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LUSAKA

ASSESSING AGRICULTURAL EXPANSION IN UPPER LUNSEMFWA RIVER CATCHMENT: A CASE STUDY OF THE UPPER LUNSEMFWA RIVER CATCHMENT, CENTRAL PROVINCE, ZAMBIA

By
Natasha Zulu

A Thesis submitted to the University of Zambia in fulfilment of the requirements of the degree of Master of Science in Integrated Water Resources Management.

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DECLARATION

This thesis was written and submitted in accordance with the rules and regulations governing the award of the Master of Science in Integrated Water Resource Management in the School of Mines of the University of Zambia. The research described in this Thesis was carried out at the IWRM centre-geology department, School of mines at University of Zambia under the supervision of Professor. Kawawa E. Banda and Professor Imasiku I. Nyambe.

Natasha Zulu

Signature:

ABSTRACT

Understanding dynamics occurring in land utilization and land cover is essential for analysing and assessing long-term transformations. These transformations in land cover primarily result from deforestation, which involves the conversion of forests into other land cover types such as agricultural land and human settlements or infrastructure development for economic growth. The problem highlighted in this study is the increasing dominance of agricultural activities in the Upper Lunsemfwa River Catchment (ULRC) and their potential impact on land cover. It also emphasizes the threats posed to land and water resources by agricultural expansion and the loss of natural resources due to economic development. To help with understanding and assessing the magnitude of change and possible future changes in the study area land use and land cover classification was done using remote sensing and GIS. This was done using remotely accessed imagery for the years 1990, 2005 and 2020 from climate engine (Landsat 5 and 8). The images where processed and analysed using QGIS and IDRISI. The main objective of this study was to evaluate the extent agricultural expansion within the Upper Lunsemfwa River Catchment, focusing specifically on the evaluation of various land uses. With specific objectives to evaluate Land Use and Land Cover change trends in the Upper Lunsemfwa River Catchment and Simulate future scenarios of land cover and agricultural expansion of the study area. The findings showed that from 1990 to 2020 observations indicate a -10.3% decrease in forest cover and a 25.90% increase in agriculture land cover, accompanied by minimal changes of -0.4% in water bodies, and stable decrease in built-up areas from 3.20% to 1.9% and 68% to 54.01% in grasslands. The results also showed a dominance in agriculture and a decline in non-agricultural land. Agricultural land increased from 13.60 % to 39.52 % between 1990 and 2020 respectively. On the other hand, there was a reduction in non-agricultural land from 86.38 % to 60.48% in 2020. From the predicted 2050 land cover map, the observations suggest a positive trend of 16.24% towards increased forest coverage, a reduction of -20.66% in crop land, stabile reduction of -0.16% in water bodies. Built-up areas showed an expansion of 2.98%, and an increase of 1.69% in grassland. This shows a clear trend of agricultural expansion and a corresponding reduction in non-agricultural land over the decades. Thus, the importance of monitoring and managing these changes sustainably to ensure the well-being of both humans and the environment.

DEDICATION

“This Master of Science Thesis is dedicated to my loving children Twalumba and Thantwe, who inspire me to work hard. May my work inspire you both to reach greater heights”

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LIST OF ABBREVIATIONS

CA-ANN	Cellular Automata-Artificial Neural Network
DEM	Digital Elevation Model
FAO	Food and Agriculture Organisation
FISP	Farmer Input Support Program
GIS	Geographical Information System
GRZ	Government of the Republic of Zambia
ILUA	Integrated Land Use Assessment
LC	Land Cover
LU	Land Use
LULC	Land Use Land Cover
LULCC	Land Use Land Cover Change
MCE	Multi Criteria Evaluation
ML	Maximum Likelihood
MLP	Multi-Layer perception
MOA	Ministry of Agriculture
MOFL	Ministry of Fisheries and livestock
MOLUSCE	Modules for Land Use Change Evaluation
MRB	Multi Resolution Budget
MW	Mega Watts
NASREC	Natural and Applied Sciences Research Committee
OLI	Operational Land Imager

QGIS	Quantum Geographic Information System
ROI	Region of Interest
TM	Thematic Mapper
ULRC	Upper Lunsemfwa River Catchment
UNEP	United Nations Environment programme
USGS	United States Geological Service
WARMA	Water Resources Management authority
ZDA	Zambia Development Agency
ZEMA	Zambia Environmental Management Agency

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CHAPTER ONE: INTRODUCTION

1.1 Background

The Food and Agriculture Organization (FAO) and the United Nations Environment Programme (UNEP) jointly emphasized in 1999 the critical importance of land as a natural resource essential for the survival and prosperity of humanity as well as the preservation of ecosystems (FAO and UNEP, 1999). They highlighted that human activities exert a significant influence on land and its resources, which can have detrimental consequences such as land degradation and the diminishing availability of land for the sake of environmental sustainability. The utilization and coverage of land within a specific area are shaped by a combination of natural factors, socio-economic factors, and the actions of humans across different periods of time and geographical space (Tewabe and Fentahun, 2020). In order to gain a comprehensive understanding of the changes occurring in land use and land cover (referred to as LULC), it is crucial to analyse and examine these transformations. This analysis provides valuable insights into the global shifts in the environment and aids in conducting studies on sustainable development. Such studies are of utmost importance for decision-making processes, as they contribute to informed choices that account for the long-term well-being of both humanity and the planet (Hu *et al.*, 2019).

When assessing potential land use (LU), the focus lies on predicting and determining the suitability of land for various types of productive land utilization. This process involves evaluating the land's capacity to support different activities and identifying the most appropriate and sustainable uses for maximizing its potential (Hu *et al.*, 2019). By undertaking such assessments, policymakers and stakeholders can make informed decisions regarding land management, resource allocation, and planning for future development, all while considering the needs of the environment and promoting sustainable practices. The term "land" refers to the physical and biological surface covering of the Earth (Ellis *et al.*, 2010). It encompasses both the natural attributes of the Earth's surface (referred to as land cover) and the human activities and intentions associated with the use of that land cover (referred to as land use) (Lambin *et al.*, 2001). Land use and land cover change (LULCC) occur as a result of a complex interplay between various factors, including social, political, economic, technological, and biophysical variables (Lambin *et al.*, 2001; Song *et al.*, 2001; Geist and Lambin, 2002).

The exploitation of natural resources, such as forests, land, water, animal diversity, and vegetation, has played a pivotal role in driving significant environmental changes and resource degradation (Mucova *et al.*, 2018). The consequences of such exploitation include the reduction of ecosystem services and resources, as well as compromised food production. The increase in human population is mostly responsible for Land use change, deforestation, food types and demand for energy and fibre (Lungomesha *et al.*, 2022). These transformations encompass a range of detrimental outcomes, including the release of pollutants, greenhouse gas emissions, and the emergence of global climate change, the decline in biodiversity, and the depletion of crucial soil resources.

The continuous increase in global population has led to a growing demand for food production and income generation. As a result, there is a heightened pressure on natural resources, including wetlands. The need to meet these demands often leads to unsustainable practices, including the overexploitation of wetland resources and the adoption of inappropriate agricultural methods (Nguyen *et al.*, 2017). These activities can result in the degradation and conversion of wetlands, which are vital ecosystems providing numerous ecological services such as water filtration, flood regulation, and habitat for biodiversity.

Zambia's population has over the years grown. According to the census of population summary report of Zambia of 2010 Central Province population density had increased from 1,012,217 in 2000 to 1,307,111 in 2010 (from 13.1 to 17.4 persons per square km). Mkushi District was the fastest growing district with an annual rate of population growth of 3.7 percent (from 107,438 in 2000 to 154,534 in 2010) (2000 and 2010 census population and housing). With growing population there is need for land to meet the demand for land, food, settlement and industrialization. These needs bring about changes to land. How land is used depends on government policies of development and agricultural expansion (Central statistics office, 2022).

In the specific Zambian context, the rapid transformations in land cover primarily result from deforestation, which involves the conversion of forests into other land cover types such as agricultural land and human settlements. Agriculture-related factors have had a significant impact on the changes observed in land cover in Zambia (Phiri, Morgenroth and Xu, 2019). This ongoing process of deforestation is causing substantial modifications in the country's land composition and presents notable challenges for sustainable land management and the preservation of ecosystem integrity.

The management of river catchments and the successful implementation of integrated watershed management require the adoption of a comprehensive approach that considers multiple interconnected factors (Dagnachew *et al.*, 2020). This approach recognizes the complex nature of river ecosystems and the need to address various aspects such as water quality, land use, biodiversity conservation, and socio-economic development in a coordinated manner. By integrating diverse perspectives and stakeholders, it becomes possible to achieve sustainable outcomes that balance environmental preservation with human needs and aspirations.

1.2 Statement of the problem

Agricultural activities dominate the Upper Lunsemfwa River Catchment (ULRC) and have the potential to impact land use and land cover in the area. Since the ULRC encompasses the headwaters and the source of the Lunsemfwa River, changes in land use resulting from agricultural expansion, both at the commercial and small-scale level, pose a significant threat to the region's land and water resources. The implementation of economic policies like the Farmer Input Support Programme (FISP) has contributed to the loss of natural resources, particularly forests, which were previously relied upon as safety nets and for livelihood strategies by local communities. The consequences of land cover (LC) in the ULRC have substantial implications for the environment and the well-being of the local population. However, there is a lack of comprehensive assessment regarding the relative contributions of different human-induced land uses, such as cropland, settlements, bare land, grassland, and plantations, to the loss of woodlands or wetlands in the area (Malunga *et al.*, 2022).

The problem statement highlights the dominance of agricultural activities in the ULRC and their potential impact on land cover. It also emphasizes the threat posed to land and water resources by agricultural expansion and the loss of natural resources due to economic development. The significant consequences of LC on the environment and livelihoods are acknowledged, along with the need to assess the specific contributions of different land uses to the loss of natural forest. Therefore, this study aimed at addressing this research gap by investigating the extent of LULCC in the ULRC.

1.3 Main objective

The main objective of this study was to assess agricultural expansion dynamics of long-term changes at catchment scale for the Upper Lunsemfwa River Catchment

1.4 Specific objectives

The following were the specific objectives:

i. To assess the main land use land cover classes and the trends in the Upper Lunsemfwa River Catchment
ii. To assess agricultural expansion trends
iii. Simulate future scenarios of land use land cover and agricultural expansion of the study area.

1.5 Research questions

i. What are the land use land cover change and agricultural trends from 1990 to 2020 in the ULRC?
ii. How much LULC and agricultural expansion is expected from 2020 to 2050?

1.6 Significance of the study

Although the ULRC has experienced agricultural changes over the years due to economic growth, the assessment of agricultural expansion and prediction of future scenarios of the study area. This study helped with understanding the rate and extent of LULC. Therefore, with this understanding sustainable river catchment management will be achieved whilst expanding in the agricultural sector.

1.7 Ethical considerations

The University of Zambia Natural and Applied Sciences Research Committee (NASREC) approved (Appendix A) the study based on the research objectives, methodology and its benefits. This research met the ethical standards required for research involving human participants. This approval legitimised the study as it aligns with international standards for ethical research.

1.8 Outline of thesis

Chapter one provides a background of the research and outlines the statement of the problem, main and specific objectives, research questions and significance of the study. Chapter two reviews literature on land use and land cover and agricultural expansion. Chapter three describes the study area in terms of the location, physical characteristics, population, climate, geology and land use and land cover. Chapter four provides the methodologies used in the assessment of agricultural expansion in the study area. Chapter five presents the results and discussion on the land cover changes, agricultural expansion and future predictions. Chapter six concludes the findings and gives recommendations based on the current and predicted results obtained from the study.

CHAPTER TWO: LITERATURE REVIEW

2.1 Land Use Land Cover and Agriculture

The colonial government significantly promoted commercial agriculture in Mkushi during the twentieth century, primarily along the railway line. Much of the land was allocated to European settlers. The Mkushi farm block was surveyed for development between 1950 and 1951. In an effort to attract settlers, the government demarcated plots within each farm block, clearing 16 hectares of arable land and drilling boreholes for water supply on each plot.

Initially, the response from potential settlers was sluggish. In the first year, only the family of the original surveyor, Unwin Moffat, engaged in farming activities. By 1961, several former British servicemen began to occupy some of the plots. By 1964, a total of 74 farms had been established (Kanduza 1991). However, commercial farming and many of Zambia's economic sectors faced challenges during the 1980s, leading to a decline in agricultural productivity.

The situation shifted in the 1990s when South African farmers arrived in Zambia, attracted by the opportunity to engage in commercial farming following the end of apartheid. The Zambian government had actively invited these investors to revitalize the agricultural sector. While some of these South African farmers eventually departed, those who remained infused Mkushi with renewed energy and commitment to commercial agricultural livelihoods.

The conversion of natural areas into urban and agricultural land is a major driver of land cover changes, especially in developing countries. This shift depletes natural landscapes, dense forests, and watersheds while exerting significant pressure on hydrological cycles and river basin processes. Foley et al. (2005) highlighted widespread deforestation in regions like South America and Southeast Asia, noting that the Brazilian Amazon has been heavily cleared for soybean farming and cattle ranching. As noted by Guerra et al. (1998), this kind of changes in land cover disrupt water retention patterns within watersheds, leading to increased runoff and erosion, which can increase flooding or droughts by altering natural hydrological cycles.

Land use and land cover changes (LULCC) are among the most significant drivers of environmental transformation, with implications for ecological systems, biodiversity and socio-economic development (Foley et al., 2005; Lambin et al., 2003). The ability to understand and predict future LULCC patterns is critical for effective land management, sustainable development and the conservation of critical ecosystems (Turner et al., 2007). In recent years, advanced modelling approaches that integrate cellular automata (CA) and artificial neural networks (ANN) have emerged as tools for simulating complex spatial-temporal processes and predicting land use dynamics (Li et al., 2017; Chakraborty et al., 2022). These models provide insights into the interactions between human activities and natural systems, enabling policymakers to design strategies that mitigate adverse environmental impacts.

Human activities, particularly agriculture, have become the dominant force transforming land use patterns globally. Rapid population growth and increasing food demands have intensified agricultural activities, placing pressure on land and natural resources (Tilman et al., 2011). In developing countries, agricultural expansion is primarily driven by the need to meet food security requirements often resulting in the conversion of forests, grasslands and wetlands into croplands (Gibbs et al., 2010). On the other hand, developed nations have experienced a shift from agricultural land use to industrial, residential and infrastructural development due to economic growth and urbanization (Seto et al., 2011). In Zambia, agricultural expansion has led to significant deforestation and habitat loss particularly in watersheds where forest clearing for cultivation and settlement has disrupted ecosystems and community livelihoods (Changwe, 2020).

The demand for arable land and settlement has quickened land use changes, leading to unprecedented changes in ecosystems at local, regional and global levels (Ellis et al., 2010). These changes have caused pressing environmental challenges including climate change, biodiversity loss, water contamination, soil degradation and air pollution (IPBES, 2019). For example, the conversion of forests to agricultural land reduces carbon sequestration capacity, worsening climate change, while soil degradation from intensive agricultural practices compromises long-term agricultural productivity (Foley et al., 2005). Monitoring adverse effects of LULC change while maintaining resource production has become a priority for researchers and policymakers worldwide (Erle & Pontius, 2007). Addressing these challenges calls for a multidisciplinary approach that integrates perspectives from ecology, economics, sociology, and environmental science to develop sustainable strategies that balance human activities with ecological integrity (Lambin & Meyfroidt, 2011).

According to the Integrated Land Use Assessment (ILUA II) report, Zambia's land cover is predominantly covered by forest, with approximately 16.37 million hectares (21.76%) (FAO, 2016). Agricultural land is the second-largest land cover type, covering 6.75 million hectares (8.96%), followed by wetlands and water bodies, which cover 5.09 million hectares (6.77%).

Settlements which includes built-up areas, take up about 0.21 million hectares (0.28%), while other land types make up 0.14 million hectares (0.19%) (FAO, 2016) (see figure 1).These statistics highlight the importance of forests and agricultural land in Zambia's landscape, as well as the need for sustainable management practices to prevent degradation of these resources (The food and Agriculture orgsnisation; Forestry Department, Ministry of Lands and Natural Resources, 2016).

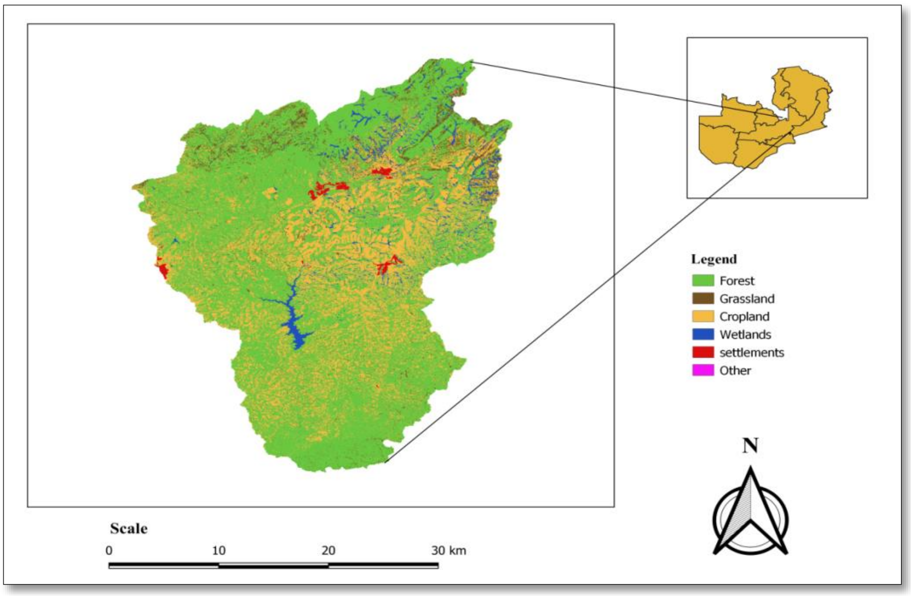

Figure 1: 2016 land use Land cover map for Upper Lunsemfwa River (source: Shakachite et al., 2016).

The expansion of agricultural land in Zambia is driven by population growth and food demand. This has led to significant environmental trade-offs. For example, the conversion of forests and grasslands to croplands has reduced biodiversity, disrupted water cycles and increased soil erosion (Kalaba et al., 2013). Additionally, the construction of dams and reservoirs for irrigation have affected hydrological systems thus affecting downstream water availability and aquatic ecosystems (Grill et al., 2019). These changes bring about the need for integrated land and water management strategies that promote sustainable agricultural practices such as conservation agriculture, agroforestry and crop diversification (Pretty et al., 2018). These practices can enhance productivity while minimizing environmental impacts and ensuring the long-term sustainability of Zambia's natural resources.

Another study that was done on land cover of Zambia (Phiri, Morgenroth and Xu, 2019) highlighted that long term studies on land cover changes in Zambia are not common. One of the findings showed that agricultural land, distance to water bodies, crop yields, temperature and elevation are major factors of land cover change. Another interesting finding was that human population had an influence on primary, secondary and plantation forest losses.

In the Upper Omo Gibe River in Ethiopia, random forest was used to classify images for the years 1991, 1997, 2004, 2016 and 2022 (Lukas, Melesse and Kenea, 2023). The findings showed that the main LULC changes where driven by built up areas and agricultural land. The study recommended that a thorough investigation to be undertaken using additional data and models to give planners and policy makers clear information on LULC changes and their environmental effects. In Ghana, a study on LULC changes was conducted for the years 1991 and 2021 (Ababio, 2023). This study apart from using MOLUSCE to model and predict also included statistical analysis of rainfall and temperature variability for 30 years. Also, local people's perceptions and knowledge on forest modification was considered. The findings showed that reduced and there was an increase in agriculture, built up and mining sites. It was also observed that there were fluctuations in climate conditions such as rainfall which reduced between 1991 and 2021 and temperature had increased.

The aforementioned studies illustrate the interplay between human activities, environmental change and climate variability. Addressing the challenges posed by LULC changes requires a multidisciplinary approach that combines scientific research, policy innovation, and community engagement. By adopting sustainable land management practices and leveraging advanced modelling tools African nations can achieve a balance between development and environmental conservation ensuring the well-being of both ecosystems and human populations.

The Food and Agriculture Organization of the United Nations (FAO) recently released a report titled "The State of the World's Land and Water Resources for Food and Agriculture" in 2021, which offers fresh insights into the condition of our land, soil, and water resources(Food and agriculture organization Of The United Nation, 2021). It also provides compelling evidence of the changing and worrisome patterns in resource utilization. This report plays a crucial role in informing us about the current state of affairs in agriculture and its impact on our planet's sustainability. Globally, the agricultural sector utilizes approximately 4,750 million hectares of land for the cultivation of crops and animal husbandry. It is worth noting that while there has been a minimal overall change in the agricultural land area since 2000, there has been a notable increase in the area dedicated to permanent and irrigated crops. This shift signifies a significant development in agricultural practices and reflects the growing emphasis on sustainable and efficient resource management.

These findings underscore the importance of comprehending and addressing the evolving trends in resource utilization. By acknowledging and analysing these changes, we can effectively identify the challenges and opportunities associated with managing our land, soil, and water resources. It is essential to consider the implications of these trends for global food production, environmental sustainability, and the overall well-being of our planet. Through in-depth exploration and understanding, we can work towards implementing informed strategies that optimize resource use while minimizing negative impacts.

Cumulative land changes play a significant role in driving global environmental transformations.

The availability of land worldwide is diminishing, highlighting the importance of improving land allocation and promoting agricultural innovation (Lambin and Meyfroidt, 2011). It is imperative to prioritize the development of innovative techniques and technologies that can help maximize productivity while minimizing the impact on the environment.

2.2 Drivers of land use change

The changes in agricultural land use can be explained as conversion from agricultural land to urban land/nature areas, change in the type of agricultural production, changes toward multi-functional land use e.g. agricultural land for business (Zondag &Borsboom, 2009). Changes I agricultural production is driven by markets for product, regulations and technology,

Technological advancements lead to increased levels of productivity such as land and employment and this will mean an increment in agricultural production leading to increased agricultural land areas.

Driving forces in land use can be caused by societal, economic, physical and policy drivers. An increasing demand forests and grasslands for agriculture and settlements. Bufebo and Elias (2021) suggested that agriculture followed by population pressure are the main drivers of LULC changes and if these changes are to continue the pose economic and environmental consequences on livelihoods of local people. Some studies show that population changes more to LULCC compared to other factors (Marther & Needle, 2000). Another driver for land use comes about as a result of population increase which demands more land for settlements, and food production for livelihood in both urban and rural areas. Others suggest that economic factors are major drivers of LULCC.

A study on global LULCC drivers carried out by Song et al. (2022) states that approximately 60% of global land changes are caused by direct human activity and the remainder is associated with indirect factors such as climate change. Other studies have been done in Mexico (Calzada, et al, 2018), assessing the decline in natural areas due to urbanisation and a simulation for 2038 was done in which agricultural and pasture land showed a reduction and settlements increased. Other studies (in Ethiopia, Tanzania and China) identified drivers of LULCC such as agricultural intensification, socio economic development and population growth these were identified as the causes of biodiversity loss and land degradation these (Dibaba, 2018; Uisso, 2021; Muhammad, 2022).

GIS and remote sensing methods are used for assessing LULCC changes, giving valuable insights into the spatial distribution and temporal changes of land use patterns. An assessment of LULCC often involves the use of satellite images (Esengulova, et al, 2024). For spatiotemporal changes analysis, an integrated approach was done by some studies like the cellular automata–artificial neural network (CA-ANN) methodology (Pulighe, et al, 2016). This method combines cellular automata and artificial neural networks for modelling and simulating complex land use dynamics. This provided a detailed understanding of the landscape changes over time. Additionally, other researchers integrated future land use simulation models into the analyses process to predict potential scenarios based on current trends and identified drivers. The techniques that were used were Dinamica (Senbeta, et al, 20180), Markov-FLUS (Chen, et al, 2021), SLEUTH cellular automata (Liu, et al, 2012), artificial neural network–Markov chains (Pahlavani, et al, 2017), and CLUE-S (McPhearson, et al, 2022). These models serve as valuable tools for understanding and predicting the dynamics of land use across different spatial scales

2.3 Land use and land cover prediction and simulation

Among several approaches and techniques of modelling and predicting land use change, Markov chain analysis is the most commonly used one (Agrawal et al. 2002). Markov chain analysis is a stochastic modelling approach that predicts a certain state of a large-scale system at a certain time on a basis of the state at an earlier time. However, it is best suited for short-term projections (Baker 1989; Weng 2002, Sinha and Kimar 2013). Different studies have integrated experts' opinions or Multi Criteria Evaluation (MCE) with CA-Markov Chain model to improve the LULC prediction capabilities. However, due to the complexity of studying LULC, these methods have limitations that include insufficient knowledge about the area of interest, subjectivity in weighting the variables, and reliability of the results (Park et al., 2011). Furthermore, due to this complexity of LULC, it seems doubtful that experts have sufficiently detailed understanding of the process of LULC to apply MCE effectively (Shafizadeh-Moghadam et al., 2017).

Therefore, there is a need to implement models that do not face these limitations and rather introduce a better understating of the change process and more accurate results. Artificial Neural Network (ANN) is one of the most powerful models that depend on artificial intelligence. ANN can capture the non-linear relationships between factors and deal with complex patterns and changes in land-use with great efficiency. For simulation purposes, ANN model identifies changes in land-use and other patterns using data that illustrate the behavioural dynamics of land-use phenomenon (Mohammady et al., 2014). Therefore, it can detect potential interdependencies through implied driving forces (Shafizadeh-Moghadam et al., 2017). Furthermore, simulating and predicting future changes in LULC using the CA-ANN model has proved to be more efficient and effective in modeling and predicting spatial-temporal changes compared to linear regression models. The integration of spatial modeling techniques with machine learning enhances the capabilities of the CA-ANN model, making it a powerful tool for simulating and forecasting LULC changes in the future (El-Tantawi et al., 2019; Muhammad et al., 2022).

MOLUSCE (Methods of Land Use Change Evaluation), is a plugin for QGIS that has been developed with the specific purpose of evaluating changes in LULC. This plugin employs raster data, which includes classified maps depicting past and present LULC categories, along with present explanatory variables or factors such as Digital Elevation Model (DEM). These data sets are utilized to train an algorithmic model, which is then employed to predict LULC changes from the past to the present and even into the future (Buğday and Erkan Buğday, 2019; Sajan et al., 2022). MOLUSCE predicts LULC maps by using Cellular Automata (CA) simulation. The accuracy of CA simulation depends on the classification algorithm used to establish the transition rule base for simulation. The transition rules are established to capture the spatial correlation of cell-to-cell interactions. These rules act as a base for CA simulation and are applied to each cell at a regular discrete time step, and the new state for a given cell is calculated by taking into account its previous state and the surrounding cells in the defined neighbourhood (Xing et al., 2020). MOLUSCE builds potential transition maps by using various algorithm such as artificial neural networks (ANN), weights of evidence (WoE), and multi-criteria evaluation (MCE). To calibrate and model land use/cover changes, each methodology uses geographic data on LULC changes.

Although CA-ANN has been used to forecast various LULC expansions (Li and Li, 2015; Klanreungsang, B and Nilsonthi, 2024), to the best of the author's knowledge, this model has not been thoroughly assessed for predicting agricultural expansion at the sub-catchment level. This assessment is crucial for addressing anticipated exponential population growth (FAO, 2021) and for effective integrated river basin catchment management. Thus, the novelty of this study lies in applying CA-ANN to investigate long-term forecasts of agricultural expansion at the sub-catchment scale, ultimately supporting food security.

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CHAPTER THREE: DESCRIPTION OF THE STUDY AREA

3.1 Location

This research was undertaken in the Upper Lunsemfwa River Catchment, a sub-catchment of the Lunsemfwa Catchment in the Mkushi Farm Block in Mkushi District of Central Province of Zambia. The Upper Lunsemfwa River Catchment has an area of 12,551.2 Km^2.

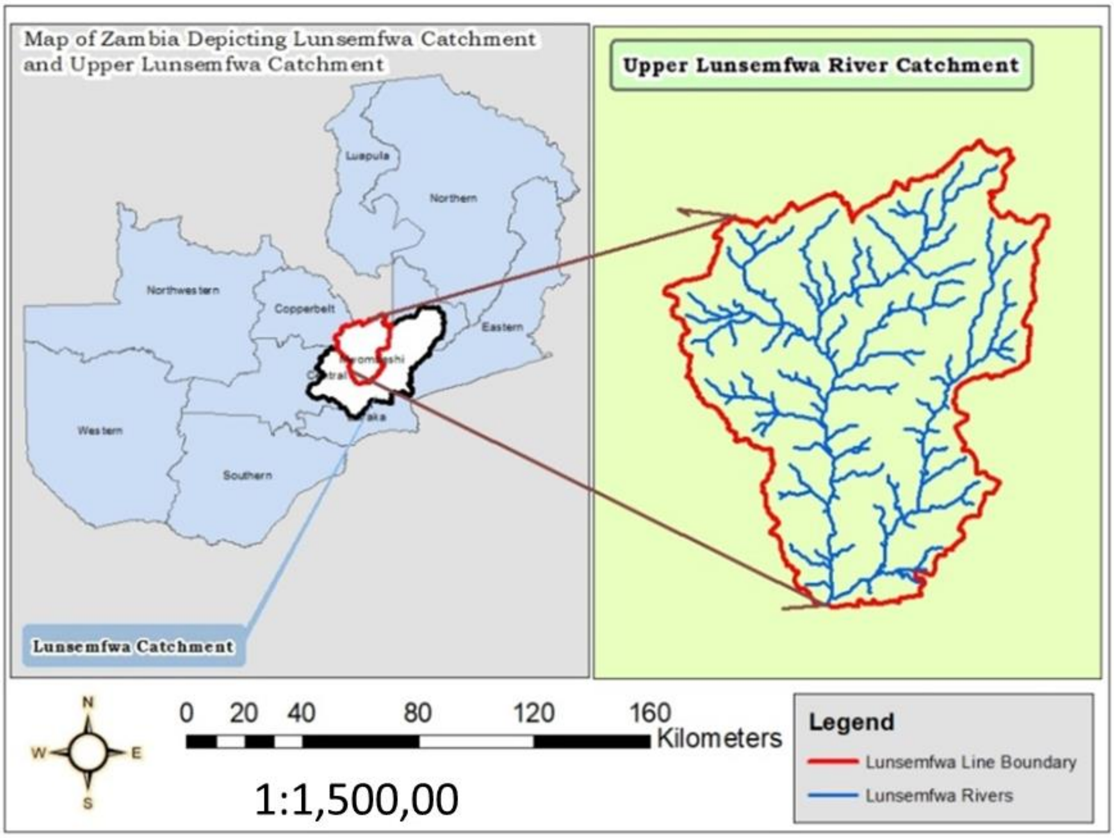

Figure 2: Location of Upper Lunsemfwa River Catchment

The study area is characterized by agriculture of both commercial and small-scale farmers and some mining activities (Provicial Administration, 2019). This is mainly because of the availability of water, land and mineral resources. The river catchment is also a source of energy generation (Provicial Administration, 2019)

3.2 Physical characteristics

The physical characteristics of the study area focus on details of the climate (temperature and rainfall), hydrology, geology, soil, Land use Land cover and its economic activities.

3.2.1 Population

Mkushi District has a population of 208,635 (Central statistics office, 2022). Between 2000 and 2010, the population grew rapidly at an annual rate of 3.7%. About 87% of residents live in rural areas, while 12.4% reside in urban areas (CSO, 2014).

3.2.2 Economic activities

The economy of Mkushi is driven by agriculture and this serves as the backbone of the region's socio-economic development. The agricultural sector comprises of both commercial farming and small-scale farming. Commercial farming is concentrated in the upper northern part of the catchment, where large-scale farmers including many investors cultivate large of arable land. These commercial activities benefit from the availability of water resources and fertile soils, enabling high productivity and contributions to the local and national economy. Maize is one of the major crops grown in this region for both domestic consumption and export markets. These farmers not only support food security but also generates income and employment opportunities for local communities (Jayne et al., 2010).

Small-scale farming dominates the lower southern part of the study area. These farmers are local residents who rely on traditional methods of farming, smaller plots of land to grow crops for subsistence and local markets and are less mechanised. Despite being small scale, these farmers play an important role in sustaining rural livelihoods and contributing to the region's agricultural output. The availability of water resources from the Lunsemfwa River supports irrigation and ensures consistent agricultural productivity across both farming systems (FAO, 2017).

In addition, the Lunsemfwa River catchment is a vital source of hydroelectric power produced by the Lunsemfwa Hydropower Company. This energy infrastructure also contributes to the national grid and enhances energy security and supporting economic growth (World Bank, 2019). Hydropower projects are critical for meeting energy demands in regions with abundant water resources but also require careful management to balance energy production with environmental and social impacts (Karekezi & Kithyoma, 2002).

The ULRC is endowed with rich mineral deposits like manganese which has attracted new mining projects and investments. The expansion of mining also poses environmental challenges such as land degradation and water pollution, which need to be carefully managed to ensure sustainable development (Hilson, 2002). For instance, the extraction of manganese and other minerals can lead to deforestation, soil erosion, and contamination of water bodies affecting both ecosystems and local communities (Kitula, 2006).

Figure 3: Major economic activities in Upper Lunsemfwa River Catchment (Source: Mudenda 2023)

In summary, Mkushi has a dynamic interplay of agriculture, energy generation, and mining. While agriculture remains the primary driver, the contributions of hydroelectric power and mining activities are equally vital. The region's economic activities are deeply interconnected with its natural resources, particularly water and arable land, thus the need for integrated and sustainable resource management practices (UNEP, 2016).

3.2.3 Climate

The Upper Lunsemfwa River Catchment falls under region IIa and III of Zambia’s three Agro-ecological regions.

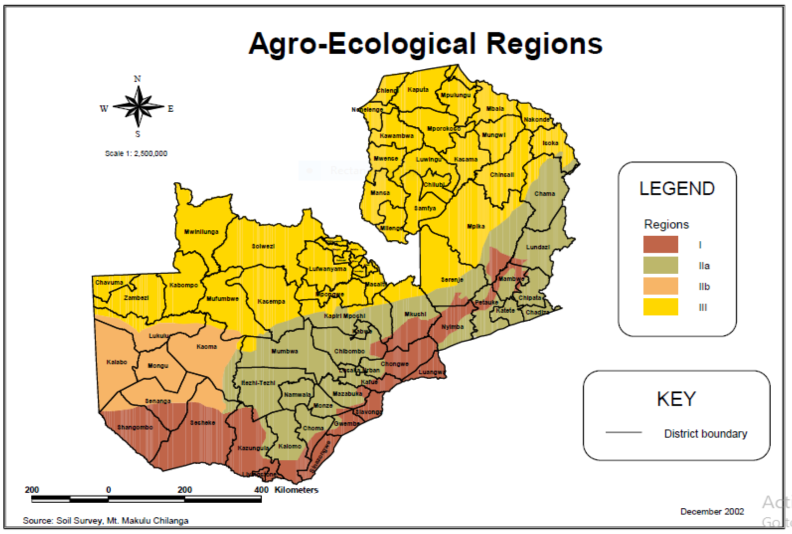

Figure 4: Agro-ecological zones in Zambia (source: Soil survey Mt Makulu, 2002)

This region receives rainfall between 800-1000mm if rainfall annually(MOA, 2015). The Upper Lunsemfwa River Catchment has an average annual minimum temperature of 4.98°C and a maximum of 38.48 °C (Figure 5).

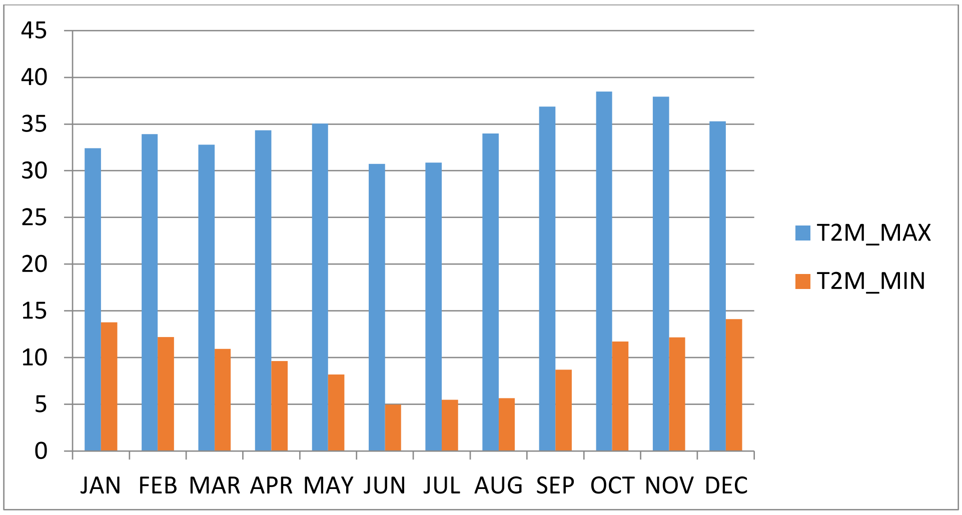

Figure 5: Average maximum and minimum temperatures from 1998 to 2008 (WWF-Zambia and Lehner, 2020)

3.2.4 Geology and Soil

The Upper Lunsemfwa River Catchment (ULRC) is located in Mkushi District and is characterized by its inherently fertile soils making it a hub for agricultural activities. According to the Ministry of Agriculture (MOA, 2015), the region's agricultural productivity is largely attributed to these fertile soils that support both commercial and small-scale farming. The area is predominantly underlain by undifferentiated basement rocks that primarily are composed of granite gneisses and metamorphosed schists and quartzite of pre-katanga formation (Stillman, 1965). These geological formations play a significant role in determining soil composition, as the soils in the ULRC are generally derived from the weathering of underlying granites and gneisses. About three quarters of the soils in the catchment comprises of moderately leached reddish to brown clayey to loamy soils (GRZ, 1969). However, soil properties can vary depending on specific locations within the catchment due to differences in topography, drainage, and erosion patterns.

Its proximity to the Luangwa Rift Valley influences its geomorphology and drainage patterns. The rift valley's tectonic activity shapes the landscape creating a network of rivers and streams that drain into the Lunsemfwa River. These hydrological features are critical for supporting agriculture, as they provide water for irrigation and sustain ecosystems. The interplay between geology, hydrology and soil fertility has made the ULRC a productive agricultural area (Burke et al., 2023).

The geology of the ULRC reflects its position on Africa's central plateau, where basement rocks such as granites and gneisses dominate. These rocks influence soil formation and the region's hydrological systems such as rivers streams and groundwater resources (Burke et al., 2023).

3.2.5 Land Use and Land Cover

The Upper Lunsemfwa River Catchment (ULRC) is predominantly characterized by agricultural activities and charcoal production, both of which are major drivers of land clearing and deforestation in the region. The clearing of trees for charcoal production and the expansion of farmland have significantly altered the landscape leading to the loss of forest cover and biodiversity. Despite these environmental challenges, the ULRC plays a critical role in supporting local and national economies through its diverse land uses (Shakachite et al., 2016).

The catchment is home to the Lunsemfwa Hydropower Scheme, which operates two hydropower plants with a combined capacity of 56 megawatts (MW) providing a vital source of renewable energy for the region. Additionally, the area hosts mining activities, particularly for minerals such as manganese, which contribute to economic development. The agricultural sector in the ULRC includes both small-scale and large-scale farmers reflecting the dual structure of farming systems common in Zambia. Land use planning in Zambia has a long history dating back to the 1950s. Following independence in 1964 the country adopted a land classification system inherited from the colonial government, which categorized land into state land, reserves and trust land (Shakachite et al., 2016).

Despite this framework available statistics indicate that only 14 percent of Zambia's total agricultural land is currently utilized (MOFL, 2016). Although this percentage has increased over the years, a significant portion of arable land remains underutilized, highlighting the potential for further agricultural development. However, this also underscores the need for sustainable land management practices to prevent overexploitation and environmental degradation (MOFL, 2016).

The ULRC was selected as the study area due to its abundant land and water resources, which are being utilized for agriculture, hydropower generation, and mining. These activities make the catchment a microcosm of the broader land use challenges and opportunities facing Zambia. The interplay between agriculture, energy production, and mining in the ULRC provides a unique opportunity to study the impacts of land use changes on natural resources and ecosystems. By understanding these dynamics, stakeholders can develop strategies to balance economic development with environmental conservation, ensuring the sustainable use of the catchment's resources for future generations.

CHAPTER FOUR: METHODOLOGY

4.1 Introduction

This chapter describes the procedure used when collecting and analysing data for the study. This is summarized in the figure 7.

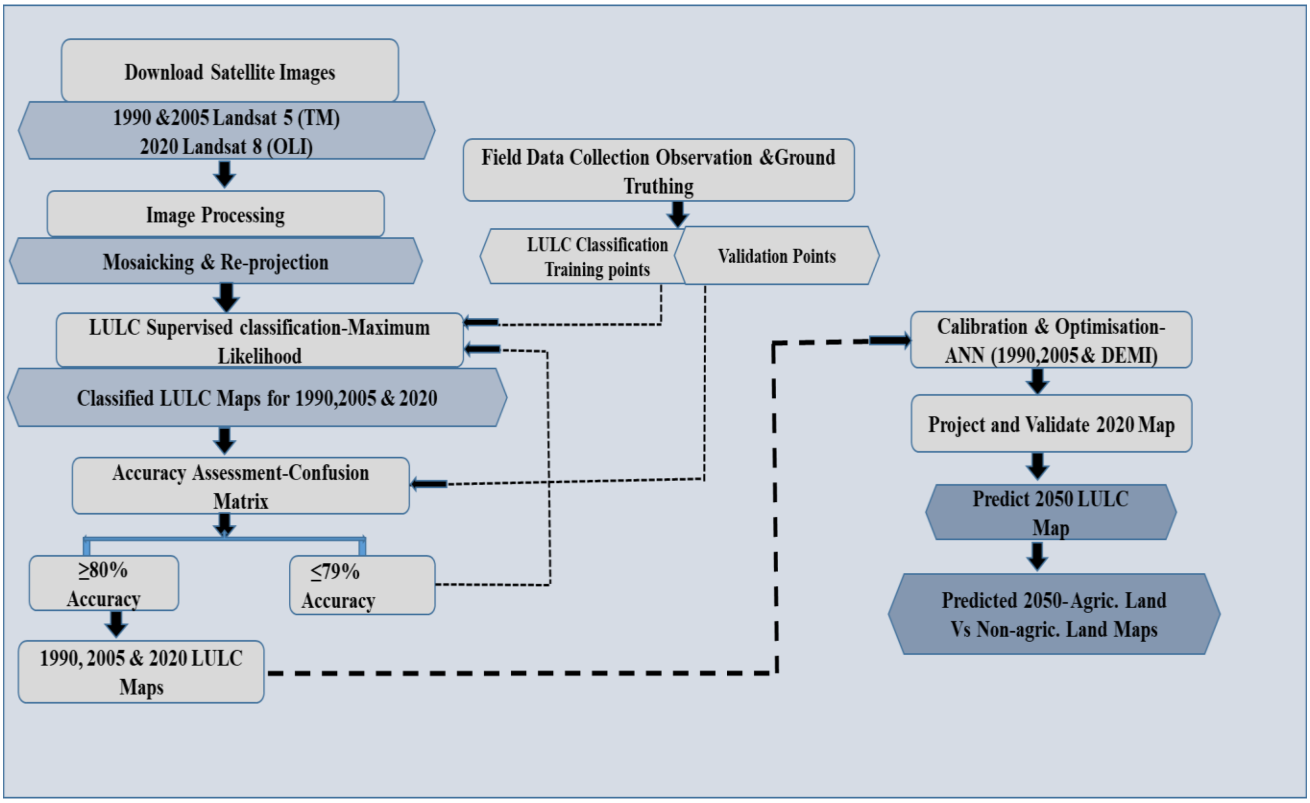

Figure 6: Methodology summary

4.2 Field and Spatial Data Collection

The field and spatial data was collected in various ways and these are discussed in the subsection below.

4.2.1 Field Data collection

Ground truth geometry points of various Land use and land cover for classification training and validation were collected from the field during reconnaissance survey of the study area which was conducted between 13th April to 22nd, 2019 and 30th August to 8th September, 2019. The geometry points included crop fields, settlements, vegetation and water bodies. 120 geometry points were collected from the field and 80 more geometry points were collected from google earth pro. This study used a total number of 200 geometry points (70% for classification and 30% for validation) for classification and validation based on (Li et al. 2014).

4.2.2 Spatial data collection

The LULC classification and assessment of agricultural expansion between 1998 and 2020 was done using the already pre-processed Landsat 5 thematic mapper (TM) (1990 and 2005) and Landsat 8 Operational land imager (OLI) (2020) which were downloaded from climate engine (http://ClimateEngine.org) and the 30-meter resolution of Digital Elevation Model (DEM) obtained from the Shuttle Radar Topography Mission (https://dwtkns.com/srtm30m/). Landsat data were utilised due to the extensive temporal coverage available for the period under study. As the longest-operating satellite program, Landsat provides a wealth of images that are crucial for analysing changes over time (Zhang et al., 2022). The images downloaded from climate engine were based on average conditions and (Huntington et al, 2017) pre-processed and the specified input images were from January to December for 1990, 2005 and 2020. The band combination used were near infrared, red and green. This combination is helpful for differentiating land cover types such as forests, water bodies and agriculture and it was based on Phiri & Morgenroth (2017) and Her & Heatwole (2007).

4.2.3 Land use land cover classification

Landsat imagery and field geometry points were imported into IDRISI Selva, where various LULC classes were identified as shown in Table 1.

Table 1: Land classification scheme

Land cover class	Description
1. Forest	All forest types (dense, medium and sparsely), think shrub.
2. Agricultural land	Land used to grow crops which may be irrigated, or rain fed for commercial and small-scale farmers around urban and rural settlements.
3.Water	Land which is waterlogged, wooded (marshland), perennial flooded plains, swampy areas, dams and surface water bodies.
4. Built-up	Urban/rural built-up areas and bare land.
5. Grassland	Land covered by different grass types, sparsely shrubs and small trees

Training samples for each class were generated using IDRISI's on-screen digitising tools, ensuring that each sample appropriately represented the heterogeneity within each class. The Maximum Likelihood (ML) classification algorithm was used to calculate the chance that each pixel belonged to each class based on the training data set. This process resulted in a classified map that indicated the predicted LULC for each pixel. The ML classification was employed because it utilises a probability framework that assigns each pixel to the class with the highest likelihood of belonging (i.e., maximum likelihood). This approach is particularly effective for managing the uncertainties and variability inherent in LULC data due to the fact that if the calculated probability for a pixel falls below a specified threshold, that pixel will remain unclassified (Ahmad & Quegan, 2012). The maximum likelihood algorithm is defined by equation 1 (Richards & Jia, 1999).

$$g_i(x) = 1\text{n}\, p(\omega_i) - {}^1\!/_2\, 1\text{n}\, |\Sigma_i| - {}^1\!/_2 (x - m_i)^T \Sigma_i^{-1} (x - m_i)$$ ……………. Equation 1.

Where:

i = class

x = n-dimensional data (where n is the number of bands)

p(ωi) = probability that class ωi occurs in the image and is assumed the same for all classes

|Σi| = determinant of the covariance matrix of the data in class ωi

Σi-1 = its inverse matrix

mi = mean vector.

To evaluate the classification procedure, confusion matrix was used. This is a common approach in categorical classes for verification of results (Lu and Weng, 2007). This was done by comparing the classified map against ground truth data or validation samples. Various metrics were evaluated, including overall accuracy, user accuracy, producer's accuracy, and the Kappa coefficient, to determine the performance of the classification algorithm.

Finally, the resulting product with five classes exported into the MOLUSCE tool in QGIS for future scenario analysis

4.3 Land use land cover future predictions

The study employed the CA- ANN model using the MOLUSCE plugin in QGIS 2.0 to monitor and simulate potential agricultural land change dynamics from 2020 to 2050. The initial model was trained using LULC maps from 1990 and 2005, incorporating a 30-meter Digital Elevation Model (DEM) as the only spatial variable. While other variables like population density and proximity to roads and water bodies, among others could have been considered, the DEM was chosen as the sole spatial variable to: Improve computational efficiency-limiting variables helps maintain accuracy; Prevent overfitting-some variables, such as distance to water bodies, have weak correlations with LULC; Address limited computational resources - the computer used for data processing had constraints in capacity and processing time as also observed by Idris et al. (2024).

In LULC simulations using the Cellular Automata-Artificial Neural Network (CA-ANN) model, the update of a cell's state is determined by its current state and calculated probabilities derived from historical data. This hybrid approach combines the strengths of cellular automata for spatial dynamics with the predictive capabilities of artificial neural networks.

The CA-ANN model incorporates the principles of CA with ANN for simulation and prediction of LULC Changes. This involves the use of several components such as;

Transitioning probability ($\boldsymbol{P}$): this calculates the characteristics of the surrounding cells and historical data and is expressed as in equation 2:

$P_{ij} = f\left(X_i, Y_j\right)$ e) ……….……………… Equation 2

Where X_i represents the features of the neighbouring cells and Y_j represents the target land use type.

Cell state update: This is determined by the current state and the calculated probabilities from the historical data. A combination of the current state of the cell and the calculated probabilities is used to determine the new state of the cell. The formula for updating the state of a cell at time t+1*t*+1can be expressed as in equation 3:

S(t+1)=f(S(t),P)$S(t+1)=f(S(t),P)$……….………………Equation 3

Where: S(t)$S(t)$ is the current state vector of the cell at time t*t*.

Training ANN: The training is done using historical LULC data. This is done to learn the relationships between input features and land use changes. To minimise the prediction error, the training process adjusts the weights in the network.

Simulation iteration: This is done by the simulation running iteratively over the time series and updating cell states on the transition probabilities from the ANN predictions.

These components bring about dynamic modelling of land us changes through capturing spatial and temporal iterations of time series and updating cell states on the transition probabilities from the ANN predictions. Figure 2 summarises the procedure used when collecting and analysing data for this study.

To validate the accuracy of the CA- ANN model's predictions for 2020, the study used the Multiple Resolution Budget method (MRB), ensuring a robust assessment of the model's performance in comparing the 2020 simulated map and the 2020 classified map. The MRB was used because it is an effective approach for allocating limited resources in accuracy assessment tasks at various spatial resolutions. By strategically allocating resources across different resolution levels, MRB aims to maximize the overall accuracy of LULC validation within the constraints of the available budget. (Leterme et al., 2007; Olofsson et al., 2014; García-álvarez, Teresa and Olmedo, 2022).

4.4 Uncertainties and Limitations

Firstly, LULC changes are influenced by a range of uncertain factors, such as human decisions, economic conditions, and environmental factors. Simulations may incorporate probabilistic elements to account for this uncertainty, but the specific outcomes of these factors can lead to differences between the simulated and actual maps (Lambin and Meyfroidt, 2011; Seto, Güneralp and Hutyra, 2012). LULC changes can occur at different temporal and spatial scales. Simulations may not fully capture the fine-scale dynamics or account for localised factors that influence land use changes, resulting in differences between the simulated and actual maps (Verburg et al., 2009).

The model used in this research for LULC classification and simulation are a simplification of reality, and built from a sample population and not from the entire population; therefore, when sample population is changed, the adjustment of the model also slightly changes. In addition, models are built based on available data and knowledge at a specific point in time, which means they may not capture all the complexities and variations present in the real system (Miller and Thode, 2007; Rounsevell et al., 2012; Verburg et al., 2016).

CHAPTER FIVE: RESULTS AND DISCUSSION

5.1 Classification accuracy assessment

Table 5 presents the accuracy results for the classification, which can be expanded upon and discussed in the context of related literature. The overall classification accuracy values were 88.4%, 92.7%, and 98.0% for 1990, 2005, and 2020, respectively. These results indicate an improvement in the classification accuracy and agreement over the years, with the highest values observed in 2020 (Rwanga and Ndambuki, 2017; El Shair, Hassani and Rawashdeh, 2023) and better data quality, advanced algorithms, or more refined analytical techniques (Foody, 2002).

The kappa coefficient values were 82.9%, 88.8%, and 97.1% for 1990, 2005, and 2020 as seen in Table 4. These values measure the agreement between the observed and predicted classifications while controlling for chance. The increase in the kappa coefficient indicated accuracy in classification and higher level of consistency and reliability in the classification processes used over time (Landis & Koch, 1977).

The producers and user's values (Table 4) ranged from 49.8% to 100% in 1990, showing some inconsistency in classification effectiveness across different categories. In 2005 it improved with values ranging from 56.3% to 100%. However, by 2020 values dropped between 17.5% to 100% in 2020. This decline may have been due to specific classifications that were not present or were less distinct in earlier years. The drop specifically calls for a deeper analysis to understand which classes underperformed and why (Congalton & Green, 2008).

Table 2: Error matrix for the 1998, 2008 and 2020 of the classified map for upper Lunsemfwa

LAND COVER CLASSES	1990		2005		2020	
	PRODUCERS ACCURACY	USERS ACCURACY	PRODUCERS ACCURACY	USERS ACCURACY	PRODUCERS ACCURACY	USERS ACCURACY
FOREST	74.6	93.1	98.0	83.7	88.2	89.3
GRASSLAND	96.6	77.3	91.9	94.2	97.8	99.5
AGRICULTURE	49.8	94.4	78.4	76.6	96.1	97.4
WATER	100	100	100	100	99.9	100
BUILT-UP	100	100	56.3	49.5	92.5	17.5
OVERALL ACCURACY	88.4		92.7		98.0	
KAPPA COEFICIENT	82.9		88.8		97.1	

5.2 Land Use Land Cover Trends

The Land Use Land Cover Trends from 1990 to 2005 and 2005 to 2020 are discussed in these sections.

5.2.1 Change assessment of land cover from 1990 to 2005

The findings for LULC trends in the ULRC reveal interesting alterations in the landscape from 1990 to 2020. The most noticeable transformation was the expansion of agricultural land, which experienced an increase of 25.9%. Agricultural areas increased from 1,761 km² to over 5,107 km², indicating a significant shift in land use priorities and this was likely driven by growing demands for food production and economic development (Seto et al., 2012).

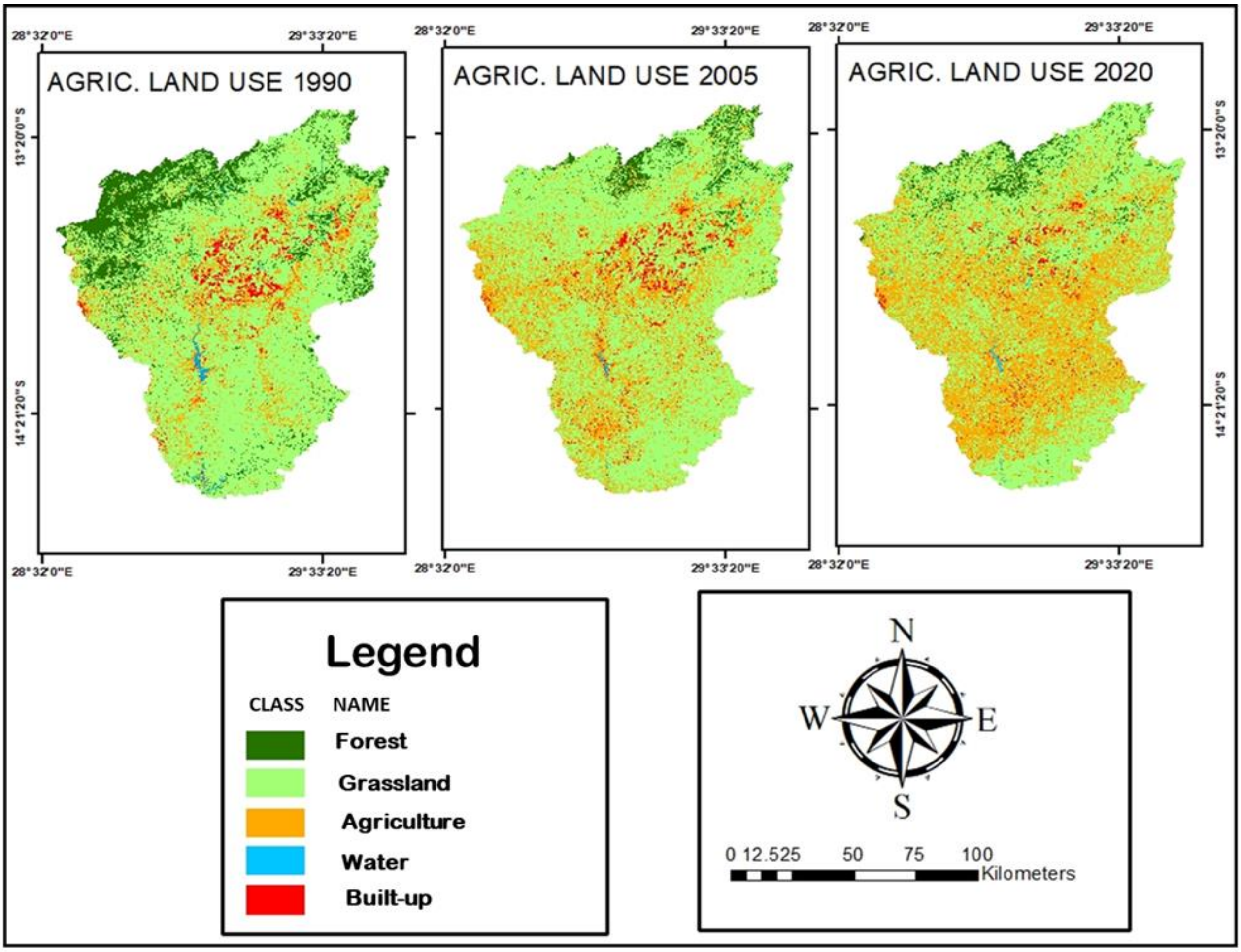

Figure 7: Classified maps for 1990, 2005 and 2020 showing each class

On the contrast, forest areas faced a decline, reducing from 1,863 km² to just 536 km². In sharp contrast, forested areas within the catchment faced a dramatic decline, shrinking from 1,863 km² to just 536 km². This is of concern, as it not only reduces biodiversity but also impacts ecosystem services such as carbon storage, climate regulation, and water quality (IPCC, 2021).

Other land cover types experienced varying changes. Grasslands decreased in area, from 8,791 km² to 6,981 km². Although this reduction is not severe than that of forests, it shows a shift in the ecological balance of the region (Fisher et al., 2014).

Built-up areas also reduced from 407 km² in 1990 to 246 km² in 2020. This could be due to classification process not being able to pick up some of the built up areas due to similar spectral reflectance with agricultural and bare land.

The water bodies-maintained stability during this period, with a slight decline from 103 km² to 54 km². This stability may mean conservation efforts or regulatory frameworks to protect aquatic ecosystems amidst widespread land use changes (Dudgeon et al., 2010).

Table 3: Land use Land cover change extent for 1990, 2005 and 2020

Land cover classes	***1990***		***2005***		***2020***		***Changes in 1990-2005***	***Changes in 2005-2020***	***Changes in 1990-2020***
	Km²	**%**	**Km²**	**%**	**Km²**	**%**			
Forest	1862.98	14.4	514.68	3.9	535.59	4.1	10.4	-0.2	10.3
Grassland	8791.08	68	8587.28	66.4	6981.17	54.01	1.6	12.4	14
Agriculture	1760.98	13.6	3405.97	26.4	5107.78	39.5	-12.7	-13.2	-25.9
Water	103.17	0.8	29.52	0.2	54.25	0.4	0.6	-0.2	0.4
Built-up	407.13	3.2	387.89	3	246.54	1.9	0.2	1.1	1.2

Land cover in the upper Lunsemfwa River Catchment provides valuable insights into the changes and trends within the study area. In 1990, Table 5 displays the land cover distribution, revealing that grassland, forest and agriculture were the dominant land cover types, covering approximately 8791.08 km^2 and 1862.98 km^2 1760.98, respectively. However, by 2020, there was a noticeable decline in grassland and forest cover to 6981.17 km^2 and 535.59km^2, while agriculture expanded significantly to 5107.78 km^2. This shift can be attributed to agricultural expansion in the Mkushi farm area and the increased presence of small-scale farmers. This secondary forest is due to a common practice of shifting cultivation by small-scale farmers.

5.2.2 Change assessment of land cover from 1990 to 2005

Between 1990 and 2005, there was a significant change in the land cover composition of a specific region. During this period, the area covered by forests experienced a notable decrease of 1348.3 km^2. In 1990, the forest class covered 14.4% of the total area. Over time, there was a noticeable decrease in forest cover, with the area shrinking to 3.9% in 2005. This indicates a significant reduction in forested areas within the study area. This is similar to the findings of a study conducted in Zambia were it was indicated that the country has undergone a transition of the forest from primary to secondary forest from 1972 to 2016 (Phiri, Morgenroth and Xu, 2019).

Other land cover classes experienced reductions in their respective areas. Grasslands vital for supporting diverse ecosystems and providing grazing land for livestock, showed notable decline of 1.8% decreasing from 68% to 66.4%. This can be primarily attributed to clearing of land for agricultural purposes. Agriculture expanded with an increase of 12.8%. This is likely to have resulted from the conversion of other land types, like forests and grasslands into agricultural lands. Similar trends are observed in regions like the US Midwest, significant areas of grassland were converted into cropland between 2008 and 2016 (Zhang, X., et al 2021). Additionally, nearly 90% of global deforestation is driven by agricultural expansion (FAO, 2021). These changes highlight the ongoing pressures on natural habitats like forests and grasslands due to increasing agricultural demands.

Water coverage experienced a decrease of 0.6%, which may be attributed to the creation of water bodies such as dams and/or reservoirs due to human intervention (Smith et al., 2010; Wang et al., 2015). In 1990, water bodies covered 103.17 km^2, but this area decreased to 29.52 km^2 by 2005. These changes often reflect the interplay between natural processes and anthropogenic influences on hydrological systems.

The built-up area, representing urban and rural settlements and development, showed a reduction of 0.2%. This could be attributed to the spectral reflectance of satellite imagery. Built-up areas could have been misclassified due to similarities in reflectance patterns with other land cover types. It should be noted that uncultivated or harvested agricultural fields often exhibit reflectance properties similar to built-up areas leading to potential misclassification (Zhang et al., 2018). This was also in observed in another study, where it was highlighted that the challenges of accurately distinguishing built-up areas from other land cover types using remote sensing data (Li et al., 2019).

Agriculture class included areas used for crop cultivation and livestock farming, expanded. In 1990, agricultural land covered 1760.98 km² and by 2005, the area increased to 3405.978 km². This shows a rise in agricultural activities driven by the changes of other land cover types, such as forests or grasslands, into agricultural land. This is likely to lead to encroachment of natural ecosystems (Foley et al., 2005; Lambin et al., 2003). Such changes are also associated with population growth, food demand, and economic development, emphasizing the dynamic nature of land use systems.

5.2.3 Change assessment of land cover from 2005 to 2020

Between 2009 and 2020, the Upper Lunsemfwa River catchment underwent noteworthy changes in its land cover composition. During this period, forest, agricultural, and water coverage experienced notable increases. Forest area expanded by 0.2%, a change likely attributed to shifting cultivation practices commonly employed by small-scale farmers in the area. Shifting cultivation has been observed to promote forest recovery in certain contexts (Hecht et al., 2006).

Water and agricultural areas increased by 0.2% and 13.2% respectively. The expansion of agricultural land reflects the growing demand for food production, driven by population growth and economic development, as well as the changing of natural lands for farming purposes (Foley et al., 2005). The increase in water area may be linked to the construction of reservoirs, dams, or irrigation systems to support agricultural increase. This is a trend observed in other catchments facing similar pressures (Wang et al., 2015). These changes highlight the interplay between agricultural expansion and water resource management in response to increasing food security needs.

An interesting change was the 12% decline in grassland coverage. Grasslands play a role in supporting biodiversity, providing grazing land for livestock, and maintaining ecosystem services (Bardgett et al., 2021). The observed reduction is likely driven by the expansion of agricultural activities and the changes of grasslands into primary forest, a process facilitated by shifting cultivation practices. And it is known that agricultural intensification and land use changes lead to the loss of grassland ecosystems (Newbold et al., 2015). The change of grasslands to other land uses highlights the trade-offs between agricultural productivity and the conservation of natural ecosystems.

5.3 Agricultural expansion assessment the Upper Lunsemfwa River Catchment

The land cover results showed noteworthy assessment of agricultural expansion by comparing changes between agricultural and non-agricultural land from 1990 to 2020. Agriculture experienced growth. The proportion of agricultural land increased from 13.62% in 1990 to 26.35% by 2005 and further expanded to reach 39.52% by 2020 (Table 6).

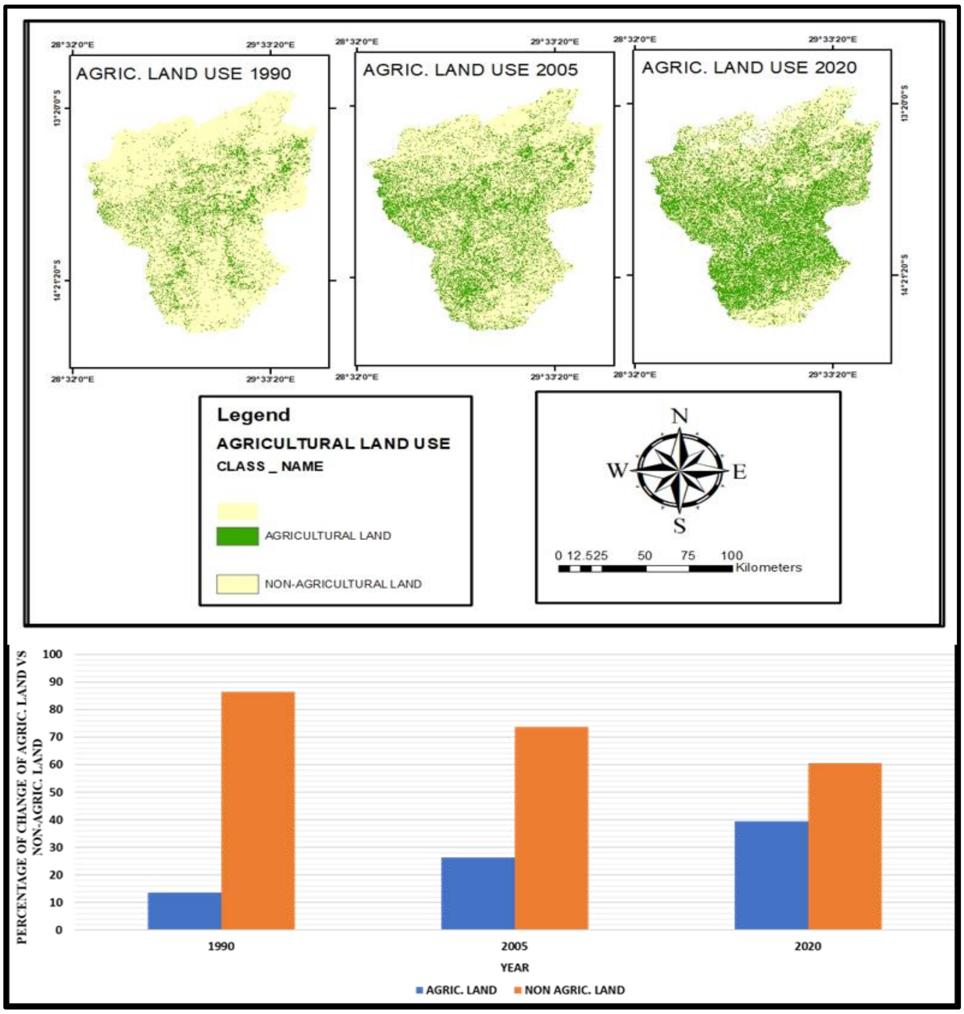

Figure 8: Rate of changes of agricultural land and non-agricultural land from 1990 to 2005 to 2020

Non-agricultural land underwent a reduction from 1990 to 2005 to 2020, decreasing from 86.38% in 1990 to approximately 73.65% by 2005 and then dropping further to about 60.48% by the year 2020. This shift may have been driven by the expansion of both commercial and small-scale farming activities within the region. Improvements in productivity have become a major driver of global agricultural output since the late twentieth century (Fuglie, K. et al, 2024). Also as the population increased over the years the need for providing food security and for income generation (Purwanto, Utomo and Kurniawan, 2016).

In Zambia, studies using remote sensing techniques have documented extensive agricultural encroachment into forest reserves between years like those examined here (e.g., between 2000 and 2018), underscoring challenges related to sustainable land use planning amidst growing demands for food production (Phiri, Darius. et al, 2019). Similarly, Ethiopia's highlands face similar pressures where rapid population growth exacerbates competition for arable lands at the expense of forests and grasslands (Tesfaye, G. et al 2024).

Table 4: Agricultural expansion from 1990 to 2005 to 2020 for the Upper Lunsemfwa River Catchment.

Land cover classes	***1990***		***2005***		***2020***	
	Km²	**%**	**Km²**	**%**	**Km²**	**%**
Agriculture	1761	13.62	3405.97	26.35	5107.78	39.52
Non-agriculture	11164.4	86.38	9519.37	73.65	7817.55	60.48

5.4 Future scenarios of land cover in the Upper Lunsemfwa River Catchment

Future scenarios of the Land Use Land Cover in the Upper River Catchment have been discussed in the following section.

5.4.1 Future LULC Simulation and Prediction using the CA-ANN model

In this research, a CA model was developed that simulated the spatial dynamics of LULC changes using the 1990, 2005 and 2020 classified maps. This procedure produced a transitioning probability matrix that was used to train the ANN for simulation of future LULC maps. The transition probability matrix in LULC cover change analysis is a square matrix that represents the probabilities of transitioning from one LULC category to another over a given time period (Buğday and Erkan Buğday, 2019).

In order to predict the LULC for 2050, a set of specific parameters was utilized in the ANN learning process (Figure 5). These parameters were carefully chosen to optimize the accuracy of the model. The process involved performing 500 iterations, with each iteration refining the model's predictions. A neighborhood value of 1x1 pixels was used, meaning that each pixel's surrounding area was taken into consideration when making predictions. The learning rate was set at 0.050, indicating how quickly the model adjusts its internal parameters based on the training data. 10 hidden layers were employed to facilitate the complex learning process of the ANN, and a momentum of 0.05 was used to help overcome local minima during optimisation.

These parameter settings were determined through trial and error, carefully fine-tuning the model to achieve satisfactory results in terms of model development and validation. The achieved kappa index of 0.967 and overall error of 0.00581 (refer to Figure 5) indicate high accuracy and precision in the model's predictions. The classified maps of the period between 1990 and 2005, along with DEM as an explanatory variable were used for calibration and optimisation of ANN algorithm. After the model development, the LULC projection for the years 2020 and 2050 was conducted. The simulated LULC map for 2020 and the corresponding reference (classified 2020) were compared for validation of the prediction accuracy.

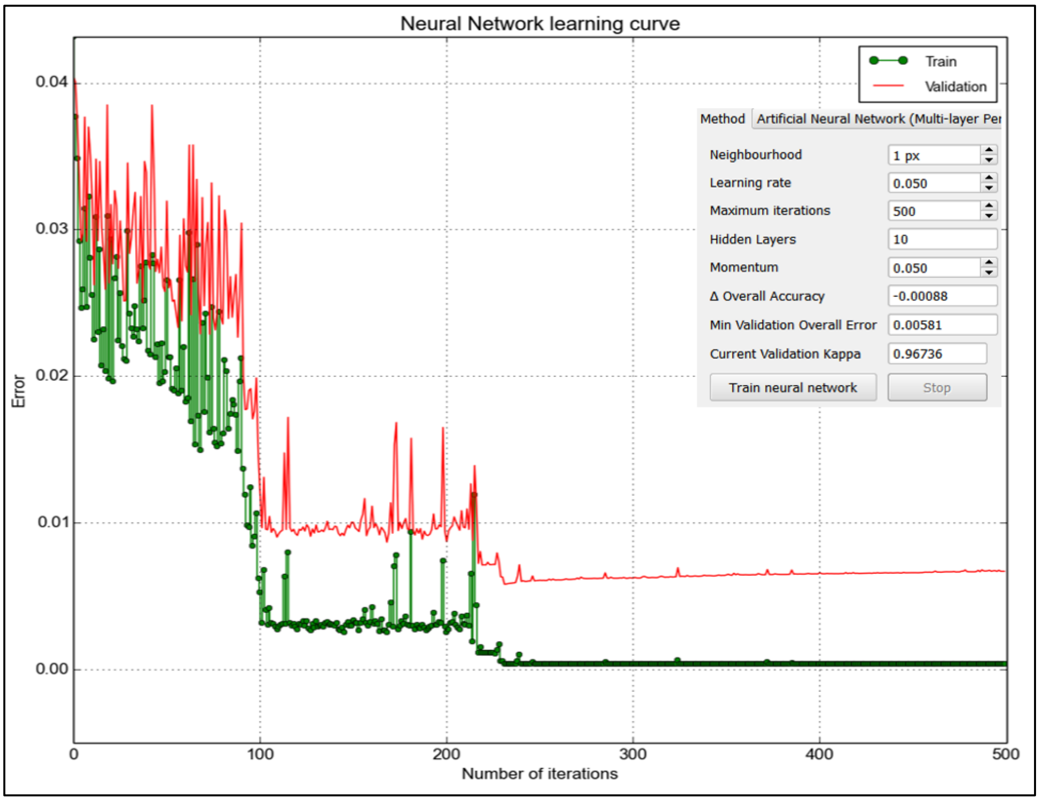

Figure 9: Model development for simulation of present and future LULC

5.4.2 Validation using Multiple Resolution Budget (MRB)

The MOLUSCE plugin facilitated the application of a kappa validation technique, enabling a comparison between the actual (2020 map) and projected (2020 map) LULC maps for model validation and assessment of prediction accuracy of the model. The CA-ANN model's output, specifically the simulated map for the year 2020, was subjected to validation using the reference classified map for 2020, as illustrated in Figure 6. This validation process was conducted to evaluate the accuracy and dependability of the model's predictions. To compare the 2020 simulated map and the 2020 classified map, a method called Multiple Resolution Budget (MRB) was employed. The MRB was used because it is an effective approach for allocating limited resources in accuracy assessment tasks at various spatial resolutions. By strategically allocating resources across different resolution levels, MRB aims to maximize the overall accuracy of LULC validation within the constraints of the available budget (Leterme et al., 2007; Olofsson et al., 2014; García-álvarez et al., 2022).

The comparison of the two maps using MRB reveals some minor differences, primarily attributed to variations in quantity and spatial location. As the spatial scale decreases, these discrepancies tend to diminish. However, it was evident that the agreement between the simulated and actual 2020 LULC conditions was predominantly strong, both in terms of quantity and spatial location. This was evident from the high kappa estimation values, with a histogram kappa of 0.989, an overall kappa of 0.979, and a location kappa of 0.989, indicating a high level of similarities. Additionally, the proportion of correctness was calculated at 98.55%, further underscoring the reliability and accuracy of the model's predictions in reflecting the actual LULC conditions for 2020.

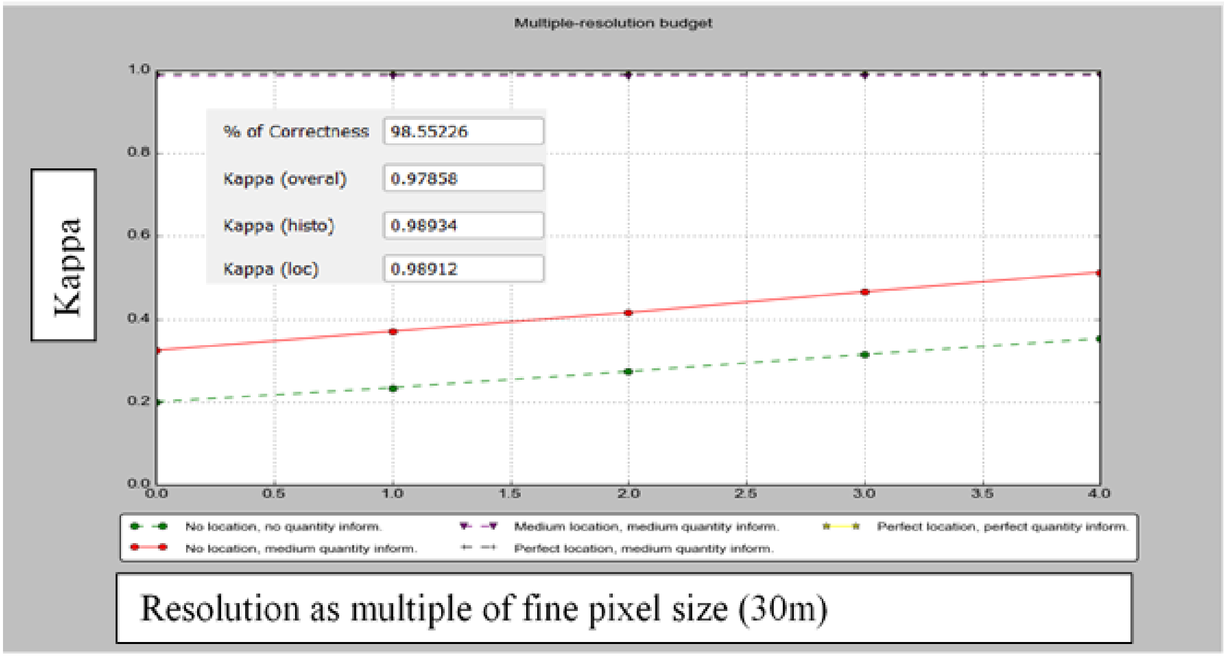

Figure 10: Validation and calibration using MRB. Percent correctness: percentage of correctly classified pixels compared to the total number of pixels. Kappa overall: Assesses the overall performance of the prediction method. Kappa histogram: Assesses distribution of classification errors across different LULC classes. Kappa location: Assesses accuracy across different scales. Location: Geographical position of a specific LULC class. Quantity: Spatial distribution of different LULC categories.

5.4.3 Land Use Land Cover prediction

The areas for the projected land cover maps for 2020 and 2050 are shown in table 8. The simulated land cover map shows a reduction in forest and water from 2020 to 2050. The forested area in the Upper Lunsemfwa River Catchment covered 6981.17 km^2, more than half (54.01%) of the entire area, but is projected to decrease to 6177.18 km^2, nearly half (47.79%) of the total area. Agriculture covered a significant portion (39.5%) of the total area at 5107.78 km^2, and is estimated to occupy 5745.08 km^2, 44.45% of the total area. Water covered a relatively small portion (0.4%) of the total area at 54.25 km^2, but the expected change is a reduction to 38.24 km^2, only 0.29% of the total area, indicating a potential shift in water usage patterns. Built-up areas covered 246.54 km^2, 1.9% of the total area, and the predicted coverage is expected to significantly increase to 465.23 km^2, 3.59% of the total area

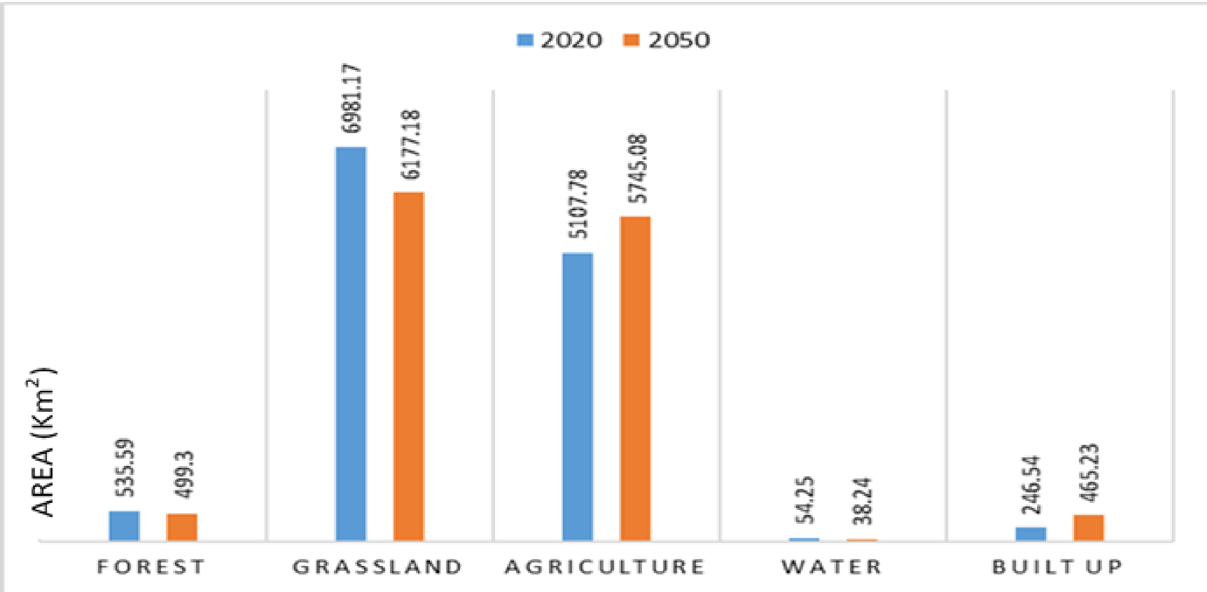

Figure 11: Predicted rate of land use land cover change from 2020 to 2050

Observations suggest that the Upper Lunsemfwa River Catchment is undergoing significant changes in land use patterns, such as the reduction in forest area and the increase in built-up areas and agricultural lands by 2050. These changes may have significant implications for the region's ecosystem and its inhabitants, and it is essential to monitor and manage these changes to ensure sustainable development (Rountree, 2018). These observations suggest that the Upper Lunsemfwa River Catchment is undergoing significant changes in land use patterns. The reduction in forest area and the increase in built-up areas and agricultural lands by 2050 indicate a shift in the region's landscape. These changes may have significant implications for the ecosystem and its inhabitants, and it is essential to monitor and manage these changes to ensure sustainable development. (Tena, Mwaanga and Nguvulu, 2019).

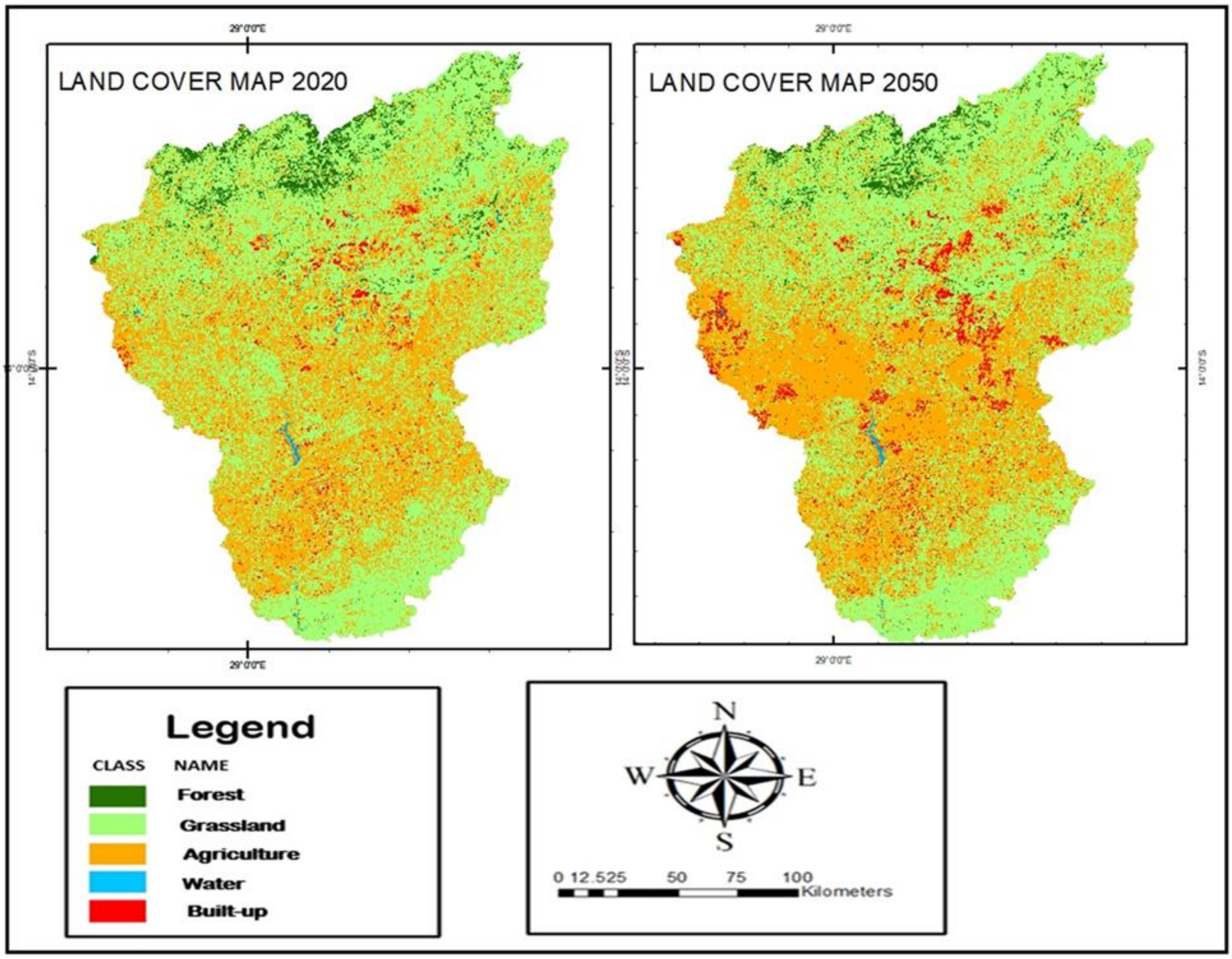

Figure 12: Classified 2020 land use land cover change map and predicted 2050 land use land cover map

Additionally, the Luangwa Upper Sub-catchment in Zambia is of great environmental significance, given its importance to the long-term water flow and quality of the Luangwa River. The degradation and loss of forest in this area threaten biodiversity, water quality, and the associated ecosystem services, highlighting the interconnectedness of land use, water resources, and ecosystem health (WWF, 2018)

5.4.4 Future agricultural expansion in the Upper Lunsemfwa River Catchment

Between 2020 and 2050, significant and transformative changes in land use are projected, with agricultural land expected to increase from 5,107.78 km² to 5,745.08 km², representing approximately 12.5%. This reflects growing global demand for food production, driven by population growth and rising incomes toward more resource-intensive foods (Tilman et al., 2011; Foley et al., 2011). Trends like these are consistent with global patterns observed in regions undergoing rapid agricultural development, where natural ecosystems are often converted to farmland to meet food security needs (Lambin et al., 2003; Gibbs et al., 2010). The intensification of agricultural production such as the adoption of high-yield crops and irrigation systems contribute to agricultural expansion as seen globally (Pretty et al., 2018). However, this growth in agricultural land use raises concerns about the sustainability of such practices particularly in terms of soil degradation, water resource depletion and biodiversity loss (Rockström et al., 2017).

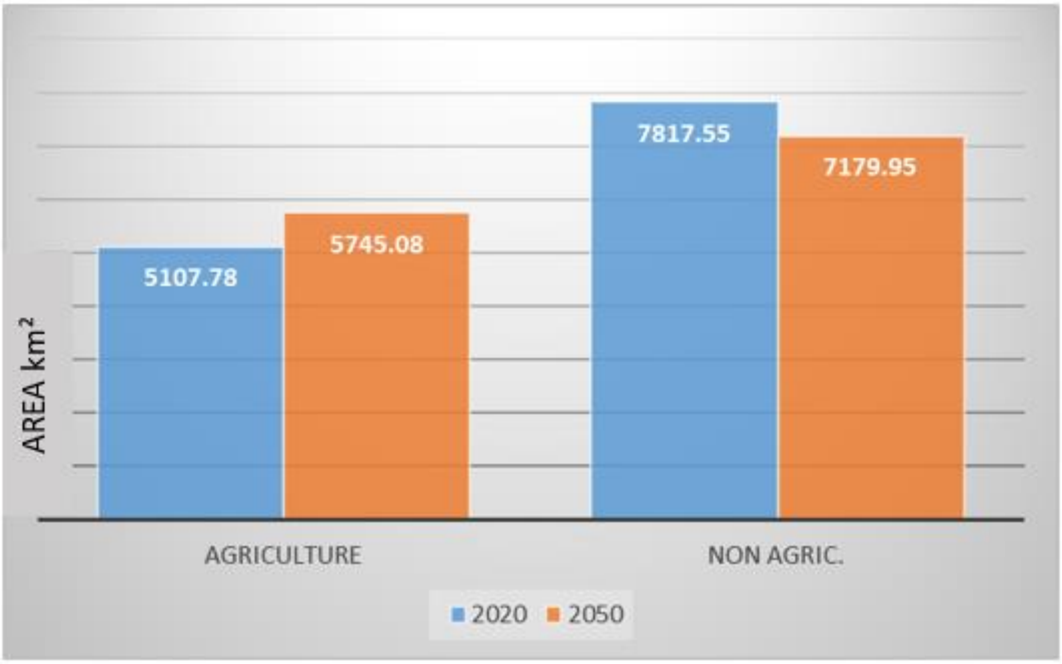

Figure 13: Predicted agricultural land use land cover and non-agricultural land for the years 2020 and 2050

Agricultural expansion has been a significant factor in land use changes, with 86% of multiple change events being related to cropland or pasture/rangeland (Winkler *et al.*, 2021). The rate of agricultural land use change can be influenced by various factors, such as political regime shifts, disruptions in globalized supply chains, nature conservation incentives, and natural hazards and extreme events like droughts (Winkler *et al.*, 2021). The US has experienced export-led agricultural growth and associated land use change, with projected land use change from 2012 to 2050 under most scenarios being on the rise (Gurgel, Reilly and Blanc, 2021).The projected increases in land, water use, and yields are feasible, but this result needs to be evaluated in the context of sustainable agricultural practices (Doering and Sorensen, 2018)

Non-agricultural land is projected to decrease from 7,817.55 km² to 7,179.95 km² during the same period, a reduction of 8.2%. This decline suggests a shift in land use priorities, with non-agricultural land being converted for farming or other purposes. Non-agricultural land includes areas designated for urbanization, conservation, forests, grasslands, and other natural or semi-natural ecosystems. The reduction in non-agricultural land could be attributed to several factors, including the expansion of agricultural activities, urban sprawl, and infrastructure development (Seto et al., 2011; Bren d'Amour et al., 2017). Urbanisation usually competes with agricultural expansion, but in regions where food security is a priority, agricultural needs may take precedence over urban development (Lambin & Meyfroidt, 2011). Conservation efforts may struggle to respond to the pressures of agricultural expansion especially in areas with high population growth and limited arable land (Newbold et al., 2015).

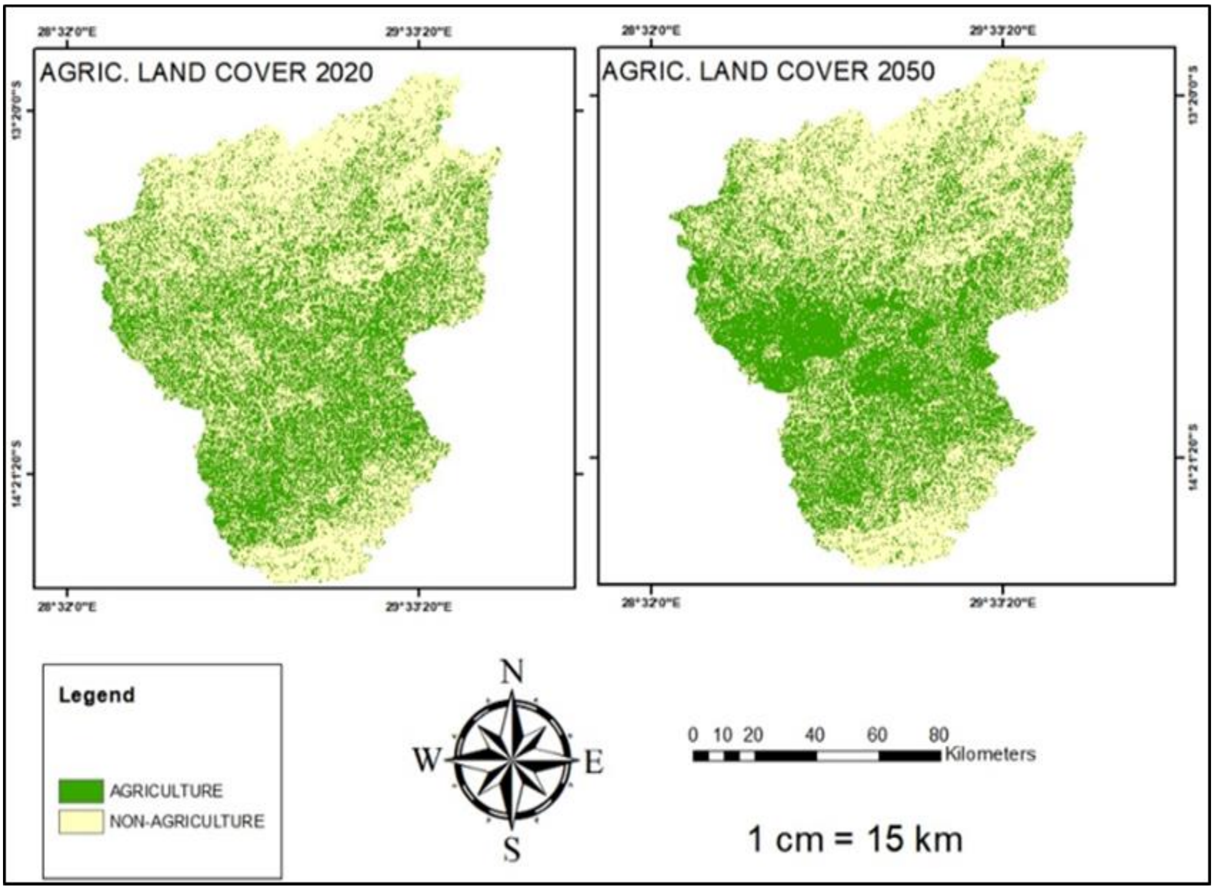

Figure 14: Classified 2020 agricultural land use map and Predicted 2050 predicted agricultural land cover map

These projected changes highlight a broader trend of increasing agricultural land use at the expense of non-agricultural land cover types. Agricultural expansion often leads to the conversion of forests, grasslands, wetlands, and other natural ecosystems (Foley et al., 2005;

Gibbs et al., 2010). Such changes often have ecological consequences including habitat loss, reduced biodiversity and disruptions to ecosystem services such as carbon sequestration, water regulation and soil fertility (IPBES, 2019). For example, the conversion of grasslands to croplands can reduce the availability of grazing land for livestock impacting both biodiversity and local livelihoods (Bardgett et al., 2021). Similarly, the drainage of wetlands for agriculture can disrupt hydrological cycles and increase the risk of flooding (Davidson, 2014).

Appendix 2 contains the paper published based on the findings of this research. The paper is based on “Temporal dynamics on Agricultural land use trends using CA-ANN model in an intensively cultivated catchment: Upper Lunsemfwa” is under review in the journal of Physics and applied sciences-Heliyon.

CHAPTER SIX: CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

According to this study the Upper Lunsemfwa River Catchment has 5 main types of LULC namely; forest, grassland, agriculture, water and built-up. Agriculture being the major land cover this could be due to the available water resources in the area. From 1990 and 2020:

a) Forest and grassland decreased, this could be due to conversion to agricultural land or built up areas

b) Agriculture indicates intense production for food demands and is a key driver of LULCC in the upper Lunsemfwa river catchment.

c) Water body areas variations could be due to human interventions such as damming or water extraction practices for agriculture production

d) Relative changes and reduction on built up was likely due to similarities in spectral reflectance with agricultural fields and bare land.

e) Minimal changes in water bodies may indicate a stress on the resource and could be due to construction of dams/reservoirs or climatic reasons

Observed trend of agricultural expansion and a corresponding reduction in non-agricultural land over the decades in the Lunsemfwa River catchment could lead to disruption of local and regional land and water cycles and pressure on water resources.

The study demonstrates the application of CA-ANN algorithm to predict historic, current and future changes in the Upper Lunsemfwa Catchment. The observed trend of agricultural expansion and a corresponding reduction in non-agricultural land over the decades in the Lunsemfwa River catchment could lead to disruption of local and regional water cycles and put pressure on limited water resources, especially in regions with scarce freshwater supplies because as more land is converted to cropland, the need for irrigation water increases to support crop growth and productivity leading to reduced groundwater recharge and increased risks of droughts and floods. This will likely lead to loss of biodiversity and disturb ecosystems in the Upper Lunsemfwa River Catchment. As Agriculture development grows to increase production for consumption and income generation the natural forests and grasslands reduces posing a threat to the environment.

Potential trend of increased agricultural land use at the expense of other non-agricultural land cover types, shows a shift or expansion in land use patterns between agric. land and non-agric. land from 2020 to 2050. As agricultural production grows to increase production for consumption and income generation the natural forests and grasslands reduces posing a threat to the environment.

6.1 Recommendations

Based on the findings of this study, the following recommendations are proposed to address land use and land cover challenges in the Upper Lunsemfwa River Catchment (ULRC) and promote sustainable development:

1. **Develop a Comprehensive Land Use and Land Cover Management Strategy**: There is an urgent need to establish a robust land use and land cover management strategy, policy, or plan for Zambia. Strengthening existing policies and institutional frameworks will help regulate agricultural expansion, promote sustainable land and water management, and ensure a balanced distribution of land use types. This strategy should aim to mitigate forest and grassland losses in the ULRC. Effective implementation will require collaboration among key stakeholders, including the Ministry of Agriculture, Ministry of Water Development, Ministry of Green Economy, the Zambia Environmental Management Agency (ZEMA), the Water Resources Management Authority (WARMA), the National Remote Sensing Centre of Zambia, and other relevant organizations.
2. **Strengthen Land Use Monitoring Systems**: Monitoring systems to track land use and land cover changes over time should be enhanced. Advanced tools such as machine learning algorithms, including the CA-ANN model, can be utilized to predict future trends and provide data-driven insights for informed decision-making. This will enable proactive management of land use changes and their environmental impacts.
3. **Promote Sustainable Agricultural Practices**: Encourage farmers and stakeholders to adopt sustainable agricultural practices such as conservation agriculture, agroforestry, and crop diversification. These methods can improve agricultural productivity while minimizing environmental degradation, reducing soil erosion, and conserving water resources. Sustainable practices will help balance agricultural expansion with environmental preservation.

4. **Integrate Climate Predictions with Land Use Analysis**: Future predictions of land cover changes and agricultural expansion should incorporate climate change scenarios to better understand the dynamics of change, particularly regarding water bodies. Comparing land use projections with climatic predictions will provide a more comprehensive understanding of how climate variability and land use interact, enabling more effective planning and resource management.

5. **Assess Livelihood Impacts of Land Use Changes**: Further research is needed to analyze the impacts of land use changes on local livelihoods, particularly the effects of agricultural expansion and the reduction of forest and grassland areas. This can be achieved through methods such as questionnaires and focus group discussions with communities in the study area. Understanding these impacts will help design interventions that support both environmental sustainability and socio-economic well-being.

By implementing these recommendations, Zambia can achieve a more balanced and sustainable approach to land use and land cover management, ensuring the preservation of natural resources, the protection of ecosystems, and the improvement of livelihoods in the Upper Lunsemfwa River Catchment and beyond.

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APENDICES

APENDIX A: Ethical Clearance Letter

THE UNIVERSITY OF ZAMBIA

DIRECTORATE OF RESEARCH INNOVATION AND DEVELOPMENT

Great East Road Campus | P.O. Box 32379 | Lusaka10101 | Tel: +260-211-290 258/291 777
Fax: (+260)-211-290 258/253 952 | **E-mail**: director.drgs@unza.zm | Website: www.unza.zm

APPROVAL OF STUDY

IORG No. 0005376
NASRECREC IRB No. 00006465
REF NO. NASREC: 2025-MAR-004

28th March, 2025

Ms Natasha Zulu
The University of Zambia
P.O. Box 32379
LUSAKA

Dear Ms Zulu

RE: "ASSESSING AGRICULTURAL EXPANSION; A CASE STUDY OF THE LUNSEMFWA RIVER CATCHMENT"

Reference is made to your protocol captioned above. The NASREC resolved to approve this study and your participation as Principal Investigator for a period of one year.

REVIEW TYPE	ORDINARY REVIEW	APPROVAL NO. NASREC-2025-MAR-004
Approval and Expiry Date	Approval Date: 28th March, 2025	Expiry Date: 27th March, 2026
Protocol Version and Date	Version - Nil.	27th March, 2026
Information Sheet, Consent Forms and Dates	• English.	To be provided
Consent form ID and Date	Version - Nil	To be provided
Recruitment Materials	Nil	Nil
Other Study Documents	Questionnaire.	

Specific conditions will apply to this approval. As Principal Investigator it is your responsibility to ensure that the contents of this letter are adhered to. If these are not adhered to, the approval may be suspended. Should the study be suspended, study sponsors and other regulatory authorities will be informed.

CONDITIONS OF APPROVAL

- No participant may be involved in any study procedure prior to the study approval or after the expiration date.
- All unanticipated or Serious Adverse Events (SAEs) must be reported to NASREC within 5 days.
- All protocol modifications must be approved by NASREC prior to implementation unless they are intended to reduce risk (but must still be reported for approval). Modifications will include any change of investigator/s or site address.
- All protocol deviations must be reported to NASREC within 5 working days.
- All recruitment materials must be approved by NASREC prior to being used.
- Principal investigators are responsible for initiating Continuing Review proceedings. NASREC will only approve a study for a period of 12 months.
- It is the responsibility of the PI to renew his/her ethics approval through a renewal application to NASREC.
- Where the PI desires to extend the study after expiry of the study period, documents for study extension must be received by NASREC at least 30 days before the expiry date. This is for the purpose of facilitating the review process. Documents received within 30 days after expiry will be labelled "late submissions" and will incur a penalty fee of K500.00. No study shall be renewed whose documents are submitted for renewal 30 days after expiry of the certificate.
- Every 6 (six) months a progress report form supplied by The University of Zambia Natural and Applied Sciences Research Ethics Committee as an IRB must be filled in and submitted to us. There is a penalty of K500.00 for failure to submit the report.
- When closing a project, the PI is responsible for notifying, in writing or using the Research Ethics and Management Online (REMO), both NASREC and the National Health Research Authority (NHRA) when ethics certification is no longer required for a project.
- In order to close an approved study, a Closing Report must be submitted in writing or through the REMO system. A Closing Report should be filed when data collection has ended and the study team will no longer be using human participants or animals or secondary data or have any direct or indirect contact with the research participants or animals for the study.
- Filing a closing report (rather than just letting your approval lapse) is important as it assists NASREC in efficiently tracking and reporting on projects. Note that some funding agencies and sponsors require a notice of closure from the IRB which had approved the study and can only be generated after the Closing Report has been filed.

- A reprint of this letter shall be done at a fee.

- All protocol modifications must be approved by NASREC by way of an application for an amendment prior to implementation unless they are intended to reduce risk (but must still be reported for approval). Modifications will include any change of investigator/s or site address or methodology and methods. Many modifications entail minimal risk adjustments to a protocol and/or consent form and can be made on an Expedited basis (via the IRB Chair). Some examples are: format changes, correcting spelling errors, adding key personnel, minor changes to questionnaires, recruiting and changes, and so forth. Other, more substantive changes, especially those that may alter the risk-benefit ratio, may require Full Board review. In all cases, except where noted above regarding subject safety, any changes to any protocol document or procedure must first be approved by NASREC before they can be implemented.

Should you have any questions regarding anything indicated in this letter, please do not hesitate to get in touch with us at the above indicated address.

On behalf of NASREC, we would like to wish you all the success as you carry out your study.

Yours faithfully,

Dr. Mususu Kaonda

CHAIRPERSON
THE UNIVERSITY OF ZAMBIA NATURAL AND APPLIED SCIENCES RESEARCH ETHICS COMMITTEE - IRB

cc: Director, Research and Development
Assistant Director, Research Support and Grants
Manager, Research Administration and Support
Ethics and Affiliation Officer

APENDIX B: Paper Submitted and Under Review

Heliyon

Temporal dynamics of agricultural land use trends using CA- ANN Model in an intensively cultivated catchment: Upper Lunsemfwa

--Manuscript Draft--

Manuscript Number:	HELIYON-D-24-68238
Article Type:	Original Research Article
Section/Category:	Physical and Applied Sciences
Keywords:	CA- ANN; Landsat; MOLUSCE; Lunsemfwa River Catchment
Manuscript Classifications:	90.140: Environmental Analysis; 90.150: Environmental Assessment; 90.230.130: Natural Resource Management; 90.230.140: Sustainable Development; 100.140: Remote Sensing; 140.280: Conservation
Corresponding Author:	Natasha Zulu, Bachelor's University of Zambia Lusaka, Lusaka ZAMBIA
First Author:	Natasha Zulu
Order of Authors:	Natasha Zulu
	Kawawa Banda
	Annie Kalusa
	Ethel Mudenda
	Imasiku Nyambe
Abstract:	Understanding the dynamics of land use and land cover (LULC) is essential for analysing and assessing long-term land transformations. These changes in LULC primarily result from deforestation, which involves the conversion of forests into other LULC types such as agricultural land. The literature at catchment level on agricultural past, present and future temporal trends is insufficient, and more research is needed to assess the trends at like the upper Lunsemfwa Catchment in Zambia. The main objective of this study was to evaluate the past, present and future extent of agricultural trend. This was done by using Landsat 5 and 8 images for the years 1990, 2005 and 2020 from climate engine. IDRISI was used to classify land use land cover changes using maximum likelihood supervised classifier. To predict future land use land cover change and agricultural expansion for 2050 Cellular Automata- Artificial Neural Network (CA-ANN) model in MOLUSCE plugin of OGIS. The findings showed that from 1990 to 2020 there was a -10.3% decrease in forest and a 25.9% increase in agriculture land, accompanied by minimal changes of -0.4% in water bodies, and a decrease in built-up areas from 3.2% to 1.9% and 68% to 54.01% in grasslands. From 2020 to 2050, the agricultural land is expected to increase from 5,107.78 km2 to 5,745.08 km2. The observed trend of agricultural expansion and reduction in non-agricultural land in Lunsemfwa River catchment could lead to disruption of already limited local and regional water resources. Water resources management for intensively cultivated catchments thus must be sensitive to potential conflicts of reduced water availability and access as a limiting factor to support and sustain food security.
Additional Information:	