ANALYZING LAND USE LAND COVER CHANGE AND ITS IMPACTS ON SURROUNDING AGRICULTURAL LAND USING CELLULAR AUTOMATA: THE CASE OF FITCHE TOWN, ETHIOPIA

Dereje Ketema Shiferaw

A Thesis Submitted to

The Department of Geomatics Engineering

School of Civil Engineering and Architecture

Presented in Partial Fulfillment of the Requirement for the Degree of Master's in Geo-informatics Engineering

Office of Graduate Studies

Adama Science and Technology University

September, 2022

Adama, Ethiopia

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Advisor: Tilahun Erduno (PhD)

Co-Advisor: Zelalem Biru (PhD)

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DECLARATION

I declare that this thesis entitled “Analyzing Land Use Land Cover Change and Its Impacts on Surrounding Agricultural Land Using Cellular Automata: The Case of Fitche Town, Ethiopia” is my own work and has not been submitted to any university for similar purpose. The references used in this thesis are duly recognized by proper citations.

Dereje Ketema Shiferaw	________________________	________________
Name of the student	Signature	Date

ADVISOR’S RECOMMENDATION

We, the advisors of this thesis, hereby certify that we have read the revised version of the thesis entitled “Analyzing Land Use Land Cover Change And Its Impacts On Surrounding Agricultural Land Using Cellular Automata: The Case of Fitche Town, Ethiopia” prepared under my guidance by Dereje Ketema Shiferaw submitted in partial fulfillment of the requirements for the degree of Masters of Science in Geo-informatics Engineering.

Therefore, we recommend the submission of revised version of the thesis to the department following the applicable procedures.

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Advisor	Signature	Date
______________________________	______________________	____________________
Co-advisor	Signature	Date

APPROVAL SHEET

We, the advisors of the thesis entitled "Analyzing Land Use Land Cover Change And Its Impacts On Surrounding Agricultural Land Using Cellular Automata: The Case of Fitche Town, Ethiopia" and developed by Dereje Ketema, hereby certify that the recommendation and suggestions made by the board of examiners are appropriately incorporated into the final version of the thesis.

Advisor	Signature	Date
Co-Advisor	Signature	Date

We, the undersigned, members of the Board of Examiners of the thesis by Dereje Ketema have read and evaluated the thesis entitled "Analyzing Land Use Land Cover Change And Its Impacts On Surrounding Agricultural Land Using Cellular Automata: The Case of Fitche Town, Ethiopia" and examined the candidate during open defense. This is, therefore, to certify that the thesis is accepted for partial fulfillment of the requirement of the degree of Master of Science in Geo-informatics Engineering.

Chairperson	Signature	Date
Internal Examiner	Signature	Date
External Examiner	Signature	Date

Final approval and acceptance of the thesis is contingent upon submission of its final copy to the Office of Postgraduate Studies (OPGS) through the Department Graduate Council (DGC) and School Graduate Committee (SGC).

Department Head	Signature	Date
School Dean	Signature	Date
Office of Postgraduate Studies, Dean	Signature	Date

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LIST OF ACRONYMS AND ABBREVIATIONS

ANN	Artificial neural network
CA	Cellular Automata
CSA	Central Statistical Agency
DEM	Digital Elevation Model
EEA	European Environment Agency
ENVI	Environment for Visualizing Images
ERDAS	Earth Resource Data Analysis System
ETM	Enhanced Thematic Mapper
FAO	Food and Agriculture Organization
GIS	Geographic Information System
GPS	Global Positioning System
IGBP	International Geosphere and Biosphere Programme
LCM	Land Change Modeler
LULC	Land Use and Land Cover
MOLUSCE	Modules for Land Use Change Evaluation
OLI	Operational Land Imager
QGIS	Quantum Geographic Information System
RS	Remote Sensing
SVM	Support Vector Machine
TIFF	Tagged Image File Format
UA	Urban Agriculture
USGS	United State Geological Survey
UTM	Universal Transfer Mercator

ABSTRACT

The rapid expansion of urban area rose with population growth, movements and demands have a substantial impact on land use land cover change (LULCC). The study aims to analyze LULC changes and its impacts on the surrounding farmlands in Fitche town during the periods of 2002 to 2022. The study employed satellite images of Landsat TM for 2002, Landsat OLI datasets for 2013 and 2022. Support Vector Machine Algorithm of Supervised Classification has been applied to generate LULC maps of 2002, 2013 and 2022 years by using ENVI software and the accuracy of classified land use land cover maps were checked by confusion matrix to derive overall accuracy and results were above the minimum and acceptable threshold level. The produced LULC dynamics have been assessed by Cellular Automata (CA) in MOLUSCE Plugins using QGIS and Land Change Modeler (LCM) model to quantify the land use transitions between land cover classes, to identify gain and losses of each class categories in relation to other land cover classes and their spatial trend. Finally, Cellular Automata has been run to model LULC changes in the study area and to predict future land use changes. The parameter, such as DEM, slope, aspect and distance from the road are used as spatial variable maps in the processes of learning in ANN-Multi layer perception to predict their influences on LULC between 2002 and 2022. The actual and projected LULC maps for 2022 indicate a good level of accuracy, with an overall Kappa value of 0.83 and with a percentage of the correctness 88.8 %. ANN-Multi-layer perception model is then used to forecast changes in LULC for the years 2050. Generally, the results of this study have shown that there was an increased expansion of built up areas in the last 22 years from 10.43% in 2002 to 16.92 % in 2013 and to 25.76% in 2022 and agricultural land was inclined from 66.40% in 2002 to 54.93% in 2013 and decreased to 36.41% in 2022. The simulated result indicate that built-up area covers 29.76% in 2030, 32.31% in 2040 and 35.74% in 2050 and farmlands was expected to be 29.74% in 2030, 26.56% in 2040 and 22.01% in 2050 of the total area coverage. The findings assist farmers and policy-makers in developing optimal land use plans and better management techniques for the long-term development of natural resources.

Keywords: Fitche town; LULC Change; CA-ANN Multi-layer perception; MOLUSCE Plugin; QGIS; ENVI.

CHAPTER 1: INTRODUCTION

1.1. Background of the study

Urbanization is worldwide phenomena that emphasize the process of both vertical and horizontal physical expansion of urban area (Ibido, 2020). It is a global process which demonstrates itself through rapidly changing human population densities and land use and land cover (Ibido, 2020). During the urbanization processes, Land use and land cover (LULC) pattern change, industrialization and social transformation occurred. LULC change respond to population explosion, anthropogenic-environment interactions or environmental degradation, climate change and other socio-economic challenges. Population increments and land demand for settlement, commercial and industrial expansion and its impact on environment have also been largely raising issues in many discussions. In spite of its small area coverage relative to the earth's surface, dynamic urban growth processes, particularly the expansion of urban population in a larger extent and urbanized area, have a significant impact on human and natural environment at all geographic scales (Terfa et al., 2019).

The LULC scenario of a region was the result of physical and natural characteristics of the earth’s surface which are utilized and altered by humans in time and space (Girma et al., 2022). LULC changes play an important role in the study and analysis of global changed scenario today as the data available on such changes is essential for providing critical input to decision-making of ecological management and environmental planning for future (Hassan et al., 2016). The spatio-temporal monitoring of land-use dynamics is also essential to observe the changing demands of an increasing population and a better understanding of the relationship between natural phenomena and human activities (Ibido, 2020). Land-use changes contribute to land degradation, land fragmentation, and loss of biodiversity significantly (Berihun et al., 2019). The changes in land-use patterns have been analyzed by different scholars to identify the drivers on a wide scale. The fastest urban population growth and consequent urbanization are the drivers of fragmentation of the natural landscape over the surface (Haregeweyn ,2012; Berihun, 2019). Urbanization led to the expansion of the city at its sub-urban and peripheral areas (Leulsegged et al., 2012). Continuous expanding built-up areas have encroached on the surrounding valuable agricultural land, forestland, natural vegetation, and wetlands, etc. (Ibido, 2020). The urban land is mostly conquered by an impervious surface which has negative impacts on the ecosystem, the hydrological processes, biodiversity, and micro-climate the ecological habitat (Mosammaam et al., 2017), water quality, air quality (Poyil and Misra , 2015).

Land cover change denotes a change in certain continuous characteristics of the land such as vegetation type, soil properties, and so on, whereas land-use change consists of an alteration in the way certain area of land is being used or managed by humans (Patel et al., 2019). This involves the transformation in the natural land use due to urban growth. It is interesting to note that this change is responsible for a number of local and global effects, including biodiversity loss and its associated effects on human health, and the loss of habitat and ecosystem services (Patel et al., 2019). It is mainly driven by urban growth and is particularly important now for developing and underdeveloped countries. Primary causes of urbanization are population eruption, migration from other places, industries, economy and proximity to resources and basic amenities (Sunil Sankhala, 2014). The built-up is generally considered as the parameter for quantifying urban. The exceptional growth of many urban agglomerations in many developing countries is the result of a threefold structural change process: the transition away from agricultural employment, high overall population growth, and increasing urbanization rates(Sunil Sankhala, 2014).

Urbanization in sub-Saharan Africa is altering traditional livelihood strategies and displacing agricultural land uses in many areas (Hashidu et al., 2019). The population growth rate in both urban and rural areas is not commensurate with the quantity of land supply. Land is fixed in nature and so does not increase with increasing population growth. Expansion of cities affects the areas surrounding them (i.e., the suburbs) by altering the natural resource base and converting vegetal land cover to new uses, thus challenging the environment and dwellers' livelihoods (Hashidu et al., 2019).

Ethiopia is the second most populous country in the African with 120 million inhabitants (UN, 2021). It is one of the least urbanized countries in the world where 19.7% of its population living in urban center (UN, 2018). In Ethiopia, as in several other African countries, urbanization is increasing in alarming rate and the competition for land between agriculture and non - agriculture is becoming intense in the peri-urban areas (Ibido, 2020). According to official figures from the Ethiopian Central Statistics Agency, the urban population is projected to nearly triple from 15.2 million in 2012 to 42.3 million in 2037, growing at 3.8 percent a year and the rate of urbanization will be even faster, at about 5.4 percent a year. This growth makes it easier for both public and private entities to seize land. Therefore, lands used for urban agriculture (UA) were becoming gradually scarcer due to high competition from other land uses and the rapid population growth being experienced in many cities of the country. Information about LULC change and its consequence on agricultural lands in town area were important for enhancing food security and for proper management of land use (Agidew & Singh, 2017).

Recently, information of LULC transformation is highly required to many groups; a substantial amount of data of the Earth's surface are collected using remote sensing tools which provides an excellent source of data from which updated LULC information and changes can be extracted and analyzed efficiently (Hassan et al., 2016). It is also fundamental for estimating levels and rates of deforestation, habitat fragmentation, urbanization, wetland and soil deprivation and many other landscape-level phenomena (Edward et al., 2010).

Detection of LULC changes is the process of identifying differences in the state of a pixel or phenomenon by analyzing images acquired on different dates (Yousafzai, S., Saeed, R., Rahman, 2012). The combined remote sensing (RS) and geographical information system (GIS) has best tool for managing the land use land cover change research and natural resources. Analyzing and tracking of regional and temporal LULC shifts benefits scientists, environmentalists, agriculturalists, legislators, and urban planners (Hamad et al., 2018). Remote sensing techniques assist in the efficient preparation of natural resources, as well as land management and long-term change dynamics tracking (Hamad et al., 2018). These changes can be integrated with social and biophysical data to determine the factors that influence the process of LULC change or its consequences.

On the other hand, LULC transition models often make an effort to predict when and how frequently these changes will occur. Land prediction models such as IDRISI's CA MARKOV, CLUE-S/ Dyna- CLUE, DYNAMICS EGO, and Land Change Modeler are being used by the researchers across the world (Hamad et al., 2018). The future prediction model proved extremely helpful in determining how previous and future LULC changes may effect soil erosion, especially on farmland (Perović et al., 2018). Several spatio-temporal prediction models, such as the Markov chain (MC) model, the Cellular Automata (CA) model, and the conversion of land use and its effects (CLUE) model, have been developed in recent years to forecast the LULC and their change (Alam et al., 2021). Among these, the CA model has been commonly utilized for land-use change analysis among the numerous spatio-temporal dynamic modeling methodologies. MOLUSCE (Modules of Land Use Change Evaluation), a new QGIS plugin that can estimate potential LULC changes is built with CA model and also includes a transition probability matrix, is being used by most researchers (Hamad et al., 2018). MOLUSCE was developed to investigate a range of applications, including studying temporal LULC shifts and projecting future land use, anticipating prospective shifts in land cover and forest cover, and detecting deforestation in sensitive locations (Aneesha Satya et al., 2020). This LULC change model, which is based on a multi-criteria analysis methodology, was created using GIS software (Mzava et al., 2019). To predict their relative effect on the model, the parameters depend on the researcher's response weight (Hassan et al., 2016; Singh et al., 2014)

In Ethiopia, there were some studies conducted on LULCC detection using GIS and RS. However, the former studies did not give attention to the issue of impacts of LULC change on surrounding agricultural land in the urban environment and they did not use the latest Model to analyze and predict LULC change. Besides, there were no studies conducted in the study area related to urban LULC change and its impacts on agricultural land at Fitche Town. Therefore, this study aimed to fill the gap by using multi-temporal satellite imagery based on AC-ANN-Multi-Layer perception approach, to analyze changes in the LULC patterns and their effects on surrounding agricultural land within Fitche town.

1.2. Statement of the problem

In developing countries, where urbanization rates are high, urban sprawl is a significant contributor of the land use change (Ibido, 2020). Sprawl generally infers to some type of uncoordinated development with impacts such as loss of agricultural land, open space and ecologically sensitive habitats in and around urban areas (Deribew, 2020). Now urban expansion is increasing at an alarming rate in developing countries. Rapid rate of urban growth lead to rapid changes of land use and land cover than ever before, particularly in developing nations, are often characterized by unrestrained urban rambling, land degradation or the transformation of agricultural land to other uses and resulting massive cost to the environment (Sunil Sankhala, 2014).

Ethiopia is still predominantly a rural country, with only 20% of its population living in urban areas. But this is set to change dramatically. Figures from the Ethiopian Central Statistics Agency, project the urban population is will triple to 42.3 million by 2037, growing at 3.8% a year. According to the 2015 Ethiopian urbanization review, the rate of urbanization will be even faster, at about 5.4% a year. That would mean a tripling of the urban population even earlier by 2034, with 30% of the country's people in urban areas by 2028.

Urban expansion in Fitche town was a rapid horizontal expansion from time to time. This will have far reaching ecological, socio-economic, and environmental consequences, especially to the urban fringe areas (B. Regasa, 2014). Particularly, the main challenge of the urbanization process in the study area is the rapid conversion of a large amount of prime agricultural land to urban land uses (both residential and industrial construction) in the peri-urban areas (Ibido, 2020). It can affect the unavailability of prime agricultural land and consequently exposes for low agricultural productivity and low standard of living (Ibido, 2020). Hence, a better understanding of the spatial and temporal dynamics of urban growth and its impact on the small-scale farmer's life in the study area is required. Since the study area, Fitche town was a zone administration so; the need for land is high both by government and non-government organization, the demand of land for urban development program increases rapidly with non-existent urbanization process. In response to these, the government is taking large tracts from peri-urban areas. As a result, large numbers of local landholders who mainly engage in agricultural activity for their livelihood have been forced to lose their land rights. Thus, this study is mainly designed to investigate the impact of land cover change on the livelihood of the peri-urban farm household and compensation they received from government while displaced from their farm land.

Fitche town was faced with urban expansion due to the existence of high population growth and being flat in land scape makes it suitable for urban expansion. Since, the expansion of the town is becoming fast, irregular and uncontrolled; it creates displacement to the farming community. Then, there were different challenge associated with this expansion. Like: loss of agricultural farm lands, reduction of grazing lands and shrubs land.

Therefore, this study aims to develop a change detection procedure that was preferable for analyzing the land use land cover change and its impacts on agricultural land, based on the comparison of extracted inflexible surface data sets from multi temporal images by carried out different change detection techniques such as Support Vector Machine algorithm of supervised classification, post classification and CA-ANN model and ground reference or field verification.

1.3. Objective of the Study

1.3.1. General Objectives

The general objective of the study was Analyze Land Use Land Cover dynamics and its impacts on Surrounding Agricultural Land from the period of 2002-2022 in Fitche Town.

1.3.2. Specific Objectives

The specific objectives of this study are to: -

i. examine the LULC change over 2002 to 2022 study period;
ii. Analysis the trends and rates of Agricultural lands over the study period;
iii. Predict the LULC maps at 2030, 2040 and 2050 years of the study area.

1.4. Research Question

As this study mainly focuses on built up areas, the following research questions were set:

i. What are the spatial extents of LULC change between 2002 to 2022 time interval?
ii. What are the trends and rates of agricultural land patterns?
iii. What are the future LULC maps of 2030, 2040 and 2050 years in the study area?

1.5. Significance of the Study

Land use and land cover change was a major aspect of the pressure on the limited land resources, that was driven by different biophysical and anthropogenic factors particularly population growth. Therefore, analyzing and modeling of land use changes provide greater importance to the research community, urban planners, stake holders as well as decision making groups in terms of understanding the impacts of land use land cover changes on agricultural land in Fitche Town. In addition, it also provides the opportunity to understand the trends of changes in built up areas as a result of driving variables. Moreover, the finding of this study was an initial input for future research direction for interested groups in the area.

1.6. Scope of the study

The spatial scope of this study was limited to Oromia Regional State, Fitche Town Administration. Whereas, the contextual scope was to examine changes in the spatio-temporal patterns, particularly land use land cover dynamics during the study period (2002 to 2022) and analysis the impacts of urban land use land cover changes using geospatial technology.

1.7. Limitation of the study

One of the major limitations was difficulty to get high resolution satellite imageries for high accuracy and precision results on mapping and classifying LULC maps of the study area. Landsat imageries were used for LULC analysis, Landsat imageries were of 30 m resolution which are not high resolution and incurred some LULC classification errors that were indicated in error matrixes of accuracy assessment. It was not possible to get high resolution satellite imageries such as Quick Bird and IKONOS. The other limitation was that parameters or criterion of spatial variable development were set by reviewing different literature and prior knowledge of the study area instead of common standards.

CHAPTER II: LITERATURE REVIEW

2.1. Concept of Land use and Land cover

Land use and land cover are terms frequently used interchangeably, but each term has its own unique meaning (Klemas & Pieterse, 2015). The visual effect of land use at a given moment is known as land cover. Land cover refers to the surface cover on the ground like vegetation, urban infrastructure, water, bare soil etc. Identification of land cover establishes the baseline information for activities like thematic mapping and change detection analysis. The term land cover also refers to the physical material at the surface of the Earth. It can be defined as the biophysical state of the earth's surface and immediate sub-surface (Turner et al., 1995). Whereas Land use refers to the purpose the land serves, for example, recreation, wildlife habitat, or agriculture. Land use, on the other hand, refers to the amount of human activity that is directly tied to the land and the utilization of its resources (Kamaraj & Rangarajan, 2022). Land use was the utilization of land cover type by human activities for the purpose of agriculture, forestry, settlement and pasture by altering land surface processes including biogeochemistry, hydrology and biodiversity (Di Gregorio and Jansen, 2000). When used together with the phrase LULC generally refers to the categorization or classification of human activities and natural elements on the landscape within a specific time frame based on established scientific and statistical methods of analysis of appropriate source materials (Klemas & Pieterse, 2015). The precision in a land use classification should match to the intended use of the analysis and is usually defined by the map user.

Land use mapping is accomplished by partitioning an image into units, usually polygons, and then assigning each unit to a specific category. LULC classifications are strictly naming systems such that each classification contains a description defining uses falling within a system of mutually exclusive categories (Klemas & Pieterse, 2015).

Research on LULC was an important to put an outline on and parameterization of urban growth pattern and to identify a driving force for land use land cover change. However, the major challenges in LULC change analysis were to link behavior of demographic information with the biophysical information in the appropriate spatial and temporal scales. LULC is gradually increased due to the following parameters interaction with climate, ecological processes, biogeochemical cycles, biodiversity, and human activities (Abdul Rahaman et al., 2017).

Conversion and modification were the two forms of land cover changes described by Meyer and turner (1992) where the former was a change from one class of land cover to another (e.g. from grassland to cropland). The latter is, however, a change within a land cover category (e.g. thinning of a forest or a change in composition). Land cover changes due to human activities drive land use and hence a single class of cover could support multiple uses (forest used for combinations of timbering, slash and burn agriculture, fuel wood collection and soil protection). On the other hand, a single system of land use can maintain several covers (as certain farming systems combine cultivated land, improved pasture and settlements).

Urbanization, which results in the loss of agricultural and forested lands and a considerable increase in impervious surface cover, is the most extreme form of LULC change (Klemas & Pieterse, 2015). These effects, combined with associated decreases in vegetative cover, result in significant local hydrologic modifications and habitat destruction.

Human activities generally affect the land cover of an area mainly through shifting land use patterns by a variety of social causes which can be resulted in land cover changes that includes biodiversity loss, water pollution, trace gas emissions and other processes that come together to affect climate and biosphere (Vyas, 2008). Hence, in order to use land optimally, it is not only necessary to have the information on existing land use land cover but also the capability to monitor the dynamics of land use resulting out of both changing demands of increasing population and forces of nature acting to shape the landscape.

Global earth system is bounded to remain balanced otherwise it may produce irreversible impacts on the existing land resources. Therefore, for sustainable development, spatial and temporal monitoring such as LULC change detection and modeling is an effective tool (Girma et al., 2022). Previous studies documented that modeling LULC change is crucial to understand its spatiotemporal trends to implement necessary measures and protect the land resources sustainably (M. S. Regasa et al., 2021).

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

2.2. Drivers of land use land cover change

Environmental changes and challenges to sustainable development can highly be linked to adverse human activities at the expense of demand for land (Girma et al., 2022). Worldwide, particularly in developing countries, extensive LULC changes are predominantly common in recent decades (Kafy et al., 2021). LULC change, as one of the major driving forces of global environmental transform processes, is essential to the worldwide sustainable development debate (Guidigan et al., 2019). The observed modifications of the natural landscape of the Earth are generally termed as LULC change (Lambin & Meyfroidt, 2010).

Understanding the mechanisms leading to LULC changes in the past was crucial to understand the current changes and predict future LULC dynamics. Hence, LULC change research needed to deal with the identification; qualitative description and parameterization of factors which drive changes in LULC as well as the integration of their consequences and feed backs (Alemayehu, B., 2017).

Many researchers agrees that the main cause of LULC change and related impacts in Ethiopia are anthropogenic in origin even though natural processes may also contribute to change (Agarwal et al., 2002; Ali, 2009 and Birhan and Assefa , 2017). Changes in the LULC reflect the history and, perhaps, the future of humankind. Such changes are influenced by a variety of factors related to human population growth, economic development, technology and environmental changes (Houghton, 1994). Population growth is one of the major factors for LULC change. People are the most important natural resources, which is mutually inter-related and interdependent for their sustainable development (Santa, 2011).

Changes in land use and land cover caused through direct and indirect consequences of human activities on the environment for the purpose of having better life. One of the direct impacts of humans was population growth where it’s increased and decreased have an effects on land use especially in developing world at longer time scales. According to Lambin et al (2003), it can also be caused by the mutual interactions between environmental and social factors at different spatial and temporal scales as land use and land cover change is a complex process.

The other factors that contributed to the LULC change are property rights. Private ownership protected forests to some extent during the imperial reign (Adugna et al., 1996). Land degradation is the most series impact of LULC changes happened in Ethiopia. land degradation, which is decreasing of potential of productivity of land is caused by different processes including soil erosion and nutrient depletion and so on These processes are interrelated and could occur due to natural drivers but they are invariably accelerated by human intervention in the natural environment (Agray-Mensah, W., 1985).

2.3. Land use and Land cover Change Studies in Ethiopia

Similarly, Ethiopia experienced pronounced LULC changes during the last decades with a considerable expansion of cultivated land at the expense of other LULC types (Girma et al., 2022). In the country, anthropogenic activities take the lion-sharing part adversely changing the landscape, which exerts unfavorable and adverse impacts on the environment and livelihood (Regasa et al., 2021). In the Ethiopian Rift, alarming trends in LULC change have been observed due to diverse driving factors. The ever-increasing human population and the subsequent demands on land resources were identified as the underlying major key drivers in the region (Ariti et al., 2015; Garedew et al., 2009)

As 85% of the total population live in rural areas, 85% of the economy is dependent on agriculture with traditional farming (plough), the growth of urban population from time to time, with an increase of migration of rural population to cities for better life and the encouraging land lease policy to investors become important to study land use and land cover changes and its impacts in Ethiopia to design management and monitoring policies.

Researches on LULC change in Ethiopia involved in different regions and disciplines depending on the availability of data and tools to perform analysis. However, most of the studies have focused on deforestation, the expansion of cultivated land to land degradation, river catchments and watersheds, natural ecosystems and forests as well as the associated consequences. Among these: (Amsalu, A., Stroosnijder, L., & de Graaff, J. , 2007); (Bewket, W., & Abebe, S. , 2013); (Tekle, K., & Hedlund, L. , 2000); (Zeleke, G., & Hurni, H., 2001) were found.

Amsalu et al (2007) showed a significant decline in natural vegetation cover, however, there was an increase of plantation in Beressa watershed, in the central highlands of Ethiopia between 1957 and 2000. Yeshaneh et al (2013) also showed a significant decrease of natural woody vegetation of the Koga catchment since 1950 due to deforestation in spite of an increasing trend in eucalyptus tree plantations after the 1980's. Bewket and Abebe (2013) reported a reduction of natural vegetation cover, but an expansion of open grassland, cultivated areas and settlements in Gish Abay watershed, north-western Ethiopia.

From most of these studies it is evident that population pressure is one of the major drivers of LULC changes through destruction of forest and vegetation cover for the purpose of agricultural and urban expansion as discussed by Zeleke and Hurni (2001) and Amsalu et al (2007). Population growth coupled with migration from rural to cities leads to further expansion of urban areas at the expense of vegetation cover which is commonly practiced in western highlands of Ethiopia according to Zeleke and Hurni (2001) study.

2.4. Impacts of Land use Land Cover changes

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

Due to several reasons, most of the urban centers expanded to the surrounding environment. The outskirts of urban areas, usually referred to as rural-urban-fringe, are characterized by farming land/irrigated fields, forest cover and source of water supply (Tefera B, Ayele G, Atnafe Y, Jabbar, M.A., and Dubale, 2002). The trend of urban growth towards the urban-rural-fringe has an impact on the surrounding ecosystem. One of the major impacts of urban land cover change is diminish in surrounding forest and agricultural land. It is also likely that large amounts of valuable agricultural or irrigated lands are converted to non-agricultural areas (e.g. built up areas). Urban land cover change detection is a very important phenomenon, which characterizes the nature of the cities and their surrounding areas (George J.,, 2005).

LULC changes have significant consequences on climate change, hydrology, air pollution and biodiversity. Meyer and Turner (1992) mentioned in their study that it caused a various microclimatic change. The rise in global surface temperature is associated with deforestation through changes in land use. This in turn caused a strong warming in urban environment called urban heat island. Their study also showed water pollution occurred due to land cover changes from cultivation to settlement (urban areas). It has been reported also that loss of forest species has wide range of effects on biodiversity.

Since, Land is fixed in supply and does not increase with increasing population growth, The pressures exerted by increases in population and rapid urbanization deprive other sectors of the needed land (Naab et al., 2013). Agricultural lands are most affected by rapid urbanization and its functions of demand. Land uses for residential, industry and commercial, civic and culture tend to dominate agricultural lands in the bid for space in the urban place (Naab et al., 2013). This dominance tends to deprive farmers of arable land to cultivate thereby reducing agricultural productivity.

Identified the causes and impacts of LULC change require understanding both how people make land-use decisions and how specific environmental and social factors interact to influence these decisions (Lambin, E. F. , 2001). In order to understand the impacts of dynamic LULC, the use of land use change models become an advantage since they provide information of land use trajectories by projecting for the future. This ability of models were important for better environmental management and land use planning (Verburg, P. H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V., & Mastura, S. S., 2002).

The ability to monitor urban land cover and land use changes is highly desirable by local communities and policy decision makers. Due to the increased availability and improved quality of multi spatio-temporal data and new analytical techniques, nowadays it is possible to monitor urban land cover and land use changes and urban sprawl in a timely and cost-effective way (Yang, L., Xian, G., Klaver, J. M., & Deal, B. , (2003).). Therefore, the use of satellite data provides for regional planning and urban ecology.

2.5. Land Use Land Cover Change and Agriculture land

Urban growth, particularly the movement of residential and commercial land use to rural areas at the periphery of metropolitan areas, has long been considered as a sign of regional economic vitality (Yuan, F., Sawaya, K. E., Loeffelholz, B. C., & Bauer, M. E., 2005). However, its importance becomes unbalanced with impacts on ecosystem, greater economic differences and social fragmentation. It can be defined as the rate of increase in urban population. Dynamic processes due to urban change, especially the tremendous worldwide expansion of urban population and urbanized area, affect both human and natural systems at all geographic scales (Brockerhoff, M., 2000).

The rate of population growth is linked to the fast expansion of urban slum areas, with high levels of unemployment, food insecurity and malnutrition (Girma et al., 2022). Such rapid urbanization engendering the harsh reality of urban poverty requires adapted strategies to ensure adequate access to food for all in a context of escalating levels of urban food insecurity together with its adverse health and social consequences. This change is driven by such factors as economic demands, consumption patterns and lifestyles (Naab et al., 2013). Since land is now needed for uses besides agriculture and forestry in the urban Centre, its value has shifted from a consideration of its fertility and other favorable bio-physical characteristics to that of its functions. This has resulted in the acquisition of some of the most suitable agricultural lands for residential developments, particularly those near the centre. There is a consequent decline in the farmed area and an increasingly limited access to the natural resources on which the livelihoods of the poorest depend. There is not only the reduction in the total area of land available for farming but most importantly, there is a drastic loss of soil fertility due to intensive use to support plant growth and for that matter agriculture. A large number of youth are also opting out of farming because of growing insecurity in land ownership. The rapid rate of natural population growth and the emigration to various municipalities have made the loss of agricultural land to urbanization possible. The peri-urban farmer is the most affected by all of these since his source of livelihood is dependent on agriculture.

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

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

According to the Food and Agriculture Organization (FAO), urban and pre-urban farming supply food to 700 million city dwellers about one quarter of the world's urban population (Marcotullio, P. J., Braimoh, A. K., & Onishi, T., 2008).The situation was not different in Ethiopia (Egziabher, 1994) stated that the 13 livelihoods of many urban citizens in Ethiopia (Addis Ababa: economic capital and which accounts for over thirty percent of the total urban population) is heavily dependent on urban farming, but urban policy makers fail to give due attention to urban agriculture during urban planning policy reforms. But according to (Edward, 2010) as is the case in Ethiopia, urban agriculture can be characterized in to three farming systems on the basis of location. These are the pre-urban, household or homestead gardening, and vacant-space cultivation. The pre-urban cultivation takes place on lands just outside the built-up areas of the city. Vacant-space cultivation is done in open spaces usually in residential areas, beside water ways (natural and man-made such as drainage channels), and road sides.

2.6. Change Detection Analysis

Change detection was the process of identifying differences in the state of an object or phenomenon through observing its variation overtimes by using remote sensing techniques. Change detection is currently being used to monitor natural processes such as long-term effects from changes in climate due to astronomical causes as well as short term processes including vegetation succession and geomorphologic processes (Story, M., & Congalton, R. G., 1986). It is also used to monitor anthropogenic effects such as deforestation, agricultural expansion, urbanization and human induced climate change

(Congalton, R. G., 2009). Similarly, environmental changes are a reflection of how the land has been managed and change detection methods can help to evaluate these.

2.7. Application of Geospatial Technology in LULCC

2.7.1. Application of Remote Sensing in LULCC

The emergence and development of geospatial tools has opened the way for collecting, storing, processing, analyzing and displaying spatial data for various environmental applications. Remote sensing is a cost-effective technology for mapping land cover and land use and for monitoring and managing land resources (Pouliot et al., 2016). Remote sensing refers to the science or art of acquiring information of an object or phenomena in the earth's surface without any physical contact with it. And this can be done though sensing and recording of either reflected or emitted energy or the information being processed, analyzed and applied to a given problem (Campbell, 2002). The remote sensing literature shows that a tremendous number of efforts have been made for mapping, monitoring, and modeling LULC at the local, regional and global (Pouliot et al., 2016). Accurate information of LULC change is therefore highly essential to many groups. To achieve this information, remotely sensed data can be used since it provides land cover information

Remote sensing has a tremendous advantage over ground survey methods due to the large area coverage of its data and the ability to map inaccessible areas (Baban, 1999). It provides detailed, accurate, cost effective and up-to-date information with respect to different vegetation types and land uses. The frequency (temporal resolution) at which remotely sensed images are acquired also renders the technology suitable for monitoring LULC changes. Images of the same area acquired on different dates (multi-temporal) can be quickly analyzed to quantify these changes. Remote sensing data are important for estimating levels and rates of deforestation, habitat fragmentation, urbanization, wetland degradation and many other landscape-level phenomena.

Following this, a number of applications of remote sensing for urban studies have shown the potential to map and monitor urban land use and infrastructure. Moreover, Herold and Menz (2001) showed urban land use information in high thematic, temporal and spatial accuracy, derived from remotely sensed data, is an important condition for decision support of city planners, economists, ecologists and resource managers. Generally, land use and land cover changes have a wide range of impacts on environmental and landscape attributes including the quality of water, land and air resources, ecosystem processes and functions (Rimal, B. , 2011). Therefore, the use of remote sensing data and analysis techniques provide accurate, timely and detailed information for detecting and monitoring changes in land cover and land use.

2.7.2. Application of Geographic Information System (GIS) in LULCC

GIS was an information system that integrates stores, edits, analyzes, shares, and displays geographic information. It can be used in inventorying the environment, observing and assessing the changes as well as forecasting the changes based on the existing situation (Ramachandra and Kumar, 2004). Both remote sensing and GIS tools are applied in a wide variety of application areas including detecting and monitoring environmental changes, location and extent of urban growth, environmental impact assessment (EIA).

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

2.8. Image Classification

Image Classification is a fundamental task that attempts to comprehend an entire image as a whole. The goal is to classify the image by assigning it to a specific label. Typically, Image Classification refers to images in which only one object appears and is analyzed (Lu & Weng, 2007). Image classification approaches and techniques in remote sensing have gained the attention of most researchers in the field; because the efficient, accurate, and reliable information on the surface feature was the base for many application areas (Lu & Weng, 2007). In addition, valuable land information extraction and analysis was well performed using image classification. Image classification was the process of assigning pixel images to predefined land cover classes. Information extraction using image classification was a complex and time-consuming process.

In remote sensing, there are different image classification techniques. Their appropriateness depends on the purpose of land cover maps produced for and the analyst's knowledge of the algorithms was used. Classification methods can also be viewed as pixel-based, object-oriented, fuzzy classification, ENVI classification, etc. Selection of appropriate classification methods and efficient use of multisource remotely sensed data are useful for minimizing the classification errors and improve the accuracy (Lu & Weng, 2007).

2.8.1. Object-Oriented Image Classification Methods

This method of image classification was based on identifying image objects, or segments with similar texture, color and tone of spatially contiguous pixels (Lu & Weng, 2007). This approach allows for consideration of shape, size, and context as well as spectral content (MacLean & Congalton, 2012). The classification stage starts by grouping the neighboring pixels into meaningful areas. Qian et al (2007) noted that in object-oriented classification approach, single pixels cannot be classified rather homogenous image objects are extracted during segmentation step. Image analysis in object-oriented is based on contiguous, homogeneous image regions that are generated by initial image segmentation.

2.8.2. Pixel-Based Image Classification Methods

Pixel-based classification methods automatically categorize all pixels in an image into land cover classes fundamentally based on spectral similarities (Qian, J.(2007) :Weng, 2012). It is the most commonly and widely used classification method, in which each pixel is classified based on the spatial arrangement of edge features in its local neighborhood (Im, J., Jensen, J. R., & Tullis, J. A. , 2008). Image classification at pixel level could be supervised or unsupervised. In the supervised classification method (Maximum Likelihood), the analyst is responsible to train the algorithm. In the unsupervised method, input from the analyst is very limited i.e., in specifying number of clusters and labeling the classes. According to (Santos, 2006), the statistical properties of training datasets from ground reference data are typically used to estimate the probability density functions of the classes. Each unknown pixel is then assigned to the class with the highest probability at the pixel location. However, information extraction at pixel level is associated with mixed pixel problems, although it is the most commonly used technique.

In this study Support Vector Machine (SVM) supervised classification algorithm technique was used. Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression (Jakkula, 2011). They belong to a family of generalized linear classifiers. In another terms, Support Vector Machine (SVM) is a classification and regression prediction tool that uses machine learning theory to maximize predictive accuracy while automatically avoiding over-fit to the data (Jakkula, 2011).

2.9. Change Detection Techniques using a Remotely Sensed Data

The selection of suitable method or algorithm for change detection is important in producing a more accurate change detection result since constraints such as spatial, spectral, thematic and temporal properties affect digital change detection. Some techniques such as image differencing can only provide change or non-change information, while some techniques such as post classification comparison can provide a complete matrix of change directions. According to (Bekalo, 2009), different change detection methods could produce different changes of maps depending on the algorithm they followed.

Although there are many change detection methods in remote sensing of image classification, recently researchers divided in to image ratio, image regression, image differencing and the method of change detection after classification (post classification method) (Bekalo, 2009). The classification of methods mainly depends on data transformation procedures if exists and analysis techniques applied. So, based on these conditions the current common methods of change detection are discussed below:

2.9.1. Image Regression Method

In image regression method of change detection, pixels from time t1 are assumed to be a linear function of the time t2 pixels (Singh, 1989). Under this assumption, it is possible to find an estimate of image obtained from t2 by using least-squares regression. According to Abuelgasim et al (1999), image regression technique takes in to account differences in the mean and variance between pixel values for different dates. This consideration minimizes the influence of differences in atmospheric conditions. In detecting changes of urban areas the regression procedure has more advantage than image differencing technique.

2.9.2. Image Ratio Method

In image ratio method, images must be registered beforehand and rationed band by band. The results of image ratio are interpreted with a threshold of values. If the ratio of the two images is 1, it means that there is no change in the land cover classes where as a ratio value of greater or less than 1 indicates a change in land cover classes (Singh, 1989; Bekalo, 2009). This method rapidly identifies areas of changes in relative terms.

2.9.3. Image Differencing Method

Image differencing is one of the most extensively applied change detection method. It can be applied to a wide variety of images and geographical environment. In this technique, images of the same area, obtained from times t1 and t2, are subtracted pixel wise. It is generally conducted on the basis of gray scale which used to show the spatial extent of changes in the two images. A threshold value is required for the gray of difference image in order to examine the changed and unchanged regions (Xu, 2009).

2.9.4. Post Classification Method

This method is the most simple and obvious change detection based on the comparison of independently classified images (Singh, 1989). Maps of changes can be produced by the researcher which shows a complete matrix of changes from times t1 to time t2. Based on this matrix, if the corresponding pixels have the same category label, the pixel has not been changed, or else the pixel has been changed (Xu, 2009).

2.10. Land use Land Cover Change Prediction

Land is utilized for multiple purposes and it is critical that land cover change be monitored and evaluated for both its negative and positive consequences. Dynamic urban land use and land cover change processes caused due to human activities have a wide range of effects on the global climate change and agricultural land either directly or indirectly (Herold et al, 2005; Lambin, E. F. , 2001). It also affects human and natural systems and contributes to changes in carbon exchange and climate through a range of feedbacks. Its future changes are also a function of numerous driving variables (Lambin, E. F., Geist, H. J., & Lepers, E.

, 2003). Some of these drivers are population change, economic activity and growth as well as biophysical conditions and are most important at a range of geographic scales.

Therefore, modeling of urban growth is a very essential step for further improvement of urban planning and land use management. The rising awareness and importance of land use models in the land use and land cover research community has led to the development of a wide range of land-use change models (Verburg, P. H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V., & Mastura, S. S., 2002).

Because of the significance impacts of land use and land cover changes, the use of land use change models become important to understand these changes and driving factors (Verburg, 2004). Models are representations of the real world, based on theoretical assumptions that represent systems (Verburg, P. H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V., & Mastura, S. S., 2002). Over the past decades, a range of land use change models have been invented by the land use modeling community for the land management needs as well as to analyze and project impacts for the future. Lambin et al (2001) described integrated modeling in a wider scale is an important technique in order to predict future scenarios.

Literature has described a number of models depending on different disciplines such as on: landscape ecology, urban planning, statistics and geographic information science (Verburg, P. H., Soepboer, W., Veldkamp, A., Limpiada, R., Espaldon, V., & Mastura, S. S., 2002; Verburg, 2004). Comparing the performance of models is a complex issue because of its high dependency on disciplinary perspectives, applied methods, data types used and modeling goals. For example: the GEOMOD model simulates change between two land categories whereas Markov chain and the cellular automata Markov model simulate change among several categories (Brown et al, 2004).

2.10.1. Spatially-Explicit Econometric Models

Spatially-explicit econometric models were developed by economists for the purpose of characterizing decisions of agents converting land between uses. The spatially explicit economic models are known by conceptualization of the conversion decision as an economic transaction where expected payoff must exceed costs. The advantage of these types of models is that its ability to share explanatory variables with other types of models developed by other disciplines (Irwin & Geoghegan, 2001). However, these models have limitations of detailed data of regionally consistent formats and also unable to model conditions that deviate from historic norms.

(Suarez-Rubio, 2012) Reported that such model provide information by projecting spatial distribution of land use conversion by using transaction data. This enables to determine the maximum profits by considering factors that affect the expected result. Understanding how likely land development is changing with different policy scenarios was one of the expected importances of spatially-explicit econometric models.

2.10.2. Spatial Allocation Models

Spatial allocation models have been developed for the purpose of identifying neighborhood conditions that have connections with land conversion specifically for residential and commercial development. They can also use for generating future land use changes. A transition rule is required for modeling the drivers of changes of new land use. Verburg et al (1999) also noted that the spatial pattern of land use through time can be determined by the components of landscape such as: human factors (population, technology and economic conditions) and biophysical constraints (soil, climate and topography). In order to describe the relationships between these factors, a decision rule is used. These models have the capability of generating a diffusion of growth near the areas of existing urban centers. Thus, there should be sufficient growth rules which help to generate new urban centers by limiting the diffusion otherwise variables that recognize patterns of land use must be considered (Wainger et al, 2007).

2.10.3. Agent-Based Models

Agent-based models comprises of simulation models where much attention has been given by the land use research community. They characterize systems in terms of independent but interconnected “agents” that have the ability to make “decisions” based on changing conditions. For most of the agent-based models which used for land use modeling, higher temporal complexity could be taken as an accurate criterion to be chosen (Parker, 2005). The majority of these models are referred to as cellular models which include spatial modeling techniques such as cellular automata and Markov models. However, Parker et al (2003) showed they have different applications as cellular models focused on landscapes and transitions, whereas agent-based models focused on human actions.

Agent based models have a wide range of applications such as archaeological reconstruction of ancient civilizations, modeling of infectious diseases as well as modeling of economic processes. Matthews et al (2007) have identified the five purposes of agent-based models in the land use modeling community. These are policy analysis and planning, participatory modeling, explaining spatial patterns of land use, examining social science concepts and demonstrating land use functions.

2.10.4. Markov Chain Models

Markov chain models are relatively simple and more powerful to model complex processes and changes in land use for planning purposes. They provide better information for analyzing time series of system evolution (Levinson & Chen, 2005). A Markovian process is one in which the state of a system at time t2 can be predicted by the state of the system at time t1given a matrix of transition probabilities from each cover class to every other cover class.

A stationary property is one of the importance of these models since it integrates a transition probability matrix. This property is critical to Markov chain model especially for future predictions of land use. The stationarity of the transition matrix in turn helps to inspect the validity of the model (Iacono et al, 2012). The MARKOV module in IDRISI can be used to create such a transition probability matrix (Eastman, 2012).

2.10.5. Land Change Modeler

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. It was developed by Clark Labs for the purpose of assessing a variety of land change scenarios and contexts. This model adopts the Markov Chains analysis for time prediction, but with an automatic Multi-Layer Perceptron for a spatial allocation of simulated land cover scores (Eastman, 2012).

In LCM, according to Eastman (2012), 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. Also, there is a facility in LCM to support projects aimed at Reducing Emissions from Deforestation and Forest Degradation (REDD). The REDD facility uses the land change scenarios produced by LCM to evaluate future emissions scenarios. Because of its ability to integrate various transitions involving same explanatory variables in to a single sub model, LCM is applied in this study.

2.10.6. Cellular Automata

Cellular Automata (CA) was a discrete dynamic system in which space was divided into regular spatial cells and time progresses in discrete steps. CA models can generate complex global patterns based on transition rules for simulation processes. The transition rules determine how a cell will evolve under certain conditions. These models have been widely used for simulating urban sprawl and land use dynamics (Cao et al, 2013). This study has integrated Cellular Automata and Land Change Modeler. The descriptions and approaches of these models are discussed below.

Several spatio-temporal prediction models, such as the Markov chain (MC) model, the Cellular Automata (CA) model, and the conversion of land use and its effects (CLUE) model, have been developed in recent years to forecast the LULC and their change detections (Alam et al., 2021). Among this the CA model has been frequently used for land-use change analysis among the several spatio-temporal dynamic modeling approaches. MOLUSCE (Modules of Land Use Change Evaluation), a new QGIS plugin that can estimate potential LULC changes is built with CA model and also includes a transition probability matrix, is being used by most researchers (Rahman et al., 2017). Four well-known algorithm models are employed in this plugin: Artificial Neural Networks (ANN), Logistic Regression (LR), Multi-criteria Evaluation (MCE), and Weights of Evidence (WoE). A CA-ANN model in MOLUSCE is a reliable tool for predicting future LULC that may be utilized in land use planning and management. This approach is being used for predicting the spatial LULC shift because it estimates the pixel's current condition based on its initial situation, adjacent neighborhoods eventuality, and changeover laws. Moreover this accurately depicts nonlinear spatial stochastic LULC change processes and produces complex patterns (Saputra & Lee, 2019). CA models are also increasingly being used in urban planning studies. They are capable of replicating the spatio-temporal complexity of urban areas as well as deforestation caused by natural disasters or human actions (Saputra & Lee, 2019). MOLUSCE was developed to investigate a range of applications, including studying temporal LULC shifts and projecting future land use, anticipating prospective shifts in land cover and forest cover, and detecting deforestation in sensitive locations. (Aneesha Satya et al., 2020). This LULC change model, which is based on a multi-criteria analysis methodology, was created using GIS software. (Mzava et al., 2019) To predict their relative effect on the model, the parameters depend on the researcher's response weight (Hassan et al., 2016; Singh et al., 2014) .When dealing with human activities that may alter the region suited for biological populations temporally, the LULC has a significant impact on species distributions, which is one of the most essential environmental aspects to be considered. Using the ANN-Multi-Layer perception approach, the Fitche town was situated to classify the changeover of land-use changes for the period 2002-2022, as well as to forecast and establish potential land-use changes in the years 2030, 2040 and 2050.

2.11. Review of Empirical Studies

Available studies have indicated that because the rate of population growth is linked to the fast expansion of urban slum areas the land that is now needed for agriculture has shifted to residential development use. This has resulted in peri-urban dwellers being seriously threatened by rapid urbanization because of the problem of scarcity of land for agricultural purposes that will arise. Farmers are often left with little or no land to cultivate and this renders them vulnerable, and also the environment is degrading (Purevtseren et al., 2020).

Several studies (Beckers et al., 2020; Doye et al., 2014) have also shown that the impact of urbanization on farming practices goes beyond the simple conversion of farming land into urban area. European Environment Agency (EEA) documented a considerable decline of agricultural land and increases in urban areas in the 25 European states covered in the study. Land converted from agricultural to urban uses can significantly impact on the sustainability of the wider environment (ecosystem functioning and biodiversity, soil and water resources, carbon sequestration, climate change), as well as economic and social welfare (Ustaoglu & Williams, 2017).

A study undertaken by (Ayele & Tarekegn, 2020) on the impact of urbanization expansion on agricultural land in Ethiopia used a remote sensing and GIS approach, showed that there is a loss of farmland and displacement of households who had been involved in farming. The study conducted by (Leulsegged et al., 2012) on Impact of urbanization in addis abeba city on peri-urban environment and livelihoods using remote sensing and GIS technology The research revealed the livelihoods, especially on agriculture and to identify how household livelihood outcomes were built. A study undertaken by Belay (2014), on the impact of urban expansion on agricultural land, used a remote sensing and GIS approach. This showed that there is a loss of farmland and displacement of households who had been involved in farming. Built-up area expansion had occurred by expanding the urban boundary at the expense of open land, agricultural land, and forests. Generally, one can say that the higher rate of urban expansion leads to a higher loss of agricultural land.

2.12. Research and knowledge gaps

Most of the studies were carried out in Ethiopia were focuses on assessing urban expansion and its socio-economic impacts on the livelihood of the farming community in the peri urban areas (Ibido, 2020; Leulsegged et al., 2012; M. S. Regasa et al., 2021; Tadesse & Imana, 2017; Tefera B, Ayele G, Atnafe Y, Jabbar, M.A., and Dubale, 2002; Yimam, 2017) and Regassa et al., 2020). Their focus is mainly on expansion of urban area and its impact on environment and socioeconomic impacts on the livelihood of the farming community in the peri-urban areas in relation to population growth. Generally, in Ethiopia studies made on urban expansion and its impact using GIS and RS techniques particularly for different urban related studies are minimal and due to this there is a limited literature in the area. However, the effect of farmland conversion on peri-urban livelihoods was not highlighted. The researchers believed a better comprehending vis-à-vis the effects of farmland conversion on livelihood assets is required. Therefore, this study aims to fill the prevailing literature gaps by enlarging the existed body of knowledge for a better understanding of the effects of farmland conversion on livelihood assets. Additionally, the former studies employed the older methodology to analyze the impacts of LULC dynamics on agricultural land and not well addressed. But, this study employed multi-temporal satellite imagery based in AC-ANN-Multi-Layer perception model, to analyze changes in the LULC patterns and their impacts on surrounding agricultural land within Fitche town.

CHAPTER III: MATERIALS AND METHODS

3.1. Description of the Study Area

3.1.1. Geographic Location

Fitche town is situated in the Oromia National Regional State of Ethiopia (Figure 1), in the northern direction of Addis Ababa. The Town is located about 112 km along the northern of Addis Ababa. Geographically, it is located at 9°48′N latitude and 38°44′E longitude with an average altitude of 2,738 m (8,983 ft.) above mean sea level. Fitche town is the administrative town of the North Shoa Zone, Oromia. Today, Fitche is a rapidly expanding town. In this town the fast growth of population has been observed in 20th century. The town has four kebeles occupying a total population of around 136,541, of whom 66,758 were men and of whom 70,143 were women.

The rapid growth of population of the city has put great pressure on the demand for urban spaces. In response to this demand, efforts are being made by the city government to incorporate the peripheral areas of the city, which is resulting in hastening the expansion of the built-up area of the city.

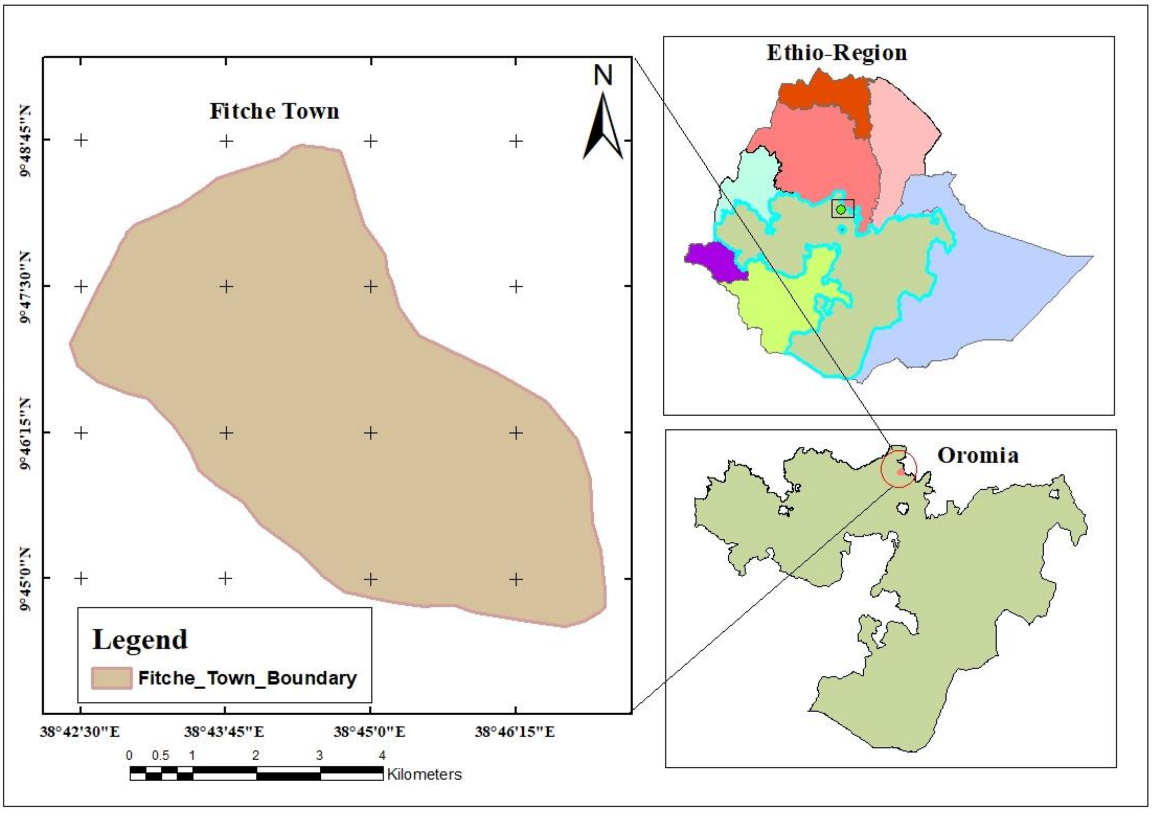


Figure 1: Location map of study area

3.1.2. Topography

Fitche town geographical area is mostly characterized by flat plain topographic landscape which promising opportunity to undertake various urban development activities in the centers and their vicinities in particular. The topography of an area like slope and elevation parameters has important contribution in urban land use land cover development. The study area is particularly flat with slopes varying between 0 and 41.0088 (Figure 2). According to the extracted elevation of the study area from DEM, the study area is located along an elevation range from 2562m -2963m (Figure 2).

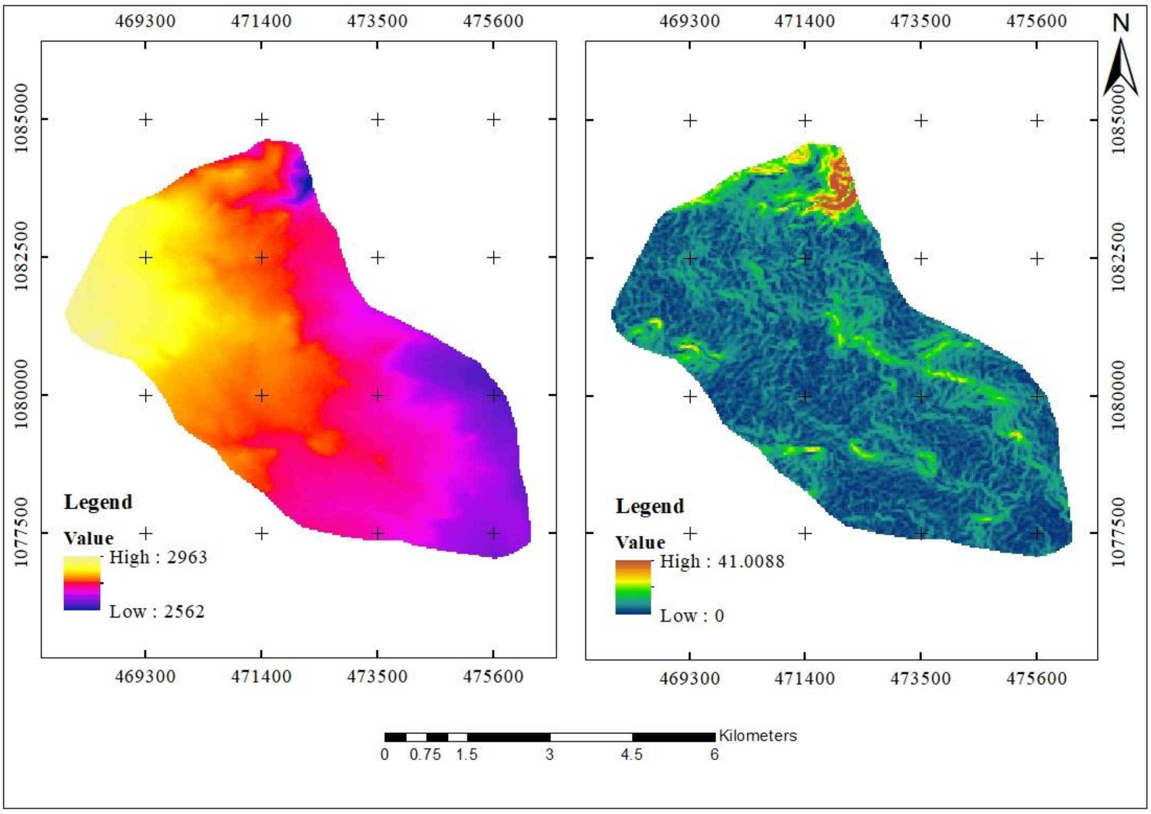


Figure 2; Elevation and Slope map of the study area

3.1.2. Demographic / population

According to the statistical censuses conducted in the country, Fitche Town showed a large increase in population. The Ethiopian population and housing census conducted in 1994 reported that Fitche town had a total population of 21,187 of whom 10,004 were males and 11,183 were females. The 2007 national census reported a total population for Fiche of 27,493, of whom 12,933 were men and 14,560 were women. Fitche town Administration reported the population data in 2020 were around 136,541, of whom 66,758 were men and of whom 70,143 were women (CSA 2020).

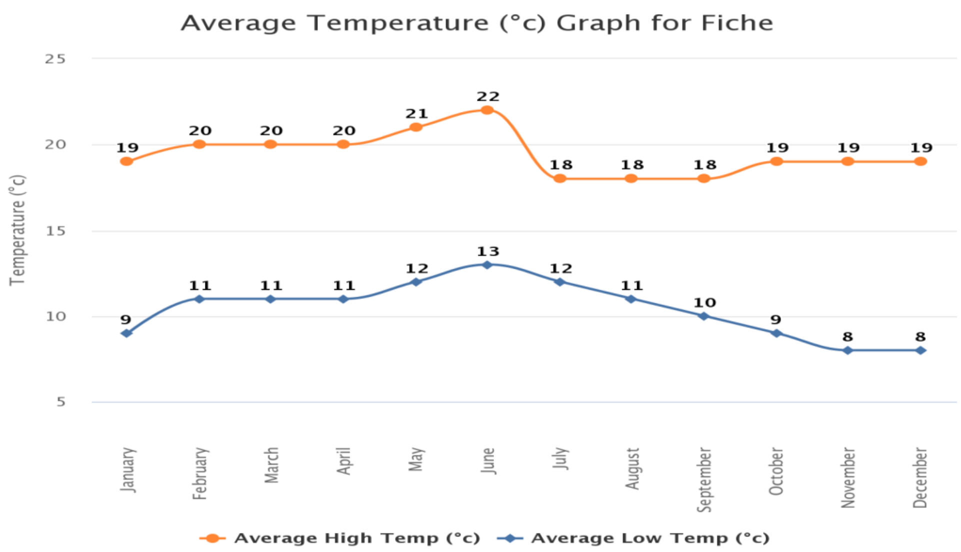
Table 1; Total Population of Fitche Town 1994 - 2020.

Year	Male	Female	Total Population
1994	10,004	11,183	21,187
2007	12,933	14,560	27,493
2020	66,758	70,143	136,541

Source: (Socio-economic profile of Fitche town, 2020)

3.1.3. Climate of the study area

The Fitche Town enjoys favorable climatic conditions that experiences moderate temperature and rainfall which is favorable for life. The climate pattern of town is characterized by subtropical climatic condition and experienced mean annual rainfall ranging approximately between 800 mm and 1600mm. Rainfall mostly occurs during the summer season. It receives abundant and heavy rainfall every year during this season. During summer seasons the rainfall reaches 324mm in July and 330mm in August at Fitche town. Maximum temperature for the study areas is high during March to May months. Fitche town experiences mean annual temperature ranging between 10 and 25°C.



Source: (Ethiopian Metrological Agency, 2020)

Figure 3: the average temperature of the study area

3.2. Data source and materials

3.2.1. Data Source

The main sources of the data in this research were both primary and secondary sources. To obtain information on spatio-temporal land use land cover change analysis, geo-spatial information data were collected. Collecting accurate and reliable data is the most determinant factor for any research as it determines the quality of the research. In this particular study, the first steps was identify the relevant LULCC factors to be considered for analysis and modeling LULC followed by setting criterion based on international and local rules. The following table describes data required, types of data used in the study, formats and where the data were gathered from (Table 2).

Table 2: Data Source

S. No.	Data		Source	Data format	Resolution	Purpose
	Satellite image	**Year**				
1	Landsat7 ETM+ Landsat 8 OLI Landsat 8 OLI	2002 2013 2022	USGS	Tiff	30m	to map the earth and track changes as seen from space
2	Digital Elevation Model (DEM)	-	USGS	Tiff	30m	To provide topographical details
3	Structural Plan of Fitche Town		Fitche municipality office	CAD file	-	To subset / clip boundary
4	Population data		Fitche municipality office	Number	-	To explore population density in the study area.

3.2.2. Materials / Software Used

In this research various software's and materials were used based on the capability to work on the existing problems in order to achieve the predetermined objective. These, software were used for collection, organization, analysis, interpretation and presentation of data. The following table shows software used in the study and their purposes (Table 3).

Table 3: Software used

S.No.	Name of software	Version	Purpose
1	ArcGIS	10.8	Data processing and thematic map preparation
2	ENVI	5.3	Image preprocessing, as well as atmospheric correction, for image classification.
3	Google Earth Pro	**-**	Use as a base map in visual image interpretation, and generate coordinate points for the images
4	Microsoft Word and Excel	2016	Integrating attribute data and compositing final thesis
5	TERRSET	2020	Land change modeling and time series analysis, multi criteria, compare and predict for the future.
6	QGIS MOLUSCE Plugin	2.18	For LULCC analysis and prediction.

3.3. Data Processing

The Landsat images of Remote Sensing data used in this study were acquired from the United States Geological Survey (USGS) which covers the entire study area. Despite its medium spatial resolution and mixed pixel challenge the Landsat image is commonly used for urban LULC mapping (Lu & Weng, 2007). The United States Geological Survey included all images from each year with less than 10% cloud pollution (USGS). Therefore, Landsat images of 2002, 2013, and 2022 were downloaded to proceed to subsequent phases.

3.3.1. Image Data Processing

Once data were collected, the study undergoes the processes of manipulating, sorting, and pre-processing collected data to analyze the LULC dynamics of the study area which is precisely dedicated to achieving the objective of the study. The satellite image of 2002, 2013, and 2022 was processed using ENVI 5.3 software. The coordinate system, layer stacking, and layer extraction took place. Then Landsat images were corrected for the atmospheric, sensor, and an illumination variance through radiometric calibration procedures.

3.3.2. Image classification

Image classification was defined as the extraction of different classes or themes, land use and land cover categories, from raw remotely sensed digital satellite image. It was a technique to identify different features such as urban land cover, vegetation types, anthropogenic structures, mineral resources, or changes in any of these properties from the satellite image. Additionally, the classified raster image can be converted to vector features (e.g., polygons) in order to compare with other data sets or to calculate spatial attributes (area, perimeter) using different statistical methods including QGIS software.

3.3.3. Land covers classification Scheme

The land use/land cover classes applied in this paper are adopted from AFRICOVER land use land cover classification scheme which is widely applied in East African Countries (Di Gregorio & Latham, 2003). Land use and land cover map for 2002, 2013 and 2022 were produced by supervised classification using the support vector machine classification algorithm of ENVI 5.3 software. LULC classes were mapped from digital remotely sensed data through a supervised classification method (training sample process), based on the field knowledge to perform the classification. Based on selected training sample, drive signatures, were subsequently classified with the supervised classification type and used support vector machine classification algorithm in ENVI 5.3 software. Supervised classification is based on the quality and quantity of training samples to produce good quality classification results. For the sake of simplicity, the researcher modified the descriptions of some of the land use/land cover classes considering the land use/land cover diversity of the study area. Therefore, the images were classified in to major land-use/land-cover classes such as built-up area, farm land, open-space land and shrub.

Table 4 : Land cover classification scheme for the study area.

LULC	Descriptions
Built-up area	Urban and rural built-up including homestead area such as residential, commercial, industrial areas, villages, settlements, road network, pavements.
Farmland	Includes all agricultural lands (both annuals and perennials) and grazing.
Open-space land	Includes a surface with little vegetation, open land exposed soil, rocks, and sand and also include the vacant space & small amounts of grassland.
Shrubs	Includes all forest vegetation types (evergreen, deciduous and wetland), and non-forest vegetation futures that are not typical of forest (pasture grasslands and recreational grasses.

3.3.4. Accuracy Assessment

The final step of the satellite image classification involves the accuracy assessment stage (Abbas & Jaber, 2020). The term accuracy is typically used to express the degree of correctness of a map or classification in thematic mapping from remotely sensed data. Accuracy assessment is a quantification of estimation with aid of remotely sensed dataset to classification conditions and it is useful for evaluation of classification approach, and it is also important to determination the error that might be involves (Abbas & Jaber, 2020). The increased usage of remote sensing data and techniques has made geospatial analysis faster and more powerful; however, the increased complexity also creates increased possibilities for errors (Gelan, 2021). Therefore, the assessment of the accuracy of mapping generated from remote sensing data is a critical and essential step in the classification process (Gelan, 2021). The error matrix is the most common tool in terms of determining the accuracy of the classification results (Fan et al., 2007). User accuracy, producer accuracy, overall accuracy and Kappa statistics were then derived from the error matrices for LULC classes. According to Moller-Jensen (1997), Kappa analysis is a discrete multivariate technique used in accuracy assessments. In other words, Kappa analysis is a standard component of accuracy assessment and is considered as a required component of most image analyses (Abbas & Jaber, 2020).

Producer's Accuracy (Errors of omission):- Producer's Accuracy measures the percentage of correctly classified pixels from a sample data or indirectly indicates errors of omission for a particular class. Producer's accuracy was calculated from dividing the number of correctly classified pixels in each category (on the major diagonal) by the number of training set pixels used for that category (the column total). It is calculated as:

Producer's Accuracy = $\left(\frac{\mathrm{Ci}}{\mathrm{Ct}}\right) * 100$ ……………………………………….Equation (1)

Where, C_i = correctly classified sample locations of the reference data or column and

C_t = total number of sample locations of the column.

User's Accuracy (Commission error):- user's accuracies are computed by dividing the number of correctly classified pixels in each category by the total number of pixels that were classified in that category (the row total). This result is a measure of commission error. It is calculated as:

User's Accuracy $= \left(\frac{\mathrm{Ri}}{\mathrm{Rt}}\right) * 100$ ………………………………………….Equation (2)

Where, R_i = correctly classified samples in the row and

R_t = total number of samples in the row.

Overall Accuracy:- Overall accuracy was computed by dividing the total diagonal (i.e., the sum of the correctly classified sample units) by the total number of sample units in the error matrix. This value is the most commonly stated accuracy assessment statistic.

Overall Accuracy = $\left(\frac{Sd}{n}\right) * 100$……………………………………..Equation (3)

Where, Sd = sum of values along diagonal and, n = total number of samples.

Kappa Coefficient:- Kappa coefficient can be used as another measure of agreement or accuracy. Kappa was used to measure the agreement or accuracy between the remote sensing derived classification map and the reference data as indicated by the major diagonals and the chance agreement. This was indicated by the row and column totals. Kappa values can range from +1 to –1. But, as there should be a positive correlation between the remotely sensed classification and the reference data, positive values were expected. Landis and Koch (1977) taken the possible ranges for kappa into three groups: a value greater than 0.80 (i.e., 80% and above) represent strong agreement; a value between 0.40 and 0.80 (i.e., 40%–80%) represents moderate agreement; and a value 0.40 (i.e., 40% and below) represents poor agreement.

$$K\wedge = \frac{n \sum_{i=1}^{r} xii - \sum_{i=1}^{r}(xi+.x+i)}{N^2 - \sum_{i=1}^{r}(xi+.x+i)} \quad \text{……………………………………………Equation (4)}$$

Where r = number of rows in the error matrix; Xii = number of observations in row i and column i (on the major diagonal); Xi+ = total of observations in row i (shown as marginal total to right of the matrix); X+i = total of observations in column i (shown as marginal total at bottom of the matrix) and N = total number of observations included in matrix.

3.4. Data Analysis Method

In order to answer the objective, the study was used both qualitative and quantitative techniques. The methods involved the usage of geospatial techniques and remote sensing data to produce the LULC maps of 2002, 2013 and 2022 and analysis the impacts of LULCC on agricultural land. In the Cellular Automation model, the transition probabilities from the ANN learning process are employed to describe the LULC changes. The (MOLUSCE) plugin in QGIS 2.18 software is used for this method (Fig. 4). The MOLUSCE plugin features six LULC prediction phases (Hakim et al., 2019).

3.4.1. LULC Change Analysis

The Panel of Change Analysis provides a fast quantitative assessment of changes so that researchers produce gain and loss evaluations, net change, persistence, and specific transitions both in a map and graphical form. The main issue is to define the dominant changes that can be grouped and modeled, termed sub-models (Christman et al., 2016).

In this study the change detection was assessed using two software packages ENVI 5.3 and QGIS. Image classification algorithm in ENVI software was employed to produce LULC maps of the years 2002, 2013 and 2022 that generate change maps between 2002 - 2013, 2013–2022 and 2002-2022 in the QGIS MOLUSCE Plugin. The algorithm operates on continuous data by subtracting pixel values of the before theme from the after theme, and providing two outputs viz, image difference and highlight change image (Kafy et al., 2021). Since change detection calculates the change in brightness values over time, the image difference file reflects those changes using gray scale image composed of single band continuous data. The highlight changes file creates a thematic layer clustered into decreased, unchanged, and increased classes (Kafy et al., 2021). Based on the principle of land change analysis, maps of gains and losses, contributions to net change, transitions of land cover classes between different categories, and spatial trend analysis were examined both in a map and graphical form.

Total LULC changes in hectares were calculated using the following equation:

Total LULC change = Area $_{\text{final year}}$ – Area $_{\text{initial year}}$……………………..Equation (5)

Where, area is extent of each LULC type. Positive values suggest an increase whereas negative values imply a decrease in extent.

Percentage LULC change were calculated using the following equation:

Percentage LULC changes = $\left(\frac{\text{Area of final year} - \text{Area of initial year}}{\text{Area of initial year}}\right) * 100$ …..Equ. (6)

Where, area is extent of each LULC type. Positive values suggest an increase whereas negative values imply a decrease in extent.

Rate of change (ha/yr.) = $\left(\frac{Later\ year - Initial\ year}{Time\ interval}\right)$ ……….…………….……Equation (7)

3.4.2. Transition Potential Modeling

While there were several methods for calculating transition potential maps, the MOLUSCES plugin includes artificial neural networks (ANN), weights of evidence (WoE), logistic regression (LR), and Multi-Criteria Evaluation (MCE) (Kamaraj & Rangarajan, 2022). In this study, multi-layer perceptron artificial neural network (MLPANN) based on great significance of LULC transitions that occurred on the geographical area was used to study LULC changes between 2002 and 2022. It allows generating a class statistics and a transition matrix of land use and land cover change. The class statistics describes changes that occurred in LULC between initial and final periods. The transition matrix depicts the number of pixels that change from one of LULC type to another. The outputs from this analysis were used to predict the future land use land cover using MOLUSCE (Modules for Land Use Change Evaluation) (Kamaraj & Rangarajan, 2022).

3.4.3. Sensitivity of ANN-CA

There were numerous ways for creating a transitional potential map; this module includes computational intelligence aspects such as artificial neural networks (ANN). LULC data is used as an input in every approach for calibrating and modeling LULC change. This strategy is justified in handling problems where the algorithm must deal with enormous amounts of uncertain or difficult-to-implement input data. As a result, a continuous index is created that describes the terrain on a scale of 0 to 1 (Kamaraj & Rangarajan, 2022). Since ANN incorporates fuzzy logic requirements, a continuous range, such as 0 and 1, is determined based on terrain usability. The interactions between linked neurons and the alteration of the weight connections between them are the important elements of ANN (Kamaraj & Rangarajan, 2022). The parameters were finally arrived while predicting the LULC map for the year 2050 viz., neighborhood - 1, iterations – 411 1000 nos., hidden layer – 10 nos., momentum value - 0.06, learning rate - 0.001 (Kamaraj & Rangarajan, 2022).

3.4.4. Selection of Spatial Variables

LULC change simulation needs to take into account the potential power of the independent variables (Gharaibeh et al., 2020). The main spatial variables considered in this study were: Distance from road, determinate of accessibility, is one of the major drivers in attracting more urban uses and expansion (Gharaibeh et al., 2020). Distance from urban can be a very strong driver of change where the closer the land to urban centres the easier it is for land to change to urban uses (Gharaibeh et al., 2020). Population density is the most prominent anthropogenic factor in land use change where the higher the density more frequent land use change. Anthropogenic disturbance has a strong association with the land cover type (Chowdhury et al., 2021). Elevation is recognized as the imperative topographic factors affecting LULC change (Girma et al., 2022). Slope affects the spatial trends of land cover change suppose that the gentler a land slope is, the easier it is to have land use changes (Gharaibeh et al., 2020).

The correlation of spatial variables between the two raster images, which are used to examine the correlation among the spatial variables factors, is evaluated using coefficient (Hakim et al., 2019). Then, between the initial year (2002) and the final year (2022), the category of each area and the LULC changes are calculated. The transition matrix, which indicates the fraction of pixels changing from one type to the next, is also produced by the algorithm.

3.4.5. Model Validation and LULC Prediction

At this stage, validation is carried out between the reference map (actual LULC map) of 2022 and simulated LULC map 2022 by calculating the overall kappa value. (Hakim et al., 2019). After the overall kappa value is in accordance with the assessment standard, then return to the cellular automata simulation stage to predict future LULC (Hakim et al., 2019). The LULC map of 2030, 2040 and 2050 were predicted by using LULC maps 2002, 2013 and 2022 along with the same spatial variable factors combinations.

The following flow chart explains the general analytical procedure to carrying out this research work (Figure 4).

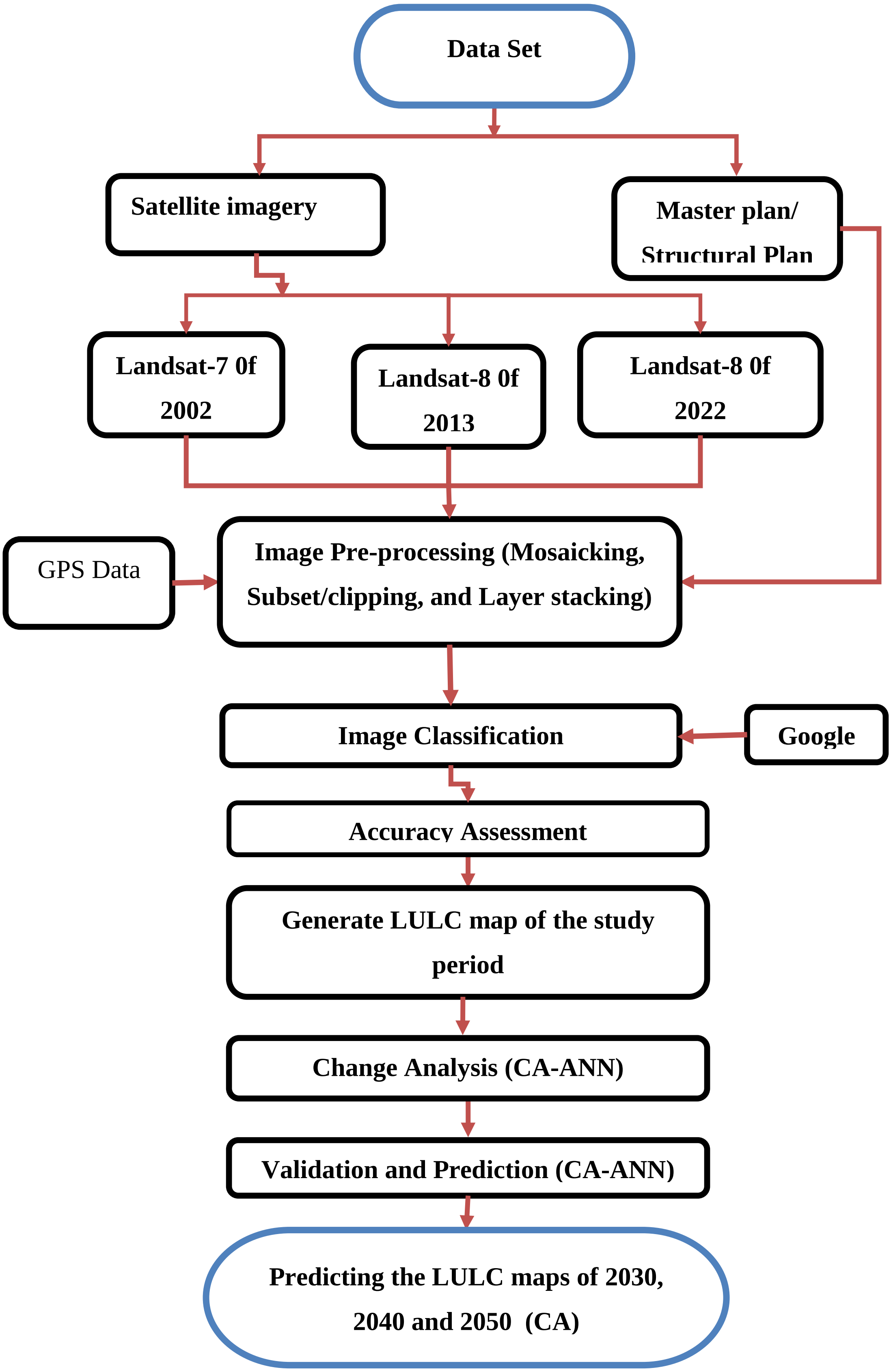


Figure 4: Technological scheme of the study

CHAPTER IV: RESULT AND DISCUSSION

4.1. Dynamics of Land Use Land Cover

In this section, the trends of urban LULC in Fitche town were assessed by observing the physical expansion and area coverage of Fitche Town over the last 20 years. Different data sets were used to examine changes in the LULC patterns and its effects on land use class. The land cover maps generated after running support vector machine supervised classification using ENVI software, as well as a post-classification algorithm. Based on the data gathered and data analysis performed, LULC maps developed for 2002, 2013 and 2022 years presented on figure 5 and figure 6. The classified Landsat satellite images summarized in Table 8 demonstrate the spatial extents, percentage changes over time and the annual rate change of the four LULC classes (built-up area, agricultural land, open-space and shrubs) in fitche town between 2002 and 2022.

An overall change in LULC of all the three reference years was shown on figure 12. The results show the spatial variation of LULC maps in fitche town over the study period. Farmland was dominant class at the beginning of the study period, but declined with the continuous increase of built-up area and open space land. Over the period 2002–2022, the percentage area covered by Farmland ranging between 66.4% and 36.4% of the total area. Furthermore, Figure 5 and 6 depicts the spatial variation of LULC from 2002 to 2022. The trend of LULC change from 2002 to 2022 is summarized in Tables 8 and Table 9, which show the percentage of area covered under each LULC classes.

4.2. Accuracy Assessment

Accuracy assessment in this study revealed the overall accuracies of 94.9%, 96.6% and 98.7% with the Kappa statistics of 0.932, 0.955 and 0.983 were calculated for the three reference years 2002, 2013 and 2022 respectively. This indicates that all classifications are in acceptable range because an overall accuracy of each year was greater than 85% and kappa coefficient greater than 0.80 represents strong agreement is an indicator for a strong accuracy. Hence, the maps met the accuracy requirements for change detection analysis and there is a positive correlation between the remotely sensed classified samples and the reference data. The details of error matrix tables‟ results are shown in Table 5, Table 6, and Table 7.

Table 5: Confusion matrix for the land use land cover map of 2002

Classified Map	Reference Map	Built-Up Area	Farmland	Shrubs	Open-Space	Grand -Total	User Accuracy
	Built-Up Area	28	0	0	1	29	96.6%
	Farmland	0	26	1	1	28	92.9%
	Shrubs	0	0	29	1	30	96.7%
	Open-Space	0	2	0	28	30	93.3%
	Grand-Total	28	28	30	31	**117**	
	Producer Accuracy	100%	92.9%	96.7%	90.3%		
	Overall Accuracy = 94.9%						
	Overall, Kappa Coefficients = 0.932						

Table 6: Confusion matrix for the land use land cover map of 2013

Classified Map	Reference Map	Built-Up Area	Farmland	Shrubs	Open-Space	Grand-Total	User Accuracy
	Built-Up Area	37	0	0	0	37	100%
	Farmland	0	36	0	2	38	94.7%
	Shrubs	0	1	35	0	36	97.2%
	Open-Space	0	2	0	34	36	94.4%
	Grand-Total	37	39	35	36	**147**	
	Producer Accuracy	100%	92.3%	100%	94.4%		
	Overall Accuracy = 96.6%						
	Overall, Kappa Coefficients = 0.955						

Table 7: Confusion matrix for the land use land cover map of 2022

		Reference Map					
		Built-Up Area	Farmland	Shrubs	Open-Space	Grand -Total	User Accuracy
Classified Map	Built-Up Area	39	0	0	1	40	97.5%
	Farmland	0	40	0	0	40	100%
	Shrubs	0	0	36	0	36	100%
	Open-Space	0	1	0	38	39	97.4%
	Grand-Total	39	41	36	39	**155**	
	Producer Accuracy	100%	97.6%	100%	97.4%		
	Overall Accuracy = 98.7%						
	Overall, Kappa Coefficients = 0.983						

Over the study period, the result shows an uneven shift of land use land cover due to rapid urban expansion in Fitche town. The spatial area coverage of built-up area was 10.43% of the total area in 2002 year. It moderately increased to 16.92% within 11 years interval. In the final year this proportion rose to 25.76%. Temporally, the rate of built-up expansion was comparatively low between the years 2002 and 2013, which showed nearly 6% increase, then it was increased by nearly 10% which peaked about 26% of the total area in the last year. In contrast, the area statistics of farmlands was 66.4% at the beginning of study timeframe. It slightly decreased to 54.93% in 2013 year, these digits dramatically declined to 36.4%, which shows a linear decrease in farmland and halved from its initial spatial extent.

On the other hand, Open-space area increased from 20.3% to 36.53% over the study period, with an annual increase rate of 3.65%. In contrast, during the study periods the area coverage of shrubs land decreased from 2.9% to 1.3% at fitche town.

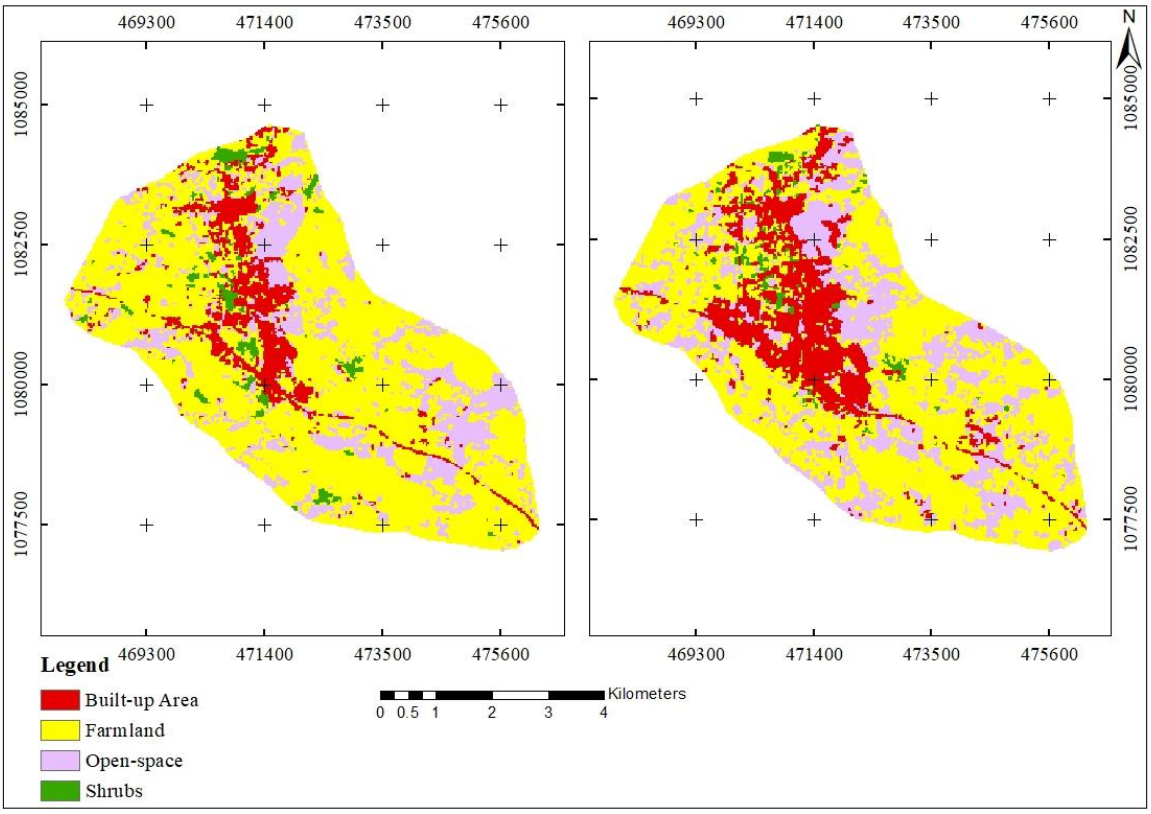


Figure 5: LULC Map of Study Area in 2002 AND 2013

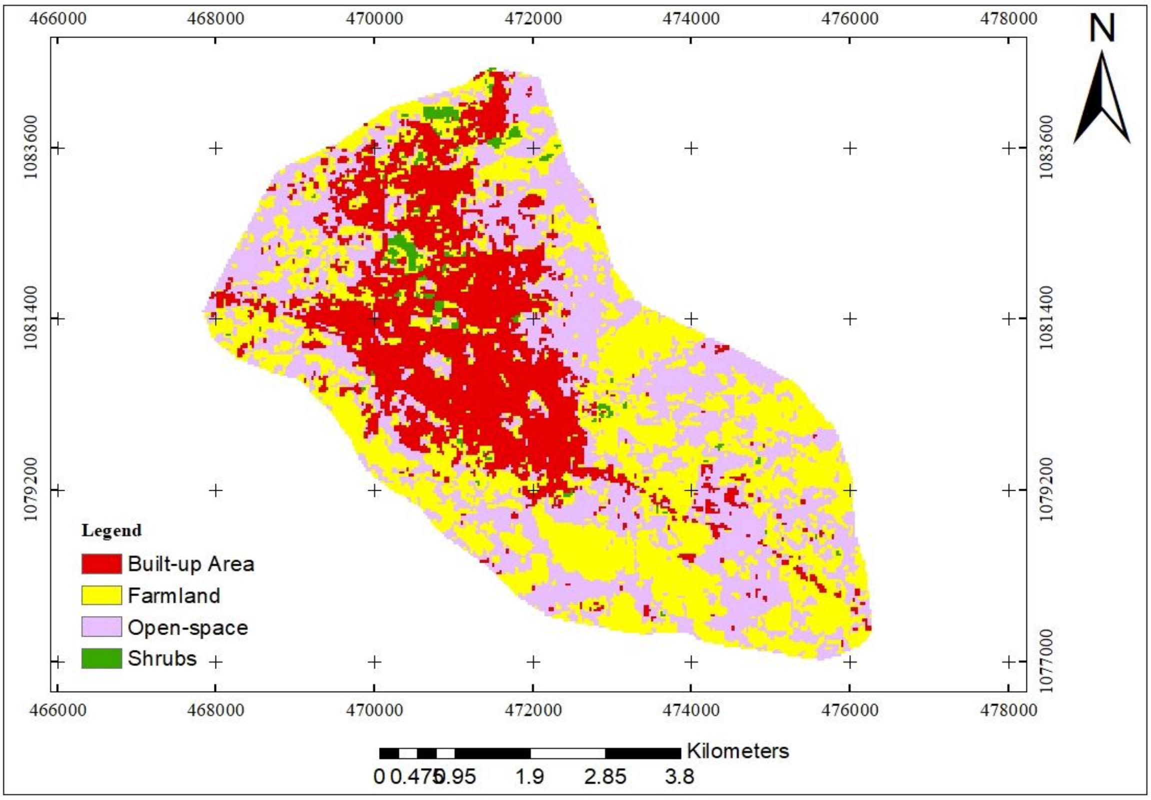


Figure 6: LULC map of study area in 2022

Built-up area increased 361.30 ha to 586.07 ha (10.43% – 16.93%) during 2002-2013 and also increased 586.07 ha to 891.89 ha (16.93% - 25.75%) during 2013–2022. Additionally, open-space faced a continuous increasing phenomenon 702.31 ha to 910.92 ha (20.28% - 26.30%) during (2002 - 2013) and 910.92 ha to 1265.4 ha during 2013 - 2022 period.

Farmland and shrubs areas were decreased 2299.65 ha to 1902.54 ha (66.4% – 54.93%) and 100 ha to 63.73 ha (2.89% - 1.84%) during 2002-2013 respectively. Similarly, farmland and shrubs decreased 1902.54 ha to 1261.18 ha (54.93%–36.42%) and 63.73 ha to 44.79 ha (1.84- 1.3%) during 2013–2022 period respectively. Generally, The LULC maps, area statistics, and annual rate of change were shown in Figure 5 and Table 8.

Table 8: Area statistics and Annual rate change of the LULC from 2002-2022

LULC Types	2002		2013		2022		ARC (%)
	(ha)	(%)	(ha)	(%)	(ha)	(%)	
Built-up Area	361.30	10.43	586.07	16.92	891.89	25.75	6.69
Farmland	2299.65	66.40	1902.54	54.93	1261.18	36.42	-2.05
Open-space	702.31	20.28	910.92	26.30	1265.4	36.55	3.65
Shrubs	100.00	2.89	63.73	1.84	44.79	1.29	-2.5
Total	3463.26	100%	3463.26	100%	3463.26	100	

4.2.1. Land Cover Variations of Built-up Area

The LULC change analysis explores the spatial dynamic variations in the LULC pattern during the study period. The results from 2002 to 2022 show a notable expansion in built-up area and a shrinking phenomenon in the Farmland and shrubs land. Figure 7 and Table 9 show the spatiotemporal area and percentage change of built-up area. The proportion of built up areas was about 10.4% in 2002, 16.9% in 2013 and 25.8% in 2022 of the entire study area.

Table 9: Built-up and non-built-up areas (2002- 2022).

LULC	2002		2013		2022	
	Ha	%	Ha	%	ha	%
Built-up Area	361.30	10.43	586.07	16.92	891.89	25.76
Non-Built-up Area	3102	88.57	3077	83.08	2571	74.24

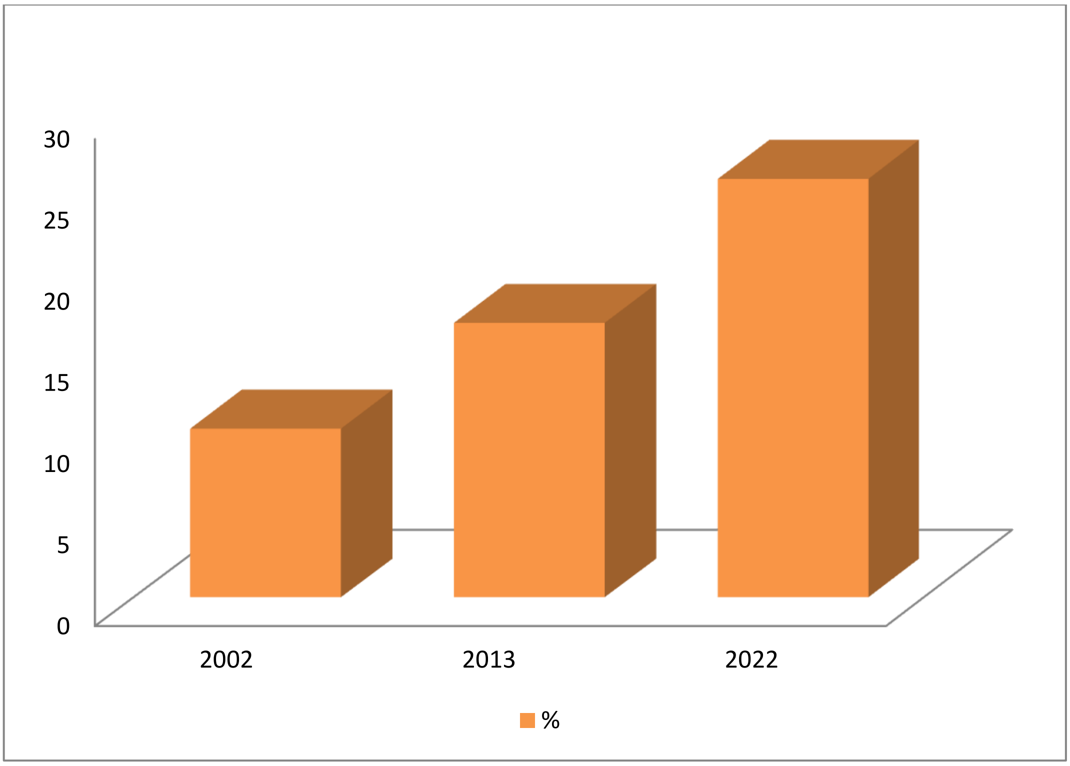


Figure 7: Trends of Built-up Area from 2002-2022

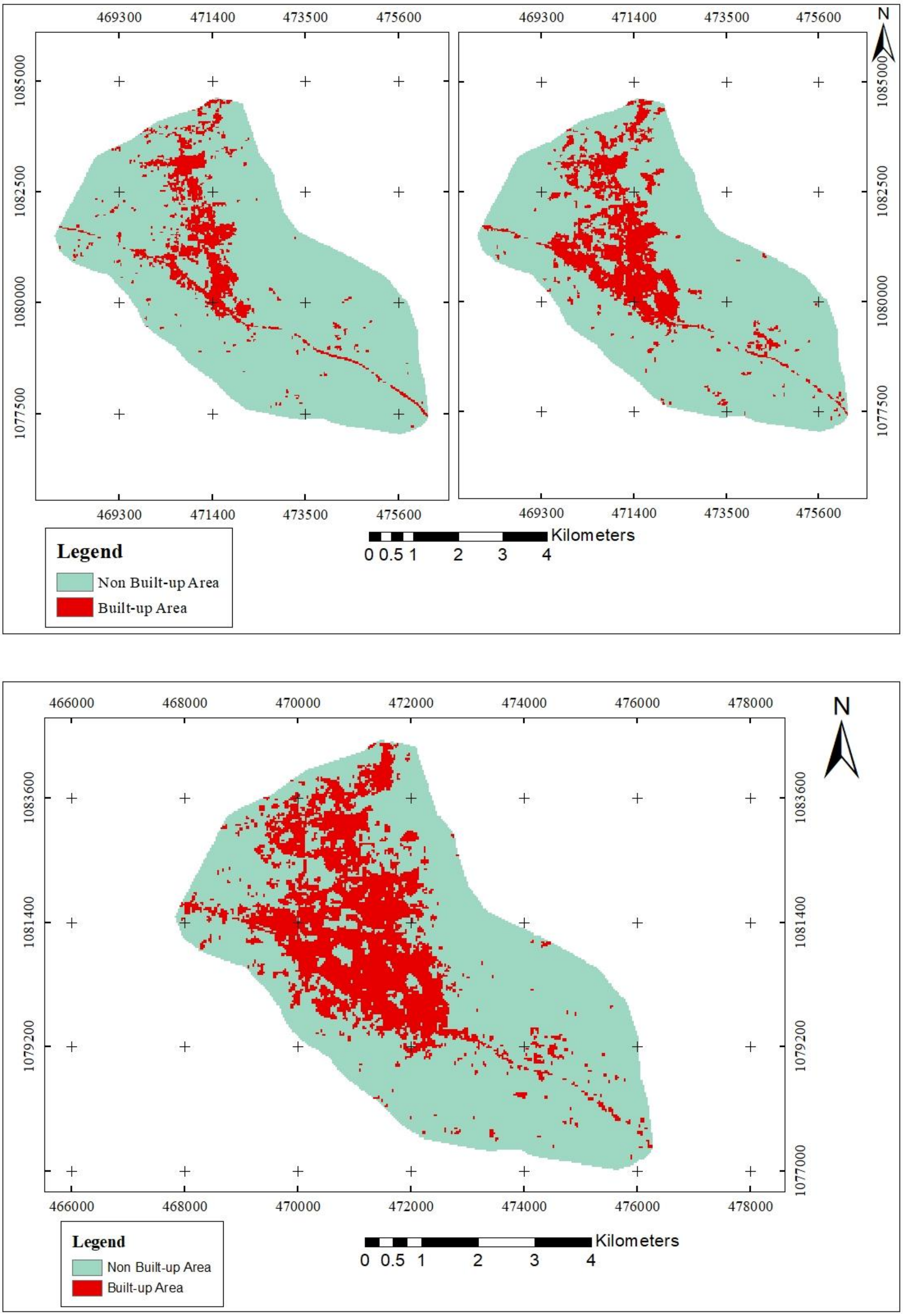


Figure 8: built up and non-built up map of 2002, 2013 and 2022

4.2.2. Change trends and Magnitude of Agricultural lands over the study period

In order to visualize and examine the spatial decline of agricultural land during the study time periods, the agricultural land was exported from classified LULC map. Due to the corresponding horizontal expansion as well as conversion of land cover classes during the distinct study periods, farmland areas were the most dynamic classes which contributed to the increase of built up areas. There was a huge decrease of farmland areas from 2002 to 2022. The Figure 9 shows the spatiotemporal destruction pattern of farmland in the study area. As clearly seen in the table 10, the proportion of farmland areas was 66.4% in 2002, 54.93% in 2013 and 36.31% in 2022 over the study period in fitche town.

Table 10: Trends of agricultural land during the study period

LULC	2002		2013		2022	
	Ha	%	Ha	%	Ha	%
Farmland	2300	66.4	1903	54.93	1261	36.31

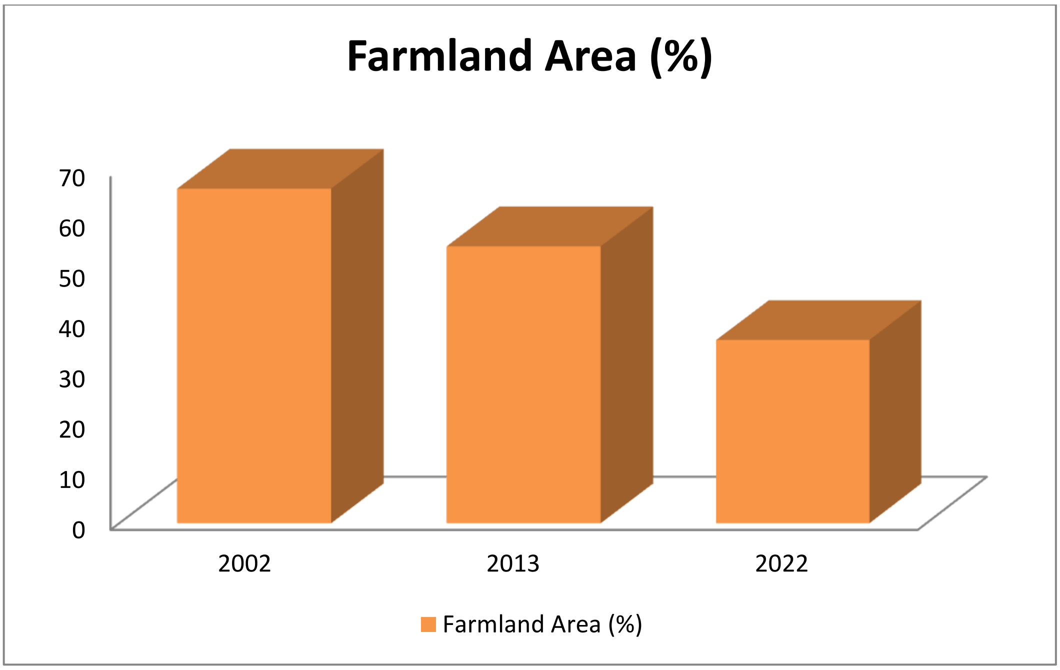


Figure 9: Change Trends of Farmland Area from 2002-2022

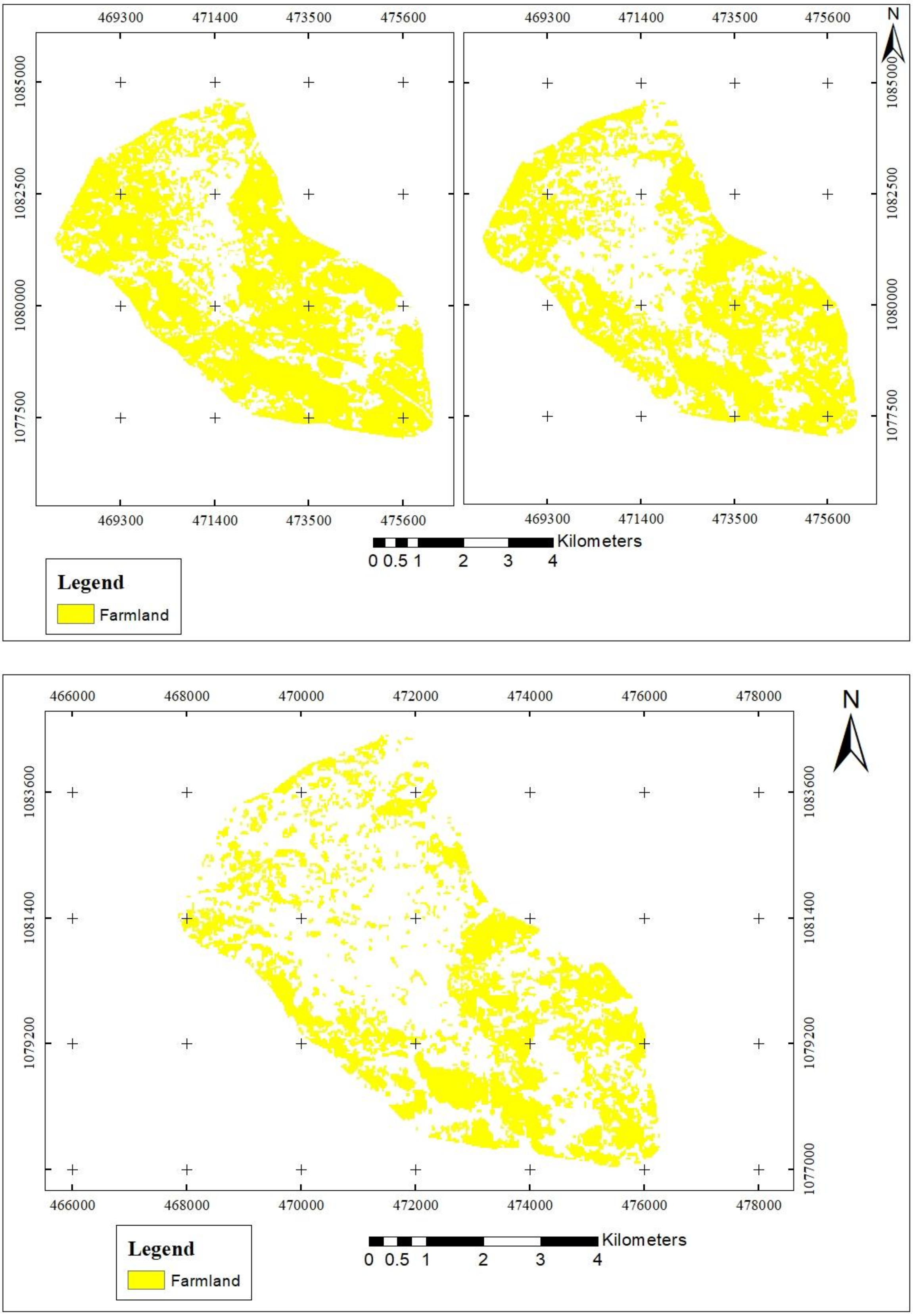


Figure 10: Distributions of farmland map in 2002, 2013 and 2022

4.3. LULC Change Analysis

After the preparation of land use maps, the changes that occurred over the studied periods in each land class were analyzed. Over the past two decades, land covers in study areas such as shrub land and Farmland shows the in continuous decline. In general, out of the whole LULC class in the study area, built-up areas and open-space, were continuously increased over the past 20 years. The change of spatial area extent in hectares, percentage change and the annual rate change within the study area of the each individual land cover categories were presented in Table 11 and table 12 below over the period of 2002 to 2022.

Table 11: Change of Land Use Land Cover between 2002 and 2022.

LULC Types	2002-2013		2013-2022		2002-2022	
	Δ(ha)	Δ (%)	Δ(ha)	Δ (%)	Δ(ha)	Δ (%)
Built-up Area	224.8	62.2	305.4	52.1	530.59	146.9
Farmland	-397.1	-17.3	-640.5	-33.7	-1038.47	-45.2
Open-space	208.6	29.7	354.03	38.9	563.09	80.2
Shrubs	-36.3	-36.3	-18.94	-29.8	-55.21	-55.2

Table 12: Annual Rates and trends of Dynamics occurred in LULC over the study period

LULC Types	2002-2013		2013-2022		2002-2022	
	Δ(ha)	ARC(ha)	Δ(ha)	ARC(ha)	Δ(ha)	ARC(ha)
Built-up Area	224.8	20.4	305.4	33.9	530.59	26.5
Farmland	-397.1	-36.1	-640.5	-71.2	-1038.47	-51.9
Open-space	208.6	18.9	354.03	39.3	563.09	28.2
Shrubs	-36.3	-3.3	-18.94	-2.1	-55.21	-2.8

The LULC change analysis explores the spatial dynamic variations in the LULC pattern during the study period. As it was shown in table 11 and 12, the amount of change that has taken place between 2002 and 2022 was extensive.

The results indicate that between 2002 and 2013 (11 years period), the areas covered by built-up area and open space land rose by +224.8ha (+62.2%) and +208.6 ha (+29.7%) with annual rate change of 20.4ha and 18.9ha respectively that shows a great increasing trend. While farmland and shrubs cover decreased by -17.3% (-397.1ha) and (-36.3%) - 36.3ha at annual a rate of -36.1ha and -3.3ha respectively that shows a decreasing trend.

The results also demonstrate that between 2013 and 2022 (9 years period), the areas covered by built-up area continued to increase by +305.4ha of land which accounts +52.1% of the built-up area increasing at annual rate of 33.9ha while the farmland continued to decrease by -640.5ha which accounts -33.7% of farmland at annual average rate of -71.2ha. This shows urban land mass expanded rapidly between 2013 and 2022 (305.4ha) compared to between 2002 and 2013 (224.8ha). Additionally, open space land cover area increased by +354.03ha (+38.9%) with annual rate change of 39.3ha and the area covered by shrubs decreased by -18.94 (-29.8%) at an annual a rate change of -2.1ha.

Over the timeframe covered by the study (2002-2022) the area showed great land-use changes, 530.59ha (146.9%) of built-up areas was increased at annual rate of 26.5ha/per which shows a constantly increasing trend. In contrast, 1038.47ha (-45.2%) of farmland was converted to other land uses at annual rate of -51.9ha/yr. while the area covered by open space land increased by 563.09ha (+80.2%). During this period, the area covered by shrubs decreased by 55.2% with annual rate change of -2.8ha.

The result shows a notable expansion in built-up area and an increase in open-space land and a shrinkage phenomenon in the farmland and shrubs during the study period (2002 to 2022). The study area has experienced spatial variations and trends (figure 10) on different land use and land cover classes due to the corresponding horizontal expansion as well as conversion of land cover classes during the distinct study periods. The reclassified images in figure 11, 12 and 13 showed that there had been a rapid land cover conversion of each LULC categories to another classes.

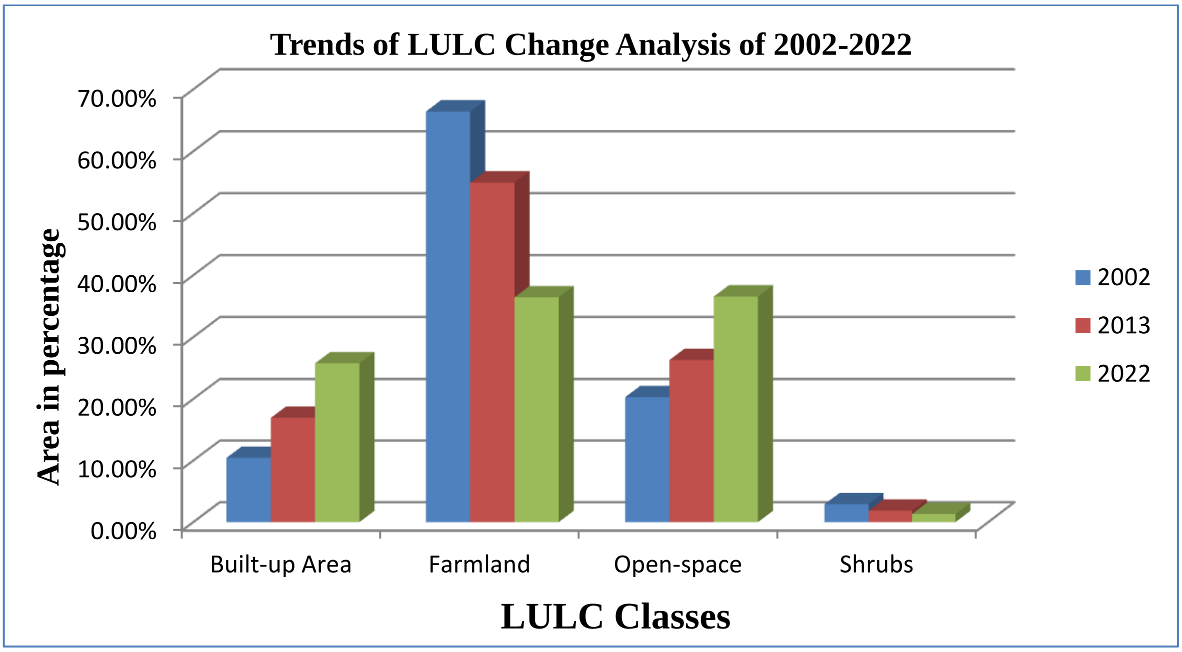


Figure 11: Trends of LULC Change from 2002 to 2022

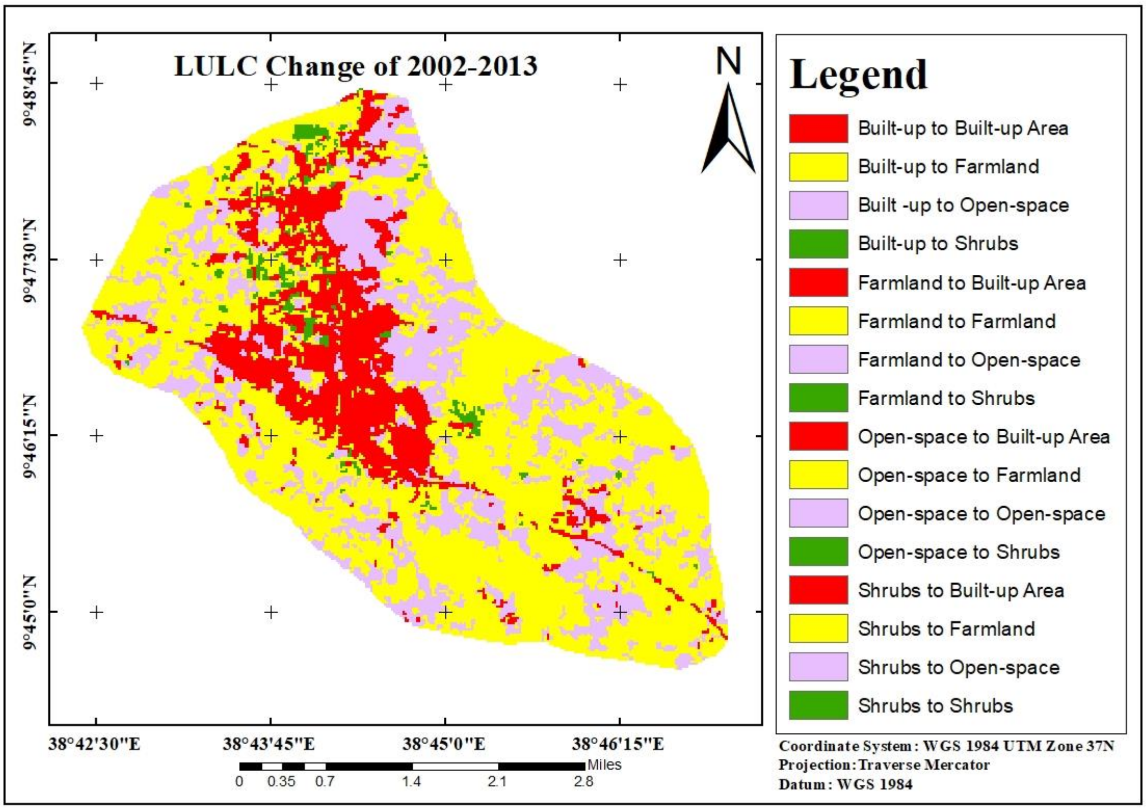


Figure 12: LULC change map of 2002-2013.

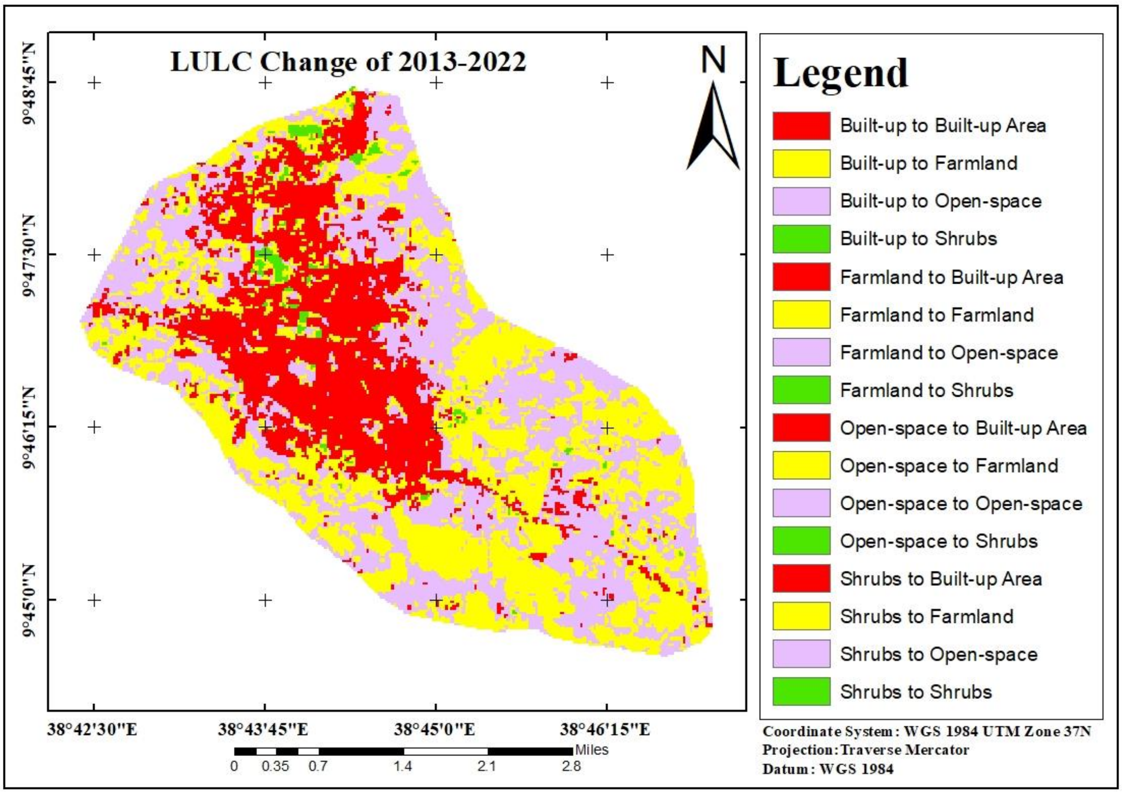


Figure 13: LULC change map of 2013 to 2022.

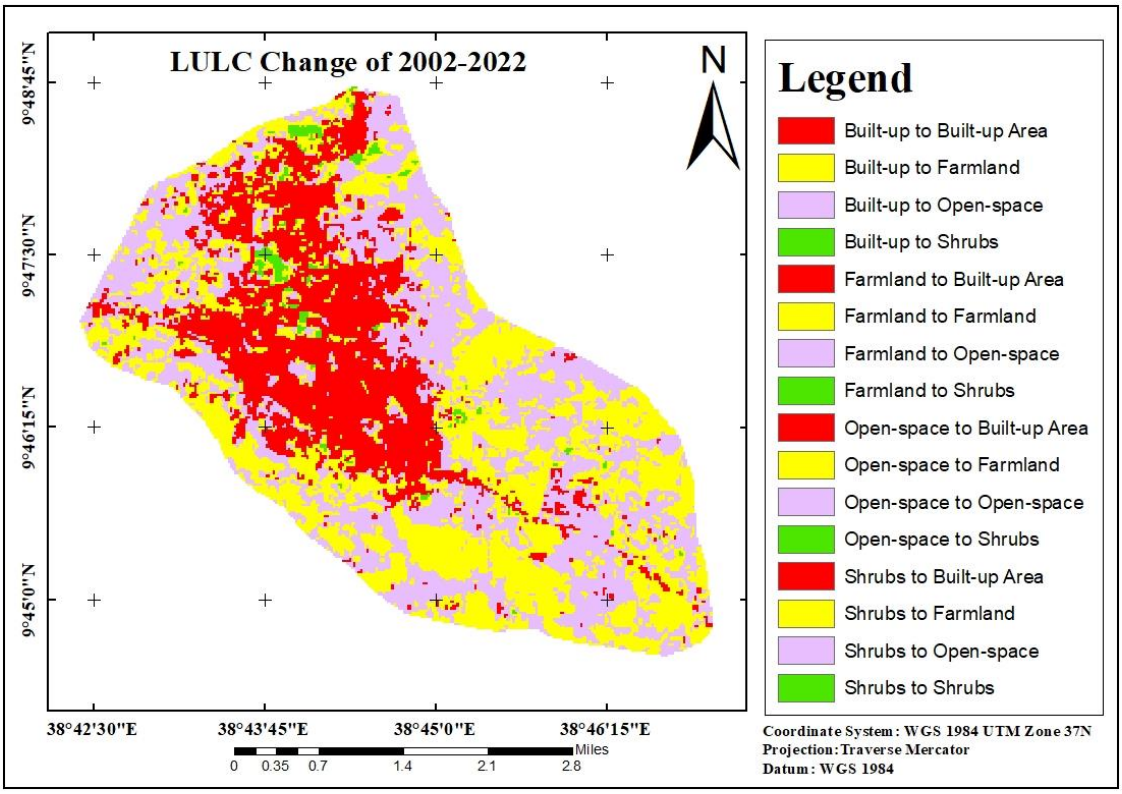


Figure 14: LULC change map of 2002-2022

4.3.1. LULC Transition Analysis

The transition matrix plays an essential role in analyzing spatio-temporal changes within a set of LULC categories. The matrix represents the proportions of pixels changing from one land use category to another. The rows of the matrix table represent the categories in the initial year, while the columns show the same order of LULC categories in the final year. The diagonal entries show the size of class stability, and each off-diagonal entry represents the size of the transition from one class to different classes. Values close to 1 in diagonal entries represent the stability of a category. Researchers mostly use transition matrices to compare the temporal changes in different regions. To show how each LULC type was projected to change in our study area, we calculated the transition potential matrix with the help of the MOLUSCE plugin during the periods 2002-2013, and 2013-2022 and 2002-2022 based on the existing LULC conditions and explanatory variables.

Table 13 shows the transition potential matrix during the period 2002–2013, in which Built-up area and farmland area were the most stable categories with probabilities of 0.783 and 0.689, respectively. As indicated on transition potential matrix the probabilities value 0.082 of farmland was contributed to built-up area. And also the probability values 0.214, 0.015 of farmland area were contributed to open-space and shrubs respectively. While open-space transition probabilities probability matrix value 0.556 was remain unchanged. The values of open space land 0.142, 0.299 and 0.002 contributed to built-up area, farmland and shrubs respectively. Transition probabilities of shrubs 0.256 was unchanged and 0.141, 0.456 and 0.147 were contributed to built-up area, farmland and open-space land respectively.

During 2013-2022 (Table 14), the diagonal values from cross tabulation matrix show LULC that were unchanged in the given years. The transition probability matrix values of Built-up, farmland, open-space and shrubs were 0.866, 0.578, 0.743 and 0.382 which were unchanged over the time span respectively. The probability values of farmland 0.129, 0.285 and 0.009 were contributed to built-up, open space and shrubs land respectively. The values of open space land contributed to built-up, farmland and shrubs were 0.142, 0.114 and 0.001 respectively. The values 0.152, 0.434 and 0.031 of shrubs class were contributed to built-up areas, farmland and open spaces respectively.

moreover, as LULC data from 2002-2022 used along with spatial factors to predict LULC map of 2050 and the transition probability matrix, the transition matrix between 2002 and 2022 (Table 15) showed that built-up area was still stable with a value of 0.833, while farmland, open-space, shrubs had fragmentation values of 0.452, 0.572 and 0.180, respectively. The transition probability value of farmland 0.182 was contributed to built-up area, 0.356 of farmland was contributed to open space and 0.010 of farmland was contributed to shrubs areas. Furthermore, the transition values 0.208 of open space was converted to built-up, 0.217 of open space land was contributed to farmland and 0.003 of open space was converted to shrubs. In a similar way, probability values 0.275, 0.301 and 0.244 of shrubs feature class was contributed to built-up, farmland and open space classes respectively. Therefore, Figure 14 and Table 16 elaborate the gained and lost areas of each category over each time interval.

Table 13: Transition matrix from 2002-2013.

		2013			
	Categories	Built-up Area	Farmland	Open-space	Shrubs
2002	Built-up Area	**0.782857**	0.169938	0.038758	0.008447
	Farmland	0.082322	**0.689449**	0.21367	0.01456
	Open-space	0.142127	0.29908	**0.556493**	0.002301
	Shrubs	0.140934	0.456014	0.147217	**0.255835**

Table 14: Transition matrix from 2013-2022.

		2022			
	Categories	Built-up Area	Farmland	Open-space	Shrubs
2013	Built-up Area	**0.86636**	0.052567	0.077088	0.003985
	Farmland	0.128606	**0.57764**	0.284547	0.009206
	Open-space	0.142069	0.114286	**0.743054**	0.000591
	Shrubs	0.152327	0.434415	0.03103	**0.382228**

Table 15: Transition matrix from 2002-2022.

		2022			
	Categories	Built-up Area	Farmland	Open-space	Shrubs
2002	Built-up Area	**0.832712**	0.105891	0.058663	0.002734
	Farmland	0.181293	**0.452374**	0.355949	0.010384
	Open-space	0.20803	0.217491	**0.571666**	0.002813
	Shrubs	0.274933	0.300988	0.244385	**0.179695**

Table 16: Gains and losses of each category

LULC Categories	2002- 2013 (ha)	2013 – 2022 (ha)	2002 – 2022 (ha)
Built-up Area	224.8	305.4	530.59
Farmland	-397.1	-640.5	-1038.47
Open-space	208.6	354.03	563.09
Shrubs	-36.3	-18.94	-55.21

4.3.2. Selection of Spatial Variables

This first step in the model was to include the LULC maps from the beginning (2002) and end year (2022). The spatial variable factors such as distance from built-up area, distance from road, DEM map and slope map were fed in the model to get a land cover change map from which the changing pattern for the study area between 2002 and 2022 was established. The properties of the explanatory maps are extracted in the same raster format for all datasets, with the same geographical projected coordinates of UTM 37N zone and with a resolution pixel size of 30 m.

The MOLUSCES plugin calculates the percentage of area change in a given year and generates a transition matrix that shows the proportion of pixels shifting from one land use cover to another. The plugin also creates an area change map that shows the change in the land between 2002 and 2022 in all classes' within built-up area, farmland, open-space and shrubs. To project the change in LULC, the ANN-(Multi-layer perception) plugin was used (Buğday and Erkan Buğday, 2019; Msovu et al., 2019). Also, based on the classified raster images of 2002 and 2022, LULC transitions were predicted for the years 2030, 240 and 2050. The future LULC maps are predicted assuming that existing LULC pattern and dynamics area getting continued.

The correlation of geographic variables between the two raster images, which are used to examine the correlation among the spatial variables factors, is evaluated using Pearson’s correlation, Crammer's coefficient, and Joint information uncertainty. (Hakim et al., 2019). Then, between the initial year (2002) and the final year (2022), the category of each area and the LULC changes are calculated. The transition matrix, which indicates the fraction of pixels changing from one type to the next, is also produced by the algorithm.

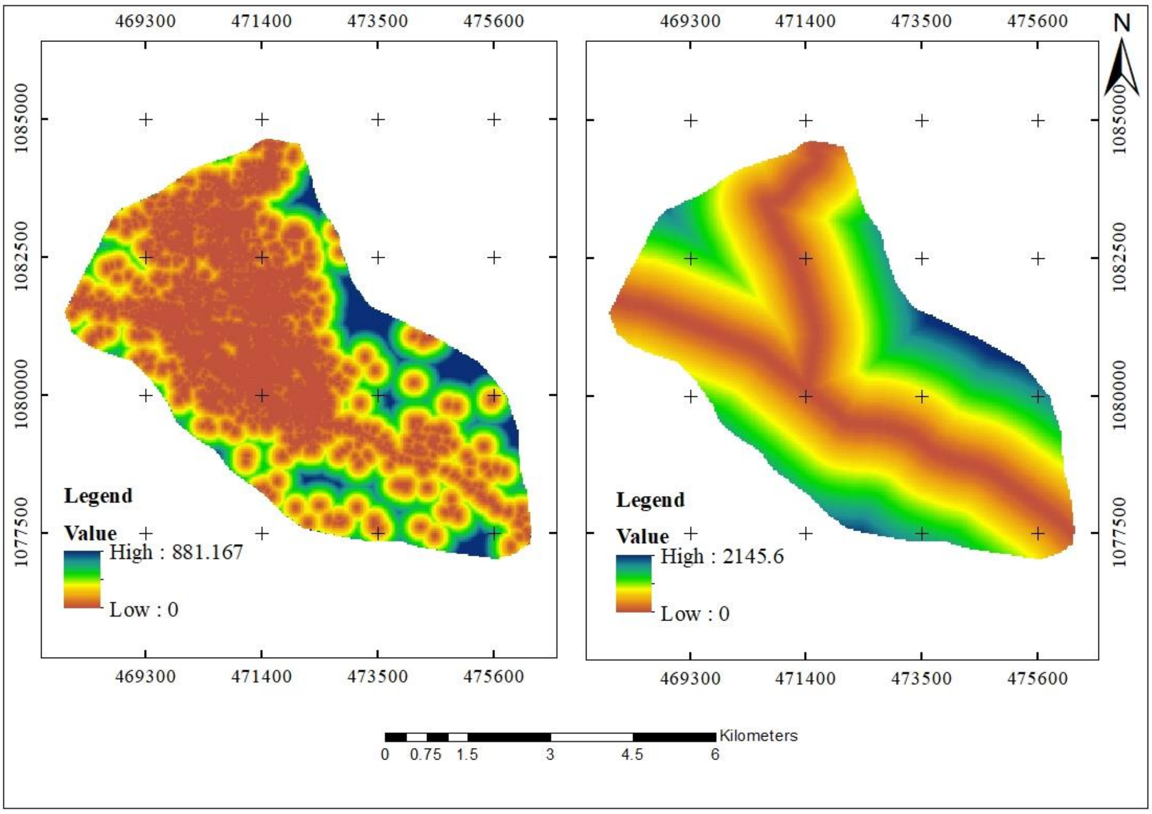


Figure 15: Spatial parameter maps of distance from built-up and distance from major road

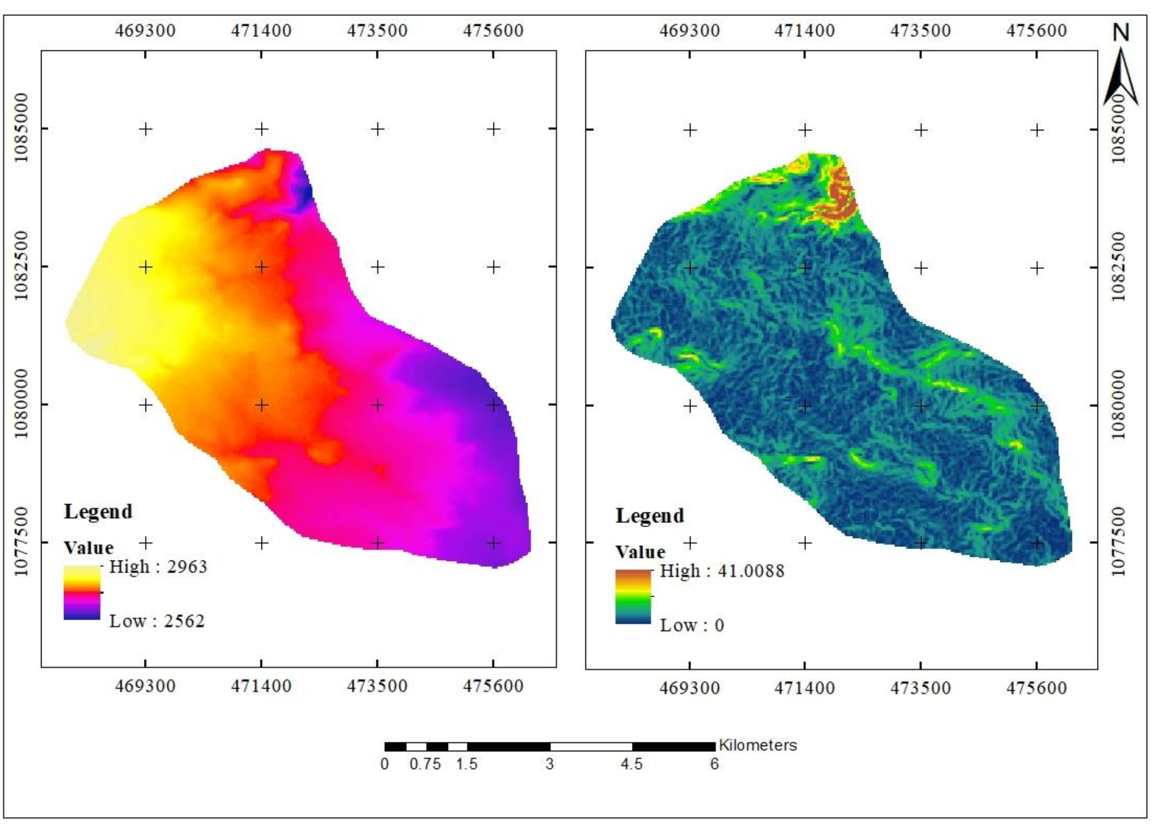


Figure 16: spatial parameter maps of DEM and Slope.

4.4. Model Validation and Prediction

4.4.1. Transition Potential Modeling and Model Validation

The MOLUSCE plugin integrates some well-known algorithms for transition potential modeling, such as the ANN (multilayer perceptron), weights of evidence, multi-criteria evaluation, logistic regression, and CA algorithm, for future simulation. The spatial variables for model calibration were chosen based on their relatively strong association with LULC, as measured by Cramer's coefficient.

This study employed CA-ANN approach that was used for transition potential modeling and prediction. LULC data from 2013–2022 was used along with spatial variables to project LULC for 2022 and obtained a validation kappa value of 0.95. After obtaining the projected LULC, compare the actual LULC of 2022 with the projected data and obtained an overall accuracy of correctness 88.8%, Kappa (overal) 0.83, Kappa (histo) 0.90 and Kappa (loc) 0.93. Figure 8 and Table 11 show the actual and forecasted maps and statistics for 2022.

Table 17: spatial extent for Actual and projected LULC maps of 2022.

LULC	Actual 2022		Projected 2022			Kappa Value	
	Ha	%	Ha	%	Accuracy	ANN	Validation
Built-up Area	891.89	25.75	1031.1	29.77			
Farmland	1261.18	36.42	1030.4	29.73	88.8	0.95	0.83
Open-space	1265.4	36.55	1347.2	38.90			
Shrubs	44.79	1.29	55	1.56			

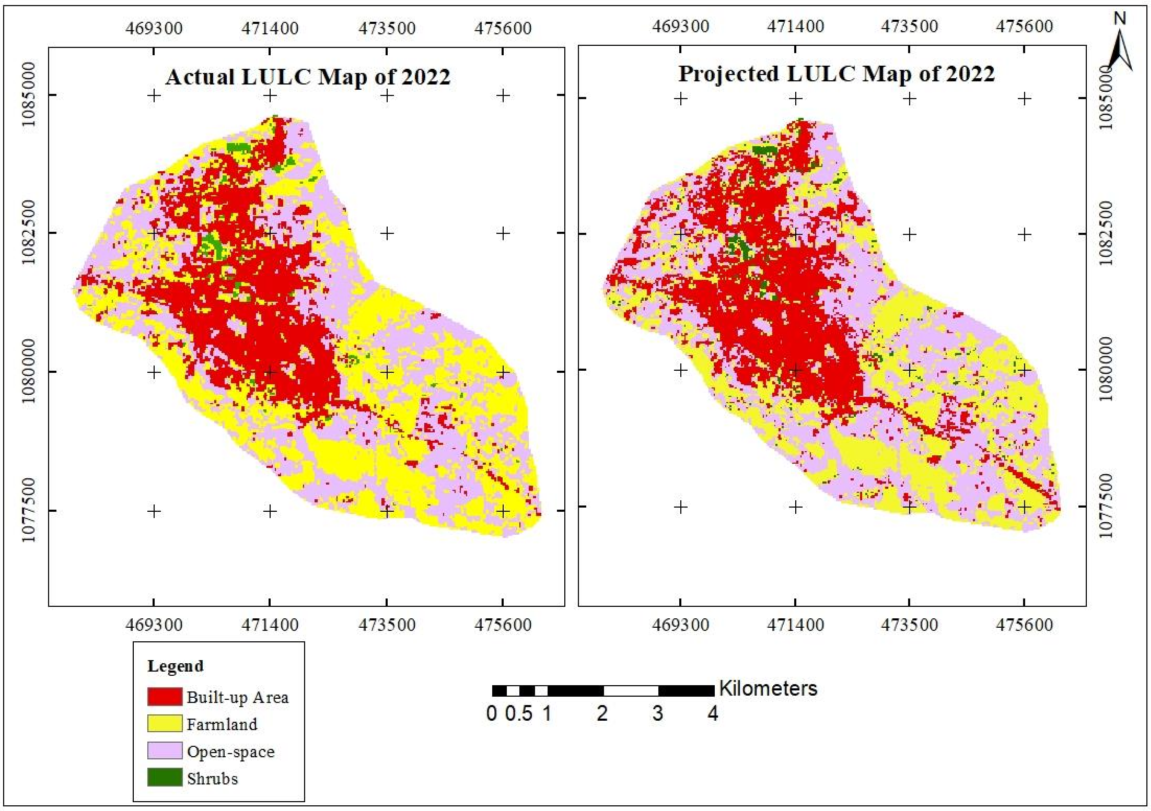


Figure 17: Actual and Projected LULC 2020

4.4.2. Prediction of LULC

The LULC change analysis explores the spatial dynamic variations in the LULC pattern during the study period. After obtaining satisfactory results from model validation, the LULC for 2030, 2040, and 2050 were predicted. By employing the temporal LULC data from 2013 and 2022, the spatial variables, and the transition probability matrix (Table 14) to predict the LULC for 2030, 2040 and 2050, and obtained a kappa value of 0.95. Figure 13 and Table 18 represent the map, and area statistics of the predicted LULC of 2030, 2040, and 2050.

The simulation results of the Molusces model prediction during the period of 2022 to 2030 years were demonstrated. The built-up area will increase from 891.89ha in 2022 to 1043.6ha in 2030. Farmland area will decrease from 1261.2ha in 2022 to about 1030.3ha in 2030. The open space land will increase from 1265.4ha to about 1347.2ha during the period between 2022 and 2030. The area of shrubs land will decrease from 44.79ha in 2022 to 42.29ha in 2030.

Similarly, the simulation model over 2022 to 2040 timeframe revealed a predicted built-up area will increase from 891.89ha in 2022 to approximately 1140.5ha in 2040. Farmland area cover will increase from 1261.2ha in 2022 to about 920.2ha in 2040. The area of open space land will increase from 1265.4ha in 2022 to nearly 1363ha in 2040. Shrubs land will decrease considerably from 44.79ha in 2022 to 40.2ha in 2040 during the study period of 2022 and 2040years.

According to model simulation, the change in land covers classes between 2022 and 2050 was depicted that built-up area will be increased from 891.89ha in 2022 to 1268.7ha in 2050. In contrast farmland will be expected to decrease from 1261.2ha in 2022 and dropped to 762.2ha in 2050. On the other hands, open space area 1265.4ha covered in 2022 will be increased to 1400.3ha in 2050. Additionally, shrubs area covered will be decreased from 44.79ha to 35.5ha during period of 2022 to 2050 years.

Generally the simulated change in areal extent, the percentage change (%) and annual rate change of LULC category were presented in table 19 and 20. The results show unceasing expansion of built-up area increased by 376.81ha and percentage change of 42.2% at annual rate change of 13.5ha/yr. during timeframe of 2022 to 2050. While farmland areas declined by -499ha and the percentage change -39.6% at annual rate change -17.8ha/yr. the simulation model depicted the increment in open space land by 134.9ha and percentage change 10.7% at annual rate change of 4.8ha/yr. and also shrubs land decreased by -9.29ha (-20.7%) at annual rate change of -0.3ha/yr. between the years of 2022 to 2050 period.

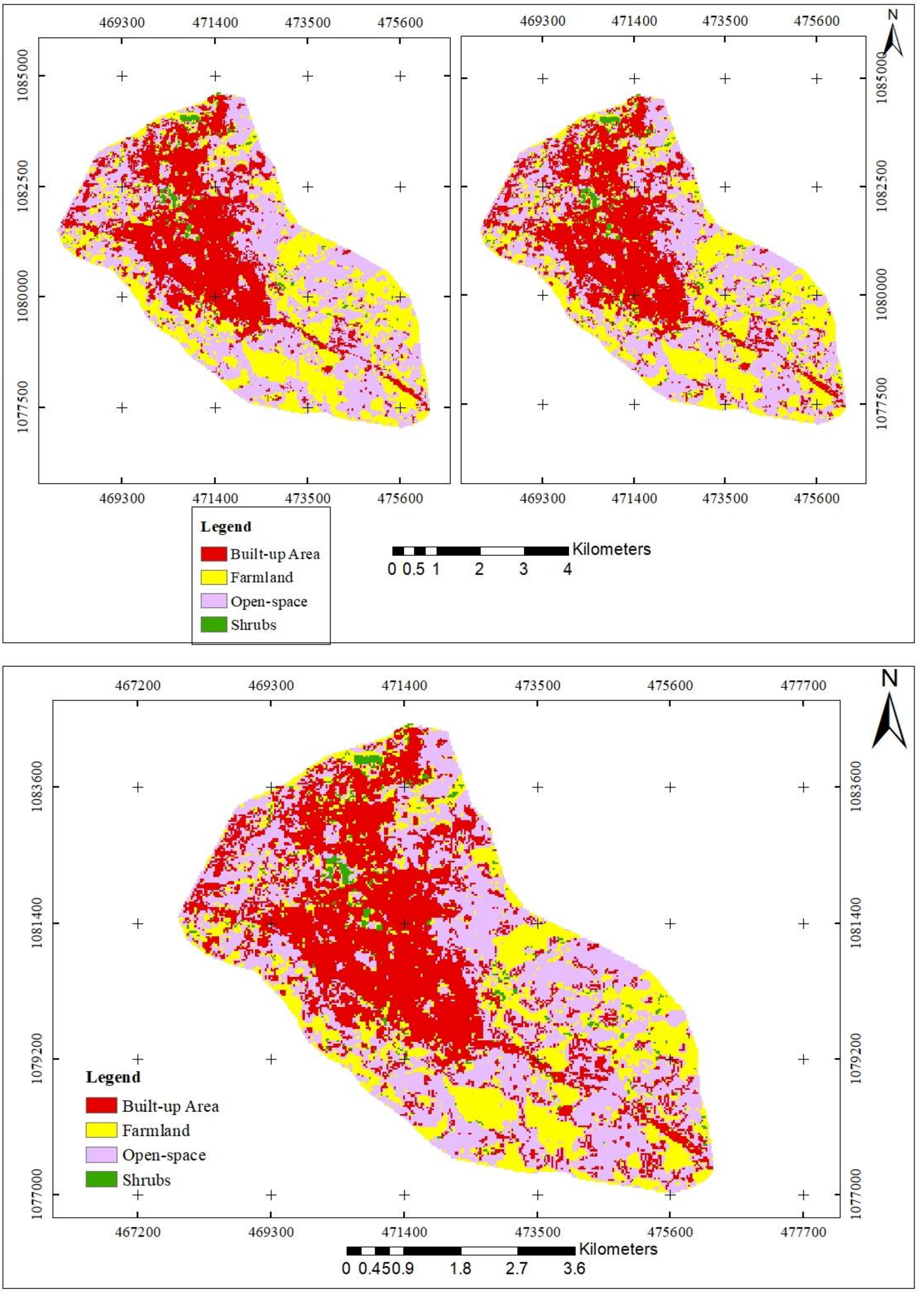


Figure 18: Predicted LULC maps for the year's 2030, 2040 and 2050

Table 18: Spatial area extent of predicted LULC of 2030, 2040 and 2050 years

LULC Classes	2022		2030		2040		2050	
	Area(ha)	%	Area(ha)	%	Area(ha)	%	Area(ha)	%
Built-up Area	891.89	25.8	1043.6	29.8	1140.5	32.3	1268.7	35.7
Farmland	1261.2	36.4	1030.3	29.7	920.2	26.6	762.2	22.0
Open-space	1265.4	36.6	1347.2	38.9	1363	39.4	1400.3	40.4
Shrubs	44.79	1.29	42.6	1.60	40.2	1.77	35.5	1.8

Table 19: Spatial area extent change and percentage changes of LULC from 2022 to 250

LULC Classes	2022-2030		2022-2040		2022-2050	
	Area(ha)	%	Area(ha)	%	Area(ha)	%
Built-up Area	151.71	17.0	248.61	27.9	376.81	42.2
Farmland	-230.9	-18.3	-341	-27.0	-499	-39.6
Open-space	81.8	6.5	97.6	7.7	134.9	10.7
Shrubs	-2.19	-4.9	-4.59	-10.2	-9.29	-20.7

Table 20: Spatial area extent change and Annual Rates change of LULC from 2022- 2050

LULC Classes	2022-2030		2022-2040		2022-2050	
	Area(ha)	ha/yr.	Area(ha)	ha/yr.	Area(ha)	ha/yr.
Built-up Area	151.71	19	248.61	13.8	376.81	13.5
Farmland	-230.9	-28.9	-341	-18.9	-499	-17.8
Open-space	81.8	10.2	97.6	5.4	134.9	4.8
Shrubs	-2.19	-0.3	-4.6	-0.3	-9.29	-0.3

4.5. Discussion

The study performs the analysis of LULC shift from 2002 to 2022 using spatiotemporal LULC data and available spatial variable factors and produced a transition probability matrix for each interval using the MOLUSCE plugin within QGIS software. and the study have predicted the LULC map for 2030, 2040, and 2050 using the CA-ANN multilayer perceptron technique using MOLUSCE plugin, that provides an answer to the research question of LULC change trend in the past two decades. Based on the current and predicted land cover map, the impact's LULC change on agricultural land was assessed in the study area.

In study area Farmland and shrubs were practiced downward trends in most of LULC types during the study period whereas open-space shows minor increments, while built-up area was the land cover that showed surpassing expansion along the past two decades. This implies that there has been continuous expansion of built-up areas and an increment of small scale open-space which results the shrinking of agricultural land in the study area. The most common understanding of the use of change analysis is to provide relevant data on changes concerning extent, trend, location, and how the change was distributed spatially. The present study argued with the earlier studies that unsustainable agricultural land conversion in the urban fringes has had negative implications by reducing farmlands and crop yields which threaten the livelihoods of local people. For instance, Ayele & Tarekegn (2020) stated that urban LULC Change has many impacts on farmers in peri-urban areas. Similarly, Efa & Gutema (2017) argued that urbanization has a negative impact on the rapid conversion agricultural lands into other land uses causing the farmers landless and also because they were forced to move farther away from their homes in order to access land for farming. Hence, the study is important to indicate the trend of land cover change pertaining to enhance the prediction of future land cover.

According to these findings, Fichte's LULC has undergone a remarkable transformation over the last two decades due to rapid urban LULC dynamics, most notably in the rapid conversion of farmland and shrubs to built-up areas in Fitche town. Moreover, small scale of farmlands and shrubs Classes were converted to open-space during the study period. From 2002 to 2022, the built-up increased from 10.43% to 25.75%, and open-space increased from 20.28 to 36.53%. In contrast, farmland decreased from 66.4% to 36.42%. Additionally, the future simulation results show that built-up areas will continue to increase from 2022 to 2050 with percentages of 25.73% to 35.74%, and open-space will increase by small amounts of percentages 36.55% to 40.41%. Farmlands will be expected to decrease with percentages of 36.42% to 22.01% from 2022 to 2050.

Ultimately, dramatic changes in LULC, particularly urban growth and fragmentation of farmlands, could loss natural resources, the environment, and food security. Thus, the spatiotemporal and prospective LULC simulation results will aid policy-makers in analyzing the change in LULC intensity and the socio-economic elements that influence it, as well as in promoting environmental conservation and sustainable development policies.

5. CONCLUSION AND RECOMMENDATION

5.1 Conclusion.

This study has been carried out to analyze land use land cover dynamics and its impact on agricultural land in Fitche town. The research has been conducted and aimed at the use of geospatial techniques to analysis the urban land use land cover change and its impact on agricultural land to detect changes of urban land use/land cover based on Landsat satellite images. Landsat imageries of 2002, 2013 and 2022 were utilized to predict LULC map in the study area through analysis of LULC changes during these periods. In this study, the land cover maps were classified into four major Land use land cover classes (built-up area, farmland, open-space and shrubs). This was to comprehensively understand the town‘s Land use land cover changes and predict the future. The model was validated using simulated and observed LULC 2022 by using kappa parameters; with the overall kappa index 0.83%; which indicates good kappa index values to predict the future Land use land cover change changes in 2030, 2040 and 2050. The result of this study presented noticeable changes in the spatial and quantitative distribution of land use/land cover. It revealed that the farmland area of the town has decreased continuously between 2002 and 2022, while built-up area increased during the study period. The result shows that the proportion of farmland area was 66.4% in 2002, 54.93% in 2013, 36.42% in 2022,with annual rate change of -2.05ha/yr. from 2002 to 2022 and the proportion of built-up area was 10.43% in 2002, 16.92% in 2013, 25.75% in 2022, with annual rates change of 6.69ha/yr. from 2002 to 2022.

The prediction of LULC plays a vital role in creating plans for balancing conservation, competing users, and developmental pressures. The ANN Cellular Automation model is utilized to simulate and predict the future LULC maps of the Fitche town. The four spatial variable factors such us, DEM, slope, distance from urban and distance from the road, had a huge effect to predict LULC map of the study area. The Kappa value of 0.83 shows a maximum level of accuracy between the observed and predicted 2022 LULC maps. The LULC map of 2030, 2040 and 2050 were predicted by using 2013 and 2022 LULC map along with same spatial variable factors combinations. The predicted LULC for the years 2030, 2040 and 2050 show significant increase in built-up areas that was 29.8%,32.3% and 35.7% respectively and farmland areas decreased to 29.7%, 26.6% and 22. % respectively. The results demonstrate that due to anthropogenic pressures the conversion of farmland and other land categories would be converted to built-up land and open-space land. The findings of the study shown the historical LULCC and highlight the future change in the next 28 years. The study successfully demonstrated the cellular automata model‘s efficiency, using remotely sensed data and QGIS techniques to monitor spatio-temporal Land use land cover changes and predict future land cover patterns. This study assists in detecting specific land-use changes and projecting which land uses will be affected by future changes. It is also possible to detect biodiversity loss and ecological concerns. The findings assist farmers and policymakers in developing optimal land use planning and management methods for the long-term development of natural resources. Such data are vital for informed decision-making in urban planning, providing the potential information required monitoring growth and improving environmental sustainability.

5.2. Recommendation

There is a need to plan for balanced physical urban expansion and population growth in the towns. This can only be possible if there is an understanding of the nature of urban growth change, the urban demographic pressure, the level of service available to supply, the source and amount of resources to future growth of cities and towns. Urban planning authorities and town planners should think about the future growth of the town and should understand the consequence of unbalanced physical urban growth and public service and infrastructure supply. They should have to depend on a GIS data base and information system to regulate their urban development in a sustainable way such that they will manage the supply of public services and infrastructures that will be needed as a result of future urban expansion.

Satellite remote sensing with repetitive and synoptic viewing capabilities, as well as multispectral capabilities, is a powerful tool for mapping and monitoring the ecological changes in the urban core and in the peripheral land-use planning. The use of remote sensing needs to be introduced for monitoring the activities of developers. This will help in reducing unplanned urban sprawls and the associated loss of agricultural lands. At current rate of population dynamic, land-use/land-cover change is certain to increase. Therefore, the following management strategies are recommended.

i. Instead of new housing development on agricultural land, renewal of older buildings and infill development of high rise buildings to meet the demands and needs of the increasing number of population in the town. In addition the construction of condominium houses is another solution. It is already beginning to implementation by the government and should be continuing in the future.

ii. For effective urban developments, Environmental Impact Assessment (EIA) and public participation in decision making are also recommended. These are essential to assess the likely impacts of urban development on the surrounding ecosystems.

iii. The use of high resolution imageries such as IKONOS and Quick Bird are important in generating good quality of land cover maps. Because urban areas have complex and heterogonous features, high resolution imagery provides better information by mapping these areas. Moreover, the use of latest model and methodology for modeling and prediction helps to get better finding.

iv. Sustainable use of land resources and avoiding agricultural land loss by uncontrolled horizontal urban expansion.

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