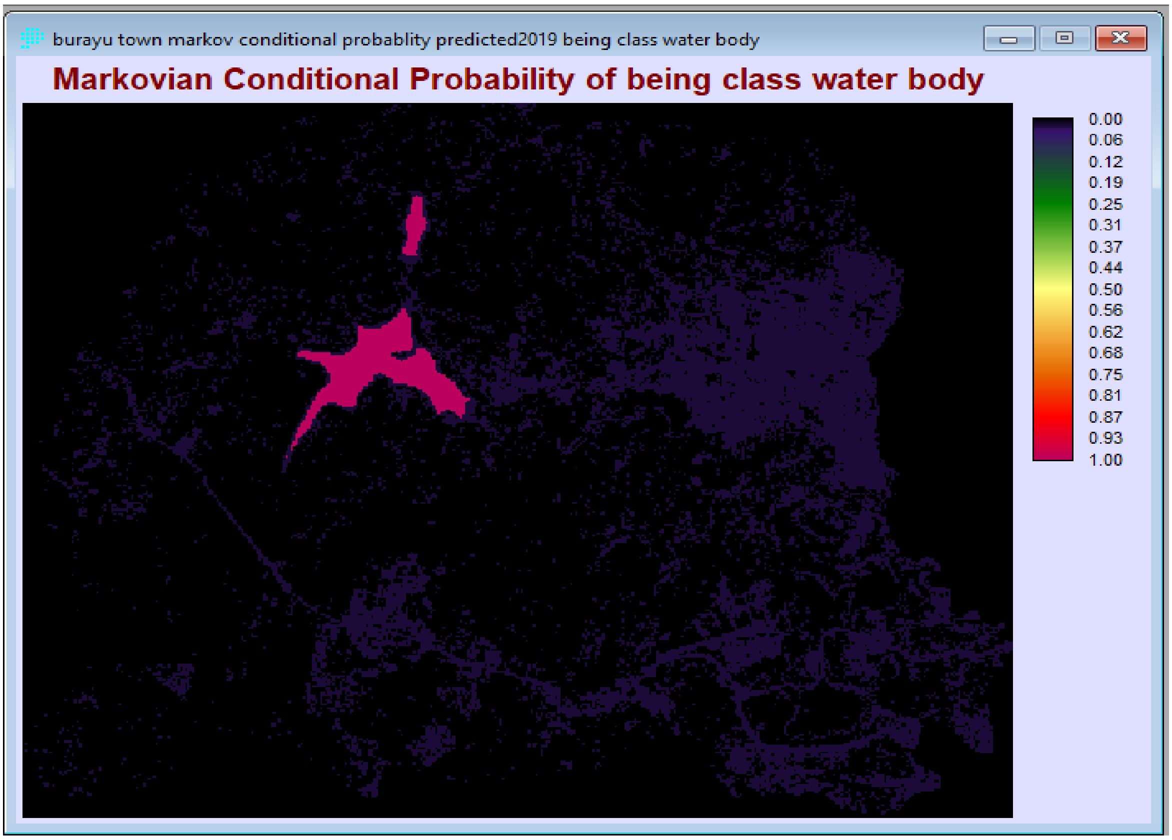


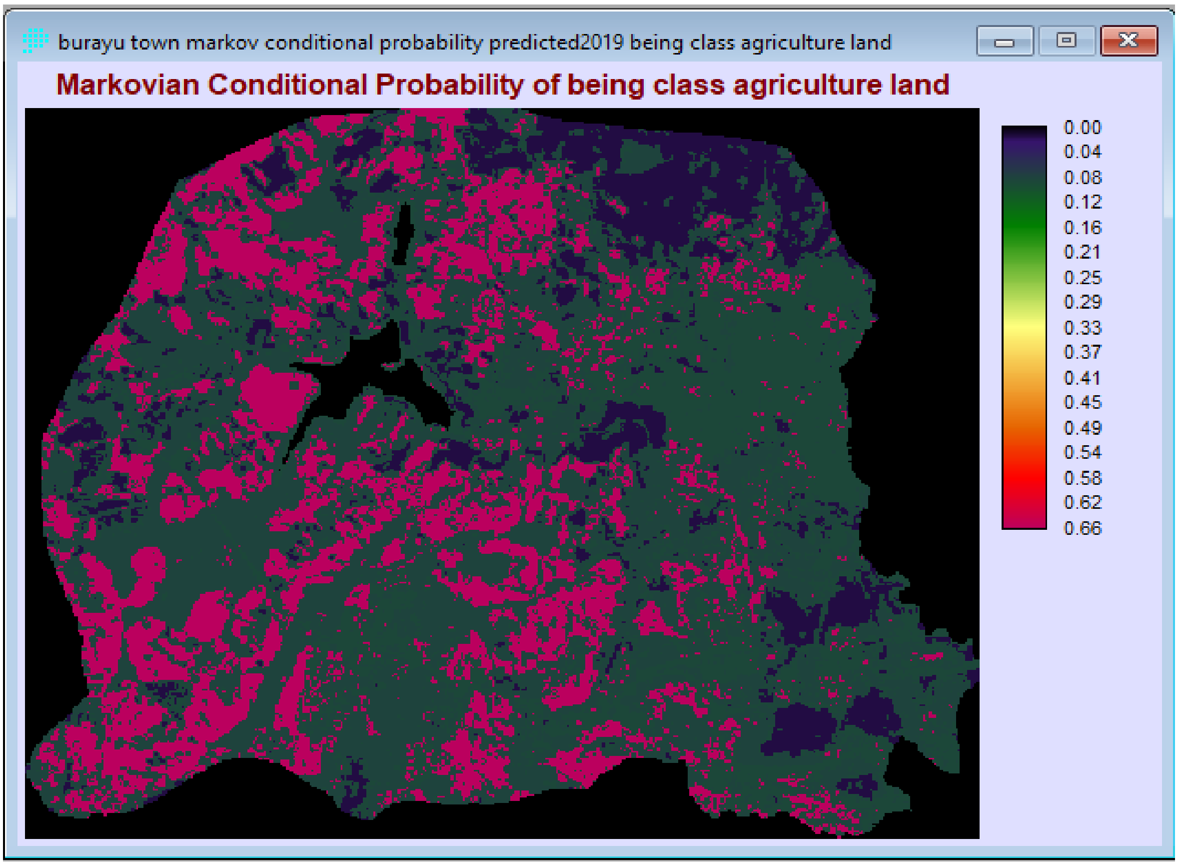


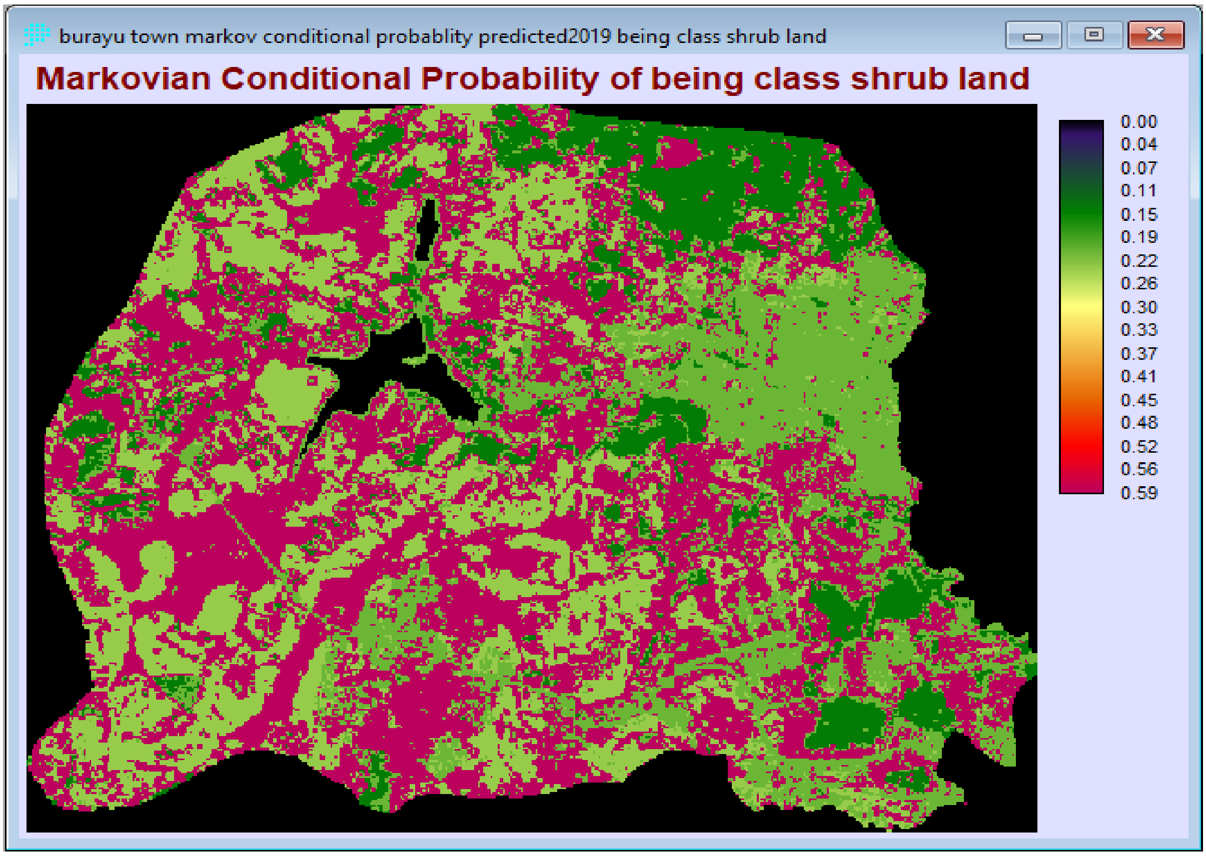
6. Appendix’ F’ Markovian conditional probablity map of predicted 2019.



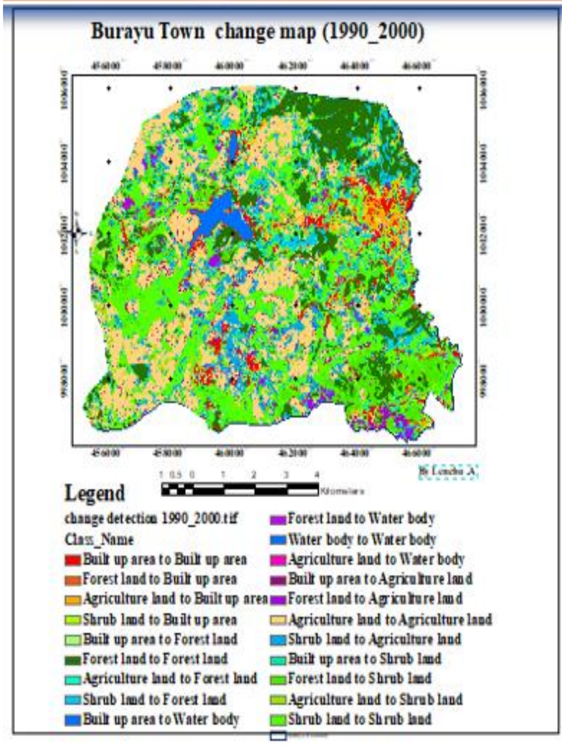

burayu town markov conditional probablity predicted2019 being class forest landrst
Markovian Conditional Probability of being class Forest land
0.00
0.04
0.09
0.13
0.17
0.21
0.26
0.30
0.34
0.38
0.43
0.47
0.51
0.55
0.60
0.64
0.68


burayu town markov conditional probablity predicted2019 being class water body
Markovian Conditional Probability of being class water body
0.00
0.06
0.12
0.19
0.25
0.31
0.37
0.44
0.50
0.56
0.62
0.68
0.75
0.81
0.87
0.93
1.00


burayu town markov conditional probability predicted2019 being class agriculture land
Markovian Conditional Probability of being class agriculture land
0.00
0.04
0.08
0.12
0.16
0.21
0.25
0.29
0.33
0.37
0.41
0.45
0.49
0.54
0.58
0.62
0.66


burayu town markov conditional probablity predicted2019 being class shrub land
Markovian Conditional Probability of being class shrub land
0.00
0.04
0.07
0.11
0.15
0.19
0.22
0.26
0.30
0.33
0.37
0.41
0.45
0.48
0.52
0.56
0.59

7. *Appendix 'G' Transition map from all LULC classes to all LULC classes* (1990-2000, 2000-2010,2010-2019 and 1990-2019)



nge detection 1990_2000.tif

OID	Value	Value_	Red	Green	Blue	Alpha	Class_name	Count	Area_km2
0	1	1	244	0	10	255	Built up area to Built up area	3776	3.3984
1	2	2	234	0	20	255	Forest land to Built up area	679	0.6111
2	4	4	214	0	40	255	Agriculture land to Built up area	2378	2.1402
3	5	5	204	0	51	255	Shrub land to Built up area	3844	3.4596
4	6	6	193	0	61	255	Built up area to Forest land	775	0.6975
5	7	7	183	0	71	255	Forest land to Forest land	13900	12.51
6	9	9	163	0	91	255	Agriculture land to Forest land	204	0.1836
7	10	10	153	0	102	255	Shrub land to Forest land	5787	5.2083
8	11	11	142	0	112	255	Built up area to Water body	174	0.1566
9	12	12	132	0	122	255	Forest land to Water body	5	0.0045
10	13	13	122	0	132	255	Water body to Water body	1342	1.2078
11	14	14	112	0	142	255	Agriculture land to Water body	2	0.0018
12	16	16	91	0	163	255	Built up area to Agriculture land	2162	1.9458
13	17	17	81	0	173	255	Forest land to Agriculture land	1673	1.5057
14	19	19	61	0	193	255	Agriculture land to Agriculture land	20899	18.8091
15	20	20	51	0	204	255	Shrub land to Agriculture land	9296	8.3664
16	21	21	40	0	214	255	Built up area to Shrub land	1399	1.2591
17	22	22	30	0	224	255	Forest land to Shrub land	6753	6.0777
18	24	24	10	0	244	255	Agriculture land to Shrub land	2766	2.4894
19	25	25	0	0	255	255	Shrub land to Shrub land	22038	19.8342

20 (0 out of 20 Selected)

nge detection 1990_2000.tif

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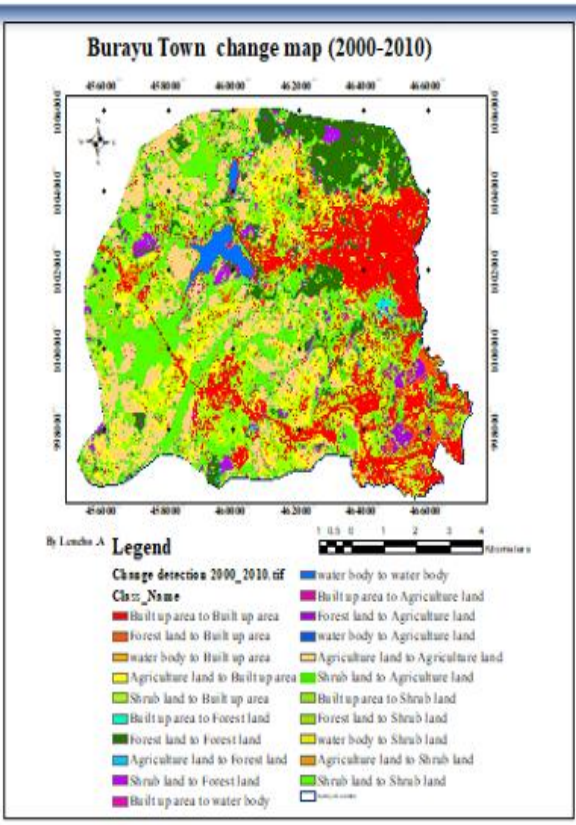

Table

Change detection 2000_2010.tif

OID	Value	Value_1	Red	Green	Blue	Alpha	Class_name	Count	Area_km2
0	1	1	244	0	10	255	Built up area to Built up area	17243	15.5187
1	2	2	234	0	20	255	Forest land to Built up area	2741	2.4669
2	3	3	224	0	30	255	water body to Built up area	109	0.0981
3	4	4	214	0	40	255	Agriculture land to Built up area	8490	7.641
4	5	5	204	0	51	255	Shrub land to Built up area	13381	12.0429
5	6	6	193	0	61	255	Built up area to Forest land	683	0.6147
6	7	7	183	0	71	255	Forest land to Forest land	8857	7.9713
7	9	9	163	0	91	255	Agriculture land to Forest land	99	0.0891
8	10	10	153	0	102	255	Shrub land to Forest land	2304	2.0736
9	11	11	142	0	112	255	Built up area to water body	31	0.0279
10	13	13	122	0	132	255	water body to water body	1457	1.3113
11	16	16	91	0	163	255	Built up area to Agriculture land	1629	1.4661
12	17	17	81	0	173	255	Forest land to Agriculture land	1032	0.9288
13	18	18	71	0	183	255	water body to Agriculture land	1	0.0009
14	19	19	61	0	193	255	Agriculture land to Agriculture land	15582	14.0238
15	20	20	51	0	204	255	Shrub land to Agriculture land	6251	5.6259
16	21	21	40	0	214	255	Built up area to Shrub land	1158	1.0422
17	22	22	30	0	224	255	Forest land to Shrub land	3000	2.7
18	23	23	20	0	234	255	water body to Shrub land	1	0.0009
19	24	24	10	0	244	255	Agriculture land to Shrub land	1065	0.9585
20	25	25	0	0	255	255	Shrub land to Shrub land	14738	13.2642

21 (0 out of 21 Selected)

Change detection 2000_2010.tif

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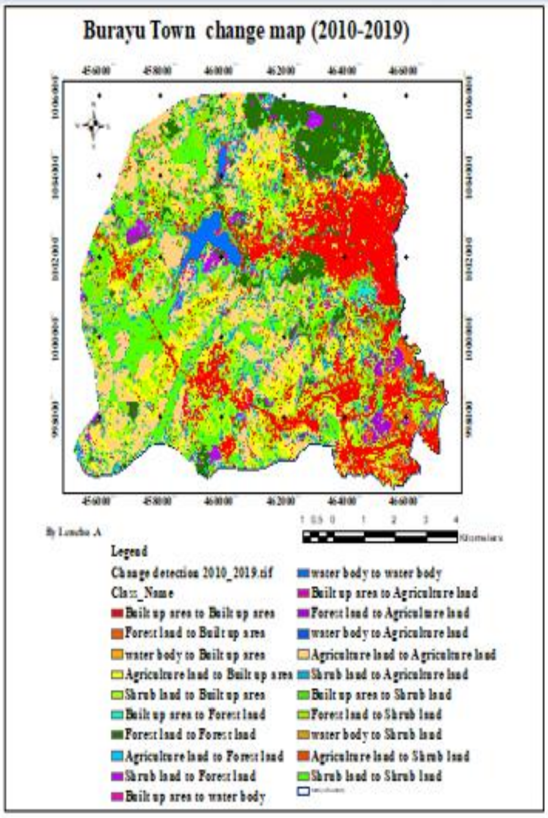
Activate Wind



Table

Change detection 2010_2019.tif

OID	Value	Value_1	Red	Green	Blue	Alpha	Class_name	Count	Area_km2
0	1	1	244	0	10	255	Built up area to Built up area	17243	15.5187
1	2	2	234	0	20	255	Forest land to Built up area	2741	2.4669
2	3	3	224	0	30	255	water body to Built up area	109	0.0981
3	4	4	214	0	40	255	Agriculture land to Built up area	8490	7.641
4	5	5	204	0	51	255	Shrub land to Built up area	13381	12.0429
5	6	6	193	0	61	255	Built up area to Forest land	683	0.6147
6	7	7	183	0	71	255	Forest land to Forest land	8857	7.9713
7	9	9	163	0	91	255	Agriculture land to Forest land	99	0.0891
8	10	10	153	0	102	255	Shrub land to Forest land	2304	2.0736
9	11	11	142	0	112	255	Built up area to water body	31	0.0279
10	13	13	122	0	132	255	water body to water body	1457	1.3113
11	16	16	91	0	163	255	Built up area to Agriculture land	1629	1.4661
12	17	17	81	0	173	255	Forest land to Agriculture land	1032	0.9288
13	18	18	71	0	183	255	water body to Agriculture land	1	0.0009
14	19	19	61	0	193	255	Agriculture land to Agriculture land	15582	14.0238
15	20	20	51	0	204	255	Shrub land to Agriculture land	6251	5.6259
16	21	21	40	0	214	255	Built up area to Shrub land	1158	1.0422
17	22	22	30	0	224	255	Forest land to Shrub land	3000	2.7
18	23	23	20	0	234	255	water body to Shrub land	1	0.0009
19	24	24	10	0	244	255	Agriculture land to Shrub land	1065	0.9585
20	25	25	0	0	255	255	Shrub land to Shrub land	14738	13.2642

21 (0 out of 21 Selected)

Change detection 2010_2019.tif

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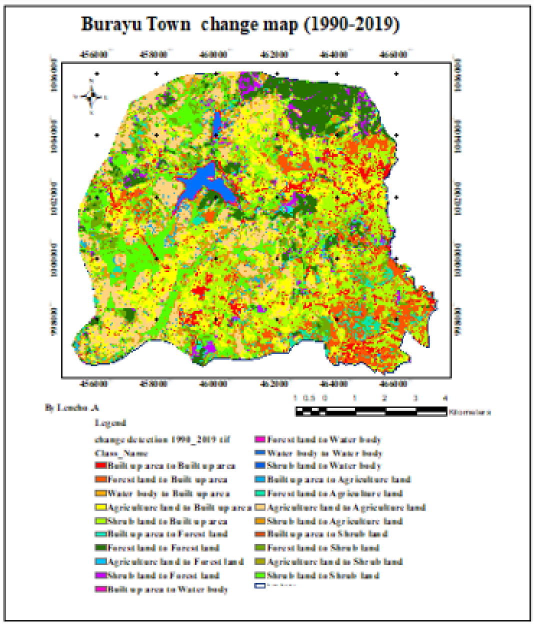

Table

change detection 1990_2019 tif

OID	Value	Value_1	Red	Green	Blue	Alpha	Class_name	Count	Area_km2	Area_km2_
0	1	1	244	0	10	255	Built up area to Built up area	5289	476.01	4.7601
1	2	2	234	0	20	255	Forest land to Built up area	7495	674.55	6.7455
2	3	3	224	0	30	255	Water body to Built up area	10	0.9	0.009
3	4	4	214	0	40	255	Agriculture land to Built up area	11937	1074.33	10.7433
4	5	5	204	0	51	255	Shrub land to Built up area	17233	1550.97	15.5097
5	6	6	193	0	61	255	Built up area to Forest land	523	47.07	0.4707
6	7	7	183	0	71	255	Forest land to Forest land	8462	761.58	7.6158
7	9	9	163	0	91	255	Agriculture land to Forest land	135	12.15	0.1215
8	10	10	153	0	102	255	Shrub land to Forest land	2823	254.07	2.5407
9	11	11	142	0	112	255	Built up area to Water body	148	13.32	0.1332
10	12	12	132	0	122	255	Forest land to Water body	7	0.63	0.0063
11	13	13	122	0	132	255	Water body to Water body	1332	119.88	1.1988
12	15	15	102	0	153	255	Shrub land to Water body	1	0.09	0.0009
13	16	16	91	0	163	255	Built up area to Agriculture land	1587	142.83	1.4283
14	17	17	81	0	173	255	Forest land to Agriculture land	2629	236.61	2.3661
15	19	19	61	0	193	255	Agriculture land to Agriculture land	12577	1131.93	11.3193
16	20	20	51	0	204	255	Shrub land to Agriculture land	7702	693.18	6.9318
17	21	21	40	0	214	255	Built up area to Shrub land	739	66.51	0.6651
18	22	22	30	0	224	255	Forest land to Shrub land	4417	397.53	3.9753
19	24	24	10	0	244	255	Agriculture land to Shrub land	1600	144	1.44
20	25	25	0	0	255	255	Shrub land to Shrub land	13206	1188.54	11.8854

2 (0 out of 21 Selected)

change detection 1990_2019 tif

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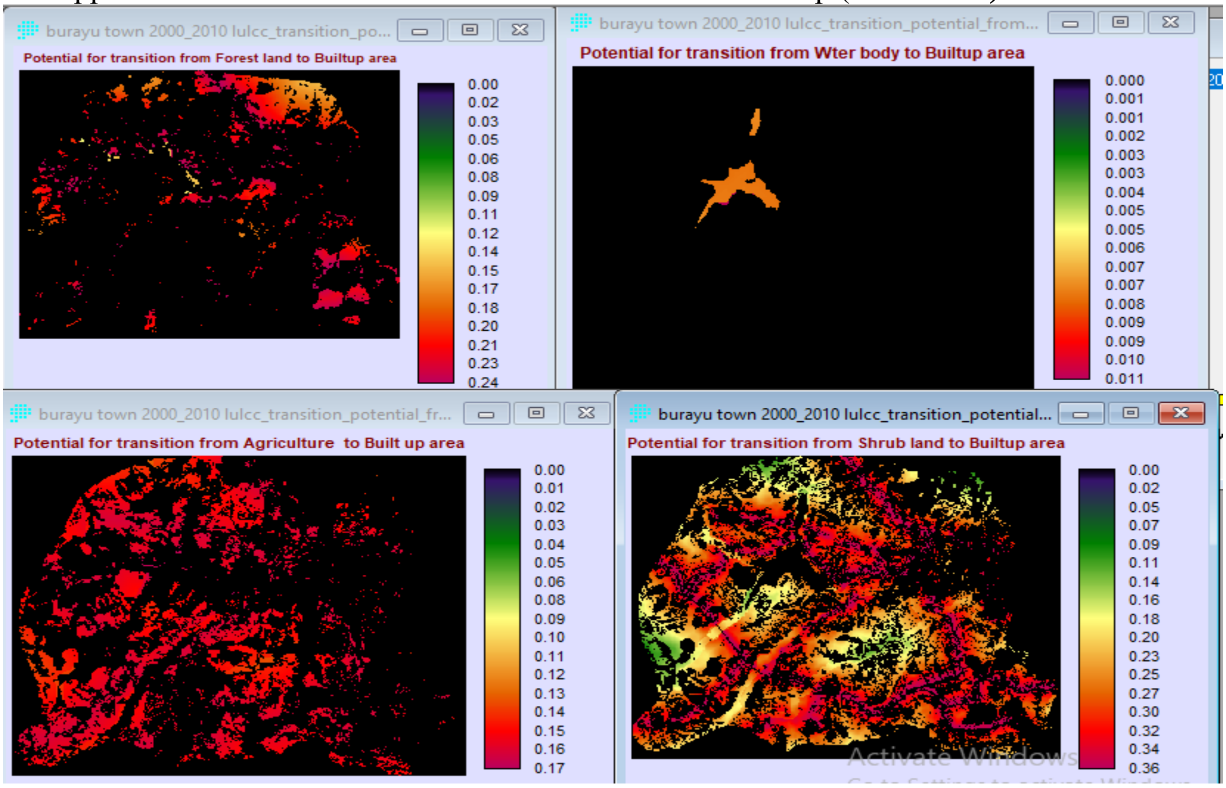
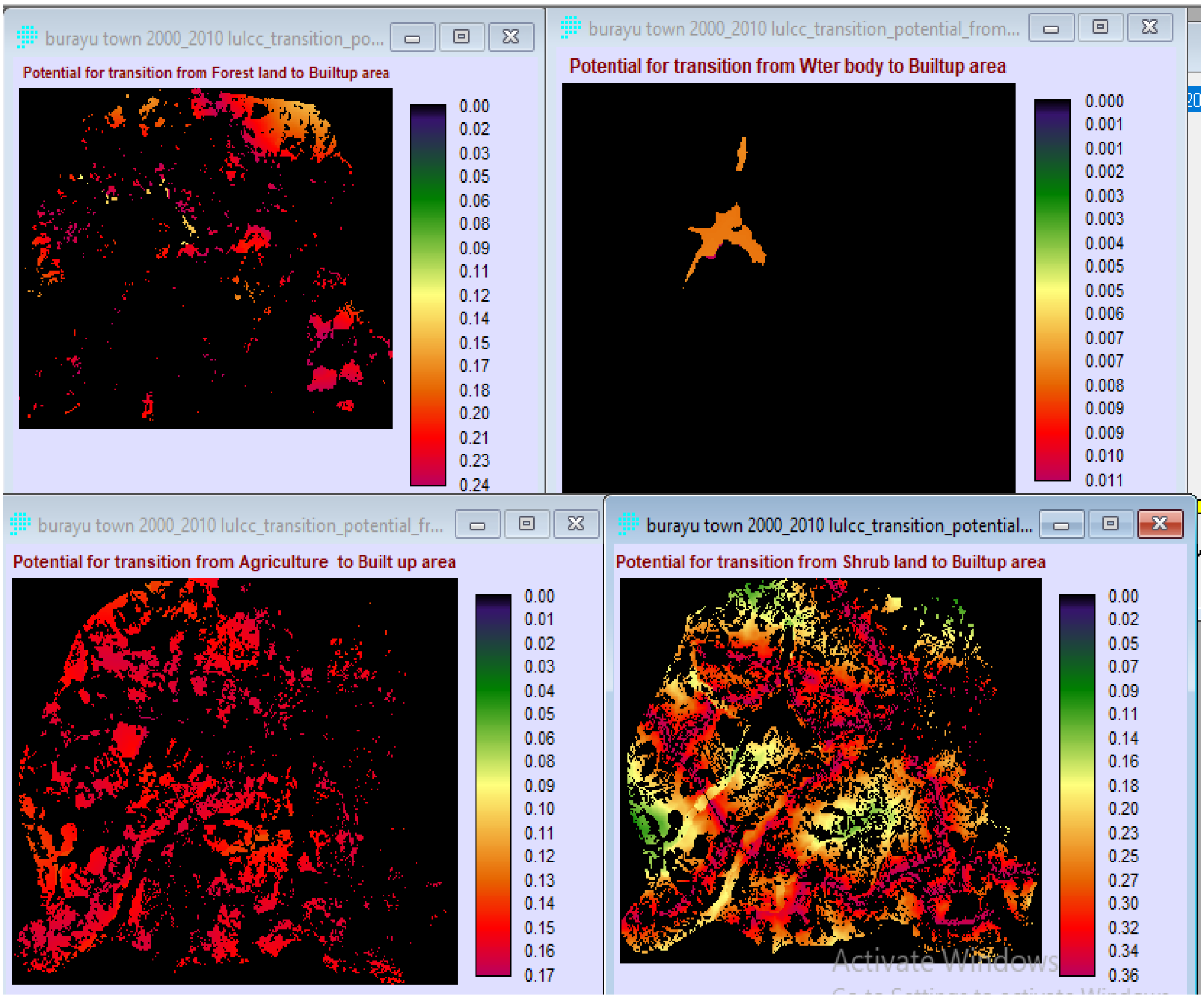
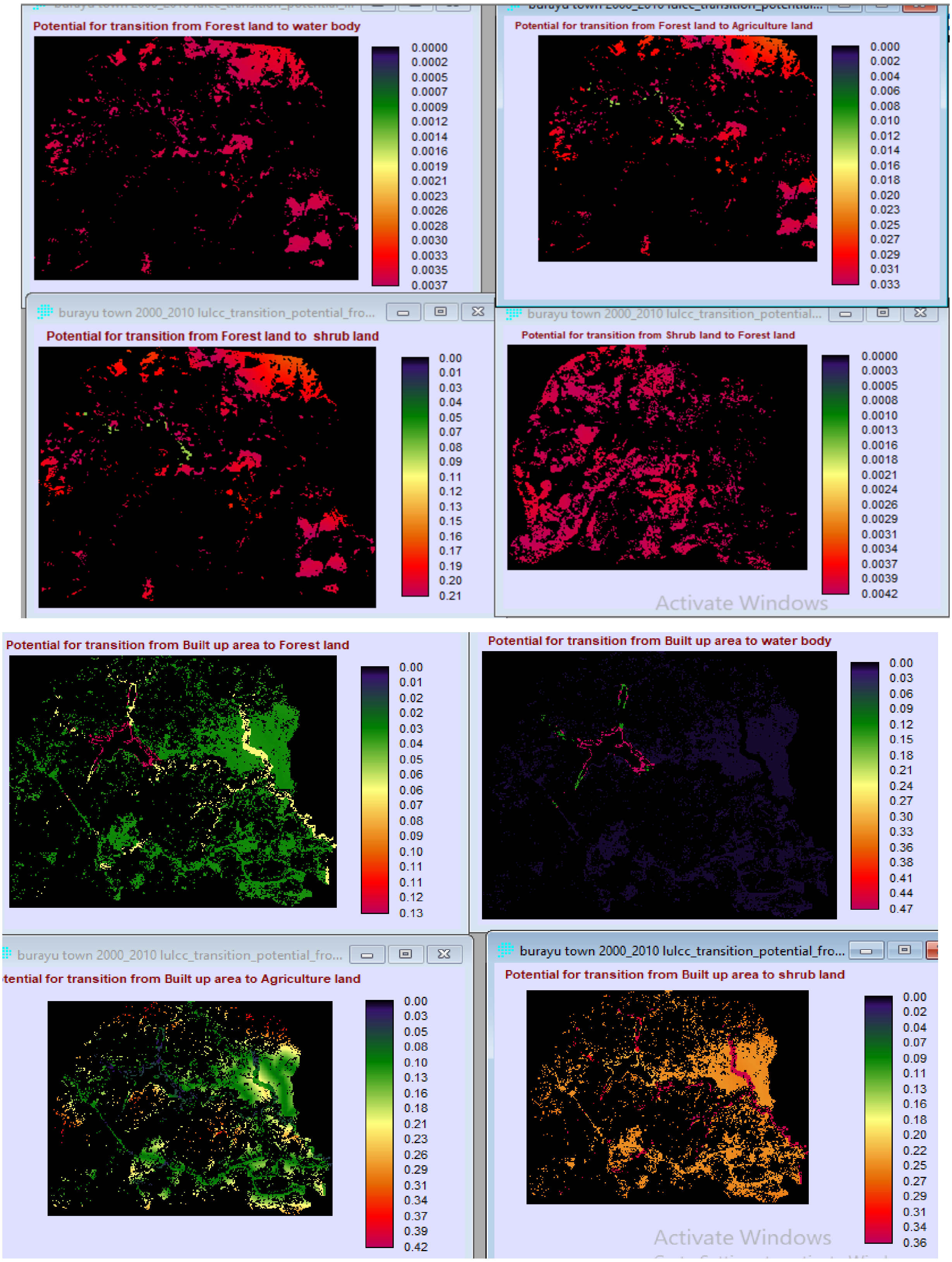
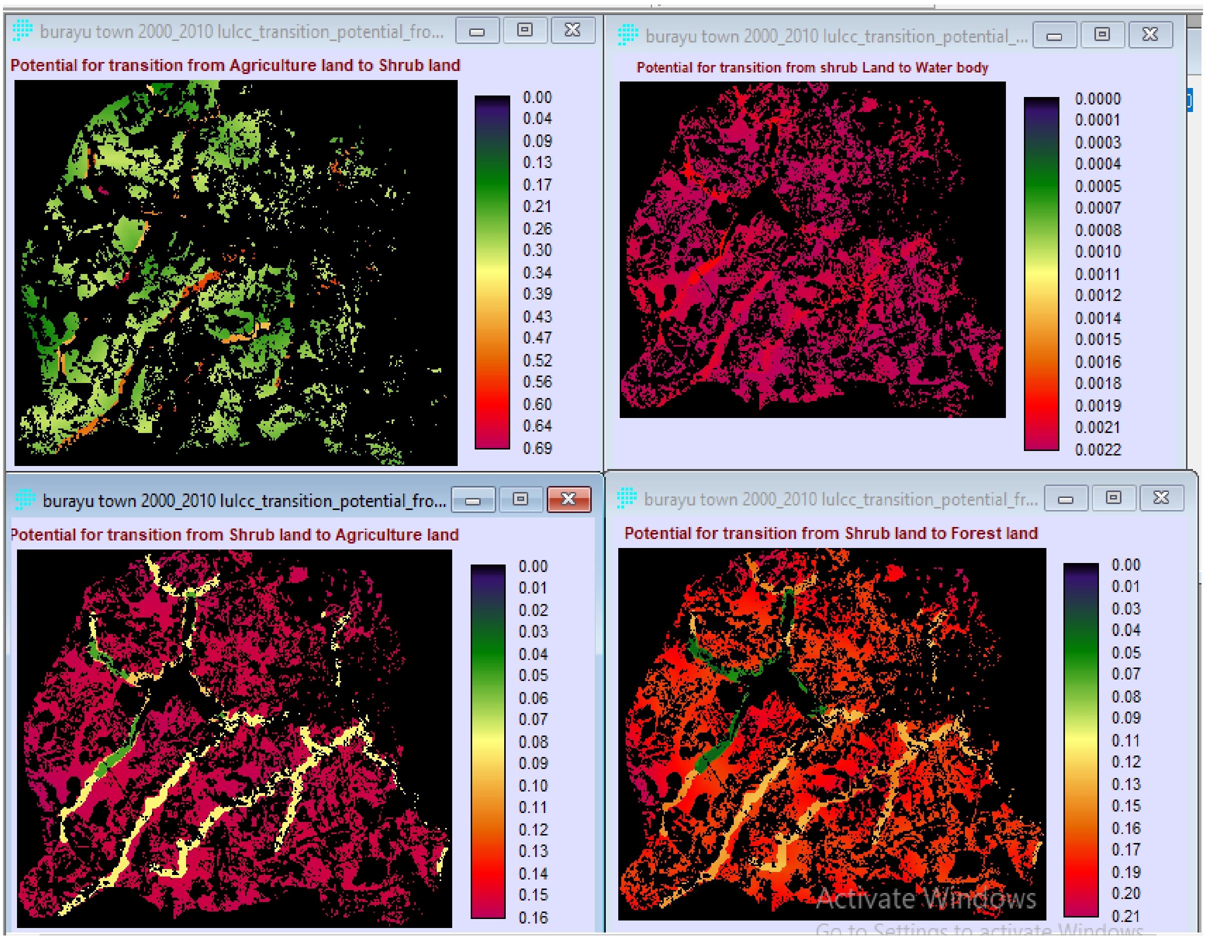
8. Appendix 'H' Potential Transition for all LULC classes Map (2000-2010)

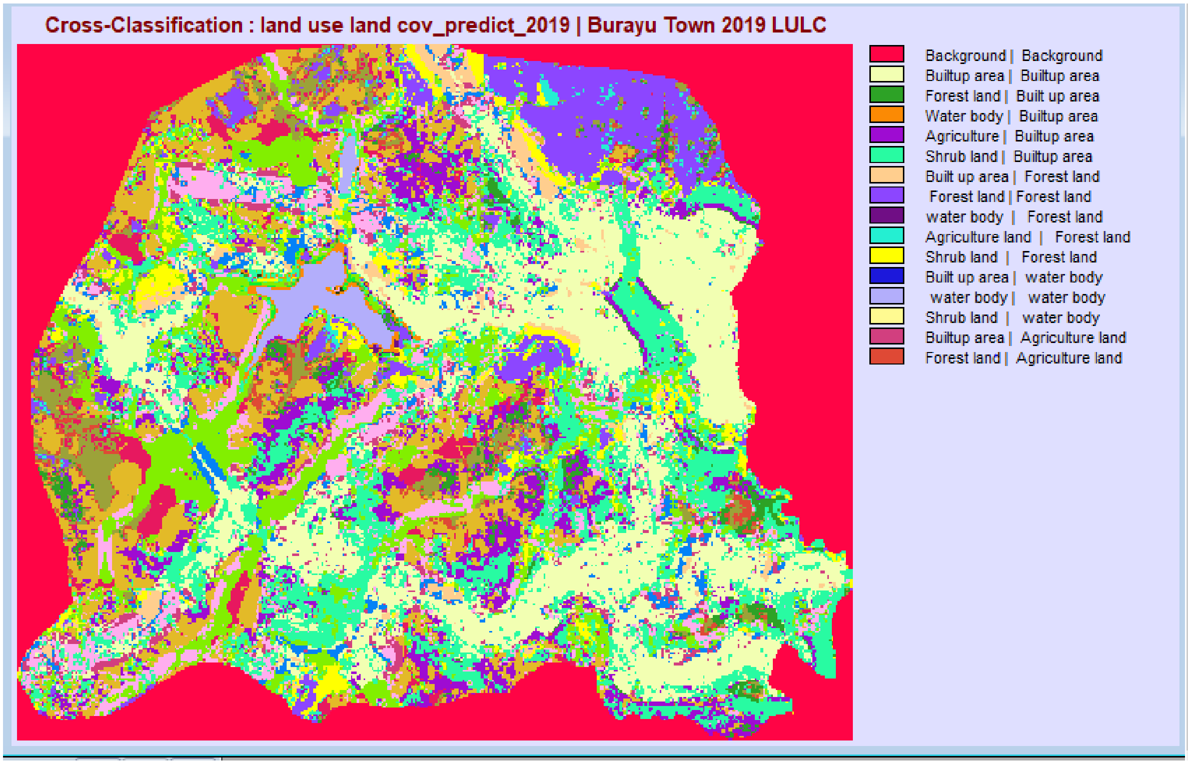




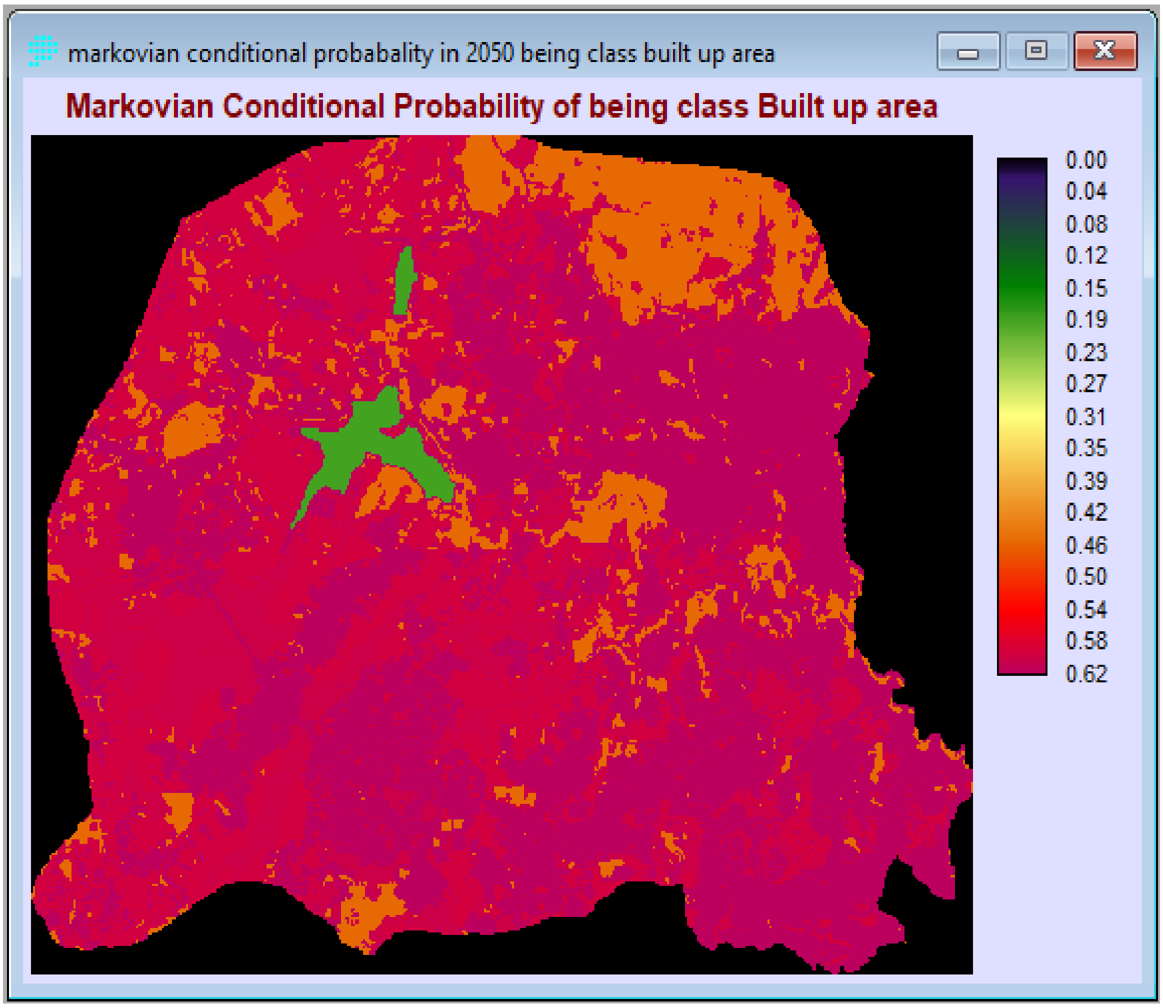

Potential for transition from Forest land to water body
0.0000 0.0002 0.0005 0.0007 0.0009 0.0012 0.0014 0.0016 0.0019 0.0021 0.0023 0.0026 0.0028 0.0030 0.0033 0.0035 0.0037
Potential for transition from Forest land to Agriculture land
0.000 0.002 0.004 0.006 0.008 0.010 0.012 0.014 0.016 0.018 0.020 0.023 0.025 0.027 0.029 0.031 0.033
burayu town 2000_2010 lulcc_transition_potential_fro...
Potential for transition from Forest land to shrub land
0.00 0.01 0.03 0.04 0.05 0.07 0.08 0.09 0.11 0.12 0.13 0.15 0.16 0.17 0.19 0.20 0.21
burayu town 2000_2010 lulcc_transition_potential...
Potential for transition from Shrub land to Forest land
0.0000 0.0003 0.0005 0.0008 0.0010 0.0013 0.0016 0.0018 0.0021 0.0024 0.0026 0.0029 0.0031 0.0034 0.0037 0.0039 0.0042
Activate Windows
Potential for transition from Built up area to Forest land
0.00 0.01 0.02 0.02 0.03 0.04 0.05 0.06 0.06 0.07 0.08 0.09 0.10 0.11 0.11 0.12 0.13
Potential for transition from Built up area to water body
0.00 0.03 0.06 0.09 0.12 0.15 0.18 0.21 0.24 0.27 0.30 0.33 0.36 0.38 0.41 0.44 0.47
burayu town 2000_2010 lulcc_transition_potential_fro...
tential for transition from Built up area to Agriculture land
0.00 0.03 0.05 0.08 0.10 0.13 0.16 0.18 0.21 0.23 0.26 0.29 0.31 0.34 0.37 0.39 0.42
burayu town 2000_2010 lulcc_transition_potential_fro...
Potential for transition from Built up area to shrub land
0.00 0.02 0.04 0.07 0.09 0.11 0.13 0.16 0.18 0.20 0.22 0.25 0.27 0.29 0.31 0.34 0.36
Activate Windows

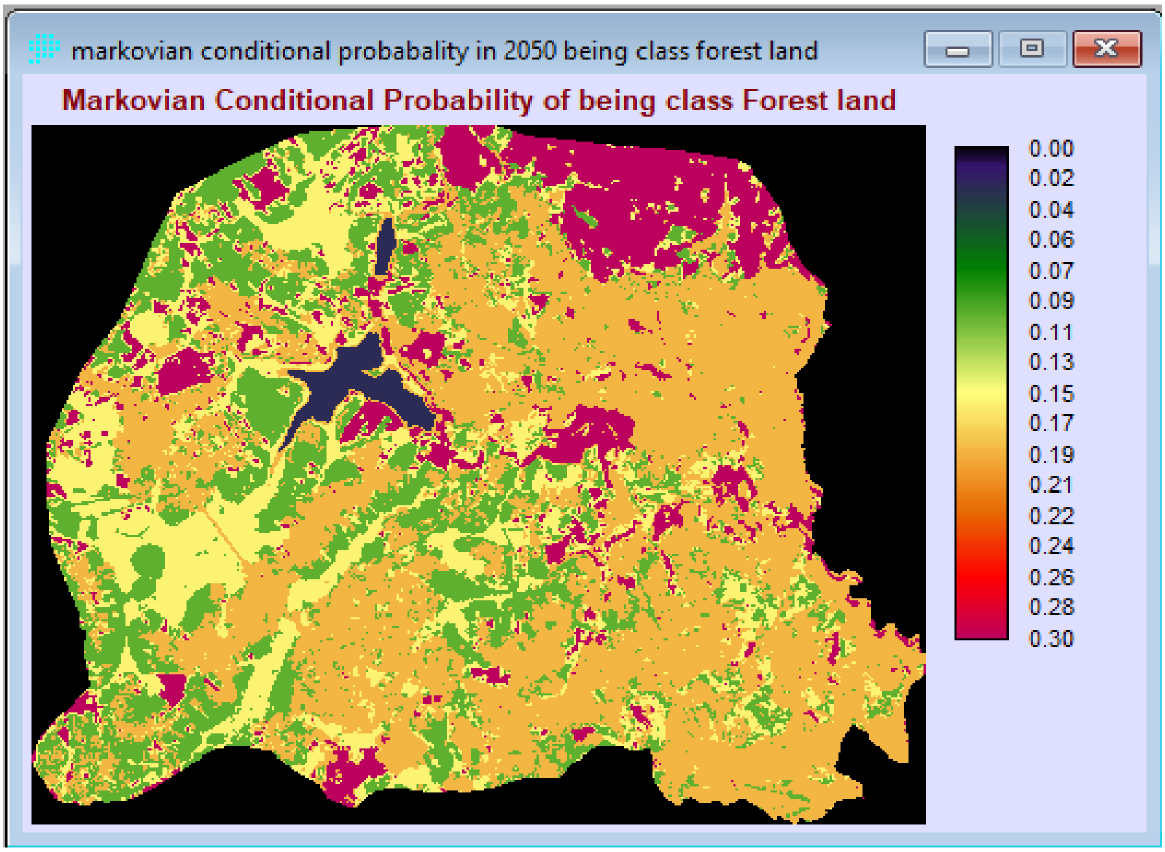


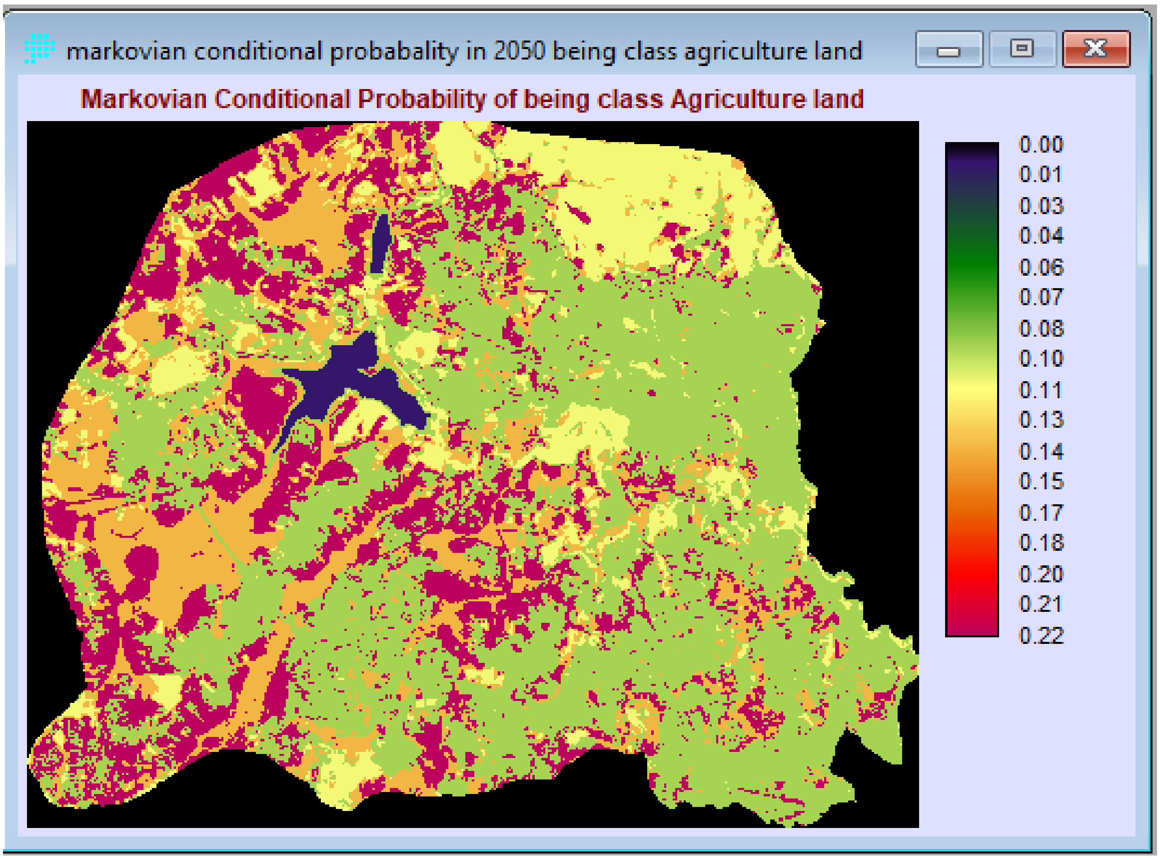
9. Appendix ''I'' Cross classification of Predicted with Classified Land use land cover of Burayu Town of 2019

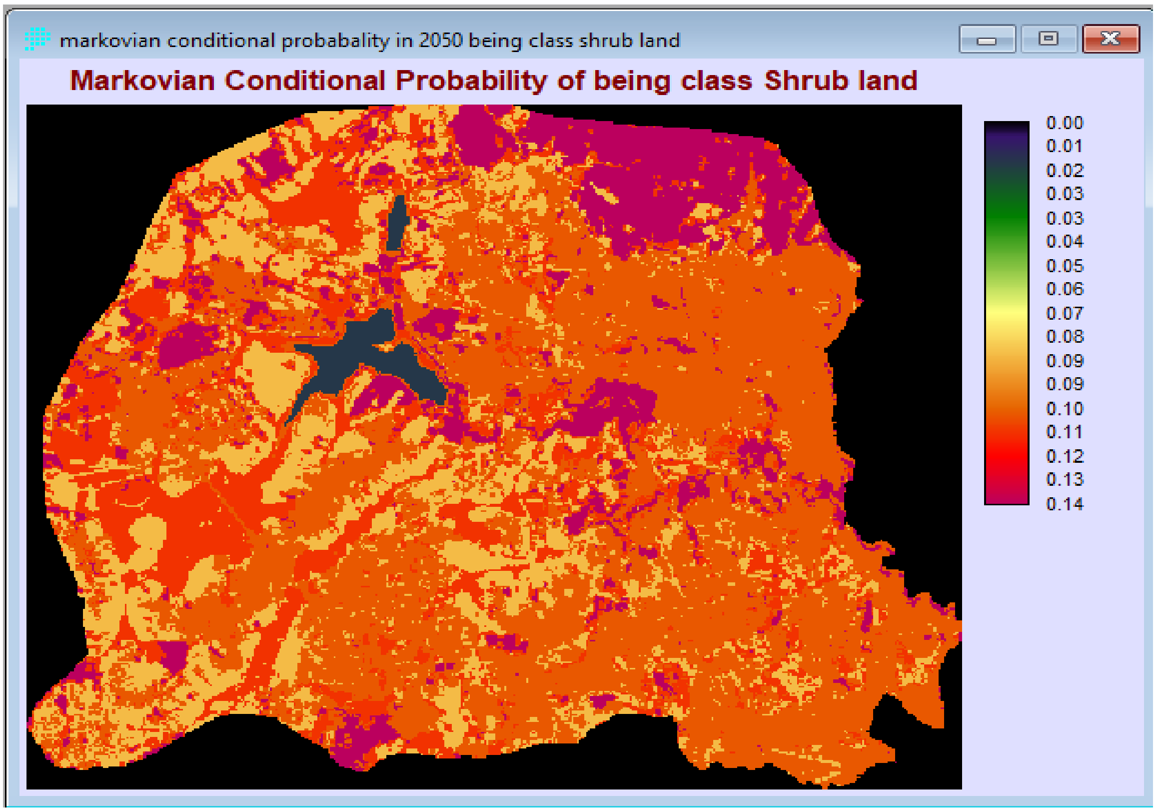


10. Appendix' J' Markovian conditional probability map of predicted 2050

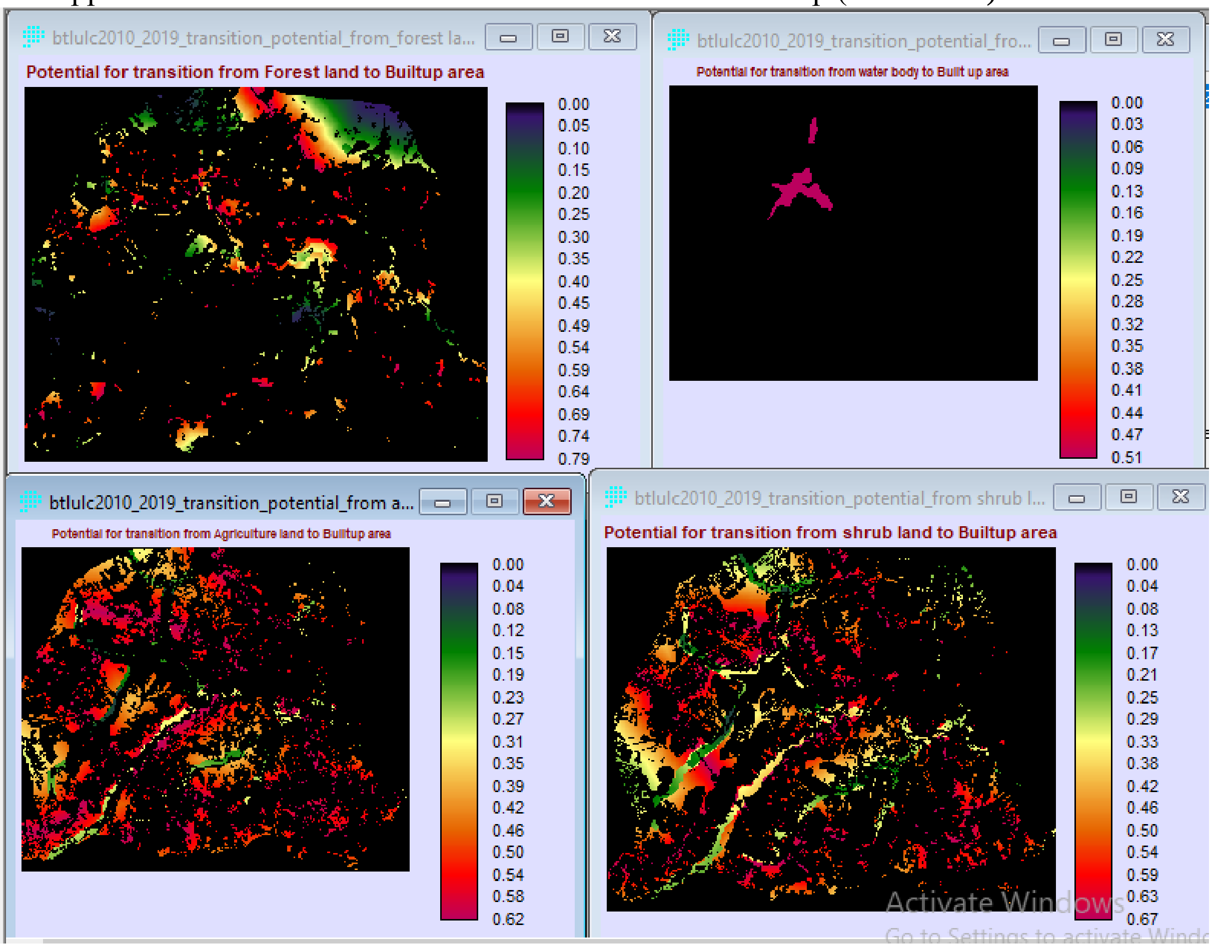


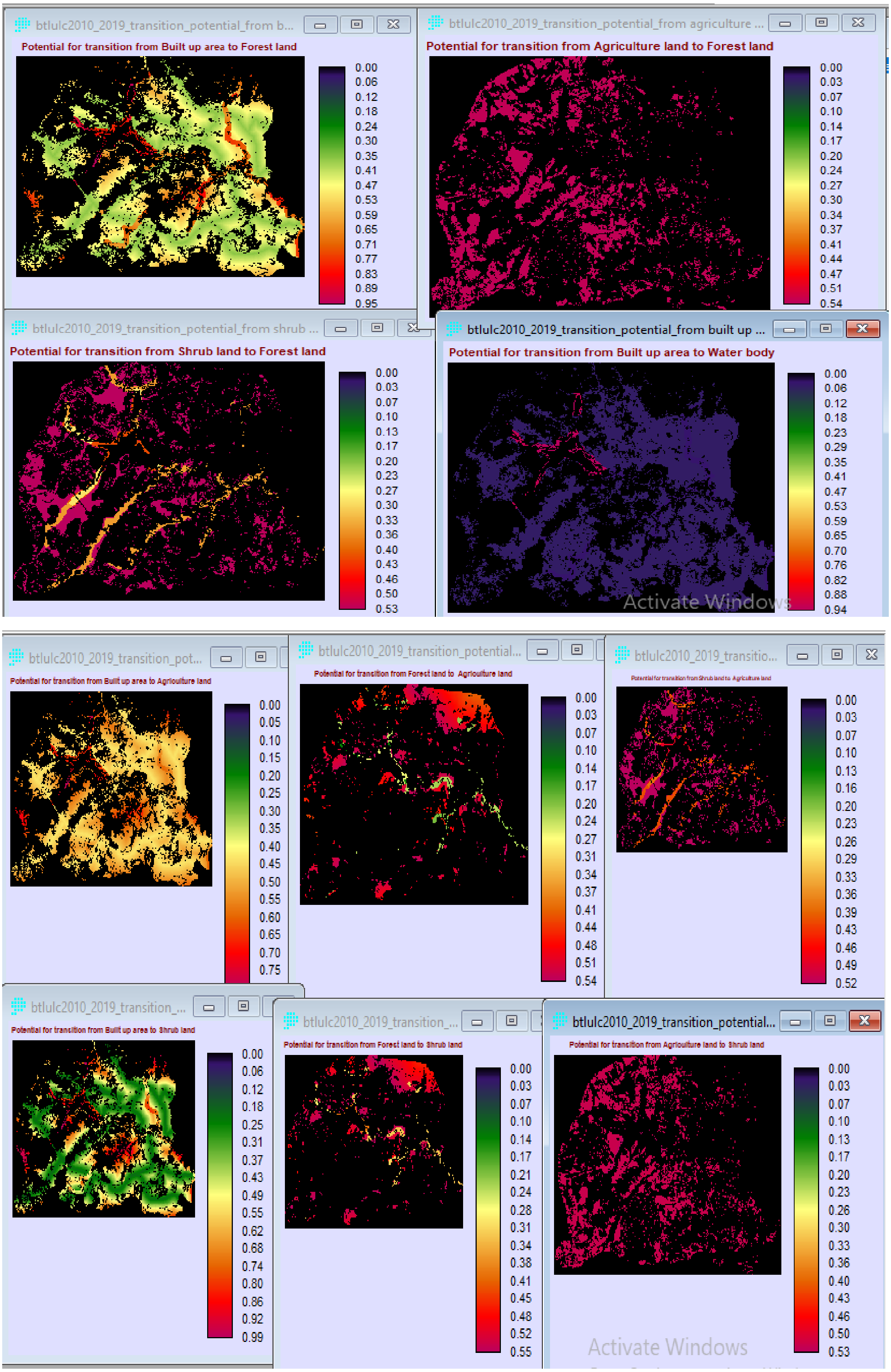

markovian conditional probabality in 2050 being class forest land
Markovian Conditional Probability of being class Forest land
0.00
0.02
0.04
0.06
0.07
0.09
0.11
0.13
0.15
0.17
0.19
0.21
0.22
0.24
0.26
0.28
0.30


markovian conditional probabality in 2050 being class agriculture land
Markovian Conditional Probability of being class Agriculture land
0.00
0.01
0.03
0.04
0.06
0.07
0.08
0.10
0.11
0.13
0.14
0.15
0.17
0.18
0.20
0.21
0.22



11. Appendix ’K’ Potential Transition for all LULC classes Map (2010-2019)




btlulc2010_2019_transition_potential_from b...
Potential for transition from Built up area to Forest land
0.00 0.06 0.12 0.18 0.24 0.30 0.35 0.41 0.47 0.53 0.59 0.65 0.71 0.77 0.83 0.89 0.95
btlulc2010_2019_transition_potential_from agriculture ...
Potential for transition from Agriculture land to Forest land
0.00 0.03 0.07 0.10 0.14 0.17 0.20 0.24 0.27 0.30 0.34 0.37 0.41 0.44 0.47 0.51 0.54
btlulc2010_2019_transition_potential_from shrub ...
Potential for transition from Shrub land to Forest land
0.00 0.03 0.07 0.10 0.13 0.17 0.20 0.23 0.27 0.30 0.33 0.36 0.40 0.43 0.46 0.50 0.53
btlulc2010_2019_transition_potential_from built up ...
Potential for transition from Built up area to Water body
0.00 0.06 0.12 0.18 0.23 0.29 0.35 0.41 0.47 0.53 0.59 0.65 0.70 0.76 0.82 0.88 0.94
Activate Windows
btlulc2010_2019_transition_pot...
Potential for transition from Built up area to Agriculture land
0.00 0.05 0.10 0.15 0.20 0.25 0.30 0.35 0.40 0.45 0.50 0.55 0.60 0.65 0.70 0.75
btlulc2010_2019_transition_potential...
Potential for transition from Forest land to Agriculture land
0.00 0.03 0.07 0.10 0.14 0.17 0.20 0.24 0.27 0.31 0.34 0.37 0.41 0.44 0.48 0.51 0.54
btlulc2010_2019_transitio...
0.00 0.03 0.07 0.10 0.13 0.16 0.20 0.23 0.26 0.29 0.33 0.36 0.39 0.43 0.46 0.49 0.52
btlulc2010_2019_transition_...
Potential for transition from Built up area to Shrub land
0.00 0.06 0.12 0.18 0.25 0.31 0.37 0.43 0.49 0.55 0.62 0.68 0.74 0.80 0.86 0.92 0.99
btlulc2010_2019_transition_...
Potential for transition from Forest land to Shrub land
0.00 0.03 0.07 0.10 0.14 0.17 0.21 0.24 0.28 0.31 0.34 0.38 0.41 0.45 0.48 0.52 0.55
btlulc2010_2019_transition_potential...
Potential for transition from Agriculture land to Shrub land
0.00 0.03 0.07 0.10 0.13 0.17 0.20 0.23 0.26 0.30 0.33 0.36 0.40 0.43 0.46 0.50 0.53
Activate Windows

12. Appendix ''L'' Land satellite 5,7,8 Wavelength and Resolution

Landsat 7 (ETM+ sensor)	Wavelength (micrometers)	Resolution (meters)
Band 1- Blue	0.45 - 0.515	30
Band 2 –Green	0.525 - 0.605	30
Band 3 –Red	0.63 - 0.69	30
Band 4 –NIR	0.75 - 0.90	30
Band 5 –SWIR1	1.55 - 1.75	30
Band 6 –Thermal	10.40 - 12.5	60 *30
Band 7 –SWIR2	2.09 - 2.35	30
Band 8- Pan Band	.52 - .90	15

Landsat 5 (TM sensor)	**Wavelength (micrometers)**	**Resolution (meters)**
Band 1- Blue	0.45 - 0.52	30
Band 2 –Green	0.52 - 0.60	30
Band 3 –Red	0.63 - 0.69	30
Band 4 –NIR	0.76 - 0.90	30
Band 5 –SWIR1	1.55 - 1.75	30
Band 6 –Thermal	10.40 - 12.50	120 *30
Band 7 –SWIR2	2.08 - 2.35	30

Landsat 8 (LC sensor)	Wavelength (micrometers)	Resolution (m)
Band 1 –Ultra blue (coastal/aerosol)	0.435 - 0.451	30
Band 2 –Blue	0.452 – 0.512	30
Band 3 –Green	0.533 - 0.590	30
Band 4 –Red	0.636 - 0.6730	30
Band 5 –NIR	0.851 – 0.879	30
Band 6 –SWIR 1	1.566 -1.651	30
Band 7 - SWIR 2	2.107 – 2.294	30
Band 8-Panchromatic	0.503-0.676	15
Band 9-Cirrus	1.363 – 1.384	30
Band 10-TIRS1	10.60 – 11.19	100*30
Band 11- TIRS2	11.50 – 12.51	100*30

13. Appendix ''M'' samples of Training site Files of Burayu Town LULCC Trains

Land Change Modeler MLP Model Results (Created: 8/3/2019 9:04:46 PM) General Model Information and Sensitivity of Model to Forcing Independent Variables to be Constant.

Training site file Burayu Town 2000_2010 LULCC Train Shrub land to Built-area	
Independent variable 1	Burayu Town Road (most influential)
Independent variable 2	Burayu town LULC2010
Independent variable 3	Burayu Town Built up area 2010
Independent variable 4	Burayu Town Gafarsa water Reservoir
Independent variable 5	Burayu town River (least influential)
Input layer neurons	5
Hidden layer neurons	4
Output layer neurons	2
Requested samples per class	35000
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.4352
Testing RMS	0.4346
Accuracy rate	72.64%

Land Change Modeler MLP Model Results (Created: 8/3/2019 8:31:29 PM)
General Model Information and Sensitivity of Model to Forcing Independent Variables to be Constant.

Training site file Burayu Town 2000_2010 LULCC Train Forest land to Agriculture land	
Independent variable 1	Burayu Town Road (most influential)
Independent variable 2	Burayu town LULC2010
Independent variable 3	Burayu Town Built up area 2010
Independent variable 4	Burayu Town Gafarsa water Reservoir
Independent variable 5	Burayu town River (least influential)
Input layer neurons	5
Hidden layer neurons	4
Output layer neurons	2
Requested samples per class	5000
Acceptable RMS	0.01
Iterations	10000
Training RMS	0.1741
Testing RMS	0.1751
Accuracy rate	96.83%
Skill measure	0.9366

14. Appendix ‘N’ Consistency Ratio (CR).

Pairwise comparison

Analytical Hierarchy Process (AHP) weight of each Factors and Constraints					
	Road	LULC (2010)	Built up (2010)	Gafarsa Water.	River
Road	1				
LULC (2010)	0.333	1			
Built up (2010)	0.2	0.33	1		
Gafarsa water	0.1427	0.2	0.333	1	
River	0.1111	0.1427	0.2	0.333	1

The Eigenvector of weights of constraints and factors.	
Factors and Constraints	Factors and Constraints weights
Burayu Town Road	0.5128
Burayu Town LULC (2010)	0.2615
Burayu Town Built up area (2010)	0.1290
Burayu Town Gafarsa water	0.0634
Burayu Town River	0.0333

Standardized Matrix of Factors and constraints.

	Road	LULC (2010)	Built up (2010)	Gafarsa Water.	River	Sum
Road	0.56	0.64	0.52	0.43	0.36	2.51
LULC (2010)	0.19	0.22	0.32	0.31	0.28	1.32
Built up (2010)	0.11	0.07	0.1	0.18	0.2	0.66
Gafarsa water	0.08	0.04	0.04	0.06	0.12	0.34
River	0.06	0.03	0.02	0.02	0.04	0.17
Total	1	1	1	1	1	5

.

Factors and Constraints	Sum	Weight	sum/weight
Road	2.51	0.51	4.9
LULC (2010)	1.32	0.26	5.18
Built up (2010)	0.66	0.13	5.13
Gafarsa water	0.34	0.06	5.52
River	0.17	0.04	5.37
Total	5	1	26.1
Lambda max (λmax)			5.22
Consistency Index (CI)			0.055
Random Index (RI)			1.12
Consistency Ratio (CR)			0.05

17. Appendix ‘O’ Burayu Town Subset Land satellite of 1990, 2000, 2010 and 2019 year.