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ANALYSIS OF LAND USE AND LAND COVER CHANGE DYNAMICS AND ITS IMPLICATIONS ON NATURAL RESOURCES IN DEDZA DISTRICT, MALAWI

by

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Analysis of land use and land cover change dynamics and its implications on natural resources in Dedza District, Malawi

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Declaration

I, **Maggie Golie Munthali**, declare that the thesis, which I hereby submit for the doctoral degree in Geography at the University of Pretoria, is my own and original work and has not previously in its entirety or in part submitted by me for a degree at this or any other tertiary institution for obtaining any qualification

01/02/2020

M.G. Munthali

Date

Disclaimer

The thesis primarily adopts the publication style of writing. The study consists of seven (7) chapters with four (4) objectives and it is intended that all the objectives would be published. Consequently, three articles have been published in peer-reviewed journals; the three articles cover objectives 1, 2 and 4. The third objective is accomplished in the 3rd paper which is currently under review.

To this end, the content and style of presentation may vary or overlap between chapters in this thesis in order to meet the specific journal requirements. There might also be repetitions of the methodology and some results sections of the 4 papers because the papers were published in different journals.

Some of the publications have more than four authors, but this does not mean that the work was done proportionately. Work in these publications is solely my effort and originally initiated by me as a principal investigator.

Dedication

I dedicate this research study to my mum, Ms. Grace Phiri, a woman of substance and Dad, Lawrence K. Munthali who have contributed to the person that I am today and every accomplishment I have achieved.

Acknowledgments

First and foremost, I am grateful to the Almighty God for keeping me in good health, all the blessings and guiding me throughout the study period (Isaiah 58:11).

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List of Abbreviations and Acronyms

AVHRR	Advanced Very High-Resolution Radiometer
ENVI	Environmental for Visualizing Images
ERDAS	Earth Resource Data Analysis System
ESRI	Environmental Systems Research Institute
ETM+	Enhanced Thematic Mapper Plus
FAO	Food and Agricultural Organization
FDGs	Focus Group Discussions
GDP	Gross Domestic Product
GIS	Geographic Information System
GoM	Government of Malawi
IMF	International Monetary Fund
IPCC	Intergovernmental Panel on Climate Change
Ha	Hectare
Kg	Kilogram
LULC	Land use and land cover
MSS	Multispectral Scanner System
NGOs	Nongovernmental Organization
NSO	National Statistical Office
PCC	Post Classification Comparison
RS	Remote Sensing
SPOT	Satellite Probatoire d'Obsersation de la Terre
SPSS	Statistical Package for Social Sciences
SSA	Sub Saharan Africa
TM	Thematic Mapper
UNDP	United Nations Development Programme
UNEP	United Nations Environment Programme
UTM	Universal Traverse Mercator

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ABSTRACT

Changes in land use and land cover (LULC) attributed to anthropogenic activities are one of the fundamental drivers of environmental changes at the local, regional and global levels. These changes continue to threaten the capacity of the ecosystems to function and provide environmental goods and services and the ability to sustain the livelihoods of rural communities. Therefore, a critical understanding of LULC patterns and dynamics is crucial for predicting future LULC patterns and changes and formulation of appropriate policies, strategies and interventions for sustainable management of natural resources. Dedza district like any other district in Malawi has experienced rapid LULC changes over the past decades. However, knowledge about LULC changes that occur, where and when they occur and the rates at which they occur is not well documented. Equally important is the examination of the drivers and processes that cause these changes and the extent to which these LULC changes have impacted on natural resources and rural livelihoods in the studied area. As such, this remains a critical challenge that needs to be addressed in order to achieve sustainable natural resource management and community development. This study aimed to investigate the nature of LULC changes that have taken place between 1991 and 2015, drivers attributing to these changes and their impacts of these changes on the natural resources in Dedza district of Malawi. The study used a mixed-method approach consisting of remote sensing and Geographic Information System (GIS)-based analysis, model simulations, focus-group discussions, key informant interviews, and semi-structured interviews covering 586 households. An overall accuracy of the classification achieved for the classified images was 91.86%. GIS-based analysis of remotely sensed data revealed that the areas under agricultural land, forest area, wetlands, water bodies drastically decreased from 71.3% (267,977.43 ha), 24.53% (9,939.15 ha), 0.96% (3,626.73 ha), 0.37% (1,380.60 ha) in 1991 to 69.41% (260,879.31 ha), 1.66% (6,237.63 ha), 0.71% (2,680.29 ha) and 0.24% (899.55 ha) in 2015. On the contrary, barren land and built-up areas substantially increased from 24.53% (92,185.38 ha) and 0.20% (761.67 ha) in 1991 to 25.85% (97,174.62 ha), 2.13% (7,999.56 ha) in 2015 respectively. Significant differences were found among the interviewed households in perceptions regarding LULC changes taken place in the studied landscape and distance to different infrastructures such as main roads, health centres, schools, and towns ($p < 0.001$). The results of the household surveys indicated that the local communities were aware of the LULC dynamics and validated the observed changes. Firewood collection, charcoal production, population growth, and poverty were identified as the key drivers of observed LULC changes in the study area. Local communities perceived that LULC changes led to a decline in agricultural land (57.3%, n = 586), crop production (82.8%, n = 586) and forest cover (87.4%, n = 586) and an increase in the distance to forest resources (50.7%, n = 586). These changes exposed rural households to major shocks such as drought, floods, food shortage, loss/damage of crops and death of household members. In order to address these shocks, communities were engaged in short-term strategies such as piecework, receiving aid from government and NGOs, receiving unconditional aid from relatives, relying on their own savings and credits. The simulation results using the CA-Markov model showed that water bodies, barren land and built-up areas will increase while agricultural land, wetlands and forest land will substantially decrease by 2025 and 2035. The undesired LULC changes, patterns and impacts observed in this study, however, pose a big threat and risk to the sustainable management of natural resources and rural livelihoods survival. Hence, the need for urgent attention by the natural resource managers, planners, researchers and decision-makers. The results found in this study are deemed useful in guiding planners and decision-makers in the field of land management and policy development towards a more sustainable natural resource management strategy in Dedza district. Results found in this study could also inform decision-making in other districts of similar settings. Thus, results of the study are expected to support decision-makers and planners in the design and implementation of holistic, tenable and coherent and sustainable development policies/strategies/ guidelines for effective natural resource management

Key words: LULC dynamics; drivers; CA-Markov; Modelling; Malawi

CHAPTER 1: GENERAL INTRODUCTION

1.1 Background Information

Land use and land cover (LULC) changes are considered as one of the most significant components of the terrestrial environment system (Lin et al. 2009) and one of the main challenges affecting the natural landscape at the local, national and global level. They are the major drivers of global environmental change; vital to the sustainable development imperatives and affect many parts of human-environment systems (Lambin et al. 2000). In recent decades, scientists have emphasized the importance of incorporating LULC change studies in investigating climate change since it is evidenced that climate can affect and be affected by changes in the condition and composition of LULC (Foley et al. 2005; IPCC 2011; Sleeter et al. 2018). The LULC changes, thus, intrinsically modify the sustainability of different biophysical resources including water, vegetation, forests, soil and agriculture resources. Consequently, there are instances where LULC changes lead to decreased availability of different products and services for agricultural and livestock production while land-use dynamics have also been linked to other detrimental impacts on the environment. The causes and consequences of land-use change on the environment have been an important area for research over the decades (Veldkamp and Verburg 2004). These include their impact on natural resources, water quality, ecosystem processes and functions, global warming and increase in natural disasters like flooding (Lambin et al. 2000); deforestation and biodiversity loss (Dwivedi et al. 2005; Mas et al. 2004; Zhao 2004), soil degradation (Trimble and Crosson 2000) and the ability of natural systems to support life (Vitousek et al. 1997).

According to Bielli et al. (2001), there is a growing concern that most of Sub-Saharan Africa's (SSA) ecological environment and natural resources are depleting primarily due to LULC dynamics. It is affirmed that the LULC pattern of any region is an outcome of natural and socio-economic factors and their utilization by man in time and space (Su et al. 2011). These changes have both beneficial and undesired impacts on the natural resource base which at times also lead to high environmental costs and in turn affect human' well-being. Historically and in contemporary context,, changes in LULC have been seen as key drivers of land-related conflicts which have contributed to increasing vulnerabilities and the undermining of existing livelihoods (Barnett and Adger 2007, Kagwanji 2009; Bob 2010) Information on LULC and its changes is, thus, an important element in forming economic, demographic and environmental issues at national, regional and global level (LTS International 2013).

Malawi like any country in the SSA region is endowed with a diversity of natural resources including diverse flora and fauna, fertile soils, forests, and abundant water (MNREE 2010). Unfortunately, many developing countries (Malawi included) are using their valuable natural resources such as land, water and forests at a faster rate than the natural rate of replacement to sustain the rural livelihoods and ever-growing population (Appiah et al. 2007; McNeill 2006; Subramanian 2018; UNEP 2019; Lampert 2019) . Like elsewhere, land is becoming a scarce natural resource in Malawi due to enormous agricultural and demographic pressure. It is worth noting that about 80% of the country's population depends on natural resources for their subsistence and household income. Nearly 90% of the population depend on fuelwood for energy (Fisher and Shively 2005). Studies carried out in the previous years convincingly confirm that Malawi has experienced LULC changes over the past decades (Haack et al. 2014; Palamuleni et al. 2010; Munthali and Murayama 2011). These changes are raising concerns on natural resources and climate change issues. For instance, studies from elsewhere show that changes in LULC does not only reflect anthropogenic activities but also significantly impacts climate by altering the physical characteristics of the earth's surface (Bonan 2008; Pitman et al. 2009; Davin and Nobletducoudré 2010; Ryoji et al. 2011; Pathirana et al. 2014). In order to understand how LULC changes impact global earth systems, information is needed about what changes occur; where they occur, the rate at which they occur and the drivers of these changes (Lambin et al. 2003). In addition, quantifying changes in the natural landscape is imperative for gaining an understanding of the spatial and structural variability in land use and their associated ecological effects (Turner et al. 2003). In other words, comprehensive information on the spatial distribution of the LULC changes is an important requirement for the selection, planning, utilization and management of natural resources to meet the increasing demands for basic human needs and welfare. The available data on LULC changes provides critical input to environmental conservation, planning, management and monitoring of natural resource base (Fan et al. 2007; Prenzel 2004) and in monitoring the dynamics of land use as a result of changing demands of the ever-increasing population.

Remote Sensing (RS) and Geographical Information System (GIS) have been the most adequate tools used for provision of repetitive, synoptic, detailed, accurate, consistent, cost-effective and timely data for the characterization of LULC. These tools are also used for monitoring the environment and, hence, comprehension of the influence of anthropogenic activities on the natural resource base (Carlson and Azofeifa 1999; Guerschman et al. 2003; Rogana 2004; Zsuzsanna 2005). They are also providing new tools for advanced ecosystem management. The RS and GIS approaches have added a new dimension to the understanding of LULC changes as well as urban landscape (Liu et al. 2005; Yuan et al. 2005; Wu et al. 2006: Jat et al. 2008). Multi-temporal remote sensing satellite data such as Landsat Thematic Mapper (TM) images have been used to monitor spatio-temporal and dynamic changes of LULC at regular intervals (Kamanga et al. 2009; Singh et al. 2015; Agidew and Singh 2017). These LULC changes are of importance in the field of environmental change (Lambin et al. 2001; Turner et al. 2003). Similarly, GIS provides the platform on which data of such images are stored, processed and analyzed for decision making. As a result, the use of RS and GIS has become an important aspect of visualizing LULC changes in order to put proper interventions in place (LTS International Report 2013).

Dedza district like any other district in Malawi has experienced tremendous modifications in terms of LULC over the past decades. There is however general lack of accurate and up-to-date information on LULC changes in the district. This calls for accurate, detailed and up-to-date spatial data that can be used for informed management decisions by natural resource managers and other decision-makers. This study, therefore, assesses the LULC changes and their implications on natural resources from 1991 to 2015 in Dedza district. It will further predict/forecast possible changes that might take place in the study area in the next 30 years by using the CA-Markov model imbedded in IDRISI software and finally recommend appropriate interventions for Dedza District.

1.2 Problem statement and rationale of the study

For the past decades, Dedza District like any other district in Malawi has witnessed significant expansion, growth and developmental activities such as housing and road construction, deforestation and many other anthropogenic activities. The rapid and accelerating population and increasing socio-economic necessities in the district have created pressure on natural resources and the environment in general. This pressure usually results in unplanned and uncontrolled changes in LULC (Seto et al. 2002). The LULC changes are usually caused by unsustainable management of natural resources such as agricultural, urban, range and forest lands which lead to severe environmental problems such as biodiversity loss, deforestation and soil degradation (Lambin et al. 2001;Maitima et al. 2010; Kamwi et al. 2015).

Additionally, the population growth and increasing socioeconomic activities in Dedza district have resulted in increased land consumption and alterations in the status of its LULC over time without any proper planning. To date, some attempts have been made to document the extent of growth of Dedza district, but information on the LULC changes that have taken place over the past decades remains sparse. In the context of Dedza, insights and knowledge about the nature of LULC changes that occur, where and when they occur and the rates at which they occur is requisite. Equally important is the need to document the drivers and processes that cause these changes in the district. In recent times, the dynamics of LULC and particularly settlement expansion in the area requires techniques used in the field of GIS and RS to provide a general extensive synoptic coverage of large areas rather than aerial photography. Thus, data on LULC changes are needed to detect the land consumption rate and predict the possible future changes that may occur in the study area so that planners can have a basic tool for planning.

A number of studies have been undertaken at the national level by Food and Agriculture Organization (FAO) and LTS International to assess the LULC changes using only satellite imagery analysis (LTS International 2013). These studies have highlighted concerns about LULC changes but there is a general lack of attempts towards examining the drivers and impacts of these changes on natural resources, the environment and the livelihoods of local communities. In other words, these studies did not look at LULC change modelling over time and its associated drivers. It should be noted that satellite imagery analysis in isolation does not reveal the underlying drivers of LULC changes. Therefore, this study employed an integrated approach utilizing RS, GIS and local communities' perceptions in establishing the drivers and impacts of LULC changes taking place in the studied landscape.

Knowledge of the interface between LULC changes, natural resource management and rural livelihoods that are required to undertake proper and coherent adaptation strategies and prioritizing management actions is generally lacking. It is, therefore, necessary for a study on the analysis and modelling of LULC changes and its implications on natural resources to be carried out in Dedza District. This study could be used to provide insights on the possible directions of changes and strategies aimed at the drivers of these changes and critically devise sustainable mitigation measures of anticipated critical impacts. Thus, the assessment of land cover for a specified period of time is very crucial for monitoring and conservation management of a natural resource base. Studies on LULC changes improve the understanding of how humans interact with the environment which results into a scientific foundation for dealing with issues related to sustainability, vulnerability and resilience of land systems and their benefits to humans (Wang 2010). Consequently, up-to-date LULC maps and future projections of LULC changes information generated in this study could be used by natural resource managers, researchers, planners and policymakers in the studied landscape for resource inventory and designing appropriate interventions for improved use and sustainable management of natural resources both in short and long-term. Further, it will contribute to a better understanding of how the LULC changes have impacted the local communities and the coping strategies used to counter the shocks exposed to them as a result of these changes.

1.3 Aim

The aim of the study is to capture historical, current and future trends in LULC changes in order to understand their implications on natural resources and rural livelihoods in Dedza district, Malawi.

1.4 Objectives

The objectives of the study are:

i. To assess the land use and cover changes that have taken place between 1991 and 2015 in Dedza District.
ii. To establish the major driving forces/causes of LULC changes in the study area.
iii. To assess the implications of the LULC changes on natural resource availability in the study area.
iv. To predict/forecast the future pattern of land use and land cover changes in the study area by using the CA-Markov model.

1.5 Research Questions

The following research questions shall be used to achieve the objectives of this study:

i. What is the extent and magnitude of the land use/cover changes that have taken place between 1991 and 2015 in Dedza District?
ii. What are the major driving forces/causes triggering LULC changes in the study area?
iii. Are the land use/land cover changes taken place between 1991 and 2015 have implications on resources and rural livelihoods in the study area?
iv. What will be the future pattern of land use and land cover changes in the study as predicted by CA-Markov model?

1.6 Malawi and Dedza District in Perspective

1.6.1 Malawi

Malawi is a landlocked country in southern Africa sharing common borders with Zambia, Tanzania and Mozambique (Figure 1.1). It covers an area of 118,484km^2. Lake Malawi which is the biggest lake in Malawi and the third largest lake in Africa covers about one-fifth of the country's total area. The country is divided into three administrative regions (Northern, Central and Southern Regions) with four main cities, Blantyre and Zomba, Lilongwe and Mzuzu. The estimated population in 2018 was 16.1 million people, making it one of the most densely populated countries in Africa (GoM 2019). About 80% of the Malawian population lives in rural areas and depends on subsistence farming for their livelihoods. The Malawian economy is relatively small and the nation relies on sizable economic assistance from the International Monetary Fund (IMF), World Bank and individual donor countries (FAO 2016). Agriculture is the most essential sector of the economy accounting for one-third of GDP and 80% of export revenues.

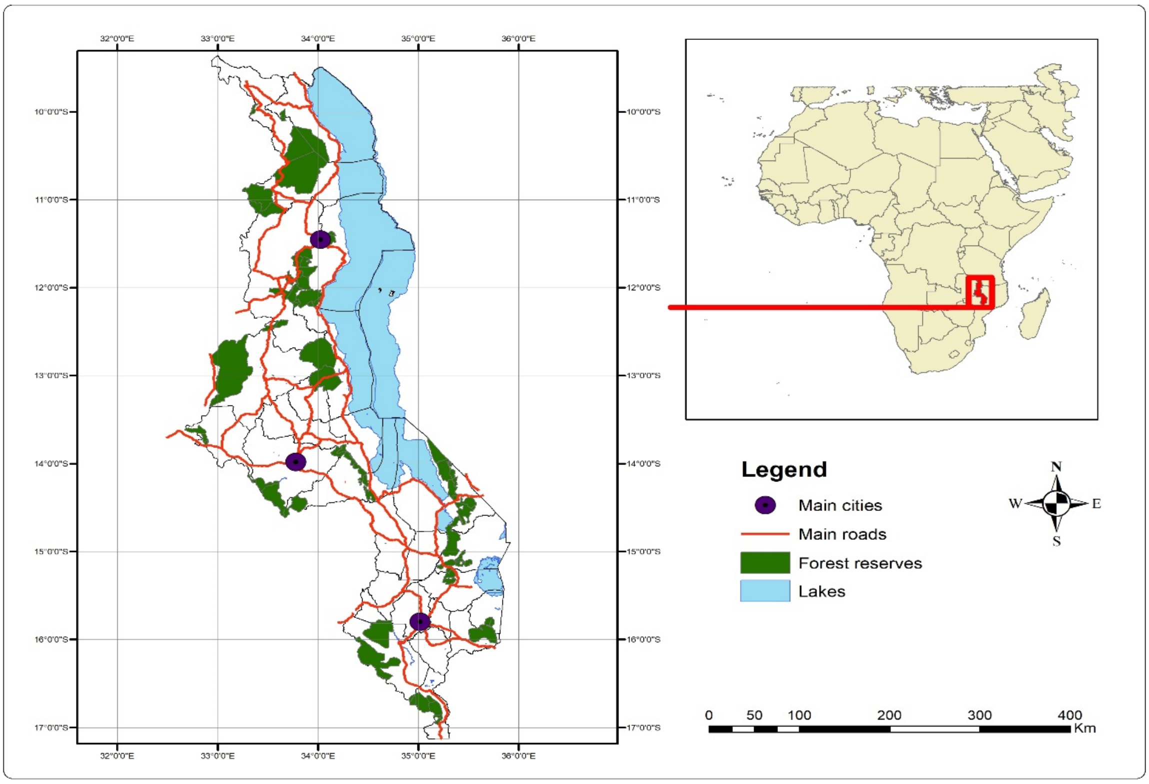

Fig. 1.1 Map of Malawi

1.6.2 Dedza District

1.6.2.1 Location and Size

Dedza District is located in the Central Region of Malawi about 86 km south of Malawi's capital, Lilongwe. It is the third-largest district in Central Region covering a total land area of 3,624 km² (Government of Malawi 2013). It borders Lilongwe district to the north, Salima district to the North East, Mangochi district to the West. Figure 1.2 displays the map of Dedza district.

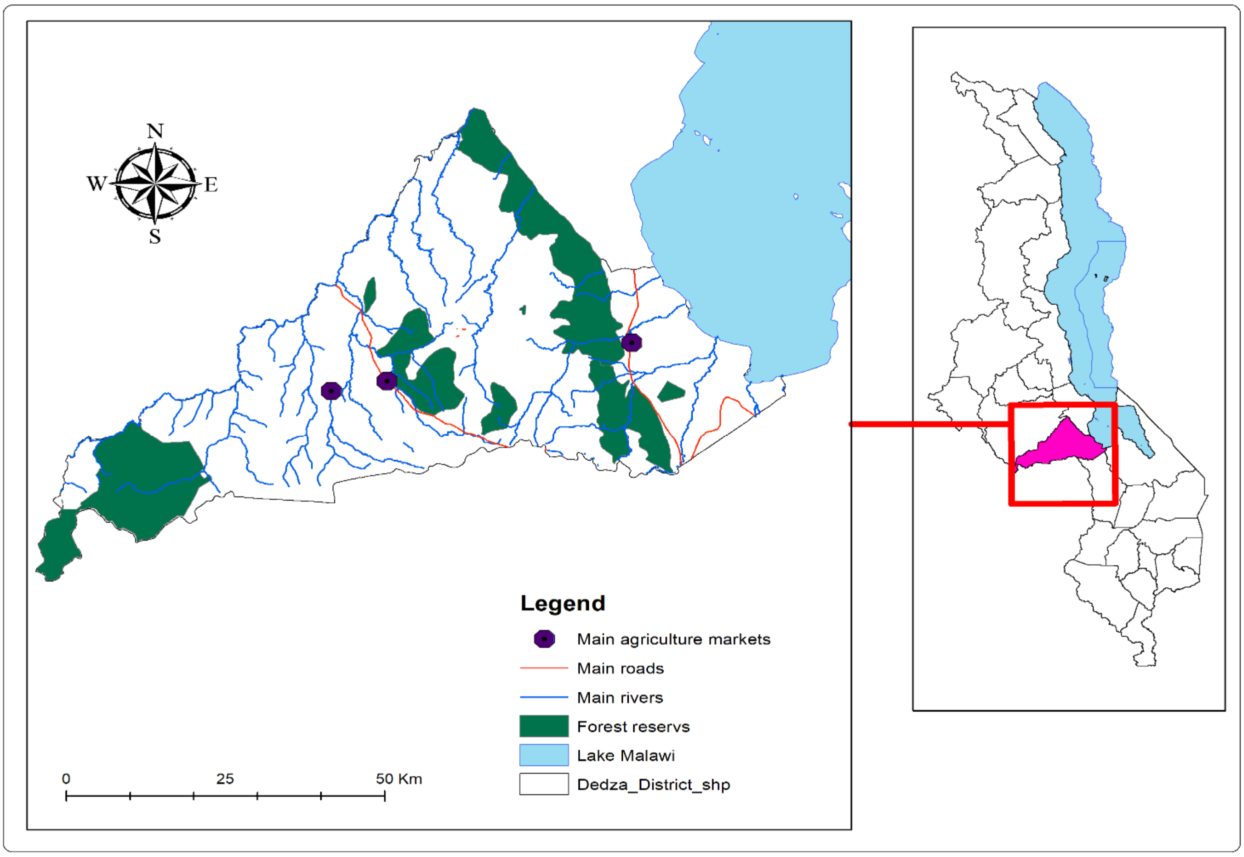

Fig. 1.2 Map of Dedza District showing Traditional Authorities

1.6.2.2 Topography, Geology and Hydrology

Dedza district is divided into three topological zones which are Lilongwe plain in the northern and western parts of the district, the Dedza highlands which are Kirk Range and Dzalanyama range in the western part of Dedza escarpments and the Dedza escarpment. These three zones are located on an altitude of 1100m-1300 m, 1200m-2200m and 1000m-1500m above the sea level respectively. Topography varies from rolling slopes to plains varying between 13-55 degrees (Government of Malawi 2013). Minerals have not yet been discovered in the district except for quarry and sand excavation at Chongoni forestry hills (Government of Malawi 2013).

The district is endowed with rivers which include Linthipe River originating from Dzalanyama Ranges (Dedza) and runs through Dedza, Lilongwe and Salima districts. Linthipe

River joins the Diampwe II River which drains the area to the west and then turns north-eastwards towards Lake Malawi. Both Linthipe and Diampwe are perennial. The South Lilongwe Plain is drained mainly by a system of broad dambo and sluggish streams. Streams to the north-east of the Tuma-Nkhoma-Lilongwe road drain into the Lilongwe River system and the north-central part of the area is drained by the Lifisi River system. Lifisi is a perennial river that flows north-eastwards joining the Linthipe River just before it reaches the lake near Salima. The eastern parts of the area are drained by a large number of fairly short streams and rivers with small catchment areas which flow eastwards either directly onto the Lakeshore Plain or into the Livelezi River. The most important of these are the Balitsa, Naminkokwe, Nadzipokwe, Nadzipulu and Ngodzi rivers.

1.6.2.3 Soils

The various parts of the district are predominated by Clay loam and sandy loam soils (Government of Malawi 1999). The soils are moderately deep and well-drained, brown to reddish-brown in colour and coarse to fine texture especially in the lower escarpments (600-1200 m above sea level) and upper escarpments (700-1500 m above sea level).

1.6.2.4 Climate

Dedza district experiences a cool climate with mean annual temperatures ranging from 14ºC to 21ºC. The lowest temperatures are experienced in the months of June and July while the highest in November. Malawi has one long growing season in a year (October to April). The annual rainfall for Dedza District ranges from 800 to 1200mm falling between mid-November to mid-April (Government of Malawi 2013). According to Government of Malawi (1999), Dedza has experienced high rainfall variability over the past three decades. There was reported high rainfall between the 1988/89 season averaging at 1367mmp per annum. The lowest rainfall was experienced in the 1998/99 season averaging at 264mm per annum. The variations in rainfall patterns and increasing temperature over the recent past have resulted in extreme weather events especially floods and drought in the district.

1.6.2.5 Demography

According to GoM (2019), the initial results of the 2018 census of the district was 830,512 an increase of 33% over the 2008 population. Approximately 95.3% of the total population live in the rural areas. The annual population growth rate in the district for the years 2008-2018 is 2.8% which is lower than the regional and national 3.1% and 2.9% respectively. The predominant tribes in the district are Chewa, Ngoni and Yao. The majority of the people live in rural villages as subsistence farmers. Apart from a commercial rice-growing project at the side of Lake Malawi, agriculture is family-based smallholdings. Small enterprises include beekeeping, farming, and livestock keeping. Larger businesses are limited to Paragon Ceramics (floor and roof tiles, Dedza Pottery ceramics), WICO Sawmill and a rose grower.

1.6.2.6 Land Use and Tenure Systems

Dedza district is characterized by three major categories of land tenure systems namely customary, government (public) and private (leasehold) land tenure systems. In the customary land tenure system, the land is managed under the jurisdiction of the Traditional Authority whereby the land is granted to a person or group under customary land rights. The Government or public land is owned, occupied, held and used under the Land Act of 2016. The land is also clearly defined by the same Land Act. In Dedza district, the public land includes government infrastructures like Dedza Stadium, government schools and hospitals, national roads plus road reserves and many others. According to the Government of Malawi (2010), 30%, 48% and 22% of the total area in Dedza district are categorized as forest, agriculture and settlement and lake respectively. In a private system, the land that is registered under the Registered Land Act which is created either from customary land or Government land. The land under private tenure system can be leased up to 99 years for residential or commercial purposes and 21 years for agricultural purposes

1.6.2.7 Forests

The majority of forest resources in Dedza district are found in protected areas such as forest reserves and plantations and on customary land such as Village Forest Areas (VFAs), woodlots, graveyards and on farms. The forest reserves in Dedza are found on mountains and hills except one forest reserve located on the Lake Malawi Rift Valley. Forests on customary land are managed with the assistance of traditional leaders. Forests on customary land sit on open access areas, on hills, along river lines and on moderate gentle slopes. The customary land forest resources are in patches growing in graveyards, communal and individual woodlots, scattered trees on farms and clustered trees, shrubs and reeds/grass along river lines and degraded natural forests on hills demarcated as Village Forest Areas. The district has two government timber plantations namely

Dedza Mountain Plantation (2,046.23 ha) and Chongoni Plantation (5,270.0 ha), which are found within Dedza and Chongoni Forest Reserves respectively. Other forest reserves include; Dzalanyama, Mua-livulezi, Mua-tsanya, Msitolengwe, Dzenza and Dedza-Salima Escarpment Forest Reserves.

1.7 Key concepts and conceptual framework

As a stated outcome of this research inquiry is envisaged in terms of findings that would contribute to sustainable natural resource management in Dedza district of Malawi as depicted in Figure 1.3. The conceptual framework adopted represents a modified version of the framework introduced by Kindu (2017). The author developed a novel framework for an improved approach for sustainable land-use systems in Ethiopia. He studied landscape-level modelling and illustrated how geoinformatics techniques could be used to contribute to sustainable management, use and conservation of the resources of Munessa-Shashemene landscape of the Ethiopian Highlands. In this regard, Kindu (2017) used four (4) key components namely; 1) LULC changes, (2) understanding their drivers, (3) estimating and quantifying changes in ecosystem service values, and (4) modelling future LULC changes.

Using the insights gained by Kindu (2017), the key components of the conceptual framework for this study include (1) LULC changes; (2) Understanding LULC drivers (3) Impacts of LULC changes and (4) modelling future LULC which constitutes the main thematic areas of this study. Each of the components is dealt with thoroughly and structured as individual articles that constitute the chapters of this thesis (Chapters 3, 4, 5 and 6). These key concepts of the thesis are briefly described in the following;

(1) *LULC changes:* Ellis (2010) defines LULC changes as the modifications of the landscape within a specified time frame due to anthropogenic activities and natural causes. Studies on LULC are considered important for understanding many of the observed phenomena that are responsible for the changes. Consequently, knowledge of the spatio-temporal LULC changes is crucial for natural resource management, wildlife habitat protection, strategic environmental assessments and sustainable land use planning and other informed decisions by planners, researchers, policymakers and natural resource managers. Recently, RS and GIS have become important tools used for LULC change detection.

(2) *Drivers of LULC changes:* Studies have shown that LULC changes are a result of human activities and natural phenomena such as floods, forest fires, shortage of farmlands, unreliable rainfall, deforestation and in other cases poverty and population growth. Therefore, a deeper understanding of the LULC changes taken place in the study area and rural livelihoods coupled with the coping strategies is very crucial for land management, use, planning and decision-making.

(3) *Impacts of LULC changes:* LULC changes have deleterious effects on natural resources and rural livelihoods. For instance, LULC changes results into vegetation cover reduction, loss of biodiversity, low agricultural production, reduction and pollution of other natural ecosystem services and changes in hydrological regimes such lakes, rivers and wetlands (Niyogi et al. 2009). These impacts can be minimized if the informed decisions are made by different stakeholders to achieve sustainable natural resource management.

(4) *Modelling LULC changes:* Modelling LULC change has been considered as one of the valuable tools in ensuring that present natural resources guarantee the future and continuous supply of the natural resource base. Recently, researchers have developed and used several LULC change models/ approaches for modelling LULC dynamics. One such model is the CA-Markov model which is a robust approach for spatial-temporal dynamic modelling of LULC changes.

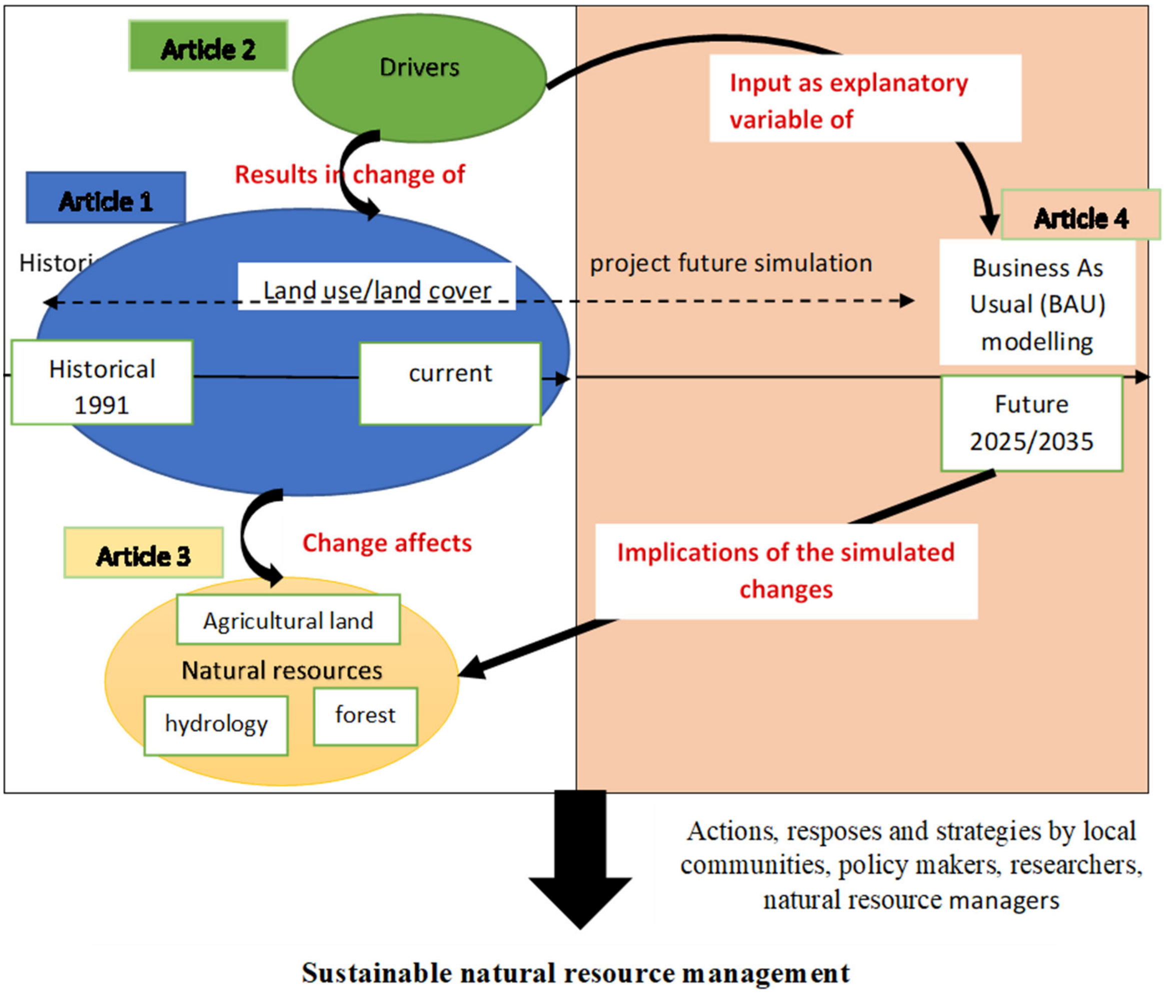

Fig. 1.3 The conceptual framework employed in this study (modified from Kindu 2017)

1.8 Organisation of the Thesis

The chapters in this study are structured following the format of the peer-reviewed journals in which the chapter was published or submitted. It consists of seven chapters as described below:

Chapter 1 introduces the general background and overview of the research. It sets out the justification, the research problem leading to the identification of the research objectives and the corresponding research questions. The chapter also provided information about the study area and key concepts and conceptual framework employed in this study.

Chapter 2 reviews existing literature on major themes of the research. Thus, it highlights the relevant literature related to the current study, specifically, the LULC studies undertaken in the SSA and elsewhere.

Chapters 3 to **6** have been prepared in accordance with the guidelines of the journals in which the papers were published or under review and this includes the citations and reference styling in these chapters. Specifically, chapter 3 focuses on the application of RS and GIS in detecting LULC changes for the period 1990, 2001 and 2015. This is Paper 1 addressing objective 1 of this study. **Chapter 4** presents the drivers of LULC changes. This is paper 2 (objective 2) and discusses the drivers contributing to the LULC changes reported in this study. It captures the implicit perceptions of local communities about the LULC changes and the perceived drivers of the changes. This was done through household surveys using a questionnaire, FGDs and key informant interviews**.** **Chapter 5** analyses the impacts of LULC changes on natural resources and rural livelihoods in the study area (Paper 3). It also highlights the shocks experienced by local communities and the strategies adopted to counter these shocks. This was achieved through household surveys using a questionnaire, FGDs and key informant interviews**. Chapter 6** presents the simulated future of the observed LULC (Paper 4). The CA-Markov model was used to predict future LULC changes.

Chapter 7 concludes by summarizing the key findings of the research. Thus, it provides the main conclusion of the research and its significant contribution to scientific knowledge. Finally, future research directions and recommendations are provided.

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CHAPTER 2: LITERATURE REVIEW

This chapter presents a short overview of the literature on the topic of LULC changes and key concepts used in the field study. The chapter highlights key trends and findings of international and regional levels studies where GIS and RS techniques have been used to assess LULC changes and patterns, impacts of these changes and stimulation of the future changes. Further, causes of these changes has been explored.

2.1 Land Use and land Cover Changes: concepts and definitions

Land use and land cover are closely related criteria and as such tend to be used interchangeably even though they are used to describe different aspects of the landscape (Fairbanks et al., 2000; Ellis 2013). Researchers, however, caution that differences in opinion about the distinction between these two terms exist. Land cover refers to the observed physical or biophysical cover on the earth' s surface including vegetation, bare soil, hard surfaces, water bodies and artificial structures (Di Gregorio and Jansen 2000; Brown and Duh 2004) According to Di Gregorio and Jansen (2000), social scientists and land managers characterize land cover more in general to involve the social and economic purposes of the land. On the other hand, natural scientists classify the term land use placing an emphasis on the different useful aspects of human activities upon land such as farming, forestry and man-made constructions. Turner et al. (1995) believe that land use involves both the manner in which the biological attributes of land are manipulated and the intent underlying that manipulation - the purpose of the land used. Di Gregorio and Jansen (2000) define land use as the intended use or utilization and management of land cover by human activities for the purposes of agriculture, forestry, settlement and pasture by altering land surface processes including biogeochemistry, hydrology and biodiversity. Land cover and land-use change refer to qualitative changes or shifts in structure and function and quantitative changes in the areal extent of a given type of land use or cover (Seto et al. 2002; Briassoulis 2003). According to Lambin et al. (2003), LULC changes can be broadly categorized into two types; conversion and modification. Basically, conversion refers to a shift from one LULC category to another while modification involves changes that affect the structure or function of the LULC type without changing its overall classification (Lambin et al. 2003; Mukete et al. 2017). Table 2.1 provides a schematic depiction of the distinction between land cover and land use as stipulated by Briassoulis (2000).

Table 2.1 Distinction between land cover types and associated land-use types

Types of land cover	Types of land use
Forest	Natural forest Timber production Recreation Mixed-use – timber production and recreation
Grassland	Natural area Pasture Recreation Mixed – pasture and recreation
Agriculture land	Cropland – annual crops Orchards, groves – perennial crops Recreation/tourism Mixed-use
Built-up land	City Village Archaeological site Industrial area Second-home development Tourism development Commercial area Transportation Mixed-use

Source: Adapted from Briassoulis (2000)

2.2 Land use and land cover change detection

Rogan and Chen (2004) define change detection as the process of determining and/or describing LULC changes at different times using remote sensing techniques. Eventually, it involves the ability to quantify the temporal effects using multi-temporal data sets. Lu et al. (2011) on the other hand stipulates that change detection involves quantitatively identifying the differences between multi-temporal data sets to see the dynamics of the phenomena of interest. According to Jensen (2005) and Lu et al. (2004), the LULC change detection procedure involves six major steps. These are the nature of change detection problem, selection of suitable remotely-sensed data, image preprocessing, image processing or classification, selection of change detection algorithms and evaluation of change detection results. Figure 2.1 depicts the summary of the LULC change detection procedure and main contents for each step as described by Lu et al. (2004).

Change detection is aimed at comparing the spatial representation of two points in time by controlling all variances caused by differences in the variables of interest (Green et al. 1994). Timely and accurate change detection of the earth's surface features provides the foundation for a better understanding of relationships and interactions between human and natural phenomena to better manage and use the resources (Lu et al. 2004). Change detection is considered an imperative process in monitoring LULC changes because it provides a quantitative analysis of the spatial distribution of the population of interest and this makes LULC study a topic of interest in remote sensing (Song et al. 2001; Gallego 2004). Therefore, Lu et al. (2004) suggest that a sound change detection research should provide the following indispensable information; area of change and change rate, the spatial distribution of changed types, change trajectories of land-cover types and accuracy assessment of detection results. The major source of data for change detection is geographic and usually in digital form such as satellite imagery; analog format (older aerial photos) and vector format (e.g. feature maps). Other ancillary data such as historic and economic data can also be used (Singh, 1989). Recently, remotely sensed data such as Landsat, Satellite Probatoire d'Obsersation de la Terre (SPOT), radar and Advanced Very High-Resolution Radiometer (AVHRR) have become the major data sources for different change detection applications because of their repetitive data acquisition, synoptic view and digital format for computer processing.

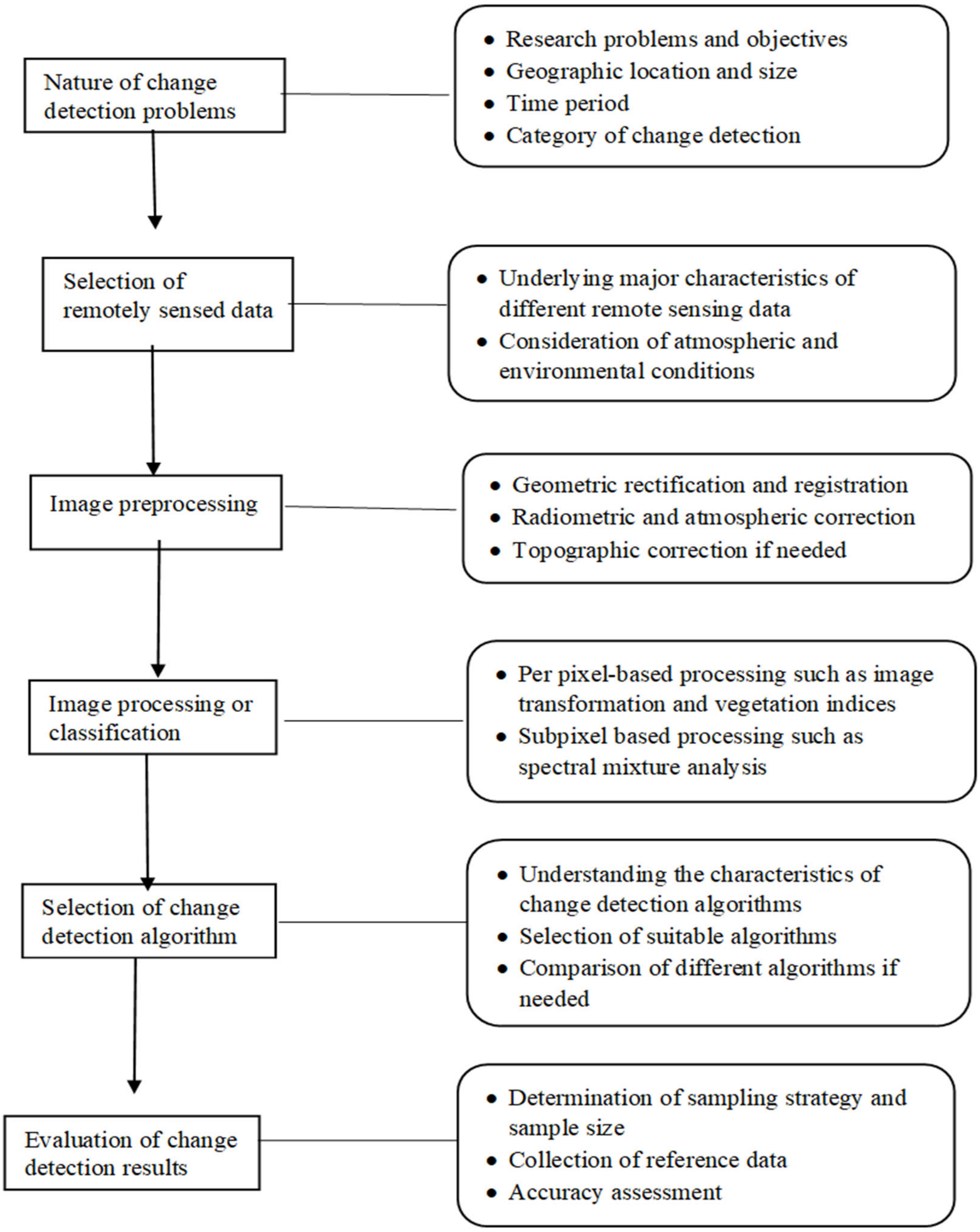

Fig. 2.1 LULC Change Detection Procedure and corresponding Main contents

2.2.1 Image Pre-processing

Image pre-processing involves the preparatory phase designed to improve the quality of the image features or data for further processing or analysis. Image pre-processing functions are grouped into radiometric correction, atmospheric correction, geometric correction and topographic correction. Radiometric correction is done in order to remove any unwanted disturbances or distortions in the image data resulting from limitations of satellite optical sensors, changes in scene illumination, atmospheric conditions and viewing geometry (Lu et al. 2004).

Atmospheric correction removes the scattering and absorption effects from the atmosphere to obtain the surface reflectance (surface properties). The atmospheric conditions at different acquisition dates influence spectral signatures for the same invariant objects. Therefore, conversion from raw data to surface reflectance using a proper atmospheric calibration method is needed (Song et al. 2001; Du et al. 2002; Vicente-serrrano et al. 2008; Chander et al. 2009).

2.2.2 Image Processing and Classification

Image classification is defined as the process of categorizing pixels of an image into a fewer number of individual land cover and land use classes based on the reflectance values (Jensen 2005; Campbell and Wynne 2011). It involves the extraction of differentiated land cover and land use categories classes from raw remotely sensed digital satellite data (Weng 2002). The classification process uses a classifier to identify and map the patterns associated with each pixel position in an image in terms of characteristics of the objects or materials present at the location on the earth when the image was captured.

According to Mather (2004), image classification involves two stages or steps. Firstly, the user determines beforehand, the number and nature of the categories in terms of which the land cover is to be described. The categorical classes could be forest, water, pasture and bare land. Secondly, numerical labels are assigned to the pixels on the basis of their properties using a decision-making procedure, usually termed a classification rule or a decision rule. The images are classified based on a sample set created according to training samples. These training samples are representative of the desired land cover and land use classes (Magidi 2010) and are determined based on ground-truthing, the researcher's personal experience and physiogeographical knowledge of the study area.

Over the past decades, researchers have developed and used several methods for analysis and classification of remotely sensed images (Campbell and Wynne 2011; Lillesand et al. 2008). The classification can be based on (1) individual pixels which are also known as spectral or point classification (Campbell and Wynne 2011) or per point or per-pixel classification based on spectral information contained in the image (Mather 1999); and (2) group of pixels also known as spatial or neighbourhood classifiers which examine areas within the image using both spectral and textural information to classify homogenous areas within the image (Lillesand et al. 2008). Image classification based on per pixel approaches is the most commonly used (Blaschke et al. 2000). Further, they are cheaper and easier to program than spatial classifiers (Campbell 2002). The per pixel classification process can be supervised or unsupervised (Foody 2002). In supervised classification, the analyst identifies and assigns the different land cover or land use categories into predetermined classes. On the other hand, in unsupervised classification, a computer algorithm identifies and clusters areas with similar spectral properties (Deer 1995). Training data and prior knowledge of the objects/studied landscape are required for the analyst to perform supervised classification unlike in unsupervised classification (Jensen, 2005).

The commonly used classification algorithms used for supervised classification are Parallel-piped, Maximum Likelihood, and Minimum-distance-to-means (Campbell and Wynne 2011, Eastman 2009, Lillesand et al. 2008). Parallel-piped classification undertakes a parallel classification of remotely-sensed data based on the information contained in a set of signature files. The parallel-piped classification is based on a set of lower and upper threshold reflectance determined for a signature on each band. To be assigned to a particular class, a pixel must exhibit reflectance within this reflectance range for every band considered. The parallel-piped procedure is the fastest of the classification routines. It is also potentially the least accurate (Eastman 2009). The Maximum Likelihood Classification is based on the probability density function associated with a particular training site signature. Pixels are assigned to the most likely class based on a comparison of the probability that it belongs to each of the signatures being considered. It is also known as a Bayesian classifier since it has the ability to incorporate prior knowledge using Bayes' Theorem (Eastman 2009). Prior knowledge is expressed as a prior probability that each class exists. It can be specified as a single value applicable to all pixels, or as an image expressing different prior probabilities for each pixel. Minimum Distance to Means classifier undertakes a classification of remotely sensed data based on the information contained in a set of signature files. The Minimum Distance to Means classification is based on the mean reflectance of each band for a signature. Pixels are assigned to the class with the mean closest to the value of that pixel (Eastman 2009). It is slower than the parallel-piped classification procedure and faster than the Maximum

Likelihood Classification. It is commonly applied when the number of pixels used to define signatures is very small or when training sites are not well defined (Eastman 2009).

2.2.3 Land Use and Land Cover Change Detection Techniques or Algorithms

Over the past decades, the availability of large archived data sets has led to the development and evaluation of many digital change detection techniques and methods for analyzing and detecting LULC changes (Dewidar, 2004). These techniques and methods have been extensively reviewed as well as provided with excellent descriptions and comprehensive summaries (Lu et al. 2004; Williams et al. 2006; Haque and Basak 2017). The selection of the suitable method of change detection is very important for producing accurate results since digital change detection is heavily affected by temporal, spatial, spectral and thematic resolutions of remotely sensed data (Lu et al. 2004). Bekalo (2009) stipulates that different change detection methods produce different change detection maps depending on the method used.

The change detection methods are grouped into seven (7) categories; algebra, transformation, classification, advanced models, geographic information system (GIS) approaches, visual analysis and other approaches. Table 2.2 summarizes the common change detection techniques or approaches and their examples.

Table 2.2. Summary of Change Detection Techniques

Technique/Approach	Examples of Method
Algebra	• Image differencing • Image regression • Image ratioing • Vegetation Index Differencing • Change Vector Analysis
Transformation	• Principal Component Analysis (PCA) • Tasselled Cap (KT) • Gramm-Schmidt (GS) • Chi-square
Classification	• Post-Classification Comparison • Spectral-Temporal Combined Analysis • Expectation-maximization (EM) detection • Unsupervised Change Detection • Hybrid Change Detection • Artificial Neural Networks (ANN)
Advanced Models	• Li-Strahler Reflectance Model Spectral Mixture Model • Biophysical Parameter Method
Visual Analysis	• Visual Interpretation
Other Change Detection techniques	• Measures of spatial dependence • Knowledge-based vision system • Area production method • Combination of three indicators: vegetation indices, land surface temperature, and spatial structure • Change curves • Generalized linear models • Curve-theorem-based approach • Structure-based approach • Spatial statistics-based method

Source: Lu et al. (2004)

Much previous research has shown that a combination of two change detection techniques as Image Differencing and Principal Component Analysis (PCA), Vegetation Index Differencing (VDI) and PCA or PCA and Change Vector Analysis (CVA) improved change detection results. The most common change detection methods used are image differencing, image ratioing, PCA, CVA and Post-Classification Comparison (Xu et al. 2009; Bekalo 2009). It should be noted that pre-classification techniques such as image differencing, PCA and CVA are the most accurate change techniques because they are straight-forward, effective for identifying and locating change and are easy to implement (Sunar, 1998). However, to achieve accurate results there is need to select suitable thresholds or vegetation index to identify the changes areas, being sensitive to misregistration of pixels and they cannot provide details of the nature of change or provide a matrix of change information (Lu el al 2004).

2.2.3.1 Image Differencing

Image differencing change detection technique is the process by which LULC change results are obtained by subtracting a digital number (DN) of a pixel on the first-date image from the second-date image (Alqurashi and Kumar 2013; Lu et al. 2004; Theau 2012). This is illustrated in Equation 2.1;

$$Dx_{ij}^{k} = x_{ij}^{k}(t_2) - x_{ij}^{k}(t_1) \qquad (2.1)$$

where Dx_{ij}^{k} is the difference between pixel value x located at row i and column j, for band k between acquisition date 1 (t_1) and date 2 (t_2).

In this technique, unchanged areas will have a pixel value of 0 but areas with significant change will have positive or negative pixel values(Lu et al. 2004). Image differencing is widely used change detection technique because it is simple, straight forward and results can be easily interpreted (Lu et al. 2004; Podesh et al. 2009). The major challenge of this technique is to select the threshold values for determining the no-change and changed areas (Xu et al. 2009; Muchoney et al. 1994; Rosin and Ellis, 1995). Further, the technique does provide adequate information about the change itself. The results of image differences are affected by atmospheric and non-surface radiance effects (Rogerson, 2002).

Sohl (1999) conducted research on landscape change detection in the Abu Dhabi Emirate using Landsat TM data using five LULC change detection techniques; univariate image differencing, enhanced image differencing, vegetation index differencing, post-classification differencing and change vector analysis. The study found that the enhanced image differencing technique provided the most accurate values of change when compared to other techniques, while change vector analysis was a useful technique for providing rich qualitative detail about the nature of the change.

2.2.3.2 Image Ratioing

Image ratioing change detection technique involves calculating the ratio of the DN values of corresponding pixels on the two images of the same bands at different times (Hafez 2011).

$$Rx_{ij}^{k} = \frac{x_{ij}^{k}(t_1)}{x_{ij}^{k}(t_2)}, \qquad (2.2)$$

where Rx_{ij}^{k} is the ratio between pixel value *x* located at row *i* and column *j*, for band *k* between acquisition date 1 (t_1) and date 2 (t_2).

In image rationing, pixels with no change values take the same value of 1 for both dates and the changes are represented by pixel values of lower or higher than 1 (Alqurashi and Kumar 2013; Theau 2012). In using image ratioing, the effects of radiance change, shadows, image noise and the angle of the sun is reduced (Lu et al. 2004). However, the researcher criticized that this method is difficult to select thresholds values and land cover types of change cannot be analyzed. A study by Chi et al. (2009) revealed that the post-classification comparison (PCC) method yielded better results than image ratioing when both methods were used to assess urban dynamic changes in southeastern China.

2.2.3.3 Change Vector Analysis

Coppin et al. (2004) defined change vector analysis (CVA) as a multivariate change detection technique that processes the full dimensionality (spectral and temporal) of the image data and represents both the direction and magnitude of the change. The direction provides information about the nature of change and the magnitude provides the information about the level of change. The total magnitude per pixel (CM_{pixel}) is computed by determining the Euclidean distance between end-points through *n*-dimensional change space (Michalek et al. 1993) as follows:

$$CM_{pixel} = \sum_{i=1}^{n} (X_2 - X_1)^2 \qquad (2.3)$$

where X_1 and X_2 are date 1 and date 2 of the pixel value in *i* band

CVA is complicated to implement, however, it has the capability to provide information about the change in all data layer as opposed to selected bands (Alqurashi and Kumar 2013; Theau 2012).

2.2.3.4 Principal Component Analysis

Principal component analysis (PCA) is a technique whereby the original dataset which is correlated variable is transformed into a simpler dataset for interpretation (Alqurashi and Kumar 2013). This allows the dataset to be uncorrelated variables representing the most important information from the original dataset (Jensen, 2005). Further, the principal components are based on the eigenvectors of the variance-covariance matrix of the merged datasets (Hafez, 2011). The PCA is performed in two ways. The first method is by adding data from both dates into a single file and analyses the component images. Secondly, PCA can be done by subtracting the second image data from a corresponding image of the first data after performing PCA separately (Lu et al. 2004). After performing PCA, the no-change areas are mapped in the first component and the changed areas are mapped in the last component (Theau 2012). The variance-covariance matric **(C)** of the multi-band images is computed as:

$$C = \frac{\sum_{j=1}^{n}(X_j - M)(X_j - M)^T}{n-1} \qquad (2.4)$$

Where **M** and **X** are multi-band image mean and individual pixel value vectors respectively and *n* is the number of pixels.

PCA reduces data redundancy and dimensionality of remote sensing datasets with assumptions that areas of change are not highly correlated (Lillesand et al. 2004). However, the method requires the selection of thresholds for identifying the change. Further, PCA results are difficult to interpret and label and do not provide a complete matrix of change class (Lu et al. 2004).

2.2.3.5 Post-Classification Comparison

Post-Classification Comparison is the most common, useful and flexible detection method for extracting LULC change information from images of different spatial and spectral resolutions acquired by different sensors (Song et al. 2001; Civco et at 2002; Alphan et al. 2009; Miettinen et al. 2011; Aguirre-Guitierrez 2012; Kindu et al. 2013; Sexton et al. 2013). The technique involves detecting changes in the land cover type and production of maps showing the complete matrix of changes by coding the spectral classification results for time one and time two either by a pixel-by-pixel or segment by segment comparison (Coppin et al. 2004). The land cover classes are defined by the analyst. Supervised and unsupervised classification algorithms are the two schemes of the post-classification comparison technique. The separate classification of pixels in post-classification comparison minimizes the atmospheric, radiometric, geometric and sensor differences between the two dates (Coppin et al. 2004; Alqurashi and Kumar 2013). However, time and expertise are imperative for performing the post-classification comparison and the quality of the classified image for each date affects the final accuracy.

2.2.3.6 Accuracy Assessment of remotely sensed images

Campbell and Wynne (2011) define classification accuracy as the degree to which image classification agrees with ground reference data. Classification accuracy can be assessed to provide an overall measure of the quality of the map to form the basis of an evaluation of different change detection algorithms (Foody 2002). It also helps to gain an understanding of classification errors or classification results for better understanding. A classified error results when there is an inconsistency between the classified data on the map and the real class on the validation data in the field or ground reference data (Foody 2008).

Classification accuracy or error is reported as the error matrix also known as the confusion matrix (Campbell and Wynne 2011). The error matrix compares, on category by category basis, the relationship between known reference data and the corresponding results of automated classification. Depending on the intentions of the user, most of the measures to determine accuracy assessment are derived from the error matrix or confusion matrix (Congalton 2001; Food 2002; Foody 2008). According to Congalton and Green (1999) and Comber et al. (2012), the common accuracy assessment statistics derived from error matrix of remote sensing image classification are Overall Accuracy (OA), Producer's Accuracy (PA), User's Accuracy (UA) and Kappa Coefficient ($\widehat{K}$).

Overall Accuracy defines how well the developed classified maps identify all land cover types on the ground (Foody 2002). It is derived by dividing the total number of correctly classified pixels (the sum of the major diagonal) by the total number of points used for assessment (Kerle et al. 2004). Producer's Accuracy expresses how well the map producer identified a land cover type on all the maps from the remote sensing imagery data. User's Accuracy explains how well a person using the map will find the land cover types on the ground. Kappa Coefficient measures the difference between the actual agreement and chance (random) agreement between the map and the validation data on the ground (Congalton 2001). The higher the classification accuracy of the map the more useful it is for land administrators and land-use planners. It should be noted that Kappa coefficient values are measured on a scale between 0 and 1. $\widehat{K}$ greater than 0.80 (80%) represent strong agreement and good accuracy; between 0.40 and 0.80 (40 – 80%) is moderate agreement, and less than 0.40 represents poor agreement (Congalton 2001; Lillesand et al. 2004); Jensen 2005). OA, PA, UA and $\widehat{K}$ are computed as below:

$$\text{Overall Accuracy} = \frac{Sum\ of\ diagonal\ tallied\ (correctly\ identified)}{total\ number\ of\ samples} \times 100 \qquad (2.5)$$

$$\text{User's Accuracy} = \frac{Samples\ correctly\ identified\ in\ the\ row}{Row\ total} \times 100 \qquad (2.6)$$

$$\text{Producer's Accuracy} = \frac{Samples\ correctly\ identified\ in\ the\ column}{Column\ total} \times 100 \qquad (2.7)$$

$$\text{Kappa coefficient } (\widehat{\mathrm{K}}) = \frac{Observed\ accuracy\ (P_0) - Chance\ agreement\ \ (P_e)}{1 - Chance\ agreement\ \ (P_e)} \times 100 \quad (2.8)$$

Where observed accuracy (P_0) is determined by diagonal in error matric and chance agreement (P_e) incorporates off the diagonal sum of the product of row and column totals for each class (Foody, 2002).

2.3 Drivers or driving forces of Land Use and Land Cover Changes

Bürgi et al. (2004) define driving forces as the factors that cause change in the phenomenon of the spatial features and are influential in the evolution processes of the land surfaces. Land use and land management increasingly represent a fundamental change in the global environment (Dale et al. 2000). The LULC changes are complex and driven by a combination of socioeconomic, political, biophysical and technological factors (also known as land use drivers) that drive and influence the development of any landscape at different spatial and temporal scales (Briassoulis 2003; Burgi et al. 2004; Dietzel et al. 2005; Sing et al. 2010; Kalaba 2014). The land is static and how it is used constantly changes in response to the dynamic interactions between underlying drivers and proximate causes (Lambin and Geist 2003). The understanding of the proximate causes and underlying forces has crucial importance in identifying the causes of LULC changes (Turner and Meyer 1994). Additionally, it also helps in developing realistic models of simulating future LULC changes (Veldkamp and Lambin 2001). The future LULC change predictions are crucial in order to propose successful management options for a given biophysical, socioeconomic and political situation (Loveland et al. 2003). Therefore, the determinants of LULC changes are still contentious issues and need further research (Beilin et al. 2014).

According to Lambin et al. (2003), drivers of LULC changes at the local level vary over time and so are their impacts as the local landscape changes. The relationship between LULC changes and their driving forces are complex and dynamic. In order to understand the drivers of LULC changes, Turner and Meyer (1994) and Geist and Lambin (2002) presented a framework for analyzing the direct and indirect drivers of LULC changes (Figure 2.3). Proximate (direct) causes are immediate actions of local people in order to fulfill their needs from the use of the land (Geist and Lambin 2002). These causes include agricultural expansion, wood extraction, infrastructure expansion and others that change the physical state of land cover (Turner and Meyer 1994). At the proximate level, land-use and land-cover change may be explained by multiple factors rather than a single variable (Geist and Lambin 2002). Proximate causes operate at the local level (individual farms, householders, or communities); on the contrary, the sources of underlying causes are at regional and national levels such as districts, provinces, or countries (Lambin et al. 2003). Underlying (indirect or root) driving forces are fundamental socio-economic and political processes that push proximate causes into immediate action on land use and land cover (Geist and Lambin 2002). Underlying driving forces, including demographic pressure, economic status, technological and institutional factors, influence land cover/use in combination rather than as single causations (Turner and Meyer 1994). Overall, underlying causes are often external and beyond the control of local communities (Lambin et al. 2003).

Studies from the SSA and other developing countries have shown that agriculture expansion, population growth, poverty and unsustainable use of biomass for energy purposes are some of the drivers that facilitate LULC changes especially local communities surrounding the natural resource base (Haller et al. 2008). For instance, a study by Brink and Eva (2009) revealed that floods, population increase, drought, globalization, climate change, economic development and landslide were the prominent drivers of LULC changes in the SSA. Chaturvedi (2004) in his study identified the use of biomass as a source of fuel as an important variable contributing to LULC changes in most developing countries. According to Feldmann and Marlis (2011), approximately 80 – 90% of the population from SSA use firewood, charcoal, animal dung and agriculture residues as sources of fuel. Additionally, higher population coupled with poverty without alternative economic opportunities results in overdependence and unsustainable extraction rates from the natural resource base causing natural resource degradation (Luoga et al. 2000; Mather and Needle 2000; Jorgenson and Burns 2007; Kangalawe and Lyimo 2010; Ahmed et al 2011). Brink and Eva (2009) also reported that LULC changes that have taken place in the SSA are due to globalization, droughts, population growth and floods. Asselen and Verburg (2013) and Kangalawe and Lyimo (2010) alluded that there is a close relationship between environmental degradation, urban population growth, rural livelihood strategies and settlements sprawls. A study by Habib-Mintz (2010) found that poverty was spread among the rural communities in Tanzania due to lack of markets for agricultural outputs, scarcity of fertile land for farming and inadequate support from the government.

Kindu et al. (2015) assessed drivers of LULC changes in the Munessa-Shashemene landscape of the south-central highlands of Ethiopia based on a combination of techniques that included GIS-based processing, descriptive statistics and regression analyses. The LULC changes documented in their study were triggered by population growth, charcoal making, livestock ranching, expansion of cultivated land, settlements and cutting of woody species for fuelwood. Another study by Kamwi et al. (2015) reported agricultural expansion, population increase and illegal logging as the most prominent drivers of LULC changes that took place in the Zambezi region of northern Namibia between 1984 and 2010. Moreover, Meyfroidt et al. (2013) studied distance drivers of land change and geographic displacement of land use and found that poor agricultural technology, expanding population and poor management were some of the determinants of forest loss globally.

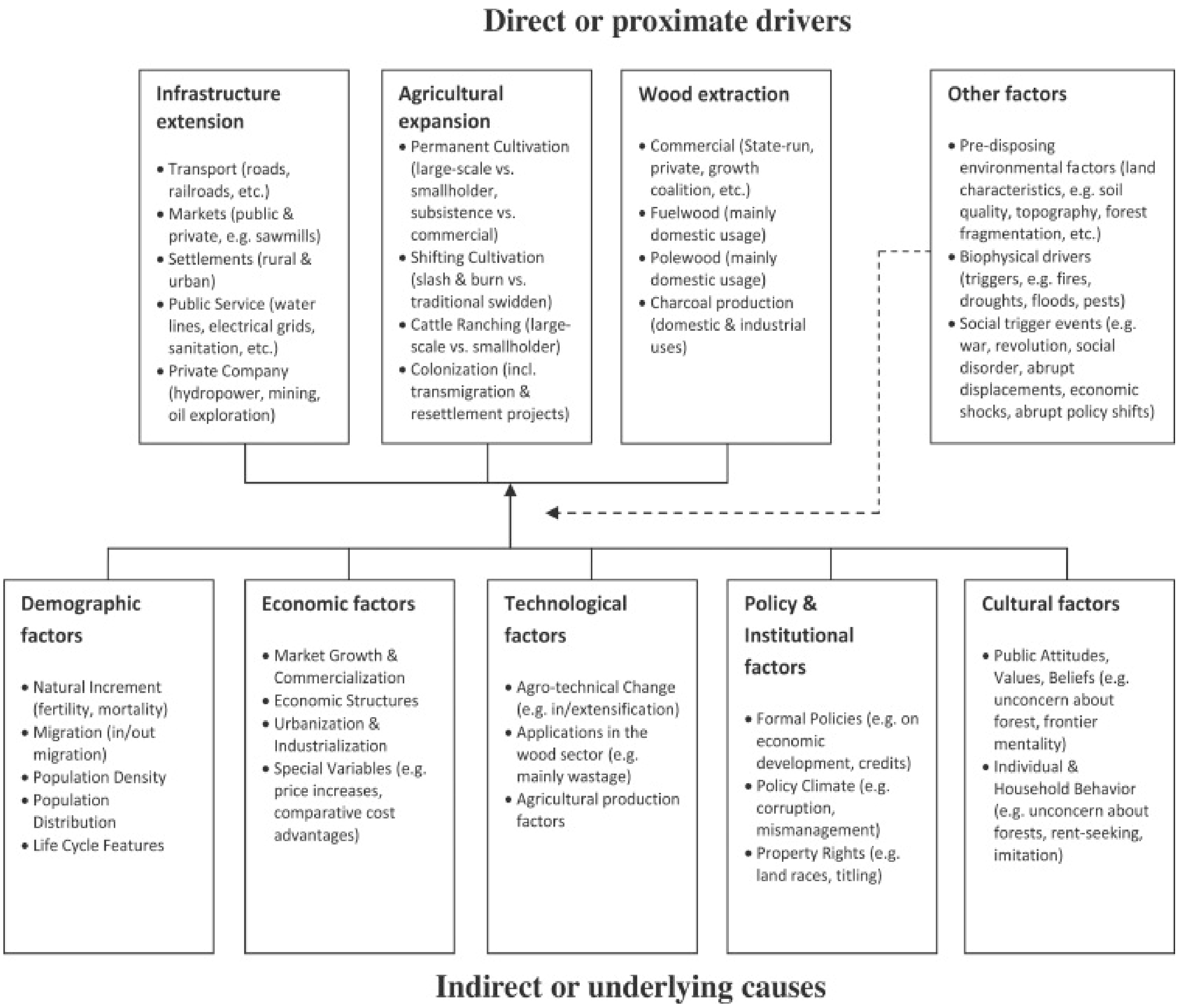

Fig. 2.2 A Framework for analyzing drivers of LULC changes (Adopted from Geist and Lambin 2001)

2.4 Impacts of LULC changes on natural resources and rural livelihoods

Changes in LULC influences the capacity of an ecosystem of any landscape to provide goods and services, sustainable management of natural resources and rural livelihoods security, welfare and human well-being at local, regional or global scale (Lambin et al. 2003; Chhabra et al. 2006; Aspinalls and Hill 2008; Maitima et al. 2010; Kamwi et al. 2015). Yan et al. (2009) contend that LULC changes in the form of agricultural practices, urban growth and deforestation have significant impacts on the environment, ecosystem services and agricultural food production. Understanding the impacts of LULC changes is essential for developing appropriate land management practices to dealing with them and also better management of available resources

(Tekle and Hedlund 2000; Brink and Eva 2009). However, assessing the impacts of LULC changes on any landscape depends on understanding the past land-use practices, current LULC changes and patterns and simulation of future changes (Campbell et al. 2005). Some of the LULC change impacts through land conversion, modification and fragmentation on natural resources are irreversible and they eventually affect the local, regional and global environment. Chhabra et al. (2006) reported that LULC changes have contributed to the inability of some ecosystems to provide food, feed, fiber and timber. The LULC changes have also been linked to declining land productivity leading to impoverished land-dependent livelihoods, agrodiversity and biodiversity loss, habitation destruction, degradation and fragmentation and to some extent poor water quality and quantity which eventually increases disease risks on human-beings. For instance, a study by Schmidt and Ostfeld (2001) suggested that forest fragmentation, urban sprawl and biodiversity loss was linked to increased Lyme disease in the North-eastern United States

Studies in Chiradzulu district of Malawi, for example, show that poverty has contributed much to the country's deforestation, as 97% of the country's population earn less than US$ 1/day (Kamanga et al. 2009). The low income in the district compelled the poorest people in the district to exploit the forest for income to meet their basic needs. Sedano et al. (2005) also reported that lack of adequate environmental monitoring and natural resource management contributes greatly to poverty and food insecurity of fragile rural livelihoods in Africa. A study by Deerege et al. (2010) reported that a decrease in land productivity as a result of changing LULC in Ethiopia in tandem with an increase in population culminated into cultivating in marginalized areas which in turn led to exploitation and degradation of land resources. Hence, monitoring the impacts of LULC changes is crucial for developing proper and coherent sustainable development policies of any landscape.

Agidew and Singh (2017) employed an integrated approach of using RS, GIS and household surveys to examine the implications of LULC changes for rural households' food security in Teleyanen sub-watershed of Northeastern highlands of Ethiopia. They found that increasing rate of soil erosion, land degradation, shortage of farmland, crop yield reduction, climate change and farmland fragmentation had major implications on the rate and extent of LULC changes which in turn compromised food security conditions for the rural households in the study area. Their study concluded that Population growth, cropland expansion, landlessness, overgrazing, climate change, land degradation, drought and shortage of rainfall were the main drivers that attributed to the changes that took place in the study area between 1973 and 2015 (Agidew and Singh 2017).

Another study by Brink and Eva (2009) reported that LULC changes in SSA resulted in natural vegetation removal leading to loss of pastures, biodiversity, stored carbon, fuelwood and habitat. This eventually resulted to the loss of ecosystem services and consequently negatively affected rural livelihoods through the loss of income from tourism. A recent study by Karki et al. (2018) who assessed the impacts of LULC changes on ecosystem services in Myanmar between 1989 and 2014 reported that local communities reiterated that quantity and quality of potable water worsened during the study period. Further, the study also reported that perennial water bodies dried up during this period which lead to reduced water levels in Lake Inle with a consequential reduction in the fish population thereby causing fishermen to shift their occupation to farming.

2.5 Modelling of Land Use and Land Cover Changes

Land cover modeling involves simulating land use and cover change using sample datasets to define probabilistic transition rules that govern how landscapes change over time (Bone and Dragicevic 2009). Studies on LULC modelling in the 1960s were studied from a discipline approach. Since the 1990s, these studies at local, regional and global levels have been changed to a multidisciplinary perspective due to advances in the earth observation techniques such as GIS and RS (Parker et al. 2003; Chaikaew 2019). Models for predicting LULC patterns and changes have been developed and used depending either on the issue or goals (land-use conversion, intensification, management) or the discipline such as geography, natural science, economics, urban planning, regional science and geographic information science (Schaldach et al. 2011; Grinblat et al. 2015). According to Verburg et al. (2004), there has been a rapid development of interest in LULC change modelling given that LULC affects livelihoods, biodiversity and global climate. Thus, different LULC change models have been developed to meet specific needs and address when, where and why LULC occurs (Brown et al. 2000; Briassoulis 2000; Lambin et al. 2000; Lambin 2004; Bhattacharjee and Ghosh 2015). Based on Bhattacharjee and Ghosh (2015) findings, LULC models can be used:

(a) To provide decision support in various decisions including development and establishing of effective policies and management strategies for sustainable natural resource management, use and conservation which requires knowledge and understanding of future LULC patterns and changes;

(b) To describe the spatial and temporal relationships between the drivers and resulting patterns of LULC changes;
(c) As explanatory vehicles of observed relations;
(d) To predict or forecast future configurations of LULC patterns under various scenarios of biophysical like climatic and socio-economic change;
(e) As an instrument to assess the impact of past or future activities in the environmental and socio-economic spheres;
(f) To prescribe "optimum" patterns of LULC for sustainable use of land resources and development;
(g) To evaluate a set of land use alternatives that have to be evaluated on the basis of specific criteria.

According to Parker et al. (2003), a comprehensive understanding of the drivers of LULC changes can only be gained by linking landscape observations at spatial and temporal scales to empirical simulation models. In light of the existing knowledge, it is widely known that different range of LULC models from various disciplinary and backgrounds have been developed over the last decades. Regardless of the current advances in modelling, however, they are limited in their ability to simulate future LULC changes using specific datasets and contents to which they calibrated. The broad categories of LULC modelling that have evolved over the past decades are shown in Table 2.3 and 2.4. Table 2.3 summaries LULC models reported by Lambin et al. (2000) and Lambin (2004) including their advantages and limitations. On the other hand, Table 2.4 depicts a brief general overview of spatially explicit and non-economic LULC modelling approaches by Kaimowitz and Angelsen (1998) and Irwin and Geoghegan (2001). The modelling approaches presented in Tables 2.3 and 2.4 are just examples of the many models been used by researchers to show the range, diversity and extreme usefulness of the LULC models.

Different researchers have used different LULC models to predict future LULC changes. Over the past decade, hybrid models have been used by a large number of researchers to simulate future LULC changes and patterns depending on the purpose of their study. One such hybrid modelling approach is the CA-Markov model, an approach used in the present study. The CA-

Markov model was adopted in this study to simulate the future LULC and patterns of the studied landscape based on the existing knowledge and reliability of the modelling approach (Arsanjani et al. 2013; Subedi et al. 2013; He et al. 2014; Rendana et al. 2015; Singh et al. 2015; Singh et al. 2018; Liping et al. 2018). Hoet and Hubert-Moy (2006) utilized CA-Markov to study LULC trajectories in one of the watersheds in Central Brittaney, France. The model predicted the plausible LULC changes for the study area for the years 2015 and 2030 to aid water resource management. Nouri et al. (2014) employed CA-Markov model as a planning support tool to predict urban LULC changes in Anzali, northwest of Iran. The authors stated that using the model to simulate the future LULC changes in the study area provided an opportunity to define and apply better strategies for environmental management to make an optimized balance between urban development and ecological protection of environmental resources. Studies have revealed that the CA-Markov has been widely used and has been shown to generate reliable outputs for sustainable planning in other countries such as Tanzania, India, Iraq and Malaysia (Hyandye and Martz 2017; Singh et al. 2015; Hamad et al. 2018; Memarian et al. 2012).

Table 2.3. Categories of land use and land cover change models

Model category	Main characteristic	Modeling approach
Empirical-statistical (Chomitz and Gray 1996; Mertens and Lambin et al. 2000; Veldkamp and Fresco 1996)	• Identify explicit causes of land-use changes Analyses of possible exogenous contributions to empirically-derived rates of changes • Predict the pattern of land-use changes • Do not establish a causal relationship • Regression models are not spatial and perform poorly outside the study area • Cannot be used for a wide-range of extrapolations • Spatial statistical models combine GIS and multivariate statistical models to predict and display future land-use pattern based on formulated assumptions (scenarios)	Multiple linear regression techniques Spatial statistical (GIS-based) models
Stochastic (Thornton and Jones 1998; White et al. 1997; Wu 1998; Lambin 2004)	• Stochastically describe processes that move in a sequence of steps through a set of states (i.e. an amount of land covered by various types of land-use) • Consist mainly of transition probability models (e.g. Markov chains) • Advantage of Markov chain analysis lies in its mathematical and operational simplicity • Probabilities of transitions are defined for changes from one land-use category to another • Only current land-use information is required • Can predict when land-use takes place in the short term under a strict assumption of stationarity of the process • Can be used when no information on driving forces and mechanisms of land-use changes is available • Other forms: spatial diffusion and Cellular automata models	Transition probability models

Optimization (Kaimowitz and Angelsen, 1998; Irwin and Geoghegan, 2001) (Briassoulis 2000)	• Mainly applied in economics • Uses a general equilibrium model either at the microeconomic level (farm) or at the macro-economic scale • Any parcel of land, given its attributes and its location, is modeled as being used in the way that earns the highest rent Investigate the influence of various policy measures on land allocation choices • Can't be used for prediction because of unpredictable fluctuations of prices and demand factors, and to the role of • noneconomic factors driving changes • Other forms: Agent-based and behavioural models	Linear programming Land rent theory of von Thünen and Ricardo
Dynamic (process-based) simulation (Stéphenne and Lambin, 2001) (Lambin 2004)	• Patterns of land-cover changes in time and space are depicted by the interaction of biophysical and socio-economic processes. • Emphasize the interactions among all components forming a system. • Condense and aggregate complex ecosystems into a small number of differential equations in a stylized manner. • Simulation models are based on an a priori understanding of the driving forces of changes in a system. • Process-based models can be parameterized based on local observations of decision making (difficult to deal with scale issue)	Behavioural models and dynamic simulation models Dynamic spatial simulation models
Integrated/Hybrid (Wassenaar et al. 1999)	• Combine the best elements of different modeling techniques in ways that are most appropriate in answering specific questions • Provide useful insights into complex land-use systems since they are developed within the framework of multidisciplinary research teams	Vary according to combined models

Table 2.4. Categories of spatially explicit non-economic and economic models of land-use changes

Model category	Main characteristic	Advantages	Disadvantages
Simulation (Cellular automata: CA) (White et al. 1997) (Briassolulis 2000; Agarwal et al. 2002; Yang et al. 2008)	• CA is a mathematical model in which the behaviour of a system is generated by a set of deterministic or probabilistic rules that determine the discrete state of a cell based on the states of neighbouring cells • Mainly used by geographers, based on cellular automata models approach to analyze the process of urban growth.	• Explicitly spatial • Instructive and offer a practical approach to understand the interaction among individual agents to determine regional patterns of urbanization •	Simulation often yield complex and highly structured patterns Absence of an economic foundation Not very useful for planning and policymaking
Estimation (Empirical models of LUCC) (Mertens and Lambin 2000; Geist and Lambin 2002)	• They focus on some aspects of deforestation that is derived from remotely sensed data (dependent variables). • Explanatory variables are deducted from diverse sources: - remote sensing and GIS (e.g. distance measures) - spatial biophysical (e.g. soil, slope, elevation) - socio-economic (e.g. population, distance to urban center, distance to the roads, distance to the water, family size, income, education level, wealth, ability to bear risk)	• Well outcome • concerning LUCC • Attempt to identify spatially the location of changes and explicitly the proximate causes of land-cover changes based on multivariate analyses. Multiple Linear Regression techniques are used • (Multiple Logistic Regression; Multinomial Logit Model for LUCC Trajectories)	Less successful to explain human behaviour that leads the outcome of LUC Some external features that explain temporal dynamics are often omitted (e.g. timber prices, subsidies, land tenure…)
Hybrid (Veldkamp and Fresco, 1997)	• Hybrid model combines estimation and simulation models. • The simulation model uses the parameters from the estimation model to predict the spatial pattern of land-use/-cover change that	• Sophisticated for treatment of ecological relationships that affect or result in LUCC	Less successful to explain human behaviour that leads the outcome of LULC

	could occur under different exogenously imposed scenarios e.g. Markov, LUCAS, CLUE models	• Very simple	Some external features that explain temporal dynamics are often omitted (e.g. timber prices, subsidies, land tenure…)
Non-spatially explicit Micro-economic models Regional economic models	• Use mainly economic theories	•	Do not offer a satisfactory approach to explain the spatial economic process of LUC at the parcel level
Spatially explicit models	• Often focused on simple model deforestation • Shows how economic theory can be applied to motivating the variables that are included in the LU conversion model and identifying potential endogeneity problems.	• Demonstrate the benefits of incorporating • economic theory into the LUC models	There is no explicit model of price formation and the policy that affect land-use No direct link between the unit of observation and the decision-maker

Source: Kaimowitz and Angelsen (1998) and Irwin and Geoghegan (2001)

Despite this inherent reliability, the use of the model has not been reported or documented in Malawi, which faces a dare need of a decision-making tool for sustainable planning and development. Therefore, this study provides the first evidence of the use of the model in Malawi to quantify future LULC and their changes. At this point, information and proper understanding of the LULC changes and patterns, drivers of these changes, impacts of such changes and simulated future changes and patterns are crucial for monitoring and sustainable management of natural resources in Dedza district and the districts of similar settings in Malawi.

2.6 Conclusion

This chapter has presented a detailed account of studies and methodological approaches used in the field of land use and land cover change analysis. The concepts of LULC changes, their drivers and the associated impacts of such changes on natural resources and livelihoods in SSA and other parts of the world have been explored. Thus, In the chapter key trends and findings from a range of international and local levels studies were also summarized to form a conceptual context for the analysis to be performed in the current study. An overview of the existing models currently being employed by different researchers to simulate future LULC changes has also been provided. The CA-Markov model used to simulate the future LULC changes and patterns of the studies landscape has also been tackled in this chapter. The results of various studies around the globe have demonstrated the need for a study focusing on location-specific changes to provide better and up-to-date information for land use planning and sustainable management of natural resources. Further, findings from different studies suggest that determinants of LULC changes of any landscape and impacts of such changes are complex, diverse and vary from one area to another depending on the interaction of location-specific factors or conditions. Further, these factors are interrelated at a local, national and global scale. Therefore, it is improper to make a generalization to other places around the world and sustainable management of natural resources begins with empirically supported and locally-specific understanding of LULC changes and their driving forces.

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CHAPTER 3: MULTI-TEMPORAL ANALYSIS OF LAND USE AND LAND COVER CHANGE DETECTION FOR DEDZA DISTRICT OF MALAWI USING GEOSPATIAL TECHNIQUES

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Abstract

Land use and land cover (LULC) changes attributed to anthropogenic activities are one of the fundamental drivers of local, regional and global environmental changes. Studies of LULC have become vital in enhancing our understanding and monitoring of environmental change. This study analyzed LULC change dynamics for the years 1991, 2001 and 2015 using remote sensing and GIS techniques in Dedza district of Malawi. In the analysis, both supervised and unsupervised classification algorithms were performed on each image. An overall accuracy of the classification achieved for the classified images was 91.86%. The results revealed that forest land, water bodies, wetlands and agricultural land drastically declined while built-up areas and barren land substantially increased between 1991 and 2015. The long-term annual rate of change declined for water bodies from 5.54% ha^{-1} to 1.74% ha^{-1} within the period of study. Likewise, the forest land, agricultural land and built-up area experienced increased annual rates of change from 1.71% ha^{-1} to 1.94% ha^{-1}, 0.02% ha^{-1} to 0.11% ha^{-1} and 7.22% ha^{-1} to 9.80% ha^{-1} respectively. Post-classification comparison of the classified images based on the transition matrix indicated that approximately 61.48% of the total forest land in 1991 was converted to barren land in 2015 while about 2.70% of agricultural land in 1991 has been converted to built-up land in 2015. This study, therefore, provides reliable LULC data which captured the extent and rate of land-use changes that have occurred in Dedza district of Malawi for the period ranging from 1991-2015. It is believed that the trends identified in this study would be useful in guiding planners and decision-makers in the field of land management geared towards a more sustainable natural resource management strategy in Dedza district and other districts of similar settings. It is recommended that a study be undertaken to establish the apparent socio-economic and spatial drivers of the LULC changes between 1991 and 2015 over Dedza district of Malawi

Keywords: LULC, supervised classification, remote sensing, geographic information system

3.1. Introduction

Land use and land cover (LULC) changes predominantly caused by anthropogenic activities are one of the central components of local, national, regional and global environmental changes

(Lambin et al. 2003; Jensen 2005). According to IGDP (1999), LULC changes also reflect the culmination of interactions between climate, ecosystem process, biogeochemical cycles and other biodiversity indicators. Studies of LULC have therefore become vital to understanding and monitoring environmental change and related processes while these types of studies also provide valuable information that can be used to inform more sustainable natural resource management strategies. The LULC changes have significant environmental and socio-economic impacts especially for rural inhabitants involved in land-based livelihoods. The direct and indirect impacts of land use and land cover changes have also been linked to losses in wildlife, deteriorating biodiversity, changes in plant species composition, desertification, deforestation, changes to nutrient, carbon and water cycles, as well as unplanned urban expansion (Verburg et al. 2000; Lambin et al. 2001; Brooks et al. 2002; Verburg et al. 2004; Ifamitimehin and Ufuah, 2006; Maitima et al. 2010; Ujoh et al. 2011; Kamwi et al. 2015). An understanding of LULC changes is also important in the context of trying to unravel land-use conflicts, especially in cases where conflicts are linked to competing for land, uses tend to escalate in proportion to rising population numbers.

In a developing country like Malawi with an increasing population and increased pressure on natural resources (linked to contending land uses), there is a great demand for accurate, detailed and current spatial data that can be used to inform management decisions. Remote Sensing (RS) and Geographic Information Systems (GIS) are well-recognized, powerful and cost-effective tools that are effective for mapping and characterizing natural resources as well as tracking alterations in the landscape over time (Miller et al. 1998; Welch et al. 2002; Parmenter et al. 2003; Wang and Moskovits 2001; Manandhar et. al 2009; Zhang et al. 2017). According to Adeniyi and Omojola, (1999) and Zhang et al. (2002), RS data covers large geographic extents and has high temporal coverage. This type of data, therefore, provides valuable information regarding the processes, location, rate, trend, nature, pattern and magnitude of LULC changes while GIS is useful for mapping and analyzing the patterns captured in the remotely sensed data. The RS and GIS technologies have, thus, added a new dimension to the interpretation and understanding of LULC dynamics (Hathout 2002; Herold et al. 2003; Lambin et al. 2003; Li et al. 2005; Yuan et al. 2005; Wu et al. 2006; Jat et al. 2008; Serra et al. 2008). The knowledge generated by means of applying these two methodological tools is therefore deemed instrumental in assessing and monitoring the availability of natural resources, which can help planners and decision makers to identify crucial resources and prioritize management/conservation efforts (Satyanarayana et al. 2001; Shriver et al. 2005; Wilkinson et al. 2008). The information about the past LULC changes also aids in understanding the present changes and their consequences on the natural resource base.

Dedza District like any other district in Malawi has experienced several major transformations in terms of LULC over the past 25 years. There is, however, a general lack of comprehensive, detailed, accurate and current LULC change maps for the district. To fill this identified information gap, this study assessed the LULC changes that occurred between 1991 and 2015 in Dedza District of Malawi. The intention of this study was, therefore, aimed towards enhancing the current understanding of the spatial pattern, trend and rate of land use and land cover changes in the district. It is anticipated that this information would help in establishing a contextual of natural resource base which would provide planners and decision-makers with a better insight into natural resource management in the broader landscape context. The results from this study could thus be used as a spatial baseline to inform land management and policy decisions made by planners, researchers, environmentalists and other stakeholders. Decisions regarding themes like urban expansion, water management, food security, climate change management, deforestation and land degradation could thus be informed by the spatial trends identified in this study. Further, reliable LULC change data over time is imperative for greenhouse gas reporting for climate change documentation and management (Haack et. al. 2014).

3.2 Materials and methods

3.2.1 Study area

Dedza District is located in the central region of Malawi with a latitude 14°15'45.8" S and longitude 44°11'01.1" E and about 86 km from Capital city of Malawi, Lilongwe (Figure 3.1). It is the third-largest district in the central region of Malawi and covers a total area of approximately 3,624 km^2 (Government of Malawi 2013). It borders Mangochi district to the West, Salima district to the North East and Lilongwe district to the north. The district is divided into three topographic zones namely; Lilongwe plain (altitude 1100-1300m), the Dedza highlands (1200-2200m) and the Dedza escarpments (1000-1500m). Dedza town experiences a cool climate with mean annual temperatures ranging from 14ºC to 21ºC. The annual rainfall for Dedza District ranges from 800mm to 1200mm and falls between mid-November to mid-April. The initial results of the 2008 census reported the population of the district at 623,789, with an increase of 28% compared to the 1998 data.

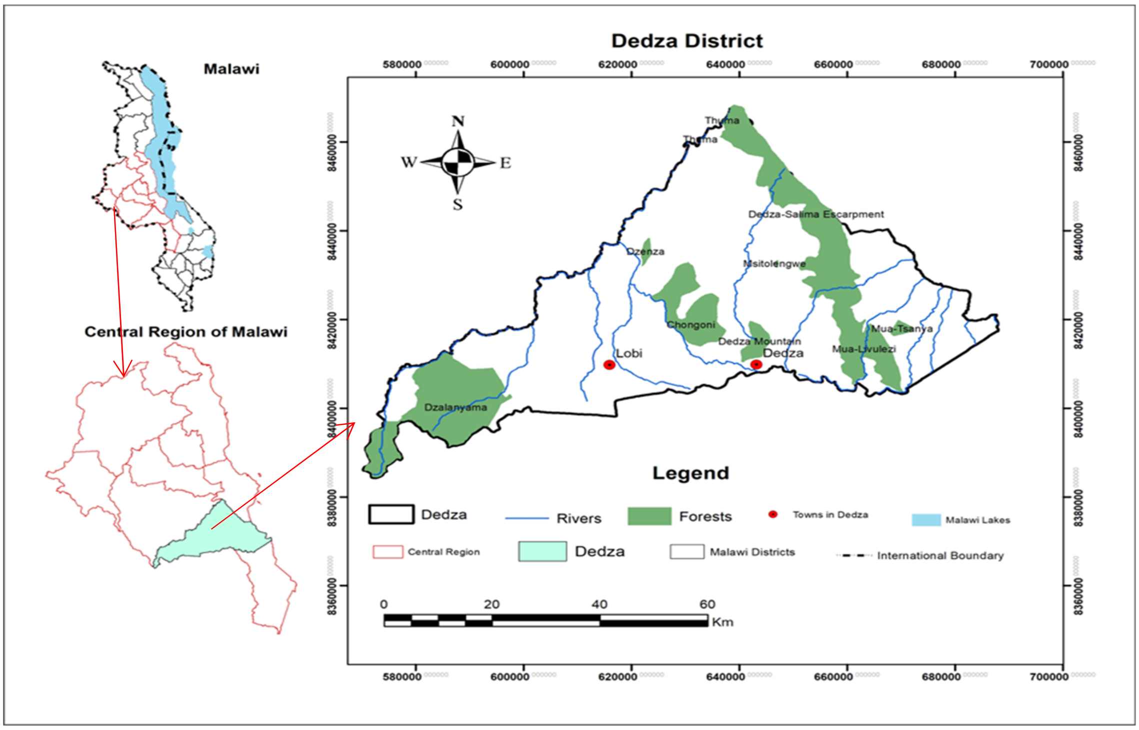

Fig. 3.1 Map of Dedza District

Most of the people in Dedza district live in rural areas where they predominantly practice subsistence farming with commercial rice growers concentrated along the lakeshore. The district is also blessed with perennial rivers which include Linthipe, and Diampwe II and Lifisi Rivers. The district has two Government Timber plantations namely Dedza mountain Plantation (2,046.23 ha) and Chongoni Plantation (5,270.00 ha) found within Dedza Mountain and Chongoni Forest Reserves respectively. Other Forest Reserves include; Mua-livulezi, Mua-tsanya, Msitolengwe, Dzenza and Dedza-Salima Escarpment Forest Reserves. The dominant land cover features include agricultural fields, forest, water and settlements.

3.2.2 Data acquisition and image processing

Different types of satellite imagery are available for LULC analysis. However, when carrying out studies to monitor LULC changes, Landsat imagery is preferred due to temporal resolution coupled with near and mid-infrared bands which allow close examination of vegetation and landscape features (Zeledon and Kelly 2009). Three cloud-free Landsat 5 (TM), Landsat 7 (ETM+) and Landsat 8 (OLI) satellite data were used in this study and the images were selected based on their availability and quality. The images were acquired within the same yearly season to help reduce seasonal and varying sun positions effects. Table 3.1 presents the detailed characteristics of the data used in this study.

Table 3.1 Characteristics of the Landsat images used for the study

Satellite	Sensor	Path/Row	Spatial resolution (m)	Date of acquisition	Source
Landsat 5	TM	168/070	30	1991-09-16	USGS
Landsat 7	ETM+	168/070	30	2001-09-19	USGS
Landsat 8	OLI	168/070	30	2015-09-18	USGS

The standard image preprocessing techniques that were performed on the three satellite images using QGIS 2.16.2 and ArcGIS 10.6 include; extraction, colour composite, geometric correction or georeferencing, atmospheric correction, topographic correction, layer stacking (band selection and combination), image enhancement and sub-setting (clipping). The three images were registered to a common UTM Zone36N with WGS 84 projection parameters.

3.2.3 Image classification

Jensen (2005) defines image classification as the process of categorizing an image into a smaller number of individual classes based on the reflectance values. The images were classified based on physiographical knowledge of the study area, ancillary information, the researcher's local knowledge and visual interpretation of each LULC class supported with the use of the historical function of Google Earth. The six (6) classes with their associated descriptions are shown in Table 3.2. A hybrid supervision algorithm was employed in this study. The unsupervised classification algorithm was first performed on each image because the supervised classification was not able to separate barren land and built-up areas from agricultural areas due to spectral reflectance confusion. Then, the supervised classification was performed.

Table 3.2 LULC classification scheme used in the study area

LULC class	Description
Water bodies	Rivers, permanent open water, lakes, ponds, reservoirs
Wetland	Permanent and seasonal grasslands along the lake, river and streams, marshy land and swamps
Agricultural land	All cultivated and uncultivated agricultural lands areas such as farmlands, crop fields including fallow lands/plots and Horticultural lands.
Forest	Protected forests, plantations, deciduous forest, mixed forest lands and forest on customary land.
Built-up area	Residential, commercial and services, industrial, socio-economic infrastructure and mixed urban and other urban, transportation, roads and airport.
Barren land	Areas around and within forest protected areas with no or very little vegetation cover including exposed soils, stock quarry, rocks, landfill sites, and areas of active excavation.

3.2.4 Accuracy assessment of the images

Accuracy assessment of a classified image is an important step in LULC change analysis. A stratified random sampling method was used to collect a total of 221 reference data to ensure that all five (5) LULC classes were adequately represented depending on the proportional area of each class. Google earth images were used to extract reference data. The accuracy assessment was performed on 2015 satellite image only. Accuracy assessment was not performed on 1991 and 2001 images due to the unavailability of ground validation data in the form of aerial photographs and archived Google earth images. The same image classification method used for the 2015 classified map was however adopted for both 1991 and 2001 images. The accuracy assessment was determined using Kappa coefficient, overall accuracy, producer's and user's accuracies derived from the confusion (error) matrix (Congalton and Green 2009; Liu et al. 2007). The Kappa coefficient reports the relationship between the classified map and reference data (Lillesand and Keifer 2000). The error matrix computed the overall accuracy of six (6) land use classes individually and collectively. The Kappa coefficient was computed using the equation proposed by Jensen and Cowen (1999).

$$K = \frac{N \sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} (x_{i+} \text{ x } x_{+1})}{N^2 - \sum_{i=1}^{r} (x_{i+} \text{ x } x_{+1})} \tag{3.1}$$

Where: K = Kappa coefficient of agreement; N = Total number of observations (sample points); X_i = Observation in the line i and column I; X_{i+} = Total marginal of the line I; X_{+1} = Total marginal of the column i

3.2.5 Change detection analysis

3.2.5.1 Land use and land cover change transition matrix

Change detection quantifies the changes that are associated with LULC changes in the landscape using geo-referenced multi-temporal remote sensing images acquired on the same geographical area between the considered acquisition dates (Ramachandra and Kumar 2004). The study employed a post-classification comparison (PCC) change detection method to detect the LULC changes of two independently classified maps that occurred between two different dates of the study period (Jensen 2005). Post-classification comparison is the most common technique used to compare maps of different sources despite having a few limitations. The approach provides comprehensive and detailed "from-to" LULC change information as it does not require data normalization between the two dates (Coppin et al. 2004; Jensen 2005; Teferi et al. 2013; Aldwaik and Pontius 2013). The use of the PCC technique resulted in a cross-tabulation matrix (LULC change transition matrix) which was computed using overlay functions in ArcGIS. Gross gains and losses were also calculated for three periods: 1991-2001, 2001-2015 and 1991-2015. The computed LULC change transition matrix consisted of rows (displaying LULC class category for time 1, T_1) and columns (displaying LULC class category for time 2, T_2) as shown in Table 3.3.

Table 3.3 General LULC change transition matrix for comparing two maps between observation times

		Time 2 (*T_2*)						
		LULC 1	**LULC 2**	**LULC 3**	**LULC 4**	**LULC 5**	**Total T_1**	**Loss**
Time 1 (*T_1*)	LULC 1	A_{11}	A_{12}	A_{13}	A_{14}	A_{15}	A_{1+}	$A_{1+} - A_{11}$
	LULC 2	A_{21}	A_{22}	A_{23}	A_{24}	A_{25}	A_{2+}	$A_{2+} - A_{22}$
	LULC 3	A_{31}	A_{32}	A_{33}	A_{34}	A_{35}	A_{3+}	$A_{3+} - A_{33}$
	LULC 4	A_{41}	A_{42}	A_{43}	A_{44}	A_{45}	A_{4+}	$A_{4+} - A_{44}$
	LULC 5	A_{51}	A_{52}	A_{53}	A_{54}	A_{55}	A_{5+}	$A_{5+} - A_{55}$
	Total T_2	$\boldsymbol{A_{+1}}$	$\boldsymbol{A_{+2}}$	$\boldsymbol{A_{+3}}$	$\boldsymbol{A_{+4}}$	$\boldsymbol{A_{+5}}$	**1**	
	Gain	$\boldsymbol{A_{+1} - A_{11}}$	$\boldsymbol{A_{+2} - A_{22}}$	$\boldsymbol{A_{+3} - A_{33}}$	$\boldsymbol{A_{+4} - A_{44}}$	$\boldsymbol{A_{+5} - A_{55}}$		

Note:

A_{ij} = the land area that experiences transition from LULC category i to LULC category j

A_{ii} = the diagonal elements indicating the land area that shows persistence of LULC category i while the entries of the diagonal indicate a transition from LULC category i to a different category j

A_{i+} (total column) = the land area of LULC category i in T1 which is the sum of all j of A_{ij}

A_{+j} (total rows) = land area of LULC category j in time 2 which is the sum of overall of i of A_{ij}

Losses ($A_{i+} - A_{ii}$) = proportion of landscape that experiences gross loss of LULC category i between time 1 and 2

Gains ($A_{+i} - A_{ii}$) = proportion of landscape that experiences gross gain of LULC category j between time 1 and 2

3.2.5.2 Annual rate of change

According to Teferi et al. (2013), the net change is the difference between gain and loss and it is always regarded as an absolute value. The annual rate of change of LULC at three different periods (1991-2001, 2001-2015 and 1991-2015) was also calculated according to procedures introduced by Puyravad (2003), Teferi et al. (2013) and Batar et al. (2017). This equation provides a benchmark for comparing LULC changes that are not sensitive to the different periods between the study periods.

$$r = \left(\frac{1}{t_2 - t_1}\right) \times ln\left(\frac{A_2}{A_1}\right) \tag{3.2}$$

where: r is the annual rate of change for each class per year; A_2 and A_1 are the class areas (ha) at time 2 and time 1 respectively and t is time (in years) interval between the two periods.

3.2.5.3 Gains and losses of LULC (Net change)

Net change is the difference between gain and loss (Teferi et al. 2013). The gains and losses of the land use and land cover during the study period were derived from the cross-tabulation of 1991, 2001 and 2015.

3.3. Results

3.3.1 Accuracy assessment

Table 3.4 shows the error matrix results for the 2015 classified map. The overall accuracy for the 2015 classification map was 91.86%. Built-up areas produced the lowest producer's accuracy (61.54%) which may be attributed to the reflectance of the roofs of the houses (iron sheets and thatching grass) that appeared to be rocks and agricultural land. Similarly, the kappa coefficient was found to be 0.866. Therefore, the map sets the minimum accuracy requirements to be used for the subsequent post-classification operations.

Table 3.4 Confusion (Error) matrix for 2015 LULC change map

		Referenced Data							
	Class	**Water**	**Wetland**	**Forest**	**Agriculture**	**Barren**	**Built-up**	**Row Total**	**User's accuracy (%)**
Classified image	Water	10	0	0	0	0	0	10	100
	Wetland	0	9	1	0	0	0	10	90
	Forest	0	1	19	0	0	0	20	95
	Agriculture	0	0	2	125	2	5	134	93.3
	Barren	0	0	5	0	32	0	37	86.5
	Built-up	0	0	0	2	0	8	10	80
	Column Total	10	10	0	127	34	13	221	
	Producer's accuracy (%)	**100**	**90**	**70.4**	**98.4**	**94.1**	**61.5**		

Overall accuracy = 91.86%, Kappa coefficient = 0.866

3.3.2 Land use and land cover change dynamics

Figure 3.2 shows the LULC maps for the 6 classes under investigation. During the entire study period (1991 – 2015), agricultural land and barren land were the predominant LULC classes (Table 5). In 1991, agricultural land, forest area, barren land, built-up area, wetlands and water covered 71.3%, 24.53%, 2.64%, 0.20%, 0.96% and 0.37% of the study area respectively. The areas under agricultural land, forest area, wetlands, water bodies drastically decreased from 71.3% (267,977.43 ha), 24.53% (9,939.15 ha), 0.96% (3,626.73 ha), 0.37% (1,380.60 ha) in 1991 to 69.41% (260,879.31 ha), 1.66% (6,237.63 ha), 0.71% (2,680.29 ha) and 0.24% (899.55 ha) in 2015. On the contrary, barren land and built-up areas substantially increased from 24.53% (92,185.38 ha) and 0.20% (761.67 ha) in 1991 to 25.85% (97,174.62 ha), 2.13% (7,999.56 ha) in 2015 respectively.

The annual rate of change revealed a varied changing progression for each LULC category throughout the study period (Table 3.5). The long-term annual rate of change considerably declined for water, wetlands and barren land from 5.54% ha^{-1} to 1.74% ha^{-1}, 2.05% ha^{-1} to 1.26% ha^{-1} and 0.27% ha^{-1} to 0.22% respectively within the entire period of study (1991 – 2015). In the same period (1991 – 2015), the forest area, agricultural land and built-up area experienced overall increased annual rates of change from 1.71% ha^{-1} to 1.94% ha^{-1}, 0.02% ha^{-1} to 0.11% ha^{-1} and 7.22 % ha^{-1} to 9.80 ha^{-1} respectively.

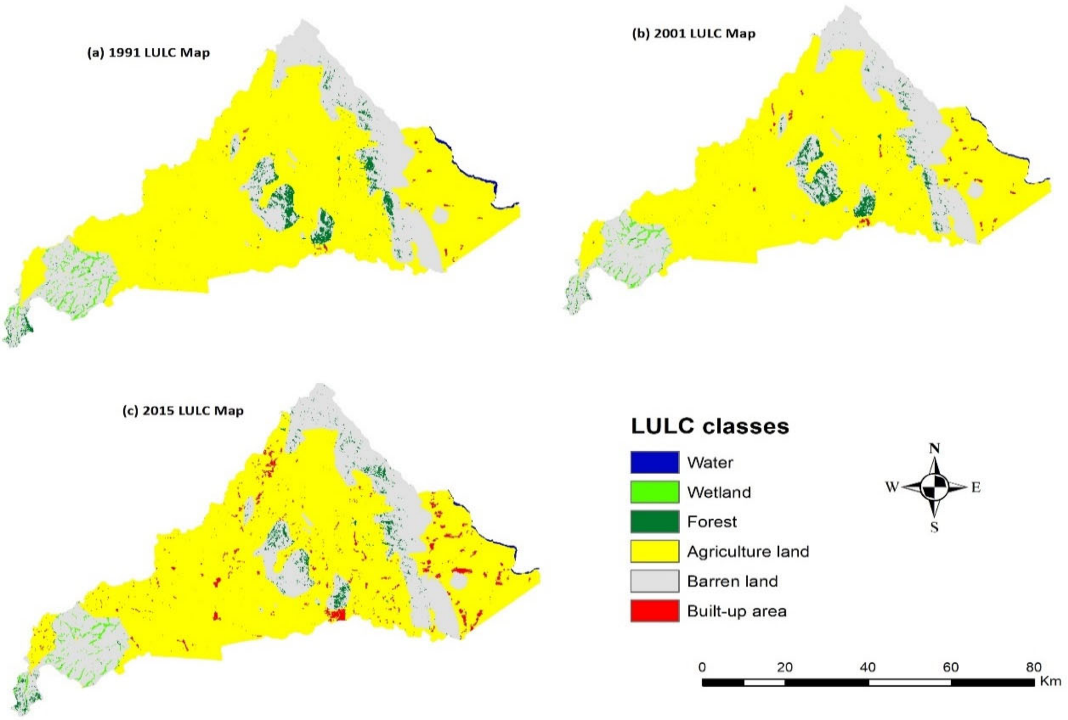

Fig. 3.2 LULC maps for 1991, 2001 and 2015

Table 3.5 LULC change trend and annual rate of change of the study area

Land cover type	1991		2001		2015		Change %[b]			Annual change rate (%)[c]		
	Ha	%[a]	Ha	%[a]	Ha	%[a]	(1991-2001)	2001-2015	1991-2015	(1991-2001)	2001-2015	1991-2015
Water	1,380.60	0.37	793.26	0.21	899.55	0.24	-0.16	0.03	-0.13	-5.54	0.90	-1.78
Wetland	3,626.73	0.96	2,954.07	0.79	2,680.29	0.71	-0.18	-0.07	-0.25	-2.05	-0.69	-1.26
Forest	9,939.15	2.64	8,354.70	2.22	6,237.63	1.66	-0.42	-0.56	-0.98	-1.74	-2.09	-1.94
Agriculture	267,977.43	71.30	267,469.83	71.16	260,879.31	69.41	-0.14	-1.75	-1.89	-0.02	-0.18	-0.11
Barren	92,185.38	24.53	94,731.66	25.20	97,174.62	25.85	0.68	0.65	1.33	0.27	0.18	0.22
Built-up	761.67	0.20	1,567.44	0.42	7,999.56	2.13	0.21	1.71	1.93	7.22	11.64	9.80
Total area	**375,870.96**	**100.00**	**375,870.96**	**100.00**	**375,870.96**	**100.00**						

[a] percentage of each class out of the total area; [b] percentage change in the class; [c] percentage the annual rate of change in each class

3.3.3 Land use and land cover change (transition) matrix

The LULC change matrix (Table 3.6, 3.7 and 3.8) for the periods 1991 – 2001, 2001 – 2015 and 1991 – 2015 shows the distribution of main transitions in the six (6) LULC categories used in this study. The study has revealed that there were major changes and transitions among the six LULC classes. Between 1991 and 2001, the forest area experienced the highest transition with 52.70% (5,237.37 ha) of its total area in 1991, the majority being converted to barren land (4,541.31ha), agriculture land (631.80 ha) and 64.26 ha to the other classes (Table 3.6). In the same period, 46.5%, 43.1%, 34.8%, 6.8% and 1.5% of the total areas of wetlands, water bodies, built-up areas, barren land and agriculture land were changed to different classes. Agricultural land experienced the least transaction when observing 98.52%, 96.74%, 96.03% of its total agriculture land in the periods 1991 – 2001, 2001 – 2015 and 1991 – 2015 respectively. Most of the agricultural land in these periods was converted to barren land and built-up areas. During the 24-year period of study, forest experienced the highest transition with 69.77% of its total area being converted to other classes (Table 3.7). The Post-classification comparison of the classified images based on the transition matrix depicts that ~61.48% of the total forest land in 1991 has been changed to barren land in 2015 while about 2.70% of agricultural land in 1991 has been converted to built-up land in 2015.

Table 3.6 Land use and land cover change matrix between 1991 and 2001

LULC	Water	Wetlands	Forest	Agriculture	Barren	Built-up	Total 1991
Water	**785.61**	7.83	0.09	587.07	-	-	1,380.60
Wetlands	0.27	**1,939.95**	51.12	34.11	1,601.28	-	3,626.73
Forest	0.18	60.39	**4,701.78**	631.80	4,541.31	3.69	9,939.15
Agriculture	3.15	23.58	201.87	**264,010.50**	2,687.58	1,050.75	267,977.43
Barren	4.05	922.32	3,399.84	1,940.94	**85,901.49**	16.74	92,185.38
Built-up	-	-	-	265.41	-	**496.26**	761.67
Total 2001	**793.26**	**2,954.07**	**8,354.70**	**267,469.83**	**94,731.66**	**1,567.44**	**375,870.96**

Note: The bold numbers indicate the unchanged LULC proportions from 1991 to 2001

Table 3.7 Land use and land cover change matrix between 2001 and 2015

LULC	Water	Wetlands	Forest	Agriculture	Barren	Built-up	Total 2001
Water	**745.56**	2.70	2.88	40.59	1.35	0.18	793.26
Wetlands	0.81	**1,749.15**	52.47	22.77	1,128.87	-	2,954.07
Forest	2.07	71.01	**2,320.56**	328.23	5,625.99	6.84	8,354.70
Agriculture	151.11	8.46	373.32	**258,741.54**	1,579.77	6,615.63	267,469.83
Barren	-	848.97	3,487.95	1,503.27	**88,836.21**	55.26	94,731.66
Built-up	-	-	0.45	242.91	2.43	**1,321.65**	1,567.44
Total 2015	**899.55**	**2,680.29**	**6,237.63**	**260,879.31**	**97,174.62**	**7,999.56**	**375,870.96**

Note: The bold numbers indicate the unchanged LULC proportions from 2001 to 2015

Table 3.8 Land use and land cover change matrix between 1991 and 2015

LULC	Water	Wetlands	Forest	Agriculture	Barren	Built-up	Total 1991
Water	**889.02**	5.31	-	484.92	-	1.35	1,380.60
Wetlands	0.72	**1,842.48**	30.96	40.14	1,712.34	0.09	3,626.73
Forest	1.08	53.28	**3,004.56**	737.19	6,110.19	32.85	9,939.15
Agriculture	8.46	16.38	397.98	**257,349.69**	2,960.01	7,244.91	267,977.43
Barren	0.27	762.84	2,803.86	2,162.61	**86,391.99**	63.81	92,185.38
Built-up	-	-	0.27	104.76	0.09	**656.55**	761.67
Total 2015	**899.55**	**2,680.29**	**6,237.63**	**260,879.31**	**97,174.62**	**7,999.56**	**375,870.96**

Note: The bold numbers indicate the unchanged LULC proportions from 1991 to 2015

3.3.4 Gain and loss of land use and land cover (Net Change)

The net change in terms of gains and losses for each LULC class during the 1991 – 2001, 2001 – 2015 and 1991 – 2015 are depicted in Figure 3.3. As shown in Figure 3, between 1991 and 2015, the highest loss was observed in the forest land (1,584.45 ha), followed by wetlands (672.66 ha), water bodies (587.34 ha) and agricultural land (507.60 ha) while barren land and built-up areas progressively gained by 2,546.28 ha and 805.77 ha respectively. On the other hand, between 2001 and 2015, agricultural land experienced the highest loss (6,590.52 ha) followed by forest cover

(2,117.07 ha). During the whole period of study (1991 – 2015), the built-up areas and barren land gained 7,237 ha and 4,989.29 ha of land respectively. In the same period, the highest loss was experienced by agriculture land (7,098.12 ha), followed by forest cover (3,701.52 ha), wetland (946.44 ha) and water (481.05 ha).

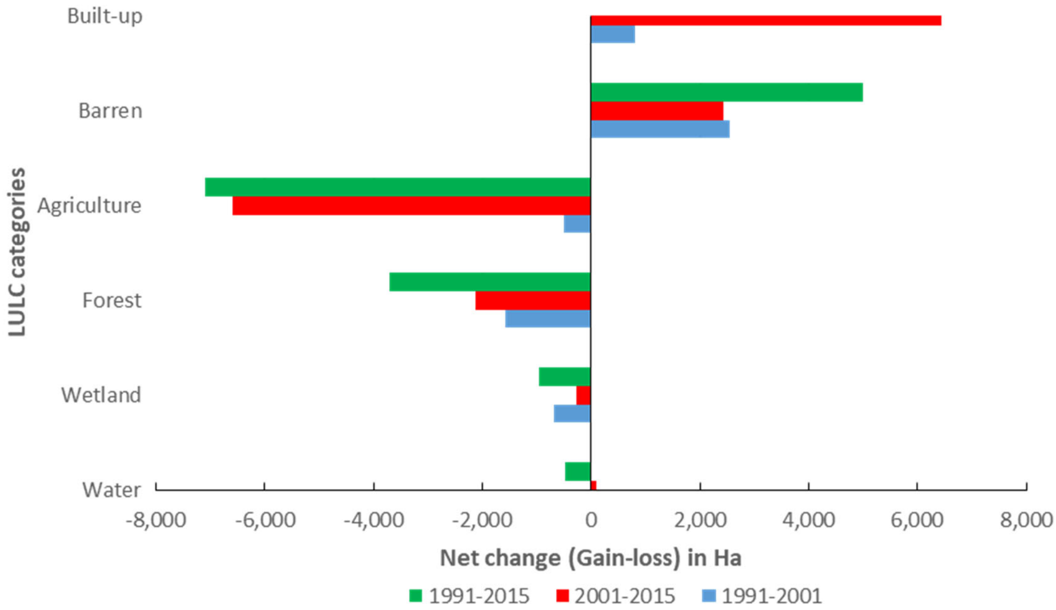

Fig. 3.3 Net change (Gains - losses) for each LULC class for the study period

3.4. Discussion

The accuracy assessment is an important step in image classification and the quality of the thematic map from satellite image is determined by its accuracy. Information on the accuracy and precision of the classified maps is essential in order for the end-users to utilize the generated maps effectively (Smits et al. 1999; Plourde and Congalton 2003; Manandhar et. al 2009). The results from an accuracy assessment of the LULC maps varied among the LULC classes. The results of accuracy assessment in this study revealed excellent results despite some errors which could be attributed to spectral confusion between built-up areas, barren land and agriculture land. Collating with the minimum 85% accuracy stipulated by Anderson et al. (1976) and Kamusoko and Aniya (2007), the overall accuracy (91.86%) statistics obtained in this study satisfied the minimum accuracy (85%) of satellite-derived LULC maps kappa coefficient (0.866) which is above 80% representing a strong agreement (Ramita et al. 2009). The results were also adequate for subsequent and continuous post-classification comparison of change detection operations. The higher overall accuracy achieved in this study could be attributed to the utilization of more ancillary data during the process of image classification.

In terms of the change detection analysis, the results reveal that significant LULC changes occurred during the 24-year study period (1991 - 2015). The major land use in Dedza district is agricultural land. This is a true reflection of Dedza district since it is characterized by farming as the main socio-economic activity (Government of Malawi 2013). Thus, most communities in the study area show a high level of dependency on agricultural activities. Moreover, the results revealed that despite being the most dominant land-use in the area, agriculture land use on customary land has been on a decline from 1991 to 2015. The results also revealed that the land originally (1991 and 2001) under agricultural production was being converted into either built-up area for settlements or has lapsed into barren land. But, while the percentage of land initially under agricultural production (customary land) has been on a decline there have also been new pockets of agricultural land emerging elsewhere in the district. This trend was evident in the percentage of forest land, water bodies and wetlands being converted into agricultural land. Echoing this trend, the study also found that barren land was increasingly being converted to agricultural land as indicated in Tables 6, 7 and 8. This trend thus provides a clear indication that there are encroachment activities through the creation of new gardens, especially in the government forests. Population growth and a loss in soil fertility on customary lands where agricultural production initially concentrated are seen as key drivers of the identified trends. The demand for cultivation increased as the population increases as well in the study area. Farmers in Dedza practice rain-fed agriculture. This type of agriculture requires more land in order to meet the needs of the growing population (Palamuleni et.al 2010).

The decline in the wetlands and water bodies identified in the study is also seen as an indication that the availability of agriculture land is becoming a problematic issue in the district. The analysis revealed that wetlands are being converted into agricultural land but this trend is happening at a slower annual rate than other land-use change trends identified during this study. During a field visit, the reasons for the reduction in the percentage of the water bodies and wetlands observed from the remotely sensed data became very clear as there was also a significant increase in cultivation along the river and stream banks in the district. The observed trend aligns with the findings of Pullanikkatil et al. (2016) who concluded that the land-use changes of Likangala River catchment in Malawi was due to cultivation of river banks, deforestation, and natural resource over-exploitation were some of the threats to the provision of sustainable ecosystem services in the catchment. Poverty coupled with increased demand for agricultural activities motivates people to cultivate in marginal lands such as hill slopes, streams, river banks and wetlands. Globally, results have shown that wetlands have decreased in the past years due to land clearance and drainage as a consequence of urban, agricultural and industrial development activities (Asselen et al. 2013).

Increased settlements were observed along the roads, lakeshore areas, wetlands and surrounding the forest reserves in the study area. An increase in built-up areas during the 24-year interval used for the study could be attributed to increasing demand for land from the growing population as well as the infrastructure developments that are taking place in Dedza district. In other words, the increase in population implies the conversion of other LULC classes into settlements and barren land could be a reason for the general increase in the settlements across Dedza district. Thus, the drastic conversion of agricultural land and barren land to built-up area is an indication that Dedza town is being developed for residential, commercial, academic and business purposes. The individual and property developers in the study are converting wetlands and agriculture land into built-up areas without any considerations of concomitant detrimental environmental impacts. An increase in the number of roads in the study area could not only promote economic development but also facilitating forest degradation and deforestation if local communities are in proximity to natural resources such as forests.

Forest resources continue to be renowned as an important natural resource for the livelihoods of local communities living in close proximity to them (Angelsen and Wunder 2003; Yemiru et al. 2010). The results from this study have shown that forest cover has significantly declined (2.64% to 1.66%) from 1991 to 2015 in Dedza district. The increase in the barren land is also an indication that there is increased deforestation and forest degradation. This declining trend in terms of forestry has also been confirmed by a study conducted by Mauambeta et al. (2010) who reported that forest cover in Malawi declined from 47% of the total land area in 1975 to 36% in 2010. The decline in forest cover might be due to unsustainable tree felling for charcoal, firewood and increased settlements in the study area. According to GoM (2013), forest resources in Dedza district continue to dwindle due to increased demand for charcoal, fuelwood, poles and timber as a result of population growth in Lilongwe City and surrounding districts which provide markets for these forest products. About 94% of the population in Malawi do not have access to electricity and depend on biomass for their energy needs (Ruhiinga, 2012). Further, the majority of the local communities surrounding forests in Dedza district are characterized by poverty and lack of alternative livelihoods. Therefore, the decline in forest cover can be attributed to poverty and rapid population growth which create enormous pressure, competition and over-dependence on natural resources such as forests, water, and land resulting in unsustainable extraction of these resources which will have an implication on biodiversity, habitat ecosystem services and people's livelihoods. Additionally, the increasing rate of deforestation in the study area can be attributed to the increasing demand for arable land for food production. The increased barren land in the study area seems to imply that forest restoration activities such as afforestation and reforestation activities are lagging behind in the study area. The conversion of forest land to agricultural land implies encroachment through farming in the forest reserves.

3.5. Conclusion

The study has demonstrated that integrated use of remote sensing and GIS techniques can assess and quantify the nature, rate and extent of LULC changes and thereby contribute towards an improved understanding of the process of LULC change. The overarching conclusion of this study is that Dedza district has undergone major LULC alterations between 1991 and 2015. During this 24-year interval, the study area has experienced a decline in forest land, agricultural land, water bodies and wetlands during the 24 years of the study period. There is also a substantial increase in built-up areas and barren land between 1991 and 2015. Forest land and agricultural land will likely continue to decrease due to population growth, human settlements coupled with poverty and demand for land to grow food to meet the needs of the people in the study area. The results have shown that the decline in forest land and increase in barren land will lead to forest degradation and deforestation with implications on people's livelihoods, biodiversity and ecosystem services. The LULC changes that have taken place during the past 24 years is a reflection of the influence of local and national policies and human impacts on the study area which has resulted in the increased built-up areas and barren land. The majority of the agricultural land being converted to built-up areas has an implication on food security and supply of forest goods and services as fertile agricultural land is lost to increased built-up areas and infrastructure development. The major LULC changes observed in this study require urgent intervention from forest managers, environmentalists, decision-makers and other stakeholders to address the issues of forest degradation and deforestations, urban or built-up area expansion, loss of agricultural land, wetlands and water bodies in the study area.

This study, therefore, provides LULC change information for understanding the LULC changes that took place in Dedza district between 1991 and 2015. The information will provide essential planning tools for planners, researchers, environmentalists and other stakeholders for sustainable management of natural resources in Dedza district. Based on the findings of this study, it is recommended that the study on the drivers of LULC change in the study area be studied to understand the proximate and underlying causes of these changes. It is also recommended that appropriate steps should be undertaken by decision-makers in the study area to protect and restore the forests and effective and efficient natural resource management plans be put in place for sustainable development programs in Dedza district.

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Disclosure statement

No potential conflict of interest was reported by the authors

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CHAPTER 4: LOCAL PERCEPTION OF DRIVERS OF LAND-USE AND LAND-COVER CHANGE DYNAMICS ACROSS DEDZA DISTRICT, CENTRAL MALAWI REGION

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Abstract

Research on Land Use and Land Cover (LULC) dynamics and an understanding of the drivers responsible for these changes are very crucial for modelling future LULC changes and the formulation of sustainable and robust land-management strategies and policy decisions. This study adopted a mixed-method consisting of remote sensing and Geographic Information System (GIS)-based analysis, focus-group discussions, key informant interviews, and semi-structured interviews covering 586 households to assess LULC dynamics and associated LULC change drivers across Dedza district, a central region of Malawi. GIS-based analysis of remotely sensed data revealed that barren land and built-up areas extensively increased at the expense of agricultural and forest land between 1991 and 2015. Analysis of the household-survey results revealed that the perceptions of respondents tended to validate the observed patterns during the remotely sensed data-analysis phase of the research, with 57.3% (n = 586) of the respondents reporting a decline in agricultural land use, and 87.4% (n = 586) observing a decline in forest areas in the district. Furthermore, firewood collection, charcoal production, population growth, and poverty were identified as the key drivers of these observed LULC changes in the study area. Undoubtedly, education has emerged as a significant factor influencing respondents' perceptions of these drivers of LULC changes. However, unsustainable LULC changes observed in this study have negative implications on rural livelihoods and natural resource management. Owing to the critical role that LULC dynamics play to rural livelihoods and the ecosystem, this study recommends further research to establish the consequences of these changes. The present study and future research will support decision-makers and planners in the design of tenable and coherent land-management strategies.

Keywords: LULC dynamics; GIS-based analysis; LULC drivers; local perceptions; sustainable resource management; rural livelihoods

4.1. Introduction

Land-use and land-cover (LULC) change has become a key research-priority area, attracting much interest from the global scientific community since the 1970s (Turner et al. 2007; Kennedy et al. 2009; Altaweel et al. 2010). Particularly, the attention on LULC dynamics occurring at the local scale has arisen due to an inherent ecosystem, and socioeconomic impact at the national, regional, and even global levels (Malhi et al. 2008; Miao et al. 2013. Natural causes and anthropogenic activities are responsible for LULC dynamics changes globally, with the latter overriding natural causes (Burka 2008; Lamichhane 2008). These changes are described by complex multitemporal and scale interactions of social, demographic, economic, institutional, and environmental factors (Geist and Lambin et al. 2002; Lambin et al. 2001; Falcucci et al. 2008; Li et al. 2009). These changes have serious socioeconomic and environmental impacts on rural livelihoods in many regions of Sub-Saharan Africa (SSA) (Maitima et al. 2010). In some parts of the SSA region, population growth, high poverty levels, settlements, fuelwood, charcoal production, and agricultural expansion were reported as contributory factors for LULC changes (Kamwi et al. 2015; Kindu et al. 2015; Mdemu et al. 2012; Hamandawana et al. 2005; Gashaw et.al. 2014; Mekuyie et al. 2018). More research with regard to location, nature, magnitude, extent, and rate of land-use and land-cover dynamics is still required in the context of SSA, where high population growth coupled with infertile land and overexploitation of other natural resources such water and forests are prevailing (Basset and Zueli 2000).

Malawi's economy is entirely dependent on agriculture and other related sectors, especially forests and fisheries. Due to its reliance on rain-fed agriculture and exposure to floods and droughts, Malawi is among southern Africa's most climate-change-vulnerable countries (NVAC 2016). Almost 85% of Malawi's population lives in rural and marginalized areas, and approximately 80% of this population entirely depends on natural-resource endowments for their subsistence, household income, and livelihoods (Fisher 2004; Jumbe and Angelsen 2007; Kambewa and Utila 2008; Yaron et al. 2011). The high dependence on natural resources such as land, forests, and water puts pressure on these resources, leading to overexploitation, forest degradation, and deforestation (Kalaba et al. 2010; Mauambeta et al. 2010). Recent studies have revealed that deforestation and forest degradation in Malawi are due to uncontrolled firewood collection, infrastructure development, agriculture expansion, illegal charcoal production, shifting cultivation, urbanization, high population, and tobacco-curing by smallholder farmers and estate owners (Kambewa and Utila 2008; Mauambeta et al. 2010).

Like any other country in the Sub-Saharan Africa (SSA) region, Malawi's LULC has experienced rapid and extensive changes over the past decades due to significant transformations caused by human-environment interactions(Haack et al. 2014). Despite the fact that few studies on LULC changes have been done in Malawi, research on the factors contributing to these changes at the national and even local level remains scant. Thus, few studies have explained LULC change dynamics at the national level (Palamuleni et al. 2010; Munthali and Murayama 2011; Munthali and Murayama 2014; Pullanikkati et al. 2016). Studies on LULC dynamics and the associated drivers on the local scale are vital for seeking viable, feasible, appropriate, and coherent natural-resource management strategies. Several researchers have emphasized that understanding LULC drivers is a perplexing question in global science, and these drivers are still a contentious issue; further research is indispensable (Geist and Lambin 2001; Chowdhury 2007; Beilin et al. 2014). The causes of LULC changes are intricate and dynamic, and they vary from one place to another (Li et al. 2016). In other words, globally identified drivers of LULC changes are location-specific, varying from region to region depending on the socio-economic and biophysical factors prevailing that location. It is worth noting that LULC change drivers are also time-specific. For instance, a driver identified 10 years ago may not be valid in recent times if remedial solutions are put in place by the actors. It is, therefore, impossible to generalize that LULC trends/changes occurring on a broader spatial scale and the drivers influencing these changes are inherent landscapes (Beilin et al. 2014; Bewket 2002). Examination of LULC driver dynamics is a requisite as far as resolving environmental and socioeconomic challenges, biodiversity conservation, reduction and management of LUCC changes impacts and consequences at local, national, regional and global level is concerned (Foley et al. 2005; DeFries et al. 2004).

It is worthwhile noting that inclusive research on the drivers and impacts of LULC dynamics in Dedza is beneficial to readily comprehend the inter-relationships between locals and natural resources. Any management intervention strategies to properly address the drivers of LULC changes and the development of sustainable land-use systems in the study area should begin with local empirical evidence and understanding the underlying drivers of changing LULC. A profound understanding of the complex interdependence between LULC changes and rural livelihoods, together with the coping strategies that local communities use to address such changes, are fundamental for decision-making by policymakers, planners, and other stakeholders (Kamwi et al. 2015). Estimating the rate, nature, type, and pattern of LULC changes in any landscape, as well as understanding factors that influence these changes, are also essential for projecting future changes (Dewan and Yamaguchi 2009; Serneels and Lambin 2001).

Remote-sensing (RS) and GIS technologies only identify the nature, extent, and rate of LULC changes on the landscape; however, they do not provide an explanation about the underlying causes of LULC dynamics on the landscape (Wondie et al. 2011; Kindu et al. 2013). Despite this, RS has demonstrated its effectiveness and applicability in investigating the relationship that exists between people and the environment in which they live (Gatrell and Jensen 2008). Therefore, this study aims at quantifying LULC changes and assessing the local perceptions of drivers of LULC change between 1991 and 2015 in Dedza. Thus, the study captured local communities' perceptions of LULC change trends and the drivers of these changes in the study area. Some researchers have reported that observed LULC dynamics on any landscape is a reflection of aggregated decisions at the household level in response to policy and an institutional environment over a period of time (Per 2001; Lambin and Geist 2003; Browder et al. 2004). The findings of this study are envisioned to form the basis for a robust understanding of the LULC change dynamics that planners, environmentalists, decision-makers, and other stakeholders could use in formulating sound management and environmental planning strategies, or guidelines for the maintenance of ecosystem services, and conservation and utilization of natural resources in Dedza or alternative districts with similar settings.

4.2. Materials and Methods

4.2.1. Study Area

The study was conducted in Dedza, located in the central region of Malawi, bordering Lilongwe district, Ntcheu to the south, Mangochi to the east, Salima to the northeast, and Mozambique to the west (Figure 4.1). The district covers a geographical area of about 362,400 ha (Government of Malawi 2008;2013). Physiography is characterized by uplands and lowlands with uneven terrain. The district is divided into three topographic zones, namely, the Lilongwe plain (altitude, 1100–1300 m), the Dedza highlands (1200–2200 m), and the Dedza escarpments (1000–1500 m). The district has a subtropical highland climate (Kottek et al. 2006). Mean annual temperatures are relatively low and fluctuate between 14 and 21 °C, with an average temperature of 15.5 °C (the coldest months are June and July, while November is the hottest month). Rainfall occurs between the months of November and March, with a mean annual rainfall ranging from 800 to 1200 mm. The district has experienced climate-related disasters and extreme events such as floods and droughts (Government of Malawi 2010). The district is characterized by generally ferruginous soils that are deep and brown to reddish in color (Government of Malawi 1999). Clay and sandy loam soils are predominant in the study area (Government of Malawi2012; 2013).

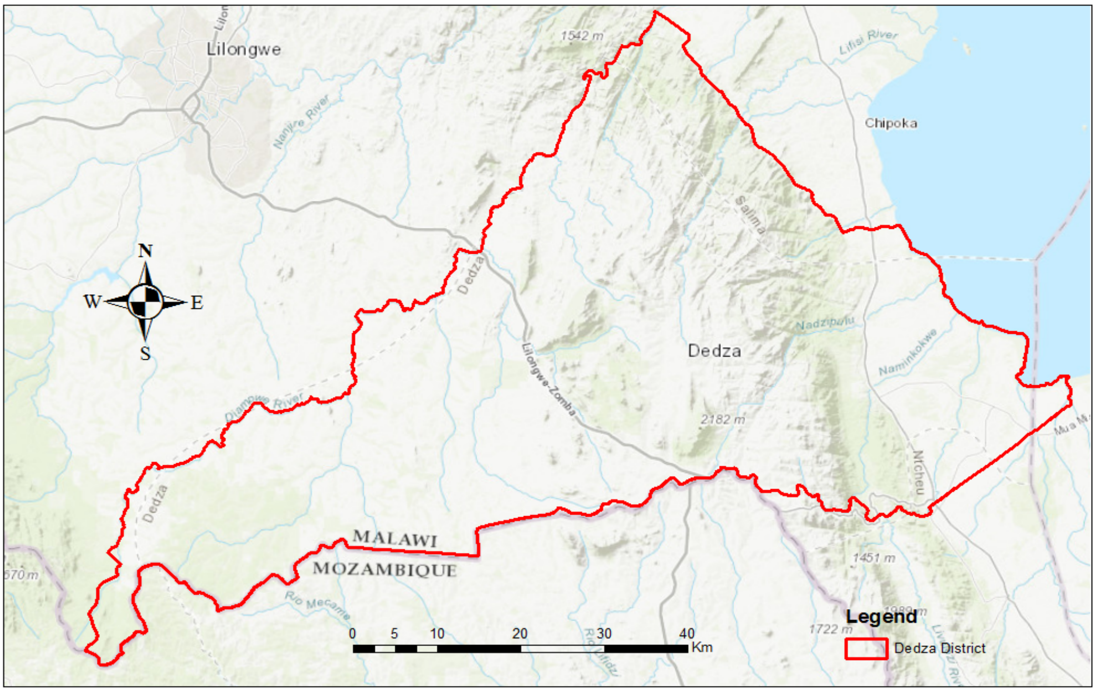


Fig. 4.1 Map of Dedza district, central region of Malawi.

Agriculture is the major land use in Dedza, with major crops grown in the area being maize (*Zea mays*), Irish potatoes (*Solanum tuberosum*), sweet potatoes *(Ipomoea batatas*), groundnuts (*Arachis hypogaea L.),* beans (*Phaseolus vulgaris L*), and soybeans (*Glycine max*). Rice and cotton are also grown along the lakeshore and valleys. People in the district also keep livestock comprising of cattle, goats, pigs, sheep, and poultry. The economy and livelihoods of the majority of the communities of the study area are primarily based on natural resources, especially land, forests, and water (Government of Malawi 2010; 2013). Other economic activities and sources of livelihood strategies include small and medium enterprises (SMEs), arts and crafts, quarrying, and fishing. The district has three land-tenure systems, namely, government land, customary land, and private-leasehold land. Dedza has an estimated population of 624,445, with an annual population growth rate of 2.6% (Government of Malawi 2010). It is one of the most densely populated districts in Malawi, with a population density of 172 persons per km2 compared to the national average of 139 persons per km^2. The average family size in the studied landscape is 6 persons against the national average of 4.4 persons per household.

4.2.2. Data Acquisition and Image Pre-processing

Geospatial and remote-sensing data are reliable sources for understanding and ascertaining the drivers of LULC changes of any landscape (Hansen et al. 2000). In this study, change-detection analysis using multiple sets of spatiotemporal Landsat images for 1991, 2001, and 2015 was used to establish LULC changes in Dedza. Table 4.1 summarizes the characteristics of the multitemporal satellite data used in this research. ArcGIS 10.6 and ERDAS IMAGINE 9.3 software were used to perform standard image-processing techniques, including extraction, geometric correction or georeferencing, atmospheric correction, topographic correction, layer stacking (band selection and combination), image enhancement, and sub-setting (clipping). The three images were also registered to a common Universal Transverse Mercator (UTM) coordinate system, Zone 36S, with World Geocoded System (UTM WGS 84) projection parameters.

Table 4.1. Detailed information on Landsat images used in this study.

Satellite	Sensor	Path/Row	Spatial Resolution (m)	Spectral Bands	Date of Acquisition	Source
Landsat 5	TM	168/070	30	1, 2, 3, 4, 5, and 7	16/09/1991	USGS
Landsat 7	ETM+	168/070	30	1, 2, 3, 4, 5, and 7	19/09/2001	USGS
Landsat 8	OLI	168/070	30	2, 3, 4, 5, 6, and 7	18/09/2015	USGS

4.2.3. Image Classification and Land-Use and Land-Cover Dynamics

Images were classified using hybrid classification that combines supervised and unsupervised classification algorithms. The two methods were used to reduce spectral reflectance noise, especially singling out agricultural land from built-up areas and bare land. A Maximum Likelihood Classification (MLC) algorithm was performed for each image. Studies have shown that MLC is the most common, successful, and widely adopted classification algorithm (Yuan et al. 2005; Manandhar et al. 2009; Prakasam 2010; Rawat et al. 2013). A classification scheme of 6 classes was developed based on physiographical knowledge of the study area, supporting ancillary data, researchers' prior local knowledge, and visual interpretation using the historical function of Google Earth. The 6 LULC classes were categorized as water bodies, wetlands, agricultural land, forest, built-up areas and barren land (Table 4.2). A stratified random sampling method was employed to collect 221 points for accuracy assessment. Google Earth images were used to extract the reference data. Accuracy assessment was determined using the kappa coefficient, overall accuracy, producer and user accuracy, which were derived from the error (confusion) matrix as discussed in References (Liu et al. 2007; Congalton and Green 2009). In order to continue with LULC analysis, the 2015 LULC map was subjected to a minimum of 85% overall accuracy as recommended by References (Anderson 1976; Kamusoko and Aniya 2007). The classified 2015 images were used as reference to classify historical images. In this case, the used signatures for the 2015 images were superimposed on older images. Considerations were made to ensure that the images were captured at comparable phenological dates during the study period. In addition, historical images (1991 and 2001) were further visually interpreted, taking into account image tone, texture, shape, and class patterns.

Table 4.2. Land-use land-cover (LULC) classes used in this study.

LULC class	Description
Water bodies	Rivers, permanent open water, lakes, ponds, reservoirs.
Wetland	Permanent and seasonal grasslands along lake, river, and streams, marshy land and swamps.
Agricultural land	All cultivated and uncultivated agricultural lands areas, such as farmlands, crop fields including fallow lands/plots, and horticultural lands.
Forest	Protected forests, plantations, deciduous forests, mixed forest lands, and forests on customary land.
Built-up areas	Residential, commercial and service, industrial, socioeconomic infrastructure, and mixed urban and other urban, transportation, roads, and airports.
Barren land	Areas around and within forest-protected areas with no or very little vegetation cover, including exposed soils, stock quarry, rocks, landfill sites, and areas of active excavation.

LULC change analysis was determined using a post-classification comparison (PCC) technique, and this resulted in a cross-tabulation (transition) matrix. The LULC change-transition matrix was computed using the overlay procedure in ArcGIS in order to quantify the area converted from a particular LULC class to another LULC category during the study period. The annual rate of change was also determined using the procedure by (Puyravaud 2003; Teferi et al. 2013; Batar et al. 2017). Equation (4.1) provides a benchmark for comparing LULC changes that are not sensitive to differing periods between study periods.

$$r = \left(\frac{1}{t_2 - t_1}\right) \times ln\left(\frac{S_2}{S_1}\right) \tag{4.1}$$

where r is the annual rate of change for each class, and S_1 and S_2 are areas of each LULC class at t_1 and t_2, respectively.

4.2.4. Primary and Secondary Data-Collection Tools

4.2.4.1. Household Surveys

Face-to-face interviews in the form of key informant interviews, focus-group discussions guided by a checklist, and semi-structured household questionnaires (Appendix 1) were used in this study. The questionnaires comprised both open- and closed-ended questions to gather information about the perceptions of the local communities on LULC changes, and the drivers of these changes in Dedza during the studied period (1991 to 2015). A questionnaire was preferred for this study as it provides insight into the drivers of LULC changes (Lesschen et al. 2005). The study employed a random sampling method to select respondents for the household interviews. The structured questionnaire was first pretested in 20 households in the Traditional Authority (TA) of Kaphuka (but not included in the sampled households for this study); then, modifications were made before the actual interviews of the sampled households. The questionnaire was administered to 586 households from 23 October 2017 to 10 November 2017 from 4 TAs, namely, Senior Chief Kachindamoto, Inkosi Kaphuka, Senior Chief Kachere, and TA Kasumbu. Additionally, the questionnaire was administered to respondents who (i) were aged 20 years and above, (ii) had lived in the respective area for at least 10 years, and (iii) were implicit decision-makers in the household, and/or, in the absence of a family head, it was made with appropriate representative and knowledgeable member of the household. The questionnaire had 7 sections covering the socioeconomic characteristics of the household, perceptions of local communities on LULC changes, and their causes (Appendix 1). Each household interview lasted between 30 and 60 minutes.

4.2.4.2. Focus-Group Discussions and Key Informant Interviews

Focus-group discussions (FGDs) and key informant interviews were carried out to triangulate the obtained information from the household interviews and gain an in-depth and detailed understanding of local people's perceptions on LULC changes that had taken place in the studied landscape, and the associated underlying causes perceived to have contributed to the changes. A total of 4 FGDs were carried out in 4 TAs targeting the Area Development Committees (ADCs) where household interviews were conducted in the same period. FGDs facilitated by the researcher were carried out according to the procedure proposed by (Hennik 2007), and were guided by a checklist of questions related to LULC changes and their driving forces. Each FGD consisted of 10–15 people and lasted between 120 and 180 minutes. A purposive sampling method was used to identify key informants based on their knowledge on the study area. In this study, key informants were exclusively technical members from Dedza district council that were familiar with the issues in the study area. These technical members included the district commissioner, and researchers and officers from agriculture, natural-resource, and environmental institutions and organizations.

4.2.5. Other Datasets

Other data used in this study were climate (temperature and rainfall) data from 1991 to 2015, which were obtained from the Malawi Department of Climate Change and Meteorological Services (DCCMS) under the Ministry of Natural Resources, Energy, and Mining. Population data were obtained from the National Statistical Office of Malawi (NSO). Population estimations before 1991 and after 2008 were calculated by extrapolating the closest census data and annual growth rates using the formula adopted by (Kindu et al. 2015):

$$P_2 = P_1 e^{rt} \tag{4.2}$$

where P_1 and P_2 are total populations at Times 1 and 2, respectively; e = exponential population constant; t = number of years between two census enumerations; and r = annual population growth rate.

4.2.6. Statistical Analysis

The study used a combination of data-analytical approaches and techniques including GIS-based processing, descriptive statistics, and regression analysis. LULC change analyses were done using ArcGIS, QGIS, and ERDAS Imagine software. The socioeconomic data derived from the questionnaire were entered, processed, coded, and analyzed using Statistical Package for Social Sciences (SPSS) version 20 and subsequently subjected to further analysis. Descriptive-statistics analysis was used to describe socioeconomic variables of the households and summarize their responses and ranking of drivers of LULC changes. Ranking the drivers of LULC changes perceived by respondents (household surveys) was computed with the principle of weighted average using the ranking index adopted by References (Musa et al. 2006; Solomon et al. 2017):

$$Index = \frac{R_n C_1 + R_{n-1} C_2 \cdots + R_1 C_n}{\sum R_n C_1 + R_{n-1} C_2 \cdots + R_1 C_n} \tag{4.3}$$

where R_n = value given for the least-ranked level (for example, if the least rank is the 10th, then R_n = 10, R_{n-1} = 9, R_1 = 1; C_n = counts of the least ranked level (in the above example, the count of the 10th rank = C_n, and the count of the 1st rank = C_1).

Data collected through FGDs and key informant interviews were qualitatively analyzed (Hsieh and Shannon 2005). A nonparametric test (Pearson's chi-square) was used to ascertain the differences/associations between socioeconomic variables and respondent perceptions on drivers of LULC changes. Logistic-regression analysis was performed to identify the key drivers of LULC changes in Dedza at the household level (Equation 4.4)). By determining the drivers of LULC changes at the household level, the dependent variable was local people's perception of drivers for LULC changes and/or the perceived drivers identified, while independent variables included socioeconomic characteristics, such as age, gender, family size, education, and land-holding size. Logistic analysis at the household level estimated the probability of the effects of the independent variables on the dependent variables (Lesschen 2005):

$$Logit\ (Y) = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n \tag{4.4}$$

where Y = dependent variable indicating the likelihood that Y = 1, α = the intercept, $\beta_1 \ldots \beta_n$n = coefficients of associated independent variables, and $X_1 \ldots X_n$ = independent variables.

4.3. Results

4.3.1. Accuracy Assessment

Accuracy assessment based on error (confusion matrices) showed an overall accuracy of 91.86%, with a kappa coefficient of 0.866 (Table 4.3). There were slight differences in user and producer accuracies of individual classes but the results of the datasets showed higher overall accuracy. These results provided a fundamental platform for subsequent analysis of LULC changes.

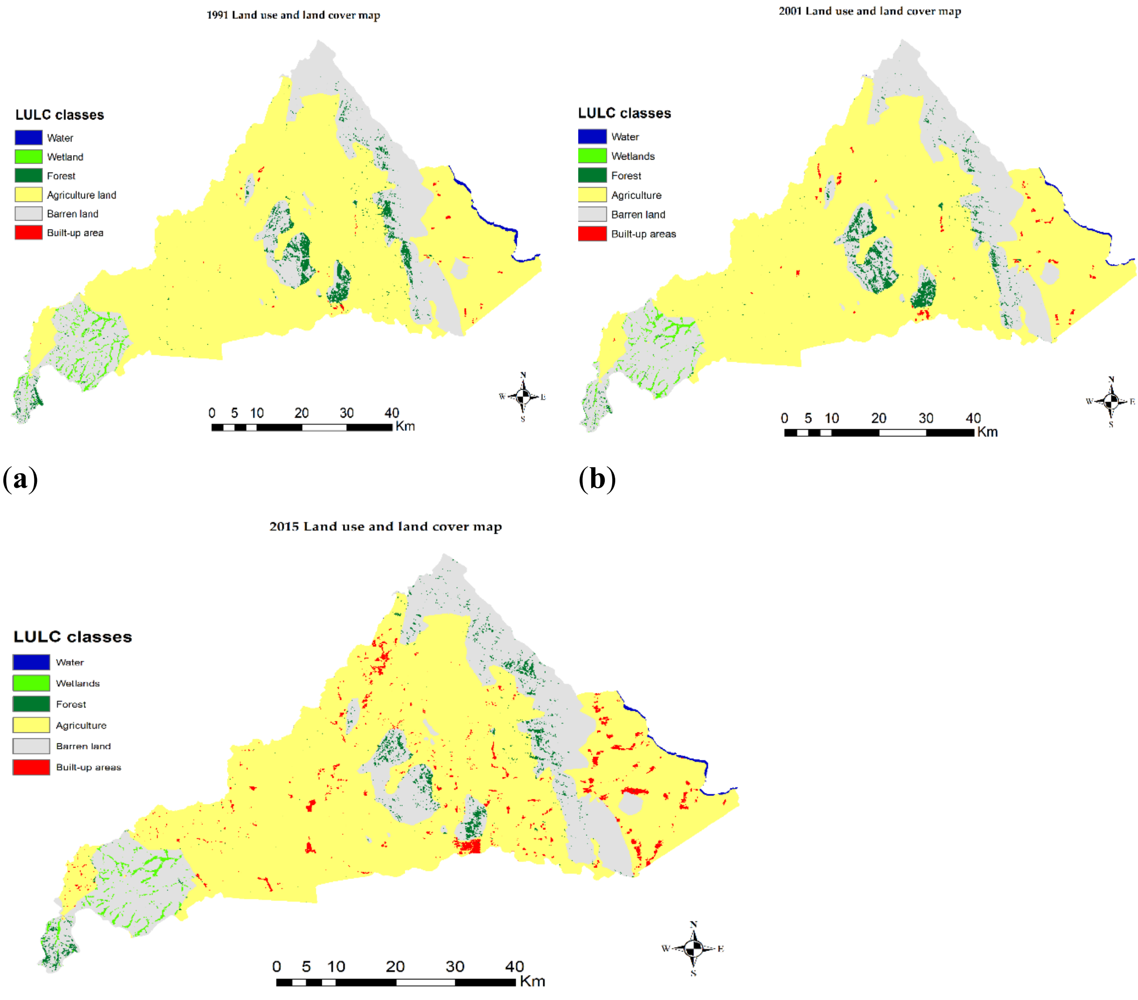
Table 4.3 Accuracy-assessment results for the 2015 LULC change map.

		Referenced Data							
	Class	Water	Wetland	Forest	Agriculture	Barren	Built-Up	Row Total	User accuracy (%)
Classified image	Water	10	0	0	0	0	0	10	100
	Wetland	0	9	1	0	0	0	10	90
	Forest	0	1	19	0	0	0	20	95
	Agriculture	0	0	2	125	2	5	134	93.3
	Barren	0	0	5	0	32	0	37	86.5
	Built-up	0	0	0	2	0	8	10	80
	Column Total	10	10	0	127	34	13	221	
	Producer's accuracy (%)	100	90	70.4	98.4	94.1	61.5		

Overall accuracy = 91.86%, Kappa coefficient = 0.866.

4.3.2. Land-Use and Land-Cover Change Dynamics

Figure 4.2 shows the spatial representation of LULC types from 1991 to 2015. The proportionate coverage area of each of the six classes extracted in Dedza from 1991 to 2015 of LULC change trends are summarized in Table 4.4 and Figure 3.3. At the beginning of the study period (1991), agricultural land was the most dominant LULC, covering 71.3% of the total studied area, followed by barren land (24.53%), forest (2.64%), wetlands (0.96%), water (0.37%), and built-up areas (0.2%) (Table 4.4). The trend continued up to 2015 except for built-up areas. During the studied period (1991–2015), built-up areas substantially expanded almost tenfold (i.e., 950%) and barren land slightly increased, from 24.53% to 25.85%. Conversely, agriculture land, forest, wetlands, and water bodies drastically decreased in the same period (Figure 4.4). The highest net loss was in agricultural land, followed by forest land (Figure 4.3). Despite these transformations, changes did not occur at equal rates. Results revealed that the area occupied by water bodies decreased by 34.8%, wetlands by 26.1%, forests by 37.2%, and agricultural land by 2.6% between 1991 and 2015. Built-up areas and barren land increased at an annual rate of 9.8% and 0.22% yr^{-1}. On the other hand, forests experienced strong loss at an annual rate of 1.94% yr^{-1}; followed by agricultural land, wetlands, and water declining at a corresponding rate of change of 0.11%, 1.26%, and 1.78% yr^{-1}, respectively.



(a) (b)

(c)

Fig. 4.2 LULC maps for (**a**) 1991, (**b**) 2001, and (**c**) 2015.

Table 4.4 LULC change trends and annual rate of change of the study area.

LULC Class	1991		2015		LULC Changes (1991–2015)	Annual Change Rate (1991–2015)
	Area (Ha)	%	Area (Ha)	%	(%)	(%)
Water	1380.60	0.37	899.55	0.24	−0.13	−1.78
Wetland	3626.73	0.96	2680.29	0.71	−0.25	−1.26
Forest	9939.15	2.64	6237.63	1.66	−0.98	−1.94
Agriculture	267,977.43	71.3	260,879.31	69.41	−1.89	−0.11
Barren	92,185.38	24.53	97,174.62	25.85	1.32	0.22
Built-up	761.67	0.2	7999.56	2.13	1.93	9.8
Total area	375,870.96	100	375,870.96	100		

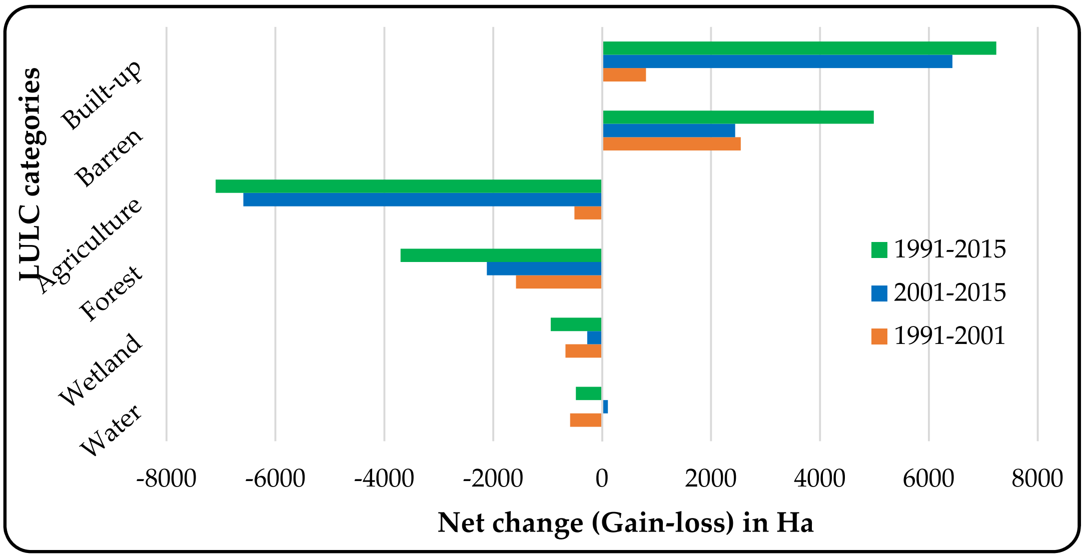


Fig. 4.3 Net change in LULC classes between 1991 and 2015.

4.3.3. Land-Use and Land-Cover Change (Transition) Matrix

Table 4.5 shows the cross-tabulation change matrix for the changed areas and their corresponding percentages from one LULC class to another in comparison with the total area of each LULC class from 1991 to 2015. Despite the fact that all LULC classes have undergone changes in the study area, the degree of these changes was inherently different. Conversions occurred across the whole study area. During the study period, 96.03% of agricultural land remained unchanged, followed by barren land (93.72%), built-up areas (86.20%), water bodies (64.39%), wetlands (50.8%), and forest (30.23%). This clearly indicates that forest experienced the highest conversion with almost 70% of its total area converted to barren land (61.48%) and the rest to other LULC classes. The majority of agricultural land was converted to built-up areas

(7244.91 ha) and barren land (2,960.01 ha), while the majority of barren land was converted to forest (2,803.86 ha) and agricultural land (2,162.61 ha). Even though built-up areas did not change much, almost 7244 ha were gained from agricultural land (7244.91 ha).

Table 4.5 LULC change matrix from 1991 to 2015.

LULC Class	Unit	Water	Wetlands	Forest	Agriculture	Barren	Built-Up	Total 1991
Water	(ha)	**889.02**	5.31	0.00	484.92	0.00	1.35	1,380.60
	(%)	**64.39**	0.38	0.00	35.12	0.00	0.10	100
Wetlands	(ha)	0.72	**1842.48**	30.96	40.14	1712.34	0.09	3626.73
	(%)	0.02	**50.80**	0.85	1.11	47.21	0.00	100
Forest	(ha)	1.08	53.28	**3004.56**	737.19	6,110.19	32.85	9939.15
	(%)	0.01	0.54	**30.23**	7.42	61.48	0.33	100
Agriculture	(ha)	8.46	16.38	397.98	**257,349.69**	2960.01	7244.91	267,977.43
	(%)	0.00	0.01	0.15	**96.03**	1.10	2.70	100
Barren	(ha)	0.27	762.84	2803.86	2162.61	**86,391.99**	63.81	92,185.38
	(%)	0.00	0.83	3.04	2.35	**93.72**	0.07	100
Built-up	(ha)	0.00	0.00	0.27	104.76	0.09	**656.55**	761.67
	(%)	0.00	0.00	0.04	13.75	0.01	**86.20**	100
Total 2015		899.55	2680.29	6237.63	260,879.31	97,174.62	7999.56	375,870.96

Note: Bold numbers on the diagonal represent unchanged LULC proportions from 1991 to 2015 and their corresponding percentages, while others are the areas changed from one class to another.

4.3.4. Socioeconomic and Demographic Characteristics of Sampled Households

The socioeconomic and demographic attributes of the sampled households are presented in Table 4.6. The results revealed that the age of the respondents ranged from 20 to 97 years, with an average of 39.2 years. About 93.3% of the interviewees lived in the study area throughout the studied period. The majority (78.7%) of the respondents were married, about 63.3% of the sampled households were female, and 71.7% of the households were male-headed. The results also indicated that household size ranged from one person to 13 people, with an average of 5.6 persons. It is also worth noting that a larger proportion (96.1%) of the interviewees owned land, with 5.9% being landless. The farm size of the respondents varied from 0.25 to 13 acres, with an average of 2.32 acres. With respect to their education status, 77.8% of the respondents were literate (64.3% and 13.5% attended primary and secondary school, respectively), and 22.2% had never attended school. Approximately 82% of the sampled households were engaged in farming activities, and a small portion of the respondents (18%) were involved in on-farm activities, such as businesses, professional work, and craft work. The mean household income of the respondents was USD721.30 (MK 286,843.26) per year. Farming was ranked as the most important source of income in Dedza. Income from self-employment opportunities, such as businesses, handcraft, and trade, were ranked second, followed by piece works or occasional jobs, Village Loan Savings (VLS), full-time private/government employment, sale of forest produce, and renting out land.

Table 4.6 Sampled household characteristics in the studied landscape (N = 586).

Household attribute	Value
Mean household age (years)	39.2
Gender (female, %)	63.3
Head of the family (male, %)	71.7
Marital status (married, %)	78.7
Education (literate, %)	77.8
Occupation (Farmer, %)	81.6
Mean household size (no.)	5.6
Mean land holding size (acres)	2.32
Ethnic group (Chewa, %)	50.7
Mean income (MK/year*)	286,843.26
Sources of income (farming, rank)	1
Domestic stove used for cooking (three-stone open fires, %)	88.2%

Note: * Malawi currency at the time of the study, 1 USD = 721.30.

4.3.5. Local-Community Perceptions on Observed Trends of LULC Changes and Proximity to Infrastructure

Significant differences were found among the interviewed households in perceptions regarding LULC changes and distance to different infrastructures such as main roads, health centers, schools, and towns ($p < 0.001$). Respondents perceived that agricultural land and forest cover significantly declined ($p < 0.001$) in the studied landscape. Results shows that 57.3% and 87.4% of local communities correctly perceived that agricultural land and forest, respectively, had declined (Figure 4.4). Almost half of the respondents (53.4%) perceived that distance from water bodies remained the same over the studied period. Conversely, distance to infrastructures such as main roads, health centers, bus stops, and towns remained unchanged except for distance to markets and schools, which significantly declined ($p < 0.001$). Key informants from different institutions and FGDs also correctly perceived that agricultural land and forest cover drastically declined from 1991 to 2015.

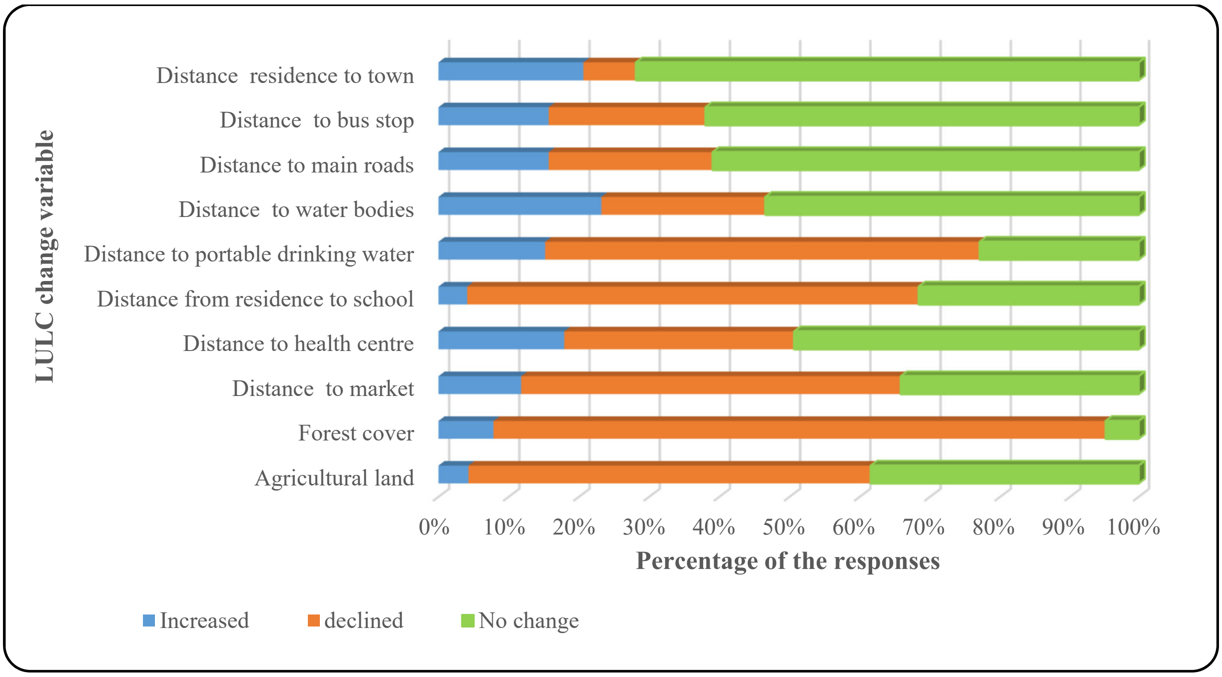


Fig. 4.4 Respondent perceptions of observed trends at the landscape level.

4.3.6. Ranked Drivers of LULC Changes

The respondents identified 24 factors (12 proximate drivers and 12 underlying drivers) as important drivers contributing to LULC changes in Dedza, especially during the period under review (Table 4.7 and Table 4.8). Fuelwood collection, charcoal production, timber, construction, and agriculture expansion were the top five ranked proximate drivers of LULC changes in the study area, with fire collection and charcoal production ranked first and second, respectively (Table 4.7). Similar results were also revealed during key informant interviews and FGDs in which firewood collection, charcoal production, settlements, and agricultural expansion were identified as the main causes of LULC in the study area.

Table 4.7 Perceived proximate drivers of LULC changes in the studied area.

LULC proximate driver	No. of Respondent Per Rank					Weight	Index	Rank
	1	2	3	4	5			
Firewood collection	231	166	49	16	12	2010	0.290	1
Charcoal production	169	102	61	27	12	1502	0.217	2
Timber	22	57	97	64	36	793	0.114	3
Construction	28	67	69	35	13	698	0.101	4
Agriculture expansion	25	39	47	42	31	537	0.077	5
Bush fires	18	28	55	51	44	513	0.074	6
Settlements	19	28	35	23	10	368	0.053	7
Traditional medicine	9	6	10	25	30	179	0.026	8
Poles	7	9	8	9	1	114	0.016	9
Burning bricks	5	10	6	5	4	97	0.014	10
Tobacco farming	5	10	7	10	7	113	0.016	11
Shifting cultivation	0	1	1	2	0	11	0.002	12

Table 4.8 Perceived underlying drivers of LULC changes in the study area.

LULC underlying driver	No. of Respondent Per Rank					Weight	Index	Rank
	1	**2**	**3**	**4**	**5**			
Poverty	126	81	9	2	4	989	0.333	1
Population growth	127	74	15	4	3	987	0.332	2
Lack of financial resources	25	24	10	4	4	263	0.089	3
Lack of law enforcement	13	18	28	11	11	254	0.086	4
Demand for timber	9	10	8	6	6	127	0.043	5
Weak government policies	2	5	5	12	5	74	0.025	6
Poor access to alternative-energy supply	0	4	10	11	3	71	0.024	7
High cost of agriculture inputs	0	3	11	7	6	65	0.022	8
Weak leadership at all levels	0	8	2	5	3	51	0.017	9
urbanization	0	6	1	0	1	28	0.009	10
Poor marketing structures	0	4	6	2	0	38	0.013	11
Political interferences	1	1	0	0	8	23	0.008	12

With respect to underlying causes of LULC drivers in the study area, the interviewed households identified population growth as the most important underlying driver contributing to LULC, followed by poverty, lack of financial resources, lack of law enforcement, and demand for timber (Table 4.8). With regard to population growth, respondents (98%) perceived that population had increased over studied period. FGDs and key informant interviews indicated poverty, population growth, unreliable rainfall, poor access to alternative-energy supply, lack of alternative livelihood strategies, and the high cost of agricultural inputs as the main underlying causes of LULC changes. To confirm the community's perception on population growth and unreliable rainfall, population and rainfall data from 1991 to 2015 was analyzed. Population increased from 456,919 in 1991 to 743,868 in 2015 (Figure 4.5). Observed rainfall data between 1991 and 2015 were consistent with the local communities' perceptions, as indicated by declining unreliable rainfall (Figure 4.6).

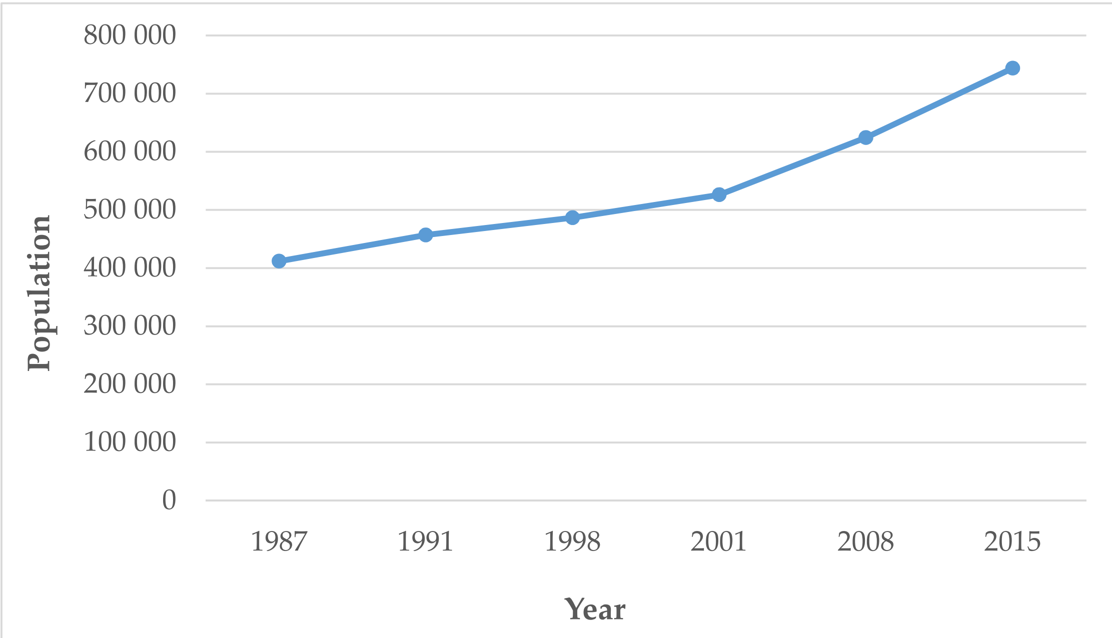


Fig. 4.5. Population growth in Dedza from 1991 to 2015.

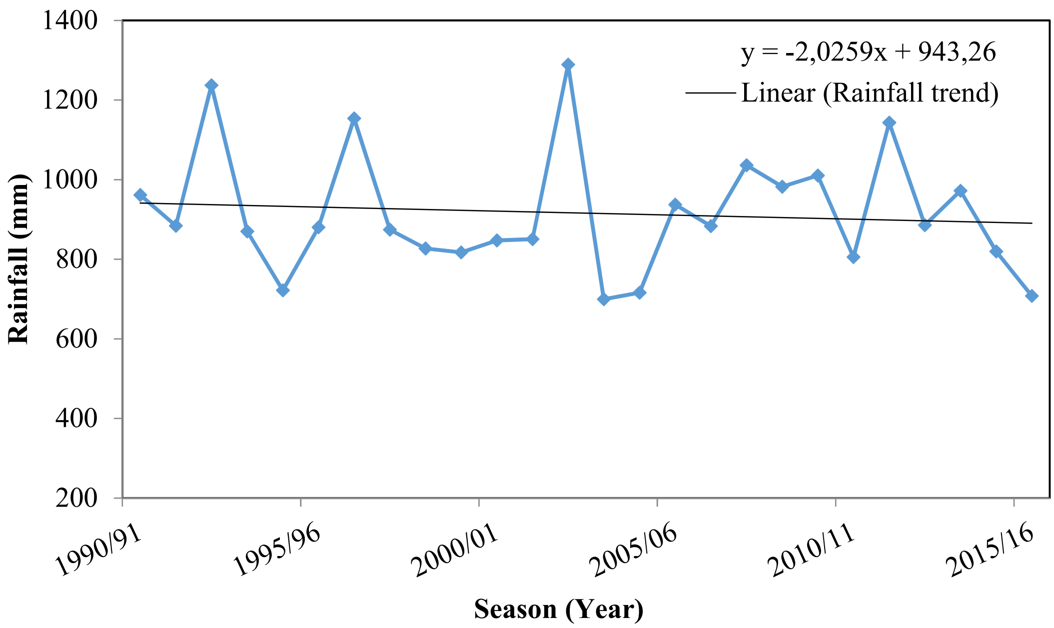


Fig. 4.6 Annual rainfall for Dedza from 1991 to 2015.

4.3.7. Household-Level Logistic Regression of Perceived Drivers of LULC Changes

Results revealed that education level negatively and significantly affected ($p < 0.05$) high perceptions of local communities on firewood collection, agricultural expansion, poverty, and population growth as LULC drivers in Dedza (Table 4.9). Charcoal production and settlements were not significantly influenced by age, gender, education level, land-holding size, and household size.

Table 4.9 Socioeconomic determinants influencing respondents on perceived drivers of LULC changes.

Perceived driver	Independent Variable	Estimate	Std. Error	Wald	*p*-Value	Lower Bound	Upper Bound
Firewood collection	Age	0.007	0.006	1.287	0.257	−0.005	0.020
	Household size	−0.021	0.044	0.233	0.630	−0.107	0.065
	Land holding size	−0.048	0.040	1.458	0.227	−0.125	0.030
	Gender (1 = Male)	0.465	0.270	2.956	0.086	−0.065	0.995
	Education (1 = Never attended)	−1.222	0.431	8.047	0.005	−2.066	−0.378
	Education (2 = Primary, 1–8)	−0.856	0.297	8.280	0.004	−1.439	−0.273
Charcoal production	Age	−0.009	0.007	1.652	0.199	−0.023	0.005
	Household size	0.007	0.047	0.021	0.886	−0.086	0.099
	Land holding size	0.045	0.056	0.642	0.423	−0.065	0.155
	Gender (1 = Male)	0.336	0.309	1.184	0.277	−0.269	0.941
	Education (1 = Never attended)	0.322	0.476	0.456	0.499	−0.612	1.255
	Education (2 = Primary, 1–8)	0.209	0.325	0.412	0.521	−0.428	0.845
Agricultural expansion	Age	0.015	0.010	2.221	0.136	−0.005	0.034
	Household size	−0.101	0.070	2.093	0.148	−0.237	0.036
	Land holding size	0.071	0.071	0.986	0.321	−0.069	0.210
	Gender (1 = Male)	−0.226	0.435	0.270	0.603	−1.079	0.627
	Education (1 = Never attended)	−1.839	0.806	5.208	0.022	−3.418	−0.259
	Education (2 = Primary, 1–8)	−2.250	0.649	12.019	0.001	−3.521	−0.978
Settlements	Age	0.003	0.012	0.079	0.778	−0.020	0.026
	Household size	−0.047	0.081	0.341	0.560	−0.206	0.112
	Land holding size	0.105	0.084	1.572	0.210	−0.059	0.270
	Gender (1 = Male)	0.026	0.440	0.003	0.954	−0.836	0.887
	Education (1 = Never attended)	−0.408	0.751	0.295	0.587	−1.881	1.065
	Education (2 = Primary, 1–8)	−0.882	0.490	3.233	0.072	−1.843	0.079
Poverty	Age	0.006	0.010	0.430	0.512	−0.013	0.026
	Household size	−0.072	0.065	1.208	0.272	−0.199	0.056
	Land holding size	0.008	0.081	0.011	0.917	-0.150	0.167
	Gender (1 = Male)	−0.436	0.465	0.881	0.348	−1.347	0.475
	Education (1 = Never attended)	1.600	0.650	6.050	0.014	0.325	2.875
	Education (2 = Primary, 1–8)	0.916	0.397	5.314	0.021	0.137	1.695
Population growth	Age	−0.008	0.009	0.663	0.415	−0.026	0.011
	Household size	0.038	0.069	0.308	0.579	−0.097	0.173
	Land holding size	−0.008	0.052	0.023	0.878	−0.109	0.093
	Gender (1 = Male)	0.460	0.458	1.007	0.316	−0.438	1.358
	Education (1 = Never attended)	−1.410	0.659	4.575	0.032	−2.703	−0.118
	Education (2 = Primary, 1–8)	−0.541	0.431	1.575	0.209	−1.385	0.304

4.4. Discussion

4.4.1. Land-Use and Land-Cover Change Dynamics

The post-classification comparison results for change-detection analysis and the change matrix from 1991 to 2015 revealed the extent of LULC changes occurring in different LULC classes throughout the study period. Dedza experienced substantial and increased rates of LULC changes between 1991 and 2015. Agricultural and barren land are the major LULC classes accounting for almost 96% of the total landscape in both 1991 and 2015. Most agricultural land, forest land, and water bodies from 1991 were intensively converted to built-up areas, barren land, and agricultural land, respectively. Recently, agricultural land in Dedza was developed for residential, commercial, and business purposes. The expansion rate of built-up areas on other LULC categories increased following the development of residential areas for commercial, academic, and business purposes. Barren land expanded at the expense of forest land and wetlands. The presence of major roads in the study area accelerated the expansion of built-up areas and exploitation of resources. Communities in the study area also correctly perceived that built-up areas and barren land had increased over the past years, with a decline in agricultural land, rivers, wetlands, and forest land. Additionally, as observed during field visits, demand for agricultural land and wetlands to be converted to residential land, and also land prices for these lands, had increased over the past years. Additionally, the use of older respondents (≥20 years) provided an accurate historical narrative of LULC changes in the study area, confirming the results of the observed LULC changes interpreted from remotely sensed data in the period of 1991–2015. Similar findings of other researchers showed that LULC changes occurred in related settings. For example, woodlands declined by 88.5%, while urban areas increased by 143% between 1984 and 2013 in the Likangala River catchment in Malawi (Pullanikkatil et al. 2016). Increased built-up areas and reduction in forest land and fresh water of the Upper Shire River Catchment of Malawi was also reported (Palamuleni et al. 2010). Contrary to the findings in this study, both authors found an increase in agricultural land in their study areas. It was reported that 20,747 hectares of forest land were lost between 1990 and 2008 in Malawi's Dzalanyama Forest Reserve, of which 64% of forest land was lost between 2000 and 2008 (Munthali and Murayama 2011). A recent study revealed that built-up areas increased by about tenfold at the expense of grasslands, shrub-bush land, and woodlands in the Central Rift Valley of Ethiopia between 1973 and 2014 (Abera et al. 2018). Similar observations of the expansion in built-up areas, accompanied by a decline in forest land and agricultural land, were also made by other studies (Mdemu et al. 2012; Munthali and Murayama 2011; Dewan and Yamaguchi 2009; Kindu et al. 2013; Solomon et al. 2017; Meneses et al. 2017).

4.4.2. Drivers of LULC Changes

The research findings, based on the household surveys, FGDs, and key informant interviews, pointed to local communities perceiving firewood collection, charcoal production, agricultural expansion, settlements, and timber as the important proximate drivers of LULC changes in Dedza. These proximate drivers were triggered by high poverty levels, population growth, unreliable rainfall, lack of law enforcement by government, poor access to an alternative-energy supply, and high cost of agricultural input.

The majority of the local communities felt that population growth increased during the study period. Indeed, the population of Dedza has increased by 28% since 1998. This is also confirmed by the results of the population model used in this study, which simulated an increase in population for the studied period in Dedza from 1991 to 2015 Government of Malawi 2008). Household surveys, FGDs, and key informants perceived that the rapid increase of the population in the study area was largely due to high fertility rates, early marriages, high birth rates, reduced mortality, polygamy, immigration, and illiteracy. Dedza shares its border with Mozambique, and during the war, economic instability, and the drought crisis, people from Mozambique would migrate to Dedza to survive. Earlier studies in Malawi also found population pressure as one of the drivers of LULC changes (. Pullanikkatil et al. 2016; Bone et al. 2017) In other parts of the world, population growth was also reported as the main driver of LULC changes (Kindu et al. 2015; Hamandawana et al. 2005; Gashaw et al. 2014; Mekuyie et al. 2018; Kidane et al. 2012).

Firewood collection and charcoal production are the top two important proximate drivers of LULC changes in Dedza between 1991 and 2015. This is also directly associated with the use of three-stone open-fire stoves by 88.2% of the interviewees, while the rest use charcoal stoves for cooking. This kind of domestic cooking stove enables households to use more firewood, thereby exacerbating deforestation and forest degradation. The use of three-stone open-fire stoves results in indoor-air pollution, which severely impacts human health, particularly the vulnerable populace, such as children and women. These results are also directly connected with the wide use of biomass as the main source of energy for the majority of the Malawi population. The use of charcoal and fuelwood for energy in the district is triggered by high poverty levels and low coverage of electricity and alternative sources of energy. Approximately 90% of Malawi's population relies on charcoal and firewood for energy (Government of Malawi 2008; Gamula et al. 2013) . This explains the forest-cover loss in the study area between 1991 and 2015. Proximity of Dedza to Lilongwe, the capital of Malawi, offers a market for forest products, and this exacerbates the collection of illegal firewood and the charcoal produced for harvested poles and timber for construction from government forest reserves in Dedza. The persistence of electricity blackouts (load shedding 8 to 24 hours) in Malawi (evidenced in Appendix 2) also encourages the overdependence of local communities and urban dwellers on charcoal and firewood in order to meet increased demand in urban and rural areas. The inefficient production and unsustainable use of biomass energy sources in Malawi adversely contributes to environmental degradation, such as high deforestation, desertification, and soil erosion.

Among the perceived important drivers indirectly contributing to LULC changes in Dedza is poverty. Local communities are unable to buy agricultural inputs due to high poverty levels, high cost of agricultural inputs, and lack of financial resources. The majority of the local communities in the district are characterized by high levels of poverty and lack of alternative livelihood sources. Harvesting and selling of forest produce and products such as poles, timber, firewood, and charcoal are among the sources of income for most of the communities in the study area. Local communities living in Dedza and the surrounding districts are also forced to clear forests for additional cultivated land or to sustain their livelihoods as an immediate and quick source of income. As perceived by key informants and through focus-group discussions, Dedza rainfall has been very variable. The rural communities in Dedza depend on the sales of forest produce as a common survival strategy in the case of land degradation, decline or failure of crop production, soil infertility, frequent and prolonged droughts, and unreliable rainfall. Overdependence and unsustainable extraction of natural resources without alternative economic strategies, such as forests, land, and water, results in serious environmental problems including soil erosion, biodiversity loss and disintegration, natural-resource depletion, water and air pollution, deforestation, and forest degradation. The results of this study resonate with other similar studies in Africa where high poverty levels were reported as the contributory factors for LULC changes (Kindu et al. 2015; Mdemu et al. 2012; Haller et al. 2008; Ariti et al. 2015) . This study has further revealed that, among main socioeconomic determinants, the education level of rural communities significantly affected their perceptions toward LULC drivers in the study area.

4.5. Conclusions

The study has examined LULC changes using multitemporal remotely sensed images in conjunction with household surveys, FGDs, and key informant interviews to establish their drivers in Dedza during the period of 1991–2015. There was a substantial decline in forest land, agricultural land, wetlands, and water, while built-up areas and barren land drastically increased over the studied period. Firewood collection, charcoal production, population growth, and poverty were ranked as the important drivers perceived by local communities to be responsible for LULC dynamics in the studied area. The findings also depict that education level significantly affected interviewees' perceptions toward some of the drivers of LULC changes. The drivers identified in this study can be used as a tool for land-use planning, as well as input for modelling future LULC changes for the development of effective land-management strategies, guidelines, and policies for informed decision-making in Dedza and other districts with similar settings in Malawi. Appropriately tenable strategies and policies are urgently needed in the study area to address or avert undesirable LULC changes taking place in Dedza. Based on these results, the study recommends further studies to investigate the impact and consequences of these LULC changes on the rural livelihoods of the studied area so that landscape-management decisions and strategies are made based on scientific findings.

Author Contributions

M.G.M is the lead author. She designed the research, analyzed the data and wrote the original draft paper. N.D, J.O.B and A.M.A supervised, reviewed and edited the work. H.L.W.C. assisted in data collection and reviewing the paper. J.M.K and O.O.I.O. reviewed and edited the paper.

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Conflicts of Interest

The authors declare no conflict of interest.

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CHAPTER 5 : THE IMPACTS OF LAND USE AND LAND COVER DYNAMICS ON NATURAL RESOURCES AND RURAL LIVELIHOODS IN DEDZA DISTRICT, MALAWI

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Abstract

The sustainable management of natural resources such as forest, land, water and wetlands requires a critical understanding of land use and land cover (LULC) changes and how these changes impact natural resources and rural livelihoods. Dedza District of Central Malawi has experienced rapid LULC changes between 1991 and 2015 but the extent to which these changes have impacted the natural resource base and rural livelihoods in the area is not known. This study examined the impacts of LULC changes from 1991 to 2015 on natural resources and rural livelihoods in relation to the shocks experienced by local communities and the coping strategies they deployed in response to these changes. In order to achieve this stated aim, an integrated approach combining remote sensing, household surveys consisting of structured and semi-structured questionnaires, Focus Group Discussions (FGDs) and key informant interviews were conducted. Members of the local communities perceived that LULC changes have resulted in the decline of agricultural land (57.3%, n = 586), crop production (82.8%, n = 586) and forest cover (87.4%, n = 586) with an accompanying increase in the distances they needed to walk to access forest resources (50.7%, n = 586) being reported. In response to observed LULC changes, respondents mentioned the need to deploy short-term coping strategies such as seeking piecework opportunities, receiving aid from government and NGOs, financial support from relatives and the need to use their savings and credits. The undesirable impacts observed in this study thus pose a considerable threat and risk to the sustainable management of natural resources and the livelihood strategies deployed by impoverished rural inhabitants in the area. The study has contributed to a better understanding of the complicated interaction between people and the environment. The consequences and undesirable impacts of the changes on natural resources and rural livelihoods observed in this study need thus highlight the need for urgent attention from the relevant authorities and natural resource managers, planners and decision-makers.

Keywords: LULC cover, livelihoods, local perceptions, coping strategies, shocks

5.1. Introduction

In many parts of the world, anthropogenic activities such as mining, deforestation, fires, human settlements and agricultural intensification have been reported as the major drivers to changing land use and land cover (LULC) locally, regionally and globally (Gamble et al. 2003; Halmy et al. 2015; Mei et al. 2016). These changes have directly or indirectly contributed to a decrease in the availability of natural resources, which have ultimately compromised the ability of the ecosystem to provide goods and services for human sustenance (Loveland et al. 2003; Leh et al. 2013; Butsic et al. 2015; Olanrewaju et al. 2018). For instance, LULC changes have led to deforestation, habitat fragmentation or destruction, biodiversity loss, ecological and natural resource deterioration, unplanned urbanization and undesired human settlements (Daye and Healey 2015; Munthali et al. 2019a; Enaruvbe and Atafo 2019). These drivers of LULC change synergistically interact with climate variations, demographic -, institutional - and socioeconomic factors to modify the landscape. The LULC dynamics of any landscape constitute a challenge for land management, ecological and natural resource management and sustainable development (Rawat et al. 2013; Beuchle et al. 2015; Chaudhary et al. 2016).

In Sub-Saharan Africa (SSA), changes in LULC have serious social, environmental and economic impacts on the livelihoods of rural inhabitants and the natural resource base they depend upon (Maitima et al. 2010; Kamwi et al. 2015). The natural resource base and local communities' livelihoods may be affected by LULC changes either positively or negatively and the consequences of these may be intended or unintended (Hansen and DeFries 2004). According to Enaruvbe et al., (2019) the sustainable management of protected areas, biodiversity conservation and the implementation of sustainable development strategies specifically targeting rural populations are some of the key challenges currently facing governments and authorities in SSA. These challenges are compounded in SSA where authorities and inhabitants also need to contend with the impacts of climate change, overdependence on natural resources, forest degradation, deforestation and rapid population growth rates (Enaruvbe et al. 2019). In this context, increasing competition for scarce natural resources may thus accelerate the incidence of land-related conflicts and unsustainable rural livelihood practices, which would ultimately shape observed LULC changes and the configuration of rural landscapes.

Dedza District like any other District in Malawi has experienced tremendous LULC changes (Munthali et al. 2019a). A recent study concluded that these changes are driven by population growth, poverty, firewood collection and charcoal production (Munthali et.al 2019b). Findings from the study by Munthali et al. (2019a and 2019b) thus clearly indicates that the livelihoods of rural people in Dedza District are highly dependent on natural resources. However, the increasing dependence of these rural inhabitants on the natural resource base has contributed to significant changes in the landscape with serious environmental consequences as reflected by the reduction of forest cover, wetlands, water bodies and agricultural land (Munthali et al. 2019b). Given the dependence of rural inhabitants on natural resources and the fact that LULC is impacting on the capacity of the natural resource base to meet the needs of local residents, there is, therefore, an urgent need to understand the nature of the impacts of LULC changes on rural livelihoods in the area. Linked to this fact, there is also a need to understand how rural residents cope or adapt to given changes in LULC. A sound understanding of the nature of LULC changes taking place in the study area and its impacts on the rural livelihoods a of inhabitants coupled with the coping strategies being deployed in response to these changes is thus seen as a crucial requirement for sustainable land management, use, planning and decision-making

To date, the impacts and implications of the changing LULC in Dedza District on natural resources and rural livelihoods and the coping strategies used by rural communities are not known. An in-depth understanding of the impacts/implications of the changes taking place in the study area on rural livelihoods and strategies used to cope with these changes is important for decision-makers in order for them to develop strategies and interventions that will assist rural communities to cope with the changing LULC in the study area. Further, understanding the linkages between the impacts of LULC changes related shocks and the coping mechanism used to counter these shocks are beneficial to resource managers. For instance, it will help resource managers to design welfare-improving policies and strategies for local communities in the study area aimed at restoring the landscape over the long term. Thus, it will assist in the development of land-use planning, management strategies and policies that promote restoration and sustainable management of natural resources and eventually sustainable development of Dedza landscape as a whole. According to Adger et al. (2005), understanding LULC dynamics and how it impacts and interact with communities is crucial for designing interventions that will positively impact the natural resource base and the communities at large. Therefore, this part of the research is aimed at exploring the impacts of the LULC changes which occurred in Dedza District from 1991 to 2015 on the communities' livelihoods and to document the adaptive strategies used by communities to cope with the observed changes. This part of the research was also concerned with exploring linkages between the socio-economic positioning of the respondents and the types of coping strategies they chose to deploy.

5.2. Materials and methods

5.2.1 Study area

The study area, Dedza District, is located in Central Malawi about 88 km from the capital city of Malawi, Lilongwe District (Figure 5.1). The altitude based on the topographic zones ranges from 1100–1300m, 1000–1500m and 1200–2200m for Lilongwe plains, Dedza escarpments and Dedza highlands respectively (GoM 2013). The rainfall pattern is bimodal spread over one (1) long growing season from November to March. The average annual rainfall spatially varies from 800 mm to 1200 mm while temperature ranges between 14ºC and 21ºC, with an average temperature of 15.5ºC. Recently, the District has experienced dry spells and droughts. According to the recent national population census, Dedza has an estimated population of 830,512 with an annual growth of 2.8% (GoM 2019). Further, the population density has increased from 172 persons per km^2 in 2008 to 221 persons per km^2 2018. Agriculture remains the primary source of livelihoods in the area with more than 80% of the population depending on subsistence farming as their main economic activity (Munthali et al. 2019b). Thus, the majority of the population's economy and livelihoods is primarily based on natural resources (GoM 2010; 2013). As a means of diversifying income, the communities are also involved in non-farm activities such as Village Loan Savings (VLS), businesses, piece works (occasional jobs) and handcraft (Munthali et al. 2019b).

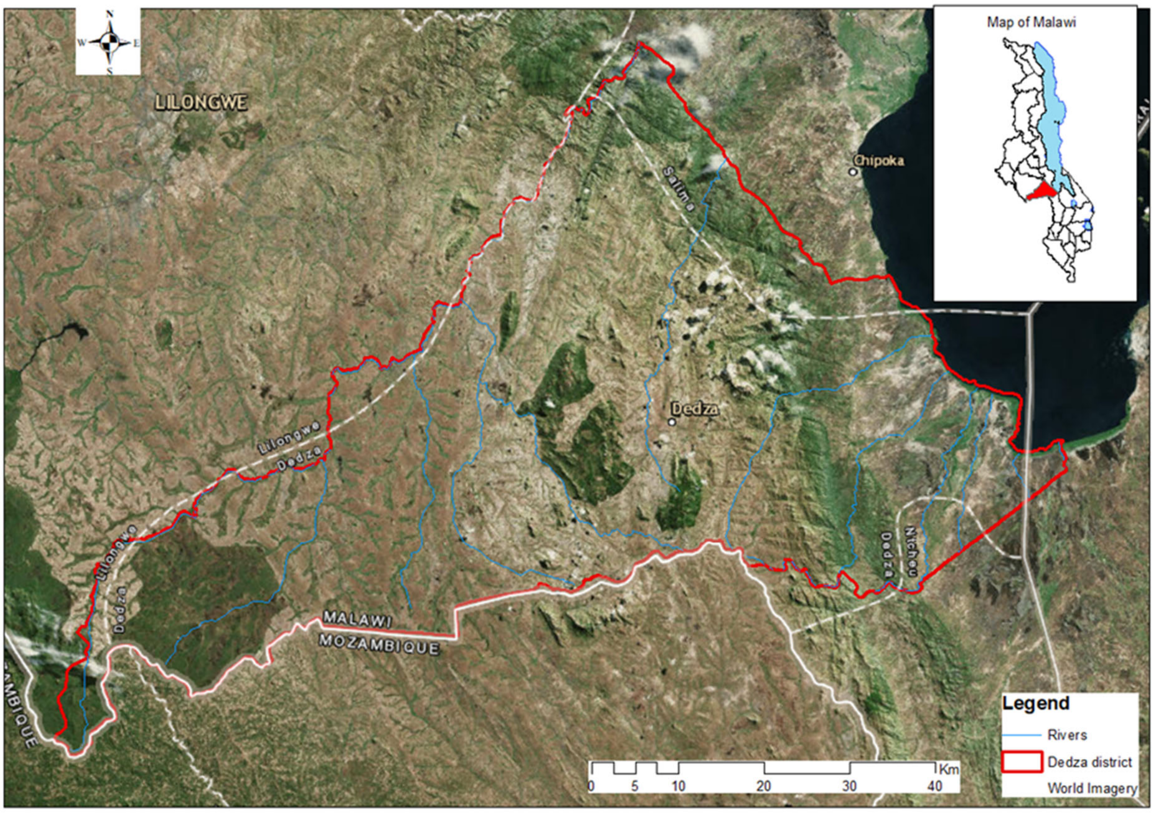

Fig. 5.1 Map of Dedza District

5.2.2 Land use and land cover dynamics

The research presented in this paper builds on the findings already reported by the authors in Munthali et al. (2019a) and Munthali et al. (2019b). As detailed in these papers, change detection was done using multi-temporal Landsat images of 1991, 2010 and 2015. Hybrid procedure using both supervised and unsupervised classification was employed to generate LULC maps using the maximum likelihood classification algorithm in ArcGIS 10.5 software. The study area was classified into six (6) LULC classes (Table 5.1).

In this study, LULC classifications results were subjected to a minimum of 85% overall accuracy as recommended by Anderson (1976) and Kamusoko and Aniya (2007). A total of 221 points for accuracy assessment were collected based on the stratified random sampling method. Accuracy assessment was achieved through a combination of Google earth professional images, ancillary data, field surveys conducted in October 2017 and the researcher's knowledge of the study area. The accuracy assessment was only performed on the 2015 classified map due to difficulties and unavailability of ground validation data in the forms of aerial photographs and archived Google earth images. The overall accuracy for the 2015 classification map was 91.86%. According to Munthali et al. (2019a & b), the change detection was done using post-classification comparison (PCC) and the results showed that agriculture land, forest, wetlands, and water bodies drastically decreased during the study period, 1991 – 2015 (Table 5.2 and Figure 5.2). Conversely, built-up areas and barren land substantially increased in the same period.

Table 5.1 Land-use land-cover (LULC) categories used in Dedza District

LULC class	Description
Water bodies	Rivers, permanent open water, lakes, ponds, reservoirs.
Wetland	Permanent and seasonal grasslands along lake, river, and streams, marshy land and swamps.
Agricultural land	All cultivated and uncultivated agricultural areas, such as farmlands, crop fields including fallow lands/plots, and horticultural lands.
Forest	Protected forests, plantations, deciduous forests, mixed forest lands, and forests on customary land.
Built-up areas	Residential, commercial and service, industrial, socioeconomic infrastructure, and mixed urban and other urban, transportation, roads, and airports.
Barren land	Areas around and within forest-protected areas with no or very little vegetation cover, including exposed soils, stock quarry, rocks, landfill sites, and areas of active excavation.

Table 5.2 LULC change trends and annual rate of change of the study area.

LULC Class	1991 Area (Ha)	%	2015 Area (Ha)	%	LULC Changes (1991–2015) (%)	Annual Change Rate (1991–2015) (%)
Water	1380.60	0.37	899.55	0.24	−0.13	−1.78
Wetland	3626.73	0.96	2680.29	0.71	−0.25	−1.26
Forest	9939.15	2.64	6237.63	1.66	−0.98	−1.94
Agriculture	267,977.43	71.3	260,879.31	69.41	−1.89	−0.11
Barren	92,185.38	24.53	97,174.62	25.85	1.32	0.22
Built-up	761.67	0.2	7999.56	2.13	1.93	9.8
Total area	375,870.96	100	375,870.96	100		

Source: Munthali et al. 2019a &b

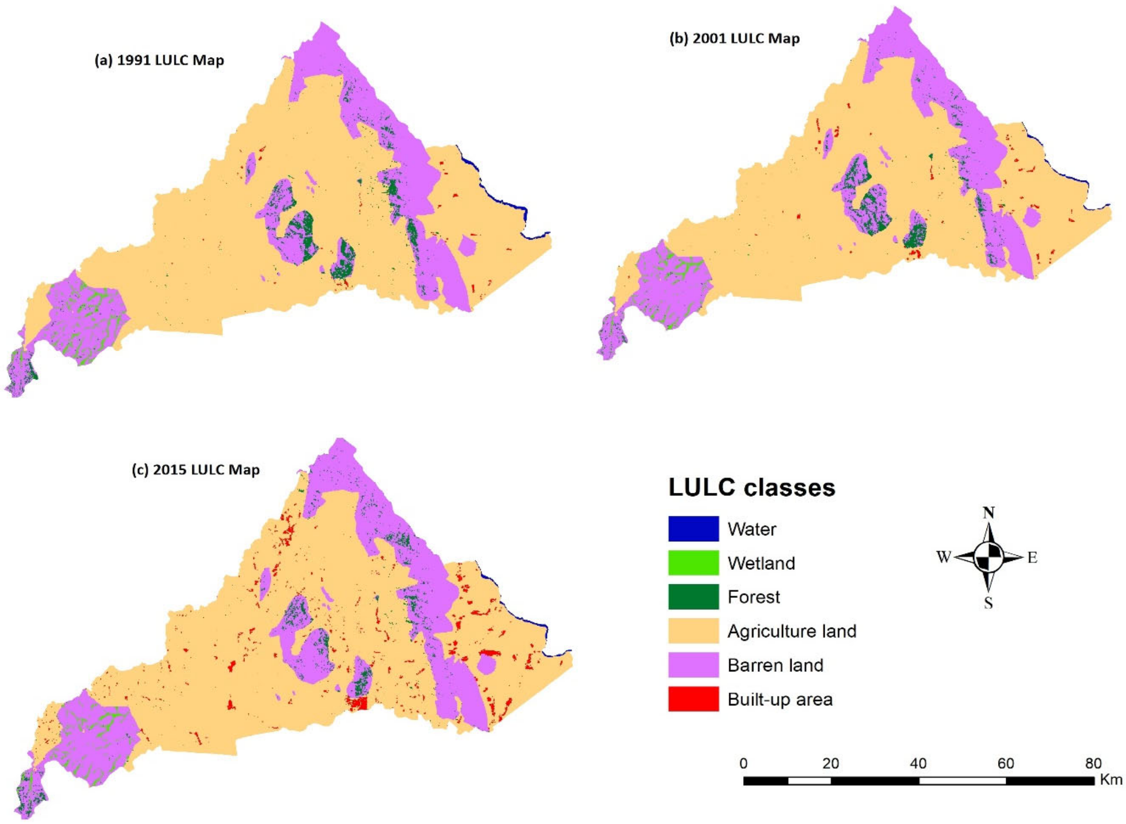

Fig. 5.2 LULC Maps for 1991, 2001 and 2015

5.2.3 Primary data collection and analysis

Primary data was collected by means of household surveys focus group discussions (FGDs) and key informant interviews. A combination of structured and semi-structured interviews was conducted with a representative from 586 households (HHs) in Dedza Districts which were randomly selected from villages under the rule of four (4) traditional authorities (TAs) namely TA Kasumbu, Inkosi Kaphuka, Senior Chiefs Kachindamoto and Kachere. The study employed a questionnaire (Appendix 1) which comprised of both open and closed-ended questions. The questionnaire was translated to the local language (Chichewa) and each HH interview lasted for about 30 to 60 minutes. A pilot survey prior to the formal HH surveys was conducted and the questionnaire was pretested on 20 HHs to ensure that all questions were clear and reliable and to collect valid data for the research study. The HH surveys covered topics related to socioeconomic and demographic characteristics of HHs, land tenure and access to resources. The questionnaires also captured information about the respondents' perception with regard to LULC changes, drivers of LULC changes, the impacts of these changes on rural communities and natural resources and finally, the coping mechanisms/strategies employed HH members in response to LULC changes.

In addition to HH interviews, FGDs and key informant interviews were conducted in order to triangulate and gather detailed and in-depth information about respondents' perceptions about LULC dynamics, the drivers behind the changes, impacts associated with these changes and the nature of the coping strategies used by the local communities. A specific checklist with open-ended questions was developed in this study to collect this information. A total of four (4) FGDs were held in the four (4) TAs of the study area where HH surveys were conducted. Each FDG comprised of 10 – 15 discussants and lasted between 2 to 3 hours.These FGDs targeted the Area Development Committees (ADCs) where household interviews were done. The key informants were purposively targeted. In this study, the researcher targeted the professionals or natural resource experts from Dedza District council. These included the technical members such as the District Commissioner, researchers and officers from agriculture, natural resource, and environmental institutions and organizations.

5.2.4 Statistical analysis

A combination of different data analytical methods was employed to analyze data collected in this research. These are descriptive statistics, inferential statistics and GIS-based processing analysis. Change detection was done using ERDAS Imagine software. The socioeconomic data derived from the questionnaire were analyzed using SPSS 25. In alignment with the qualitative techniques used by Hsieh and Shannon (2005), a thematic analysis was conducted on the data collected during FGDs and key informant interviews. Responses by the respondents regarding the impacts of LULC dynamics and coping strategies used were also ranked. The ranking exercise was computed using the principle of a weighted average ranking index as adopted in Musa et al. (2006) and Solomon et al. (2018). For this approach the following equation was applied:

$$Index = \frac{R_n C_1 + R_{n-1} C_2 \cdots + R_1 C_n}{\sum R_n C_1 + R_{n-1} C_2 \cdots + R_1 C_n} \tag{5.1}$$

where R_n = value given for the least-ranked level (for example, if the least rank is the 5th, then R_n = 5, R_{n-1} = 4, R_1 = 1; C_n = counts of the least ranked level (in the above example, the count of the 5th rank = C_n, and the count of the 1st rank = C_1).

5.3. Results

5.3.1 Socioeconomic characteristics of the respondents

The majority (93.3%) of the sampled members of the HHs interviewed had lived in the study area throughout the study period (1991 – 2015). The results have shown that the respondents' age ranged from 20 to 97 years with a mean age of 39.2 years (Table 5.3). The minimum, mean and maximum household size was 1, 5 and 13 persons respectively. The farm size owned by HHs interviewed ranged from 0.25 to 13 acres. Almost 80.2% of the HHs owned ≤3 acres of land. The larger proportion (63.3%) of the respondents were female and only 77.8% of the HH respondents were literate. Approximately, 78.7% of the interviewees were married and over 70% of the HH were male-headed. The mean annual income per HH was MK283,843.26 (US$397.68) whose majority (81.6%) primarily depend on farming as their main occupation. Most of the HHs (88.2%) use a 3-stone open fire as a common domestic stove for cooking.

Table 5.3 Household characteristics of the sampled respondents (N = 586).

Household attribute	Value
Average household age (years)	39.2
Gender (female, %)	63.3
Head of the family (male, %)	71.7
Marital status (married, %)	78.7
Education (literate, %)	77.8
Occupation (Farmer, %)	81.6
Mean household size (no.)	5.6
Mean landholding size (acres)	2.32
Ethnic group (Chewa, %)	50.7
Mean income (MK/year*)	286,843.26
Sources of income (farming, rank)	1
Domestic stove used for cooking (3-stone open fires, %)	88.2%

Note: * Malawi currency at the time of the study, 1 USD = 721.30.

5.3.2 Impacts of LULC changes on agricultural land

In the context of this study, the household members interviewed held the perception that the size of agricultural land and crop production between 1991 and 2015 has drastically declined (Figure 5.3). Approximately, 57.3% and 82.8% of the interviewees perceived that agricultural land and crop production has declined respectively. With respect to the contributing factors leading to a decline in crop production, the HHs interviewed were asked to rank the major five (5) causes. The results revealed that soil infertility, unreliable rainfall, high cost of agricultural inputs, lack of money for inputs and lack of agricultural inputs were the five (5) major causes of low crop production in the study area (Table 5.4).

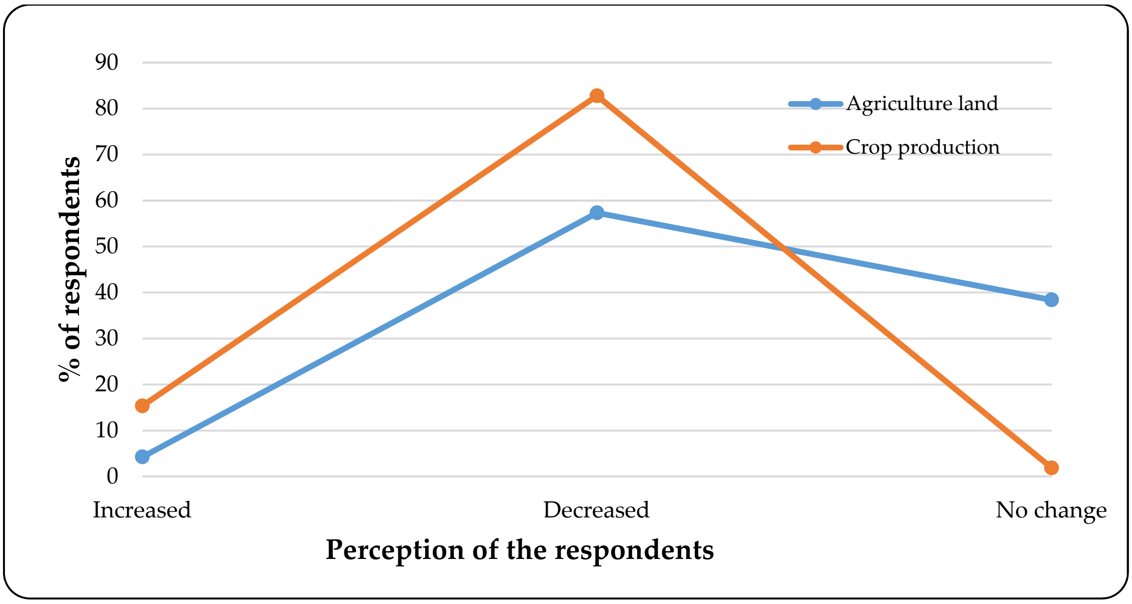

Fig. 5.3 Perceptions of respondents on agricultural land and crop production

Table 5.4 Causes of declined crop production in the study area

Causes	No. of Respondent Per Rank					Weight	Index	Rank
	1	2	3	4	5			
Soil infertility	141	85	66	33	29	1338	0.216	1
Unreliable rainfall	98	116	54	44	13	1217	0.196	2
Pests and diseases	55	37	50	24	15	636	0.103	6
Limited/inadequate land	9	20	24	25	19	266	0.043	8
Lack of agricultural inputs	46	44	56	29	12	644	0.104	5
Inadequate labour	12	13	8	12	12	172	0.028	10
Low marketing prices	12	19	14	11	9	209	0.034	9
Lack of money for inputs	38	54	57	29	23	658	0.106	4
High cost of agricultural inputs	46	59	51	25	16	685	0.110	3
Poor access to subsidy programme	22	20	17	12	17	282	0.045	7
Soil erosion and waterlogging	5	6	7	8	4	90	0.015	11
Lack of access to information on improved agricultural technologies	0	0	1	1	0	5	0.001	12

5.3.3 Impacts of LULC dynamics on forest resources

From Figure 5.4, the results reveal that forest cover of the study area has declined which resulted in increased distances that had to be covered for the collection of forest produce and products. Almost 87.4%, 7.8% and 4.8% of the HHs interviewed indicated that forest cover had declined, increased and remained unchanged respectively during the study period. On the other hand, approximately half (50.7%), 31.4% and 17.9% of these HHs perceived that distance to the collection of forest produce and products have substantially increased, decreased and remain unchanged respectively. It is clear from Table 5.5 that the decrease in forest cover as a result of deforestation and forest degradation has impacted the local communities in different ways. The households identified lack of firewood as the most important impact of increased deforestation and forest degradation in the study area followed by loss of soil fertility, floods and droughts, lack of wood for construction and finally depletion of water resources.

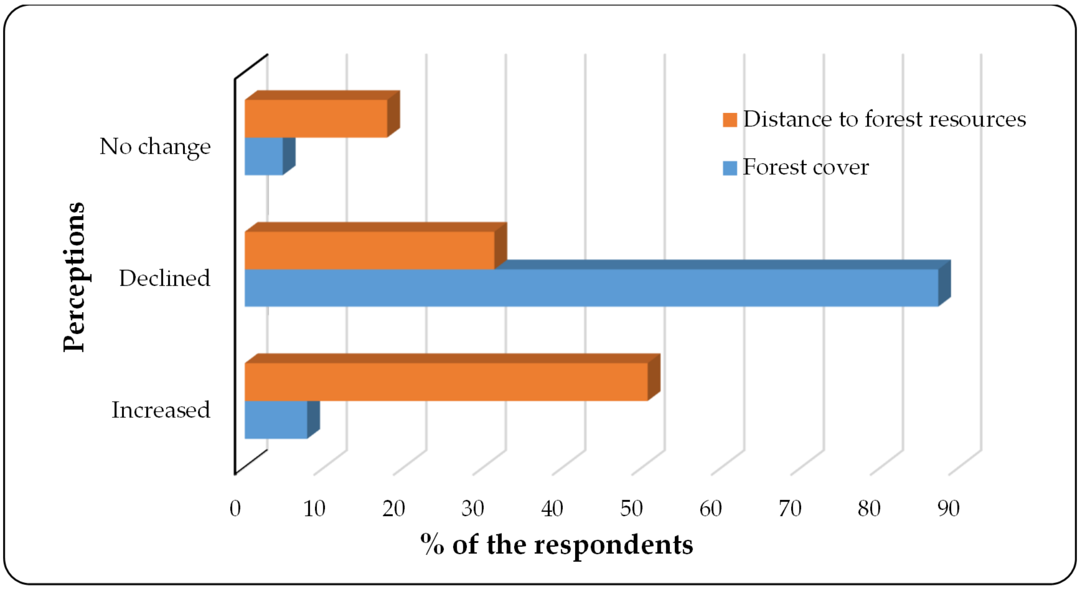

Fig. 5.4 Perceptions of respondents' forest cover and distance to forest resources

Table 5.5 Impacts of declined forest cover or deforestation to communities

Impacts of deforestation	No. of Respondent Per Rank					Weight	Index	Rank
	1	2	3	4	5			
Lack of firewood	206	135	89	34	14	1919	0.269	1
Lack of wood for construction	36	112	67	73	30	1005	0.141	4
Floods and droughts	127	72	77	37	19	1247	0.174	3
Depletion of water resources	42	50	53	49	26	693	0.097	5
Decline in scenic value	6	18	31	23	42	283	0.040	7
Loss of soil fertility	74	116	101	56	30	1279	0.179	2
Unreliable rainfall	73	35	27	14	5	619	0.087	6
Heavy winds	2	12	13	2	1	102	0.014	8

5.3.4 Shocks experienced by rural communities as a result of LULC changes

The study revealed that HHs interviewed in the study area experienced remarkable shocks over the past five (5) years as a result of LULC change impacts (Table 5.6). Drought was the highest-ranked shock reported by HHs followed by floods, food shortage, loss/damage of crops and death household members. These shocks have affected the rural communities such that the majority (>50%) of the communities lost their assets and income and there was a decline in crop yield (Figure 5.5). Additionally, results from FGDs and key informant interviews revealed that the District also experienced heavy winds/hailstorms and crop pest outbreaks.

Table 5.6 Major shocks experienced by in Dedza in the past 5 years

Major shock	No. of Respondent Per Rank					Weight	Index	Rank
	1	2	3	4	5			
Fire	27	10	4	2	3	194	0.081	6
Drought	43	25	12	10	4	375	0.156	1
Irregular rainfall patterns	17	18	6	7	5	194	0.081	6
Increase in price of inputs	5	7	9	9	6	104	0.043	10
Great loss of crops/crop damages	23	16	11	9	2	232	0.096	4
Great loss/death of livestocks	15	5	4	2		111	0.046	9
Theft/robbery and other violence	16	10	5	3	1	142	0.059	8
Floods	39	25	13	2	1	339	0.141	2
Food shortage	19	27	16	8	11	278	0.115	3
Price raise of food items	3	7	3			52	0.022	11
Illness of household member	20	14	8	2	3	187	0.078	7
Death of household member	27	10	3	6	5	201	0.083	5

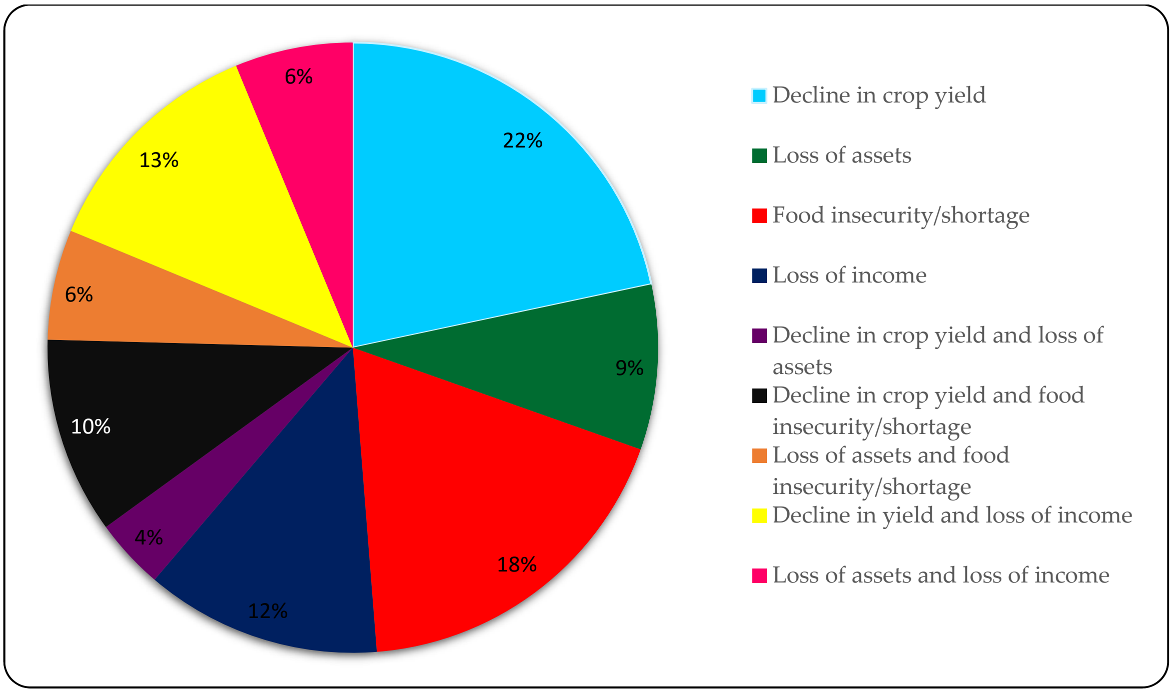

Fig. 5.5 Effects of shocks on the livelihoods of the sampled HHs

5.3.5 Coping strategies used to counter shocks experienced by rural communities

The rural communities from Dedza District are engaged in different livelihood coping strategies to counter shocks faced due to LULC changes that have taken place in the study area during the study period. The results have revealed that the most prominent coping strategies used in response to LULC change-related shocks included participation in piecework, receiving aid from government and NGOs, procuring financial support from relatives and the reliance on savings and credits (Table 5.7). Other livelihood coping strategies included the selling of agricultural assets, crops, livestock and forest produce. In addition, the focus group discussants and key informants said that people in the District coped with the shocks by planting drought-tolerant crops, collecting wild fruits and tubers, construction of dikes and practicing irrigation farming.

Table 5.7 Household/livelihood coping strategies

Livelihood coping strategy	No. of Respondent Per Rank					Weight	Index	Rank
	1	2	3	4	5			
Participated in piece works	126	23	6	7	1	755	0.360	1
Received food aid from government and NGOs	8	37	10	7	5	237	0.113	2
Relied on own savings	19	11	12	4	1	184	0.088	4
Obtained credit	17	13	9	3	13	183	0.087	5
Reduced food consumption	7	8	3	3	0	82	0.039	8
Household members migrated	6	2	0	0	0	38	0.018	12
Reduced expenditures	1	3	0	0	0	17	0.008	13
Sold Agricultural assets	15	9	2	0	1	118	0.056	6
Received unconditional aid from relatives	20	14	8	10	1	201	0.096	3
Sold livestock	9	6	6	1	1	90	0.043	7
Sold crop stock	6	4	6	2	0	68	0.032	10
Sold land/buildings	1	6	9	9	5	79	0.038	9
Sold forest produce	0	7	5	1	0	45	0.021	11

5.4. Discussion

5.4.1 Impacts of LULC changes on natural resources and livelihoods

Changes in LULC of any landscape at the spatiotemporal scale have increasingly been recognized by many researchers around the world as an important driver of environmental change. Accordingly, this has become a major issue for management and monitoring of the natural resource base (Gamble et al. 2003; Halmy et al. 2015; Mei et al. 2016). The capacity of an ecosystem to provide goods and services are impacted by LULC changes of any landscape (Burkhard et al. 2012). Thus, they have significant impacts on the functioning of socioeconomic and environmental systems. The results from this study clearly indicated that LULC modifications in Dedza District between 1991 and 2015 has resulted in declined agriculture and forest resources, depletion of water resources and wetlands. The decrease in agricultural land has resulted in declined crop production in the study area. These results are similar to findings from elsewhere in which rural communities perceived that LULC changes resulted in declined agricultural land, forest resources, depletion of water resources and wetlands (Gessesse and Bewket 2014; Kirma et al. 2016; Benti et al. 2017; Karki et al. 2018).

The households in the study area believed that the observed decline in crop production was being exacerbated by factors such as soil infertility, unreliable rainfall, high cost of agricultural inputs and a lack of money for farming-related resources. Our key informants and FG discussants also suggested that reduced crop production was due to persistent dry spells (drought), climate change effects, poor land husbandry practices and inadequate market opportunities. Accordingly, reduced crop production implies declining agricultural productivity which has been linked to the incidence of food insecurity in the study area. Scherr and Yadav (1996) projected that by 2020, land degradation in the form of soil nutrient depletion and soil erosion will negatively affect food production and livelihoods of rural people especially in poor and densely populated areas in the developing countries (Malawi and the study area inclusive). This might cause a decline in the ecological, physiological and productive capacity of the land resulting in reduced potential agriculture yields. Some of these causes of reduced crop production were reported in a study by Desalegn et al. (2014) that revealed that farmers' crop production in Central Highlands of Ethiopia was constrained by lack of access to credit, deterioration of soil fertility and shortage of land. Furthermore, a recent study by Agidew and Singh (2017) found that local communities perceived that the LULC changes that took place in Teleyayen sub-watershed of Ethiopia between 1973 and 2015 had implications on their rural livelihoods and food security. Some of the perceived implications included climate change, land degradation, shortage of farmland, crop yield reduction, farmland fragmentation, soil erosion rural-urban migration.

The depletion of water sources and declined wetlands as observed by the communities in Dedza District compromises the capacity of the landscape or ecosystem to perform its hydrological functions efficiently. The results agree with findings from remotely sensed analysis that the areas occupied by water bodies and wetlands in Dedza District decreased by 34.8% and 26.1% respectively (Munthali et al. 2019a). According to Bronstertet et al. (2002), IPCC (2007) and Gibbard et al. (2005), changes in LULC substantially affect the climate of any landscape which adversely affects water resources such as wetlands and water. The results concur with findings by ICIMOD and MoFSC (2014) who reported that water bodies (streams/rivers) and wetlands (swamps/marshes) decreased by 14% and 3% respectively in Nepal since 1976. This contributed to the loss of threatened species and other biodiversity/habitat in the country. Chaudhary et al. (2017) made similar observations in Phobjikha valley of Bhutan. The reduction in wetlands and water bodies in Phobjikha valley aggravated flooding in the open and mountainous areas of Bhutan. According to Temesgen et al. (2018), shrinkage and disturbance on wetlands and water bodies reduce their capacity to regulate flooding in any landscape.

The decline in forest cover or increased deforestation and forest degradation reported in this study has consequently resulted in a shortage of firewood and wood for construction, persistent floods and droughts, depletion of water resources and loss of soil fertility in the study area. In Dedza, forest cover loss and increased deforestation and forest degradation are highly linked to population growth and poverty (Munthali et al. 2019a). These results clearly show that rural communities from Dedza District depend almost entirely on forest resources for their daily energy needs and construction. Consequently, these two factors exert pressure on forest resource base leading to increased demand for fuelwood and wood for construction. The results are in line with findings by Sandhu and Sandhu (2014) and Wangchuk et al. (2014). They found that a decline in forest produce and products such as fodder, fuelwood, timber and litter where livelihood options are mainly limited to agriculture and livestock in the Himalayas increased their vulnerability. The types of conditions described in this study could, thus, force local communities to overexploit the remaining resources, thus reducing its availability and quality which could end up leaving them in a poverty trap (Gerlitz et al. 2012; Gerlitz et al. 2014).

With regard to impacts of LULC changes on natural resources, the findings of impacts of LULC changes on natural resources are in line with Gessesse and Bewket (2014) and Gessesse (2018) who reported that changing LULC that took in Central Highlands of Ethiopia had impacts on food security of the communities, water resource availability and agricultural land productivity. Further, Agidew and Singh (2017) found that LULC changes had implications on rural households in the North-eastern highlands of Ethiopia. These impacts included land degradation, shortage of farmland, crop yield reduction, farmland fragmentation, increased rate of soil erosion and climate change. The authors argued that the expansion of agricultural land and degraded land in their study area was at the expense of forest land, grasslands and shrublands. Several authors have also reported that mismanaging terrestrial ecosystems and other natural resources such as forests, water and agriculture land leads to severe environmental problems such as forest degradation and deforestation, soil erosion and degradation, siltation of rivers, water shortage and deterioration and loss of biodiversity (Girma et al. 2002; Seto et al. 2002; Muluneh 2003; Verburg 2006). Shiferaw

(2011) and Rientjes et al. (2011) confirmed that the negative effects of changing LULC on the environment are strongly influenced by the conversion of resources such as land and forests. Reduction in forest cover also implies a shortage of timber for construction and fuelwood supply to the communities. Thus, forest-dependent communities are affected by changing LULC. Forest degradation and deforestation hamper the rural livelihoods (especially the indigenous communities) whose basic life strongly depend on the natural resource base in proximity (Banerjee and Madhurima 2013).

5.4.2 Shocks and rural livelihood strategies

Rural households in developing countries are frequently affected by multiple shocks, either, idiosyncratic or covariate shocks, resulting from changes in LULC. These greatly threaten rural communities' livelihoods and adversely impact their welfare. As postulated by Fafchamps (2009) and Haq (2015), these shocks could be social, natural/agricultural, economic or related to health. In Dedza district, rural communities devised various strategies to cope with the shocks induced by changing LULC and these included; drought, floods, food shortage, loss/damage of crops, the death of a household member, crop pest outbreak, strong winds/hailstorms. Most of the crops were attacked by pests such as armyworms. Similar results have also been reported by Bryan et al. (2010) where local communities experienced shocks such as drought, erratic rainfall, floods, loss of income and assets, crop yield reduction, food shortages, death of livestock and increase in food prices. Other findings from Dercon et al. (2005) and Kamwi et al. (2015) indicated that rural households reported droughts and food shortages as the most important shocks affected by in Zambezi region of Namibia and Ethiopia respectively. However, Kamwi et al. (2015) also reported that some surveyed households reported irregular rainfall and fires as other shocks faced by them in the Zambezi region and these shocks were not reported in our study.

Berkes and Jolly (2001) define coping mechanisms/strategies as a short-term response to the crisis on livelihood systems in the face of unwelcome/undesired situations. These possible strategies help in reducing people's vulnerability to LULC change and climate change impacts. Rural households of Dedza District are engaged in different coping mechanisms. Rural communities in the study area adopted piecework, receiving aid from government and NGOs, receiving unconditional aid from relatives, relying on their own savings and credits as coping strategies to counter the shocks faced during the reporting period. Similar results were revealed in

West-Arsi zone of Ethiopia where local communities coped with the LULC and climate impacts through savings, aid from relatives and government and other institutions, credits, diversification and selling of wood and livestock (Senbeta 2009). In another study by Kamwi et al. (2015), rural households from Zambezi region indicated borrowing from relatives, piecework, wild food collection and food aid as the prominent coping strategies. In other countries, rural communities adopted different coping strategies from Dedza rural households in responding to the shocks. For instance, in Kenya, rural communities were able to cope with the shocks by reducing food consumption, purchasing additional food and consuming different food (Bryan et al. 2010). In order for the local communities in Nepal to cope with the changing scenario sustainably, they used the following short-term strategies; borrowing money, cutting down the living expenditure, labour migration, use of kerosene and buying food on credit (ICIMOD and MoFSC 2014).

5.5 Conclusion

This study assessed the perceived impacts of land use and land cover changes taken place between 1991 and 2015 on natural resources and rural livelihoods of Dedza district, Malawi. It further examined the shocks experienced by communities resulting from LULC and climate change impacts and the short-term strategies used to cope with these changes. Our findings show that the changing LULC in the study area has substantially impacted natural resources and rural livelihoods in Dedza district. The paramount impacts include a decline in agricultural land, crop production and forest cover and an increase in distance to forest resources. The causes of reduced crop production include soil infertility, unreliable rainfall, high cost of agricultural inputs, lack of money for inputs and lack of agricultural inputs. On the other hand, the decline in forest cover has resulted in lack of firewood, loss of soil fertility, floods and droughts, lack of wood for construction and finally depletion of water resources. With the dependency of communities on natural resources in the study, the decline in agricultural land, forest and water resources poses a big threat and risk to their subsistence livelihood.

Results on shocks have revealed that majority of rural households were exposed to shocks such as drought, floods, food shortage, loss/damage of crops, death household members, crop pest outbreak, strong winds/hailstorms. As a result, communities were engaged in short-term strategies including piecework, receiving aid from government and NGOs, receiving unconditional aid from relatives, relying on their own savings and credits.

The findings of this study contribute to a better understanding of a complicated interaction between people and the environment. The consequences and undesirable impacts of the changes on natural resources and rural livelihoods observed in this study need urgent attention by the natural resource managers, planners and decision-makers. It is very clear from findings of this study that government and other stakeholders involved in the management of natural resources and welfare of communities need to work on redesigning appropriate natural resource management and people's welfare policies to coping to the shocks resulted from the undesirable LULC changes take place in the study area. The findings of this research can also be used to develop rational, proper, holistic and integrated approaches implementing policies and strategies that promote management, protection, conservation and restoration of natural resources in Dedza landscape. This study also recommends positive steps to be undertaken through innovative approaches that combine the multi-sectoral approach and commitments of other stakeholders to work closely with communities through participatory natural resource management to reverse the undesirable current LULC change trends and impacts of these on the natural resource base and rural livelihoods. The innovative approaches should also include developing sustainable livelihood options/strategies to cope with the shocks the rural communities have been exposed to.

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CHAPTER 6: MODELLING LAND USE AND LAND COVER DYNAMICS OF DEDZA DISTRICT OF MALAWI USING HYBRID CELLULAR AUTOMATA AND MARKOV MODEL

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Abstract

The changes in landscape patterns are a result of complex interactions of social, economic, demographic, technological, political, biophysical and cultural factors. Modelling land use and land cover (LULC) changes is essential for natural resource scientists, decision-makers and planners in developing comprehensive medium and long-term plans for tackling environmental or other related sustainable development issues. The current study used an integrated approach that combines remote sensing and GIS to simulate and predict plausible LULC changes for Dedza district in Malawi for the years 2025 and 2035 based on Cellular Automata (CA)-Markov Chain model which is embedded in IDRISI Software. The model was validated using a simulated and actual LULC of 2015. The overall agreement between the two maps was 0.98 (98%) with a simulation error of 0.03 (3.0%). The more detailed analysis of validation results based on the kappa variations showed a satisfactory level of accuracy with a K_{no}, $K_{standard}$ and $K_{location}$ of 0.97, 0.95 and 0.97, respectively. The future projections indicate that water bodies, barren land and built-up areas will increase while agricultural land, wetlands and forest land will substantially decrease by 2025 and 2035 respectively. According to the transition probability matrix, almost 94.8%, 97.6% and 95.7% of water bodies, agricultural land and barren land will more likely remain constant by 2025. In contrast, forest land exhibits the highest probability of change of 64.8% and 85.9% by 2025 and 2035 respectively. Results also indicate that the majority of the forest areas will be converted to barren land with a probability of 60.8% and 79.6% by 2025 and 2035, respectively. These findings serve as an important benchmark for planners, natural resource managers and policy-makers in the studied landscape to consider in pursuit of holistic sustainable development policies/strategies/ guidelines sustainable natural resource management.

Keywords: LULC; CA-Markov; Malawi; Multi-criteria evaluation; Modelling

6.1. Introduction

The changes in landscape patterns are as a result of complex interactions of social, economic, demographic, technological, political, biophysical and cultural factors. Land use and land cover (LULC) change has become one of the fundamental concerns in natural resource management, sustainable development and environmental change in the local, national, regional and global landscape (Foley et al. 2005; Yirsaw et al. 2017). As such documentation of these LULC dynamics provides vital information for better understanding of historical land use and management practices, current land use patterns and future LULC change trajectories. Several LULC change studies on environmental changes have been widely investigated using multi-temporal remote sensed imagery approaches (see, for example, Basommi et al. 2016). These studies consistently demonstrate how human activities coupled with natural causes are key drivers of LULC dynamics at all spatial and temporal scales (Lamichhane 2008; Mishra et al. 2014; Singh et al. 2015; Basommi et al. 2016; Singh et al. 2018; Varga et al. 2019). Across the globe, authors have identified agricultural expansion, population growth, poverty, urban growth, charcoal production, firewood collection, just to mention a few, as the drivers responsible for LULC dynamics at local, national, regional and global scale (Serneels and Lambin 2001, Chomitz et al. 2007; DeFries et al.2010; Kindu et al. 2015; Pullanikkatil et al. 2016; Mannan et al. 2018; Solomon et al. 2018. Berihun et al. (2019) identified changes in farming practices as one of the major drivers of LULC changes that took place between 1982 and 2017 in three watersheds of drought-prone areas from different agro-ecological zones of Upper Nile basin in Ethiopia. In another study by Yesuph and Dagnew (2019), fuelwood and timber extraction, drought, expansion of farmlands and settlements, land tenure insecurity, population pressure, terrain features of the area and population growth were the major drivers behind LULC changes taking place in Beshillo catchment of the Blue Nile Basin of North-Eastern Highlands of Ethiopia. Like other countries, Malawi has experienced LULC changes over the past decades. Some studies reported in the literature focused on documenting the nature and extent of these historical changes as well the drivers behind these changes (Palamuleni et al. 2010; Chavula et al. 2011; Munthali and Murayama 2011; Haack et al. 2014; Munthali et al. 2014; Jagger and Perez-Heydrich 2016; Pullanikkatil et al. 2016). However, only Munthali et al. (2014) modelled Dzalanyama Forest Reserve using the Multi-agent simulation approach. Despite the focus on documenting historic changes in Malawi, very few studies, however, have been conducted to simulate the future LULC in the country which formed the purpose of this research.

Pressure on different land uses is increasing all over the world and understanding the implications of Ethiopia change patterns is deemed crucial in the context of future natural resource management and planning. This fact highlights the need for innovative global scientific research in the field of LULC modelling (Kamusoko et al. 2011; Qiang and Lam, 2015). According to Paegelow and Olmedo et al. (2010), LULC modelling is defined as the interpolation or extrapolation when the simulation exceeds the known specified period of time. Pressure on different LULC types is increasing all over the world and understanding the future land use patterns is very crucial and hence calls for global scientific research (Kamusoko et al. 2011; Qiang and Lam, 2015). Future LULC patterns and changes need to be understood as far as natural resource management of available resources is concerned. Thus, spatiotemporal LULC change modelling is imperative in order to predict the future LULC distribution for effective land use management and planning (Regmi et al. 2014; Bhattacharjee and Ghosh 2015; Dezhkam et al. 2017). Accordingly, modelling LULC dynamics also provides vital information to planners and decision-makers about current natural resource management policies and strategies and how these actions may affect the future LULC patterns (Sun et al. 2012; Omar et al. 2014; Regmi et al. 2014; Bhattacharjee and Ghosh 2015;Martinuzzi et al. 2015; Dezhkam et al. 2017). Accurate LULC trajectories are thus pivotal for natural resource scientists, decision-makers and planners in developing comprehensive medium and long-term plans earmarked to prevent the consequences arising from the undesirable LULC changes in a landscape (Theobald and Hobbs 2002; Loomis 2002; Maestas et al. 2003). Additionally, knowing the possible outcomes of the predicted LULC changes can be helpful when making and implementing difficult policy decisions (Sun et al. 2012). Further, understanding future LULC changes would enable the ecosystem service values (ESV) to be estimated in response to LULC dynamics on a landscape (Hu et al. 2008; Dallimer et al. 2015; Kindu et al. 2016). Kelly et al. (2018) used CA-Markov to combat desertification by identifying and predicting the areas that were susceptible/predisposed to desertification in Montes Claros, Brazil.

Recently, modelling LULC change has been considered as one of the most valuable tools in ensuring that the present natural resource base guarantees a future and continuous supply of natural resources. Over the last few decades, researchers have developed and used several LULC change models/approaches for modelling LULC dynamics. Some of the most widely used LULC approaches include evolutionary models (neural networks), mathematical models (linear and static), multi-agent-based models, cellular models (Cellular Automata, CA), expert system models, Markov chains and hybrid models (Stefanov et al. 2001; Verburg et al. 2002; Parker et al. 2003; Xie et al. 2007; Araya and Cabral 2010; Guan 2011; Ralha et al. 2013; Subedi et al. 2013; Han et al. 2015). According to Verburg et al. (2004), LULC models are very powerful tools for examining the spatial pattern as well as the rate and drivers/causes of LULC dynamics. Additionally, Verburg et al. (2004) highlight the value of LULC models in terms of evaluating land-use policies and predicting future land use demand. No single model is capable of considering all the processes of LULC changes at various scales (Verburg et al. 2008). Alternatively, integrated land-use models that combine one or two models are preferred. Presently, the most widely used models in LULC change monitoring and prediction are cellular, Markov chain and agent-based models or the mixed model based on these three types of models (Stevens and Dragićević 2007; Zhao et al. 2012; Myint and Wang 2013; Sol and Claggett 2013). One such mixed model is the Cellular Automata–Markov Chain (CA-Markov) model. The CA-Markov model is one of the most reliable, robust and effective LULC change approaches for predicting the long-term or decadal spatial and temporal variations of LULC in a complex system along with geographic information systems(Thomas and Laurence 2006; Wu et al. 2006; Kamusoko et al. 2009; Yu 2009; Sang et al. 2009;Steeb 2011; Arsanjani 2013; He et al. 2014; Singh et al. 2015). According to Wang and Zhang (2001), the model combines both biophysical and socio-economic data to simulate accurate LULC change in a plausible future. The CA-Markov is used in management, planning, modelling and simulation of the spatial processes (Wu and Webster 2000; O'Sullivan 2001; Wu 2002; Irwin et al. 2009; Araya and Cabral 2010; Singh et al. 2015).

Based on the background above, the present study uses an integrated approach that combines remote sensing and GIS to simulate and predict LULC changes for Dedza district for the years 2025 and 2035 based on CA-Markov using IDRISI Software. Thus, the main objective of this study is to simulate and predict the future spatio-temporal patterns of LULC dynamics of Dedza district of using the hybrid CA-Markov model. It is anticipated that the findings of this study could guide the natural resource scientists, planners and decision-makers to understand the future effects of LULC dynamics in the study area and that will enable them to develop proper interventions, land use planning and management policies for socio-economic development of the study area and districts with similar settings. The CA-Markov approach has been adopted in this study because many researchers have applied this approach in different landscapes to model, monitor, predict and simulate LULC changes in their study areas and the method obtained very accurate and reliable results (Subedi et al. 2013; Rendana et al. 2015; Sing et al. 2017; Liping et al. 2018). Equally important, Liu et al. (2007), Qiuand Chen (2008) and Yang et al. (2012) stated that the reliability of LULC change modelling approach can be tremendously improved by coupling two or more modelling techniques to integrate the advantages of each simulation model.

6.2. Materials and Methods

6.2.1 Study area

Dedza district is located in the Central Region of Malawi, approximately 81km from the Capital city of Malawi, Lilongwe (Figure 6.1). It covers an area of 3,624 km^2. It is characterized by three topographic zones namely Lilongwe plain (altitude 1100-1300m), the Dedza highlands (1200-2200m) and the Dedza escarpments (1000-1500m). Soils are ferruginous: generally deep and brown to reddish in colour (GoM 1999). Clay and sandy loam soils are predominant in the study area (GoM 2012; 2013). The district receives mean annual rainfall varying from 800mm to 1200 mm. The average annual temperature is 15.5°C. The district is endowed with rivers which include Linthipe River originating from Dzalanyama Ranges (Dedza) and runs through Dedza, Lilongwe and Salima districts. Linthipe River joins the Diampwe II River which drains the area to the west and then turns north-eastwards towards Lake Malawi. Both Linthipe and Diampwe are perennial.

Based on the latest Malawi population and housing census report, the district has a population of 830,512 (Government of Malawi 2019). The annual population growth rate is approximately 2.8 % while the population density is 221 people /km^2 which is above the average national density of 186 people/ km^2. Approximately, 52.3% of the population are female and the district has a sex ratio of 91.1. Proportionately, 2018 census reveals that about 96% of the total population lives in rural areas. The majority of these rural people are categorized as extremely poor. According to GoM (2019), literacy levels of the people in the district are low (57% of the population is literate) as compared to Likoma district (85% of the population is literate).

According to GoM (2010; 2012), the main economy and source of livelihoods of the majority of the communities of the study area are primarily based on natural resources especially land, forests and water. Rainfed and irrigation agriculture, casual labour and small-scale businesses are mainly practiced as means of diversifying income (Gom 2012). Thus, the main economic activities of the local communities are farming especially in the plains, forestry in the highlands and fishing along the lake. In terms of land use, agriculture remains the major land use in Dedza district. Other notable LULC types include settlements, forests, wetlands, water bodies and barren land. The district has two government-owned plantations namely Chongoni and Dedza Mountain Plantations. Other forests include Mua-livulezi, Chongoni, Dzalanyama, Dedza Mountain, Mua-tsanya and Dedza-Salima Escarpment Forest reserves

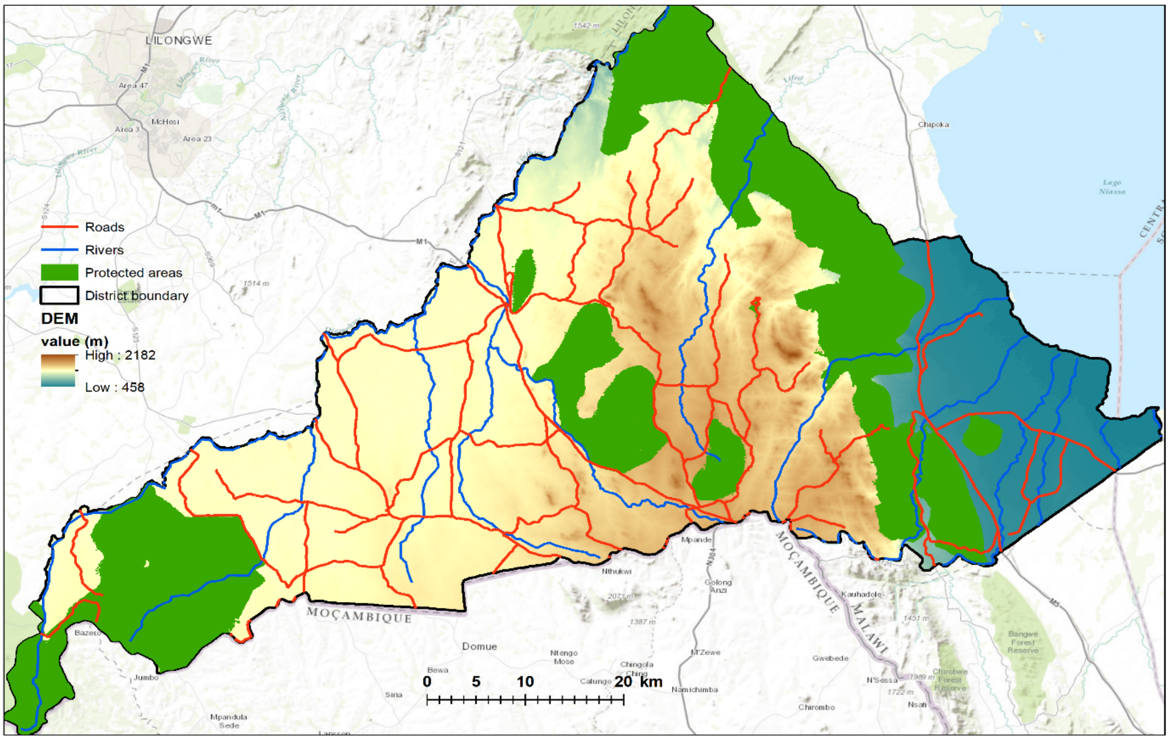

Fig. 6.1 Location of the study area

6.2.2 Data used

The data used in this study were acquired from different sources. Landsat satellite imagery from 1991, 2001 and 2015 were used to derive LULC classified maps for the studied landscape. The satellite data for 1991 and 2001 was selected based on the availability of the satellite imagesand absence of cloud cover. Shuttle Radar Topography Mission (STRM) DEM was also used. The detailed satellite data used in this study are depicted in Table 6.1.

Table 6.1 Detailed information about datasets used in this study

Dataset	Spatial resolution (m)	Date of acquisition	Source
Landsat 5 TM (Path/row: 168/070)	30	16/09/1991	USGS
Landsat 7 ETM+(Path/row: 168/070)	30	19/09/2001	USGS
Landsat 8 OLI (Path/row: 168/070)	30	18/09/2015	USGS
STRM*	30		

**Data collected from* [*http://dwtkns.com/srtm30m/*](http://dwtkns.com/srtm30m/)

6.2.3 Image pre-processing, classification and accuracy assessment

The satellite data were all preprocessed wherein the images were atmospheric, radiometric and geometric corrected. A hybrid supervised/unsupervised classification approach was employed. Image classification was done using the hybrid classification approach. Firstly, unsupervised image classification was employed using Iterative Self-Organizing Data Analysis clustering (ISODATA) to determine the number of spectral classes. Secondly, MLC supervised classification was performed on unsupervised classified images for the final land use/cover classification for the images of 1991, 2001 and 2015. Six (6) classes were identified based on physiographical knowledge of the study area, supportive ancillary data, the researcher's prior local knowledge and visual interpretation using the historical function of Google earth (Table 6.2).

Table 6.2 Description of LULC classes

LULC class	Description
Water bodies	Rivers, permanent open water, lakes, ponds, reservoirs
Wetland	Permanent and seasonal grasslands along the lake, river and streams, marshy land and swamps
Agricultural land	All cultivated and uncultivated agricultural lands areas such as farmlands, crop fields including fallow lands/plots and Horticultural lands.
Forest	Protected forests, plantations, deciduous forest, mixed forest lands and forest on customary land.
Built-up area	Residential, commercial and services, industrial, socio-economic infrastructure and mixed urban and other urban, transportation, roads and airport.
Barren land	Areas around and within forest protected areas with no or very little vegetation cover including exposed soils, stock quarry, rocks, landfill sites, and areas of active excavation.

A stratified random sampling method was employed to collect 221 ground control points and Google Earth images were used to extract reference data. The accuracy assessment was only performed on 2015 images. Accuracy assessment was not performed on 1991 and 2001 images due to the unavailability of ground validation data in the form of aerial photographs and archived Google earth images. In this case, the used signatures for the 2015 images were superimposed on older images. Accuracy assessment was determined using the Kappa coefficient, overall accuracy, producer's and user's accuracy which were derived from the error (confusion) matrix as discussed by Liu et al. (2007) and Congalton and Green (2009). The accuracy assessment based on the error (confusion matrices) showed an overall accuracy of 91.86% with a kappa coefficient of 0.866 (Munthali et al. 2019a). A detailed description of all the classification and accuracy assessment methods used to derive the LULC (Figure 6.2) is described in previous publications (See Munthali et al. 2019 a & b).

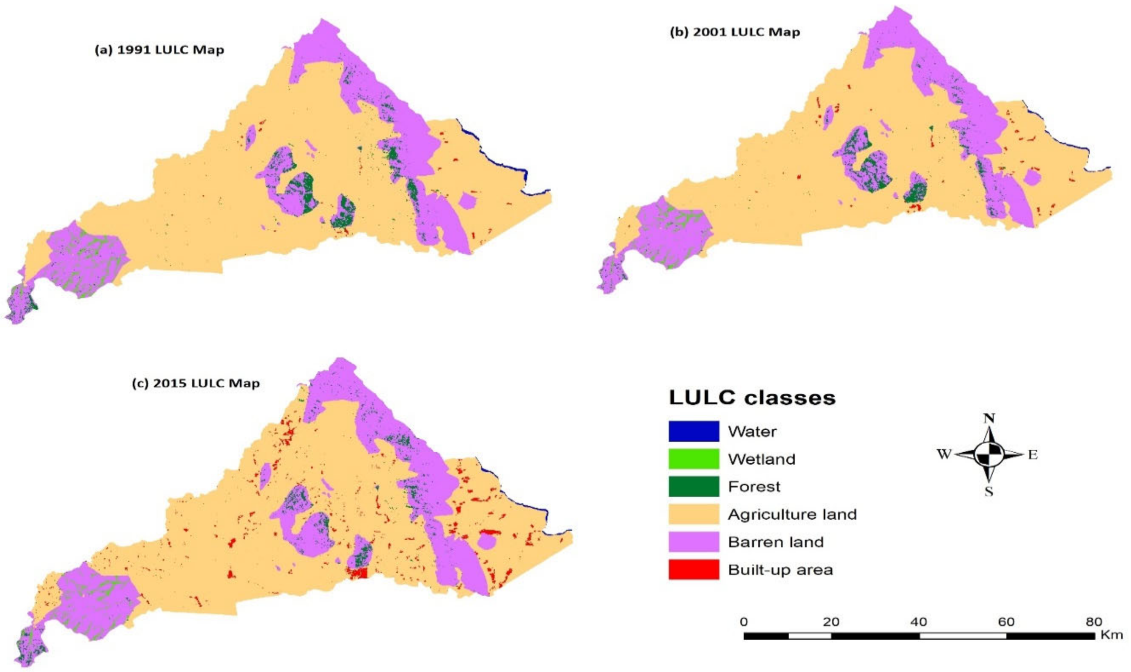

Fig. 6.2 LULC maps for 1991, 2001 and 2015 (Munthali et al. 2019a)

6.2.4 Modelling of future LULC dynamics

6.2.4.1 Markov chain model

The Markov chain model (MCM) is a stochastic model that describes the transition probability of LULC type shifting from one mutually exclusive state (S_t) to another state (S_{t+1}) over a specified period of time (Thomas and Lawrence 2006; Lu et al. 2009; Mishra et al. 2011; Liping et al. 2018). The predicted future LULC changes usually depend on the subsequent transition probabilities generated from the past or current LULC changes (Guan et al., 2008; Wu et al. 2010). However, MCM does not give the right spatial distribution (allocation) of occurrences of LULC changes rather estimate and predict the magnitude/quantity of these changes (Behera et al. 2012; Yang et al. 2012). Mathematically, MCM for predicting LULC changes can be presented using the conditional probability equation described by e.g., Yousheng et al. (2011); Ma et al. (2012); Subedi et al. (2013); Singh et al. (2015) and Mondal et al. (2016);

$$S_{(t+1)} = P_{ij} \times S_{(t)} \quad (6.1)$$

and

$$P_{ij} = \begin{bmatrix} p_{11} & \cdots & p_{1n} \\ \vdots & \vdots & \vdots \\ p_{n1} & \cdots & p_{nn} \end{bmatrix} \qquad (0 \le P_{ij} \le 1 \quad \text{and} \quad \textstyle\sum_{j=1}^{n} P_{ij} = 1, i, j = 1, 2, \cdots, n) \quad (6.2)$$

where P_{ij} is the transition probability matrix, i and j are the LULC type at time of t and $t+1$ respectively, n is the no. of LULC types; S_t and S_{t+1} is LULC status at time of t and $t+1$ respectively

6.2.4.2 Cellular automata model

According to Yang and Li (2007) and Guan et al. (2011), Cellular automata (CA) model is a discrete model with a spatially extended dynamic system based on defined transition rule that relates the new state to the previous state of LULC type and those of its neighbours. Additionally, CA-based models have the ability to represent nonlinear and complex spatially distributed processes thereby capable of providing insights into local, national, regional and global LULC change patterns (He et al. 2006; Abubakret al. 2013; Liping et al. 2018). However, the model has notable components that need to be considered to get optimum simulation results and these parameters are cells, transition rules, cell size, time and cell neighbourhoods (Wang et al. 2012; Liping et al. 2018). Thus, the spatial and temporal state of the neighbours heavily depends on the state of each cell (Kumar et al. 2014). According to Sang et al. (2011), Subedi et al. (2013), Singh et al. (2015), Mondal et al. (2016) and Liping et al. (2018), the CA model can be expressed as:

$$S\ (t, t+1) = f((S_t),\ N) \tag{6.3}$$

Where S is the set of states of the finite cells, N is the number of neighbourhood cells, t and $t + 1$ are different times and f is the transformation rule of local space

6.2.4.3 CA-Markov model

The CA-Markov approach is a model that effectively combines the advantages of Markov Chain to predict long-term LULC changes and Cellular Automata models to accurately simulate and predict future spatiotemporal LULC changes (Behera et al. 2012; Wang et al. 2012; He et al. 2014; Yang et al. 2014; Singh et al. 2015; Parsa et al. 2016). It is worth mentioning that the use of integrated CA-Markov model in LULC studies is advantageous due to its dynamic explicit simulation capability, simple calibration, high efficiency with data and ability to simulate multiple LULC types and complex patterns (Mermarian et al. 2012; Yang et al. 2012; Hyandye and Martz 2017; Singh et al. 2015; Singh et al. 2018).

This study adopted an existing modelling technique, CA-Markov model with Multicriteria Evaluation (MCE) module embedded in the IDRISI software version 17. Figure 6.3 depicts the methodology deployed for predicting LULC dynamics in the study area using the CA-Markov model. According to Eastman (2000), the model changes various LULC classes of cells by Markov transition matrix, a suitability map and a neighborhood filter.

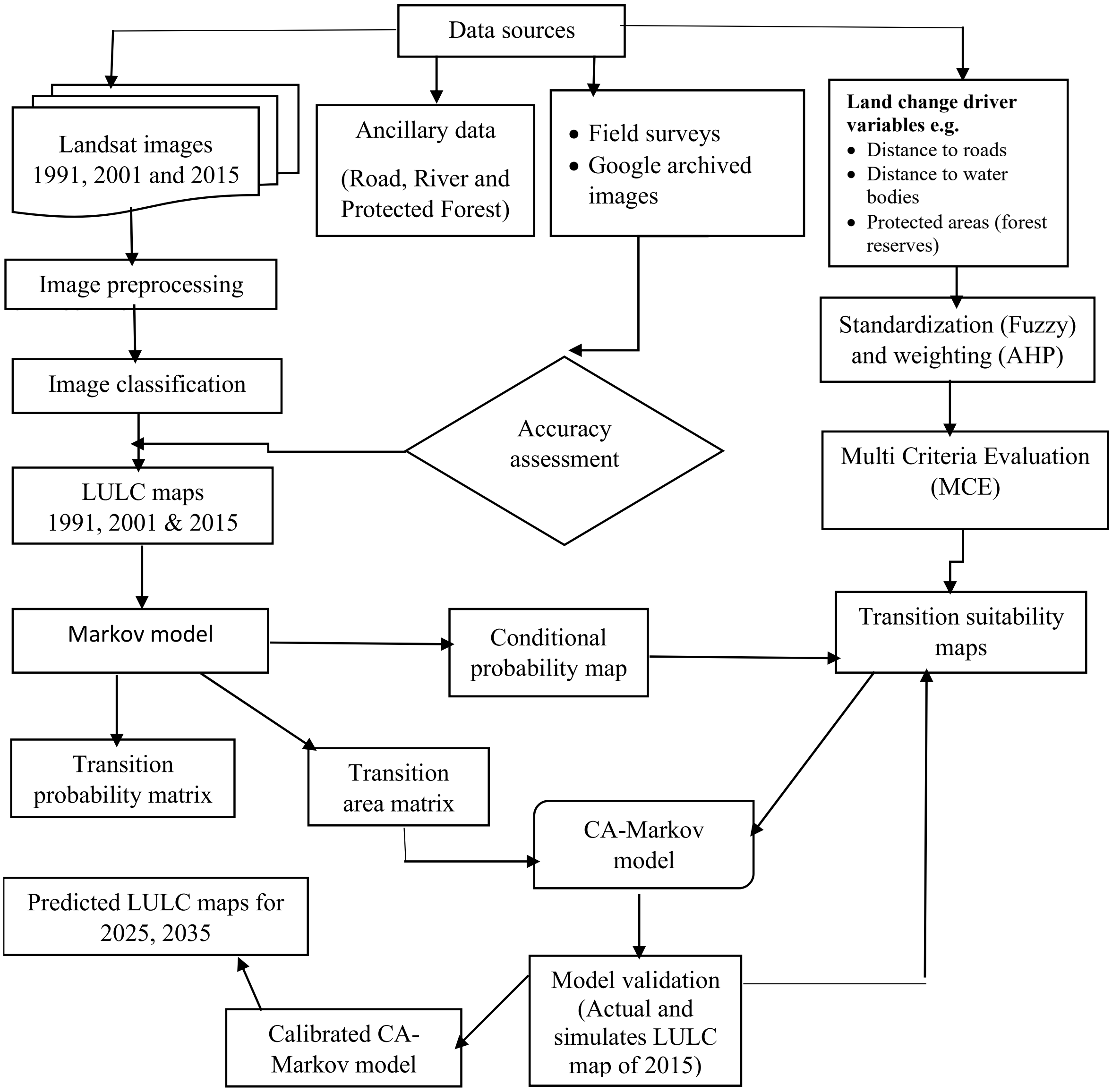

Fig. 6.3 Flow chart for predicting LULC changes in the study area

6.2.4.3.1 Preparation of suitability maps

Preparing transition or suitability maps for various LULC classes is a prerequisite for modelling LULC is reported to be a difficult step as it depends on the availability of data and information (Keshtkar and Voigt 2016; Hyandye and Martz 2017). The suitability maps were developed by applying the MCE module which includes two parts: the constraints (criteria that limit the expansion of classes) and factors (give the degree of suitability for an area) to determine the land to be considered for further development. The constraints were standardized into the form of Boolean maps where 0 represented unsuitable land and 1 was a set value for suitable land while the factors were standardized to a continuous scale of suitability from 0 (least suitable) to 255 (most suitable). The constraints included existing water bodies, existing built-up areas and protected areas especially forest reserves. Driving factors included the distance from roads, distance from water bodies and distance from built-up areas (Table 6.3). These constraints and factors were chosen based on their use in previous studies (Araya and Cabral 2010; Keshtkar and Voigt 2016; Hyandye and Martz 2017; Rimal et al. 2017; Singh et al. 2018). The Fuzzy function combined with Weighted Linear Combination (WLC) was used for the standardization of factors. During standardization, various control points were used and fuzzy functions applied in this study included Sigmoidal and linear functions with monotonically increasing/decreasing or symmetric. The weights of the factors were derived using the Analytic Hierarchy Process (AHP). The final standardized suitability maps produced are depicted in Figure 6.4.

Table 6.3 Constraints and factors (Boolean approach) criteria development

Constraint/Factor	Source	Description
LULC	Classified LULC map	Agricultural land was considered the possible LULC class available for development
Existing water bodies	Classified maps and Department of Surveys, Malawi	All the existing rivers and water bodies were considered unsuitable.
Protected areas (forest reserves)	Department of Forestry, Malawi	All the areas under government forest were considered unsuitable
Distance from roads	Department of Surveys, Malawi	All areas above a protection buffer zone of 30m from the road networks were considered suitable for development as stated in Malawi legislation.
Distance from water bodies	Classified LULC map and Department of Surveys, Malawi	Protection of buffer of 50m from the rivers and other water bodies was created and within 50m of the water bodies were considered unsuitable
Distance from built-up areas	Classified LULC map	Areas close to the built-up areas were more suitable for development than areas far from built-up areas

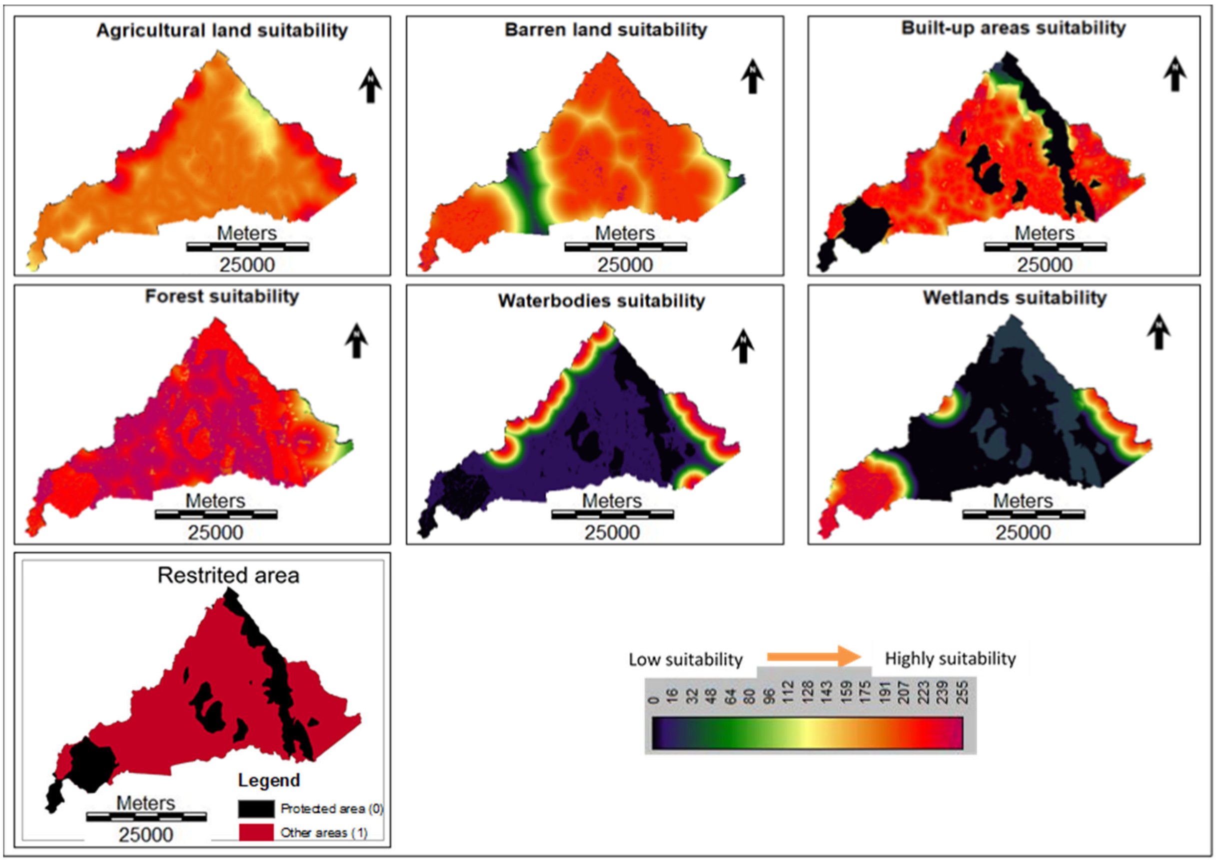

Fig. 6.4 Suitability maps for different LULC classes

6.2.4.3.2 LULC change prediction

The LULC dynamics for the studied landscape were simulated by the Markovian model in IDRISI software. The Markov module generated the transition probability matrices from 1991 to 2001 and from 2001 and 2015. The outputs from the Markov module were combined with the suitability maps using the CA-Markov module to predict LULC changes for 2015 for model validation. Classified LULC maps for 1991 and 2001 were used to produce simulated 2015 maps in order to validate the actual 2015 classified maps. The CA spatial contingency filter of 5x5 pixels was applied on suitability maps to define the neighbourhood of each cell of the LULC class as depicted in Equation 6.4. Finally, the LULC map of 2015 was used as a base map to determine LULC change predictions for 2025 and 2035 using the CA-Markov module integrated into IDRISI software. Figure 4 shows the methodology deployed in this study.

$$Contingency\ 5\ x\ 5\ filter = \begin{bmatrix} 0 & 0 & 1 & 0 & 0 \\ 0 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} \qquad (6.4)$$

6.2.4.3.3 Validation of LULC prediction model

Model calibration and validation is an important step in predicting future decadal changes where no datasets are available for accuracy of predicted data (Singh et al. 2015; Srivastava et al. 2013). In this study, the actual 2015 LULC map was used as a reference map to compare with the results of the 2015 simulated LULC map based on Kappa variations. Kappa variations have been strongly recommended and widely used to validate LULC change predictions (Pontius 2000; Subedi et al. 2013; Singh et al. 2015; Parsa et al. 2016). The Kappa variations used to validate the CA-Markov model for LULC change predictions in this study were generated in VALIDATE module included: traditional Kappa ($K_{standard}$) or Kappa for no information/ability (K_{no}), Kappa for location ($K_{location}$) and Kappa for quantity ($K_{quantity}$) as expressed by Equations 6.5 to 6.8 according to procedure described by Omar et al. (2014). According to (Pontius 2000), K_{no} indicates the proportion classified correctly relative to the expected proportion expected classified correctly by simulation with no ability to specify quantity or location accurately. On the other hand, $K_{location}$ and $K_{quantity}$ are measures of validation between the actual maps and simulated maps based on specified location and quantity respectively (Pontius and Schneider 2001; Pontius and Malanson2005; Sayemuzzaman and Jha 2014). The level of agreement of the three agreement is considered to be perfect if the values equal to 1 and unsatisfactory or imperfect is equals to 0 (Pontius and Schneider 2001; Nadoushan et al. 2015; Singh et al. 2015; Singh et al. 2018). Therefore, a value of 0.80 and above is considered strong and it is reasonable to make plausible future projections.

$$\text{Kappa for no information} = K_{no} = (M(m)N(n))/(P(p) - N(n)) \qquad (6.5)$$

$$\text{Kappa for location} = K_{location} = (M(m)N(m))/(P(m) - N(m)) \qquad (6.6)$$

$$\text{Kappa for quantity} = K_{quantity} = (M(m)H(m))/(K(m) - H(m)) \qquad (6.7)$$

$$\text{Kappa standard} = K_{standard} = (M(m)N(n))/(P(p) - N(m)) \qquad (6.8)$$

Where no information is defined by $N(n)$, medium straight information level by $H(m)$, medium grid cell level information by $(M(m)$, perfect grid cell-level information given imperfect stratum-level information by $(K(m)$ mean and perfect grid cell-level information across the landscape by $(P(p)$.

6.3. Results

6.3.1 LULC classification and accuracy assessment

Based on the first phase of the research analysis as captured in Munthali et al. (2019a), the overall accuracy of the 2015 classified map was found to be 91.86%. Thus, indicating the suitability of the derived classified maps for effective and reliable LULC change analysis and modelling. Post-classification analysis of the spatial metrics and their variations indicated that agricultural land, forest land, wetlands and water bodies drastically decreased between 1991 and 2015 in the studied landscape (Table 6.4). On the other hand, barren land and built-up areas substantially increased during the same period.

Table 6.4 Temporal distribution of LULC classes (ha) and percentages of change

LULC class	1991	2001	2015	Change in LULC structure Δ % (1991-2001)	Δ % (2001-2015)	Δ % (1991-2015)
Water	1,380.60	793.26	899.55	-74.04	11.82	-53.48
Wetland	3,626.73	2,954.07	2,680.29	-22.77	-10.21	-35.31
Forest	9,939.15	8,354.70	6,237.63	-18.96	-33.94	-59.34
Agriculture	267,977.43	267,469.83	260,879.31	-0.19	-2.53	-2.72
Barren	92,185.38	94,731.66	97,174.62	2.69	2.51	5.13
Built-up	761.67	1,567.44	7,999.56	51.41	80.41	90.48

6.3.2 Validating LULC prediction model

The 2015 simulated LULC map was compared with the actual 2015 LULC map in order to validate the LULC prediction model given by the CA-Markov model. Results of the comparison analysis of the two maps are shown in Figure 6.5 and Table 6.5. Visual comparison of the two maps clearly indicates that wetlands, forest land, agriculture land and barren areas had a strong agreement (Table 6.5). However, the simulated map shows that wetlands and barren lands were underestimated by 6.54% and 0.7%, respectively while forest land and agricultural land were overestimated by 20.46% and 2.25%, respectively. On the other hand, results from water bodies and built-up areas showed a weak agreement and they were both underestimated by 60.34% and 71.74%, respectively. Thus, intrinsic discrepancies were observed with the simulated 2015 LULC map especially for water bodies and built-up areas.

The ability of the model to simulate accurately the LULC maps for 2025 ad 2035 was validated using the observed and simulated LULC maps of 2015 (Figure 6.5). From Table 6.6, the results of the model evaluation show that the overall agreement between the observed LULC map of 2015 and simulated LULC map of 2015 is 0.98 (97.5%) while the overall simulation error is 0.03 (2.5%) which may be attributed to errors due to quantity disagreement (0.01) and allocation disagreements (0.02. The more detailed validation results based on Kappa variations are depicted in Table 6.7. The values of K_{no}, $K_{location}$, $K_{LocationStrata}$ and $K_{standard}$ were 97.06%, 96.62%, 99.62% and 95.31%, respectively (Table 6.7) showing a satisfactory level of accuracy.

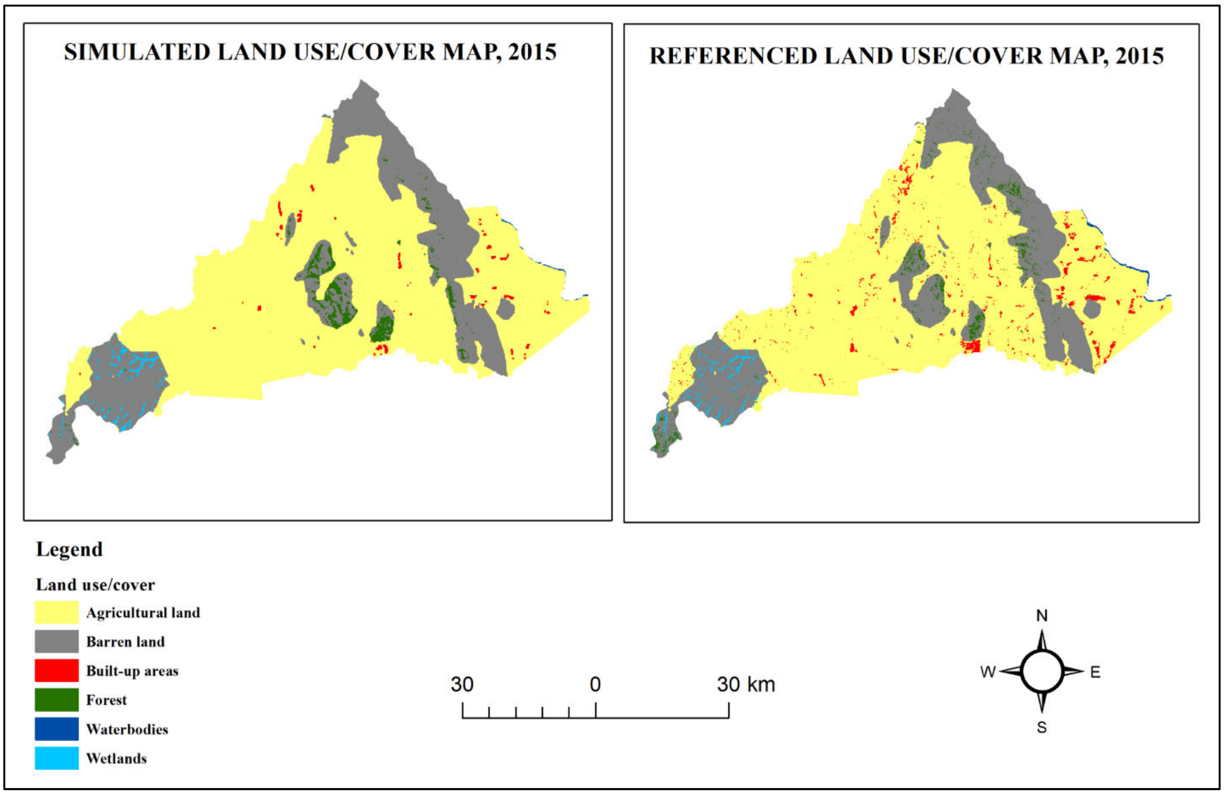

Fig. 6.5 Actual map and simulated map of LULC for 2015

Table 6.5 Comparison of the actual and simulated LULC classes in 2015

LULC class	Area (ha)		Differences between actual and projected LULC	
	Actual 2015 LULC	Predicted 2015 LULC	Δ (ha)	Δ (%)
Water	899.55	356.76	-542.79	-60.34
Wetland	2,680.29	2,504.97	-175.32	-6.54
Forest	6,237.63	7,514.10	1,276.47	20.46
Agriculture	260,879.31	266,744.43	5,865.12	2.25
Barren	97,174.62	96,490.26	-684.36	-0.70
Built-up	7,999.56	2,260.44	-5,739.12	-71.74

Table 6.6 Results of validation analysis on agreements/disagreement components

	Information of quantity		
Information of location	No [n] None	Medium[m]	Perfect [p]
Perfect[P(x)]	P(n) = 0.4030	P(m) = 0.9927	P(p) = 1.0000
PerfectStratum[K(x)]	K(n) = 0.4030	K(m) = 0.9927	K(p) = 1.0000
MediumGrid[M(x)]	M(n) = 0.3919	M(m) = 0.9948	M(p) = 0.9740
MediumStratum[M(x)]	H(n) = 0.1429	H(m) = 0.4623	H(p) = 0.4609
No [N(x)]	N(n) = 0.1429	N(m) = 0.4623	N(p) = 0.4609
Chance agreement			0.1429
Quantity agreement			0.3195
Allocation agreement			0.5124
Allocation disagreement			0.0179
Quantity disagreement			0.0073

Table 6.7 Summary of Kappa variations of the CA-Markov model

Statistic	Index
Kappa no information/ability	0.9706
Kappa location	0.9662
Kappa locationStrata	0.9962
Kappa Standard	0.9531

6.3.3 Simulated land use and land cover changes

Results on the projected LULC changes for 2025 and 2035 are depicted in Figure 6.6 and Table 6.8. About 2.13% of the total landscape area in the district was built-up areas in 2015 and is predicted to expand up to 3.16% and 4.06% in 2025 and 2035 respectively (Table 6.8). Agricultural land will continue to be the dominant LULC class by 2035. Modelling results further indicate that forest land, agricultural land and wetlands will greatly decrease from 6, 237.63 ha (1.66%) to 5, 631.03 ha (1.50%), 260, 879.31 ha (69.41%) to 253, 394.01 ha (67.42%) and 2, 680.29 ha (0.71%) to 2,471.49 ha (0.66%) by 2035 respectively. In contrast, there shall be an expansion of water bodies, barren land and built-up areas by 0.28%, 26.09% and 4.06% respectively.

Tables 6.9 and 6.10 are the LULC change transition area and probability matrices showing how each projected LULC class is projected to change between 2015 and 2035. According to the transition probability matrix, almost 94.8%, 97.6% and 95.7% of water bodies, agricultural land and barren land will more likely remain stable by 2025 (Table 9). In contrast, forest land exhibits the highest probability of change of 64.8% and 85.9% by 2025 and 2035, respectively. The majority of the forest areas will be converted to barren land with a probability of 60.8%and 79.6% by 2025 and 2035, respectively. Further, a portion of forest land will be pressured by agricultural land (3.2% in 2025 and 5% in 2035).

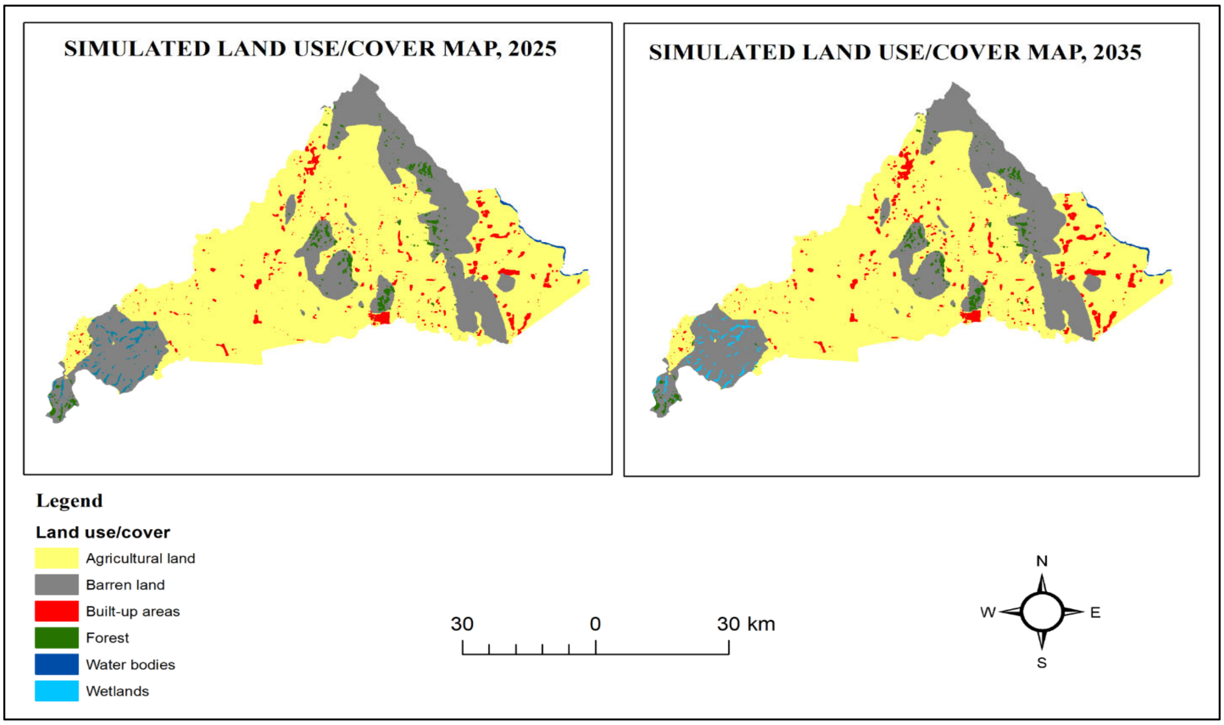

Fig. 6.6 Projected maps of LULC for 2025 and 2035

Table 6.8 Distribution of LULC changes from 2015 to 2035 (ha)

LULC class	2015		2025		2035	
	Area	**%**	**Area**	**%**	**Area**	**%**
Water bodies	899.55	0.24	970.65	0.26	1,033.65	0.28
Wetlands	2,680.29	0.71	2,555.19	0.68	2,471.49	0.66
Forest	6,237.63	1.66	5,779.53	1.54	5,631.03	1.50
Agricultural land	260,879.31	69.41	256,875.21	68.34	253,394.01	67.42
Barren land	97,174.62	25.85	97,803.72	26.02	98,076.42	26.09
Built-up areas	7,999.56	2.13	11,886.66	3.16	15,264.36	4.06
Total	**375,870.96**	**100.00**	**375,870.96**	**100.00**	**375,870.96**	**100.00**

Table 6.9 Transition probability of areas (ha) and matrix from 2015 to 2025

			Actual LULC map of 2015					
	2015/2025		**Water**	**Wetlands**	**Forest**	**Agriculture**	**Barren**	**Built-up**
Predicted LULC map of 2025	Water	Area	**860.58**	2.43	2.88	33.39	0.27	0.00
		P	**0.9566**	0.0027	0.0032	0.0371	0.0030	0.0000
	Wetlands	Area	0.54	**1818.00**	36.18	13.05	812.43	0.00
		P	0.0002	**0.6783**	0.0135	0.0049	0.3031	0.0000
	Forest	Area	1.35	41.76	**2197.17**	202.86	3791.70	2.79
		P	0.0002	0.0067	**0.3523**	0.0325	0.6079	0.0004
	Agriculture	Area	106.92	3.33	311.76	**254619.27**	1063.26	4774.77
		P	0.0004	0.0000	0.0012	**0.9760**	0.0041	0.0183
	Barren	Area	0.0000	689.85	3229.92	1089.63	**92128.50**	36.72
		P	0.0000	0.0071	0.0332	0.0112	**0.9481**	0.0004
		Area	0.0000	0.0000	1.62	917.19	8.01	**7,072.74**
	Built-up	*P*	0.0000	0.0000	0.0002	0.1147	0.0010	**0.8841**

Note: Bold numbers on the diagonal represent LULC proportions will likely remain constant/stable between 2015 to 2025, while others are the areas are likely to be converted from one class to another; P means probability

Table 6.10 Transition probability of areas (ha) and matrix from 2015 to 2035

			Actual LULC map of 2015					
	2015/2035		**Water**	**Wetlands**	**Forest**	**Agriculture**	**Barren**	**Built-up**
Predicted LULC map of 2035	Water	Area	**825.66**	4.05	3.87	64.62	3.15	0.54
		P	**0.9151**	0.0045	0.0043	0.0719	0.0035	0.0006
	Wetlands	Area	0.99	**1,231.47**	64.71	31.68	1,351.08	0.27
		P	0.0004	**0.4595**	0.0242	0.0118	0.5041	0.0001
	Forest	Area	1.89	70.38	**881.01**	313.20	4,962.69	8.55
		P	0.0003	0.0113	**0.1412**	0.0502	0.7956	0.0014
	Agriculture	Area	206.82	15.12	452.07	**249,065.55**	2,240.82	8,899.02
		P	0.0008	0.0001	0.0017	**0.9547**	0.0086	0.0341
	Barren	Area	0.54	1,150.02	4,226.85	2,209.50	**89,499.60**	88.11
		P	0	0.0118	0.0435	0.0227	**0.9210**	0.0009
	Built-up	Area	0.18	0	3.33	1,709.73	19.26	**6,266.97**
		P	0	0	0.0004	0.2137	0.0024	**0.7434**

Note: Bold numbers on the diagonal represent LULC proportions will likely remain constant/stable between 2015 to 2035, while others are the areas are likely to be converted from one class to another; P means probability

6.4. Discussion

6.4.1 Model validation analysis

Understanding future spatial and temporal LULC patterns and changes of any landscape is the pathway to scientific-evidence based sustainable management of natural resources. In this study, the decadal LULC dynamics were simulated by employing an integration of GIS, remote sensing and land change models. The modelling results showed that the observed and simulated LULC maps for 2015 were reasonably similar despite some intrinsic discrepancies observed in water bodies and built-up areas of the simulated map. This could be attributed to inadequate suitability maps and the shape of contiguity filter, limited drivers and factors used for modelling the results. Sing et al. (2015) and Hyandye and Martz (2017) also found similar results to this study and concluded that the discrepancies between the real map and simulated LULC maps were due to lack of suitable maps and choice of contiguity filter used in their study. Other researchers emphasized that the quality of any simulated LULC map is based on not only the visual interpretation of the two categorical maps but also the quality of the transition suitability maps prepared, suitable transition matrix and the validation method employed (Verburg et al. 2006; Koomen and Stillwell 2007; Pena et al. 2007; Araya and Cabral 2010; Memarian et al. 2012).

In order to justify the results above, a more detailed validation analysis was performed using the kappa variations. Thus, the CA-Markov model was validated using the observed and simulated LULC maps of 2015, where the K_{no}, $K_{standard}$, $K_{location}$ and $K_{quantity}$ were derived. According to Landis and Koch (1977), a Kappa value of > 0.80 (80%) represents strong agreement, and a value between 0.40 and 0.80 (40% - 80%) represents moderate agreement. The validation results based on the kappa values showed that the overall agreement between the observed and simulated LULC maps of 2015 was perfect. The main disagreement between the two categorical maps in this study was due to allocation error rather than quantity errors. Hyandye and Martz (2017) reported similar findings in Tanzania, however, their allocation error (0.06) and quantity error (0.02) were higher than errors reported in this study. In addition, the kappa variations K_{no}(0.97), $K_{standard}$ (0.95) and $K_{location}$ (0.97) found in this study showed a satisfactory level of accuracy. Therefore, based on the kappa values obtained in this study, the CA-Markov is suitable for accurate prediction of future spatiotemporal LULC dynamics in the studied landscape (Vierra and Garret 2005). Thus, LULC change prediction models with accuracies ≥ 80% are typically considered as very strong predictive tools (Araya and Cabral 2010). The value of $K_{standard}$ in this study is a bit higher than those which have been reported in other recent studies which employed the CA-Markov model in LULC change simulations, for instance, 0.88 (Keshtkar and Voigt 2016), 0.68 (Hyandye and Martz 2017), 0.88 (Rimal et al. 2017), 0.59 and (Singh et al. 2018). Similarly, the value of K_{no} which gives the overall accuracy of simulation of the simulated LULC maps was also higher than those reported by the same studies. This validates the fitting of the current model in this study as the best fit.

6.4.2 Simulation of LULC dynamics for 2025 and 2035

The predicted results of spatiotemporal LULC dynamics reveal that built-up areas in the studied landscape will continue to expand up to 3.16% and 4.06% by 2025 and 2035 respectively. The major decrease will be observed in forest land, agricultural land and wetlands while barren land and water bodies will continue to increase by 0.28% and 26.09% respectively. The transition probability matrix results predict that a large portion of forest land will be transformed into barren land and agricultural land. The study has demonstrated that if the current spatiotemporal LULC patterns and trends continue, only 14% of the total forest land will remain forest by 2035. This will affect the continuous supply of timber for construction to Lilongwe City and surrounding districts. The findings suggest that the continued increase in barren land is an indication of continued forest degradation and deforestation and this poses a great threat to sustainable forest management and biodiversity conservation in the district. The decline in forest cover also confirms that management decisions for protecting and conserving forest resources in the studied landscape were not properly taken or implemented by natural resource managers and planners. The observed results in the declined forest cover, wetlands and agricultural land are expected based on the historical patterns and trends of LULC changes that have taken place between 1991 and 2015 in the studied landscape (Munthali et al. 2019a). According to Munthali et al. (2019b), the LULC changes were largely as a result of poverty, population growth, firewood collection and charcoal production. It is worth noting that these drivers will continue to accelerate the undesired LULC changes to happen between 2015 and 2035. Based on the 2018 national population census, the population of Dedza has increased from 625,828 in 2008 and 830,512 in 2018 (Government of Malawi 2019). Therefore, these results imply that as the population increases, more land is expected to be subjugated to cater for the growing population for settlements and food production.Pandey and Khare (2017) and Hyandye and Martz (2017) similarly reported that the continuous higher population flux in Usangu sub-Catchment of the upper part of Rufiji Basin in Tanzania and the upper Narmada basin of Narmada river in India respectively contributed to increased deforestation and expansion of undesired settlements. Berihun et al. (2019) also identified population growth as one of the main driving forces of LULC changes taking place in the Upper Nile basin of Ethiopia.

Based on the authors' local and field visit knowledge, it has been observed that newer settlements have been predominantly expanding into Dedza township (Appendix 4). These new settlements also tended to develop in close proximity to main roads (M1, M5 and M10 roads), along the lakeshore of Lake Malawi (Mtakataka and Golomoti) and Lobi trading centres. Scattered settlements and rural growth centres were also observed in the rural areas of the district (Appendices 5-7)). The Mtakataka and Golomoti settlements situated along the lakeshore are tourist attraction sites of the districts. The increase in tourism activities attracts people to centralize along also tends to attract settlements along the lakeshore areas for job and business opportunities. It is worth noting that Dedza district does not have a land-use plan and this may contribute to the township growth and decline in agricultural land for crop production. The haphazard/unplanned nature of township growth/development and scattered settlements in the studied landscape is therefore seen as an outcome of ineffective and disorganized land-use planning in the area. Moreover, the haphazard nature of settlements growth is also an indication of the absence of long-term strategies to provide guidance for sustainable land use planning. This may contribute to the expansion of uncontrolled settlements as observed through the modelled LULC changes in the study area. Rimal et al. (2017) similarly reported that scattered settlements and random urbanization in Jhapa district of southern Nepal were also a result of ineffective urban land use planning. In order to reduce these undesired scattered settlements and random urbanization, their study recommended the promotion of consolidated and compact settlements. Further, they advised the decision-makers and land-use planners to fully implement the land-use acts, policies, laws and regulations the government of Nepal has introduced. Borrowing from the recommendations from these studies, we similarly recommend that the planners in Dedza district should also develop their land-use policies, laws and regulations to address the undesired future LULC changes for the achievement of sustainable natural resources management and development.

The modelled results have also shown that agricultural land is likely to continue being as a dominant, important and influential LULC class in the future. However, it is projected to decline. The projected decline in agricultural land in Dedza district is a great concern that will affect crop production which will eventually contribute to food insecurity in the future. This may also indirectly affect the sustainable management, use and conservation of land and other natural resources in the studied landscape. Additionally, it is expected that the expanding residential areas and increasing population will continue to highly contribute to the declining agricultural land. This will make other LULC classes such as wetlands and forests the most vulnerable LULC classes to spatial changes. The results are consistent with recent findings of declined cultivated land on remaining forest resources in SSA, for instance, in Zimbabwe (Baudron et al. 2011), Tanzania (Estes et a. 2012), Ghana (Appiah et al. 2015) and Ethiopia (Kindu et al. 2018). Hence, an integrated land-use management approach is crucial to improve the multi-functionality of Dedza landscape for natural resource management and conservation, food security and livelihood enhancement.

6.5 Conclusion

Understanding LULC spatial pattern, magnitude and trends of any landscape is imperative for effective natural resource management, planning and use and secure sustainable development. This study has demonstrated how the spatial-temporal LULC pattern and trends of Dedza district for 2025 and 2035 can be predicted using an integrated CA-Markov model (a hybrid of the Cellular automata and Markov models integrated into IDRISI software). The study prediction of future LULC changes in Dedza district and Malawi at large; using CA-Markov model is the first one of its kind as far as literature documented is concerned. In order to achieve a perfect and better future LULC results, the model was validated using the kappa variations namely; K_{no}, $K_{location}$ and $K_{quantity}$ The model validation results show that the overall agreement between the observed and simulated LULC maps of 2015 was perfect, hence, the CA-Markov has proven to be a good and useful tool for accurate prediction of future spatial-temporal LULC dynamics in the studied landscape. The model is therefore important to land use policy design and planning especially involve with LULC development which requires a framework for achieving goals and objectives of sustainable land use development.

Dedza has undergone tremendous LULC changes and these will continue as projected in this study. The predicted LULC changes for 2025 and 2035 show the continuation of the same trend and pattern of the recent past except for water bodies. The future projections indicate that water bodies, barren land and built-up areas will increase while agricultural land, wetlands and forest land will substantially decrease. The forest is being converted to agricultural land and barren land. This is not good news for forest managers in Dedza district and these forest conversions need to be controlled and a harmonized land-use plan needs to be developed that promotes forest resource rehabilitation and conservation. The undesired predicted LULC changes are an early warning signal to natural resource managers, planners, policymakers and local communities in the studied landscape to prepare better strategies and land-use policies to ensure the expected unmannered expansion of barren land and built-up areas do not cause adverse environmental impacts.

With the effective use of CA-Markov model, the study findings have provided baseline information that can contribute towards the sustainable management of natural resources and the reduction of forest degradation and deforestation. Findings from the study also highlight the need to implement sustainable land-use plans and holistic sustainable development policies/strategies/guidelines. These findings serve as an important benchmark to planners, natural resource managers and policy-makers in the studied landscape for planning and management of natural resources and rehabilitating the degraded forest areas through afforestation and reforestation. Finally, the study proposes comparative studies to be undertaken across different landscapes of Malawi for the CA-Markov model to be adapted to other districts of similar settings and Malawi at large.

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CHAPTER 7: SUMMARY, CONCLUSION AND RECOMMENDATIONS

7.1 Summary of key findings

The LULC changes are complex processes that occur on any landscape at local, regional and global level due to interaction between biophysical and human dimensions in time and space. These changes consequently influence the rural livelihoods and natural resources. Like any district in Malawi, Dedza district has undergone tremendous changes as a result of modifications of LULC. These changes have occurred at an unprecedented rate nearly for the past 24 years. The present study investigated the LULC dynamics of Dedza district from 1991 to 2015, their drivers and impacts on natural resources and rural livelihoods and finally the possible future LULC patterns and changes to take place by 2030. To achieve these objectives, the study adopted a mixed method comprising geoinformatics (remote sensing and GIS, thus, supervised and unsupervised techniques) analysis, FGDs, key informant and semi-structured interviews. Remote sensing and GIS techniques are well-recognized, powerful and cost-effective geospatial technologies for mapping, characterizing landscapes and continuous monitoring of LULC dynamics at multi-temporal and spatial scales. The generated datasets from this study provided up-to-date LULC changes for Dedza district. This will be useful in guiding planners and decision makers to better understand the LULC dynamics in the study landscape for appropriate natural resource management and livelihood options or intervention strategies; for monitoring future changes, informed decision-making during policy formulation or land use processing or other similar studies in other districts of Malawi.

The study has revealed that the major LULC classes in the study are agricultural land, forests and barren land. The forest land (2.64% to 1.66%), water bodies (0.37% to 0.24%) and agricultural land (71.30% to 71.16%) drastically declined while built-up areas (0.20% to 2.13%) and barren land (24.53% to 25.85%) substantially increased between 1991 and 2015 in the study landscape. The LULC change maps generated for 1991, 2001 and 2015 were produced using supervised and unsupervised classification. The PCC of the classified images (1991, 2001, 2015) based on the transition matrix depicted that forest area experienced the highest transition with 69.77% of its total area in 1991 being converted to barren land and agricultural land. The LULC change maps produced and understanding the historical LULC change trends established in this study are critical for strategy and policy formulations that balances restrictions on the use of land while maintaining the ecological functions of Dedza landscape. Thus, the LULC changes observed in this study require urgent interventions and formulation of rational policies that effectively and efficiently strike balance between socio-economic development and environmental conservation.

The study has also highlighted the importance of integrating indigenous knowledge in understanding the LULC change dynamics. The study has established that rural communities are aware of the changing of LULC in the study landscape. Significant differences were found among the interviewed households in perceptions regarding LULC changes and distance to different infrastructures such as main roads, health centres, schools and towns ($p< 0.001$). Research findings based on the perceptions of the households, FDGs and key informants interviewed, the detected LULC changes that occurred in the study landscape between 1991 and 2015 were mainly driven by interaction of factors related to technological, social, environmental, policy/institutional and economic factors. The significant LULC changes occurred in the study landscape has been influenced mainly by proximate drivers such as firewood collection, charcoal production, agricultural expansion, settlements and timber. These proximate drivers were triggered by high poverty levels, population growth, unreliable rainfall, lack of law enforcement by government, poor access to an alternative-energy supply and high cost of agricultural input. The study has further revealed that at household level, education level of the rural communities as the main socioeconomic determinants significantly influenced their perceptions towards the perceived drivers. The increase in population and high poverty levels has raised demands for additional land, fuelwood, timber for construction, food and land for settlements. Further, the increased population will continue exerting profound pressure on the remaining natural resources. These research findings make novel contributions to the literature on sustainable management of natural resources that seek to understand rural communities perceive LULC changes in the landscape and how their responses to these perceived LULC changes help shape various LULC change dynamics. Integration of local communities' perceptions in land use planning and management offers more informed basis to design and implementation of land use planning policies that promote active community participation, sustainable livelihoods development and responsiveness to changing LULC.

Dedza district like any other district is Malawi is facing environmental problems due to undesired and unprecedented LULC changes occurred between 1991 and 2015. These changes over time have impacted the natural resource base and rural communities in the study landscape. The study identified that LULC changes in Dedza district has resulted in declined agriculture and forest resources, depletion of water resources and wetlands. The decrease in agricultural land has resulted into declined crop production in the study landscape. Households interviewed identified soil infertility, unreliable rainfall, high cost of agricultural inputs, lack of money for inputs and lack of agricultural inputs as the factors exacerbating declined crop production. The decline in forest cover or increased deforestation found in this study has consequently resulted into shortage of firewood and wood for construction, persistent floods and droughts, depletion of water resources and loss of soil fertility.

With regard to shocks, the study found out that Dedza district was exposed to drought, floods, food shortage, loss\damage of crops, death of household members, crop pest outbreak and strong winds/hailstorms as a result of LULC changes. As a result of these shocks, rural communities devised various strategies to cope with them. Rural communities were engaged in piece work, receiving aid from government and NGOs, receiving unconditional aid from relatives, relied on their own savings and credits as coping strategies to cushion the shocks faced during the study period. It is clear from these findings that the livelihoods strategies and options available to the communities in the study landscape were as a result of changing LULC in the study landscape. Therefore, the proposed innovative approaches and strategies centered on these shocks are urgently needed to address these shocks. Thus, there is need to redesign appropriate, rational and holistic natural resource management and livelihood strategies/options that can be enacted by both the local communities and government to coping to shocks resulted from the undesirable and unprecedented LULC changes taken place in the study landscape.

The study also employed CA-Markov model to simulate the possible future LULC patterns and changes of the studied landscape. The CA-Markov model predicts future LULC changes based on the past or historical LULC transformations and transitions. The simulation results illustrate that water bodies, barren land and built-up areas will increase while agricultural land, wetlands and forest land will substantially decrease by 2025 and 2035. According to the transition probability matrix, almost 94.8%, 97.6% and 95.7% of water bodies, agricultural land and barren land will the more likely remain stable by 2025. In Contrast, forest land exhibit the highest probability of change of 64.8% and 85.9% by 2025 and 2035 respectively. Consequently, the simulated results have implications on natural resource management and community development. The modelling approach employed in this study is affirms CA-Markov model as a useful and valuable tool for simulating future LULC changes in Dedza district as the kappa variations showed the satisfactory values of K_{no} (0.09706), $K_{standard}$ (0.09531) and $K_{location}$ (0.9662) which verify the accuracy of the model. These results are needed by planners, natural resource managers, policy makers and researchers in the study area for formulation of sustainable land-management decisions and policies, e.g., identifying priority areas for conservation and protection and set alternative conservation measures.

7.2 Research contribution to scientific advancement and sustainable natural resource management

This study provides deep and important insights on LULC changes and their implications on natural resources and rural livelihoods in the study landscape. The use of earth observation data and geospatial techniques (remote sensing and GIS) in Malawi is very limited despite the advantages it offers towards monitoring natural resources as proven in other countries in the SSA region. The study demonstrates the importance of using earth observation and geospatial technologies for natural resource monitoring thereby contributing to socioeconomic sustainability of livelihoods especially those in rural homes.

This study also addresses the issue in the study of rural livelihoods and coping strategies among the poor communities and how the strategies adopted influences land usage and exploitation of natural resources in the study landscape. Evidence from the research findings affirms the critical role of land use planning in achieving sustainable forest management of natural resources and rural livelihoods sustainability to shocks resulting from LULC changes. It is, therefore, important that the natural resource agencies (e.g. agriculture, land, water and forest) focus on developing policies that embraces and balances the economic, social and environmental demands and priorities of Dedza landscape and other landscape related to Dedza district. There is sufficient evidence in this study that infers that integrated use of remote sensing and GIS technologies and local/indigenous knowledge and perceptions can contribute to sustainable natural resource management and sustainability rural livelihoods. The methods used and results from this study provide a practical guideline in bridging the gap between land use planning and natural resource management. As a result, the study can be useful for supporting the development and implementation of sustainable land use policies by natural resource managers and decision-makers of Dedza district.

7.3 Limitation of the study

The present study despite the good outputs it has produced, it is not completely free from limitations and these includes;

- use of low or medium resolution satellite imageries somehow affected the accuracy assessment and detail analysis of the data. There was spectral reflectance mixing between barren land, agricultural land and built-up areas (especially detecting settlements that were roofed with thatched grass) during image classification
- Lack of aerial photographs for accuracy assessments especially for 1995 and 2001 satellite imageries
- The present study revealed reduced crop production as one of the perceived impacts of LULC changes in the study area. However, data on crop production at the scale of the study was not available from either the District Council or Ministry of Agriculture to validate the local perceptions.

7.4 Recommendations and future research

The study has assessed the LULC changes and their implications on natural resources in the study landscape. Scientific contribution to the body of knowledge of LULC dynamics as evidenced through the use of CA-Markov model and publications have been made. In terms of practical contributions, LULC change trajectories assessed in this study could be used as a reference Atlas for natural resource practitioners.. However, gaps remain that should be addressed in the future. Based on the findings of this study, the research recommends that:

- Urgent action against the undesirable LULC changes taken place during the study period be undertaken to seek a sustainable solution that addresses proper management of natural resources and sustainability livelihoods in Dedza district
- The government of Malawi in conjunction with other stakeholders formulate plans, guidelines, strategies, policies and measures that promote land use planning, sustainable natural resource management and welfare of rural communities in the study landscape and eventually decrease pressure on the remaining natural resource base

- Government through the Department of surveys and Department of urban planning develop a spatial and development plan framework and model to prevent unplanned human settlements in Dedza district
- Government of Malawi through the Department of Forestry in collaboration with the local communities develop plans that will protect and conserve the forest reserves that are under threat through illegal charcoal production and firewood collection. There is need to devise alternative source and new rural technologies that save energy and increase efficiency and reduce the amount of wood and charcoal used for energy purposes.
- With the issues of unreliable rainfall, drought. Soil infertility and reduced crop production, there is need to promote alternative and viable source of livelihoods of the rural communities to improve the welfare of the rural people in the study area. The district has endowed water resources and these can be used to promote irrigation agriculture. This can enable farmers to produce enough food throughout the year instead of relying on rainfed agriculture which is reported unrealizable due to LULC dynamics in the study area. Consequently, land use conflicts between LULC conversions and agricultural land will be minimized in the study area.
- Improvement of agricultural activities by enabling farmers to have access to loans, agricultural inputs and subsidy fertilizers
- The current situation pertaining to involvement and commitment of different stakeholders in natural resource management is weak. There is need to promote or strengthen involvement of various stakeholders at local and district level in natural resource management and land use planning. For instance, the strategies and district action plants to be implemented in the district should follow a bottom-up approach. The communities should be actively involved in all phases of project developments that will bring last solutions in the communities and these processes include; problem identification, planning, implementing, evaluating and monitoring.
- A further research be undertaken to establish the spatial drivers of LULC changes taken place in this study since this study only relied on the drivers perceived by rural communities. Then, establish if there any relationships between the spatial drivers and perceived drivers with the actual changes occurred during the study period

- A similar study be undertaken in different regions of Malawi with similar and distinctive environmental and socioeconomic conditions so that the results can be used to guide natural resource management efforts in other similar environmental and political settings for effective use and conservation of natural resource base
- A study be undertaken to quantify and estimate the ecosystem services values (ESVs) of different LULC classes lost or gained in response to LULC changes over spatial and temporal scales in the study landscape. This is a new direction of research for LULC change studies around the world
- The present study did not cover to the extent land tenure systems of the study area contributed to the LULC change dynamics. There is need to undertake a study in the studied landscape or areas of similar settings on how land tenure systems influence LULC dynamics in Malawi

Appendix 1: Household Questionnaire (English and Chichewa version)

QUESTIONNAIRE FOR HOUSEHOLDS

Enumerator: ………………………………… Date of Interview: ………………… ………..

Respondent ID: ……………………………… Questionnaire No: …………………………..

T/A……………………… GVH …………………… Village: ………………………………

A. HOUSEHOLD CHARACTERISTICS AND HUMAN ASSETS

1 (a). Age of respondent (*Muli ndi zaka zingati?)*: ___________________

(b) Sex of respondent: Male ☐ Female ☐

(c) Marital status (*Muli pa banja?)*

Single		Divorced	
Married		Widowed	
Separated		Refused to answer	

(d) The head of the household (*Mutu wabanja ndi ndani m'nyumba muno*)
Male ☐ Female ☐

(e) What is the size of your household (*Kodi pakhomo panu muipo angati*?)_________

(f) Family size by age group and gender

Age group	**Male**	**Female**	**Total**
≤ 17			
18 – 30			
31 – 50			
> 50			

(g) What is your occupation? (*Mumapanga chani pakhomo panu kuti mupeze zosowa zanu?*)
(CHOOSE ONLY ONE THAT APPLIES)

Farmer		Construction		Other (Specify)
Business		Craft work		
Housewife		Student		
Professional		Domestic work		

(h) What is the highest level of your education *(Sukulu yanu munapita nayo patali bwanji?*

No formal education	Primary	Secondary	Post-secondary	Tertiary	Other (specify)

(i) Ethnic group

Chewa	Ngoni	Yao	Lomwe	Others (Specify)

(j) How long have you lived in this community? *(Mwakhala nthawi yotalika bwanji m'dera lino?)*

< 10 years	11-19 years	≥ 20 years

(l) If less than 20 years in ***Qn (j),*** where did you live before? (*Mumakhala kuti musanafike kuno?)* Village/Traditional Authority/District:
……………………………………………………………………………………………….

(m) What was the reason for migration? (*Chifukwa chomwe munasamuka?)*

Farming	Marriage	Employment	Death of a family member	Others (Specify)

2. What is your household's main sources of income? (**CHECK ALL THAT APPLIES** and rank them on a scale of 1 to 5, where1=, is the least important and 5 the most important) (*Kodi ndi njira ziti zikuluzikulu zimene zimakubweretserani chuma pakhomo panu) (Mwanjira mwatchulazi ndandalikani kufunikira kwake pamulingo 1 – 5)*

Source	**Tick**	**Rank**					**Estimated income**
		1	**2**	**3**	**4**	**5**	
Farming (crop & animals)							
Full time private/government employment							
Selling of forest produce (e.g. charcoal , firewood, timber, poles)							
Piece-work (occasional jobs)							
Self-employed (business, trade, handicraft)							
Renting out land							
Village saving loans/bank Mkhonde							
Other (specify							

3. What type of domestic cooking stove does the family use for cooking (*Ndi njira yanji yomwe mumagwiritsa ntchito pophikira?)*

   3-stone open fire ☐ Charcoal stove ☐ Chitetezo Mbaula ☐ Rocket stove ☐
   Other (specify): ………………………………………………………………………………

4. What type of energy source do you mostly use for the following activities? **Indicate 1= not used, 2 = Rarely used, 3=Sometimes used and 4 = Aways Used** *(Panjira zomwe nditchulezi mundiuze zomwe simugwiritsa ntchito/simmagwiritsa ntchito kawirikawiri/ mmagwiritsa ntchito mwa apo ndi apo/mmagwiritsa ntchito nthawi zonse mukafuna kuphika kapene kuwunikira*
   (a) Cooking (kuphikira)

Energy Source	**1= not used**	**2 = Rarely used**	**3=Sometimes used**	**4 = Always Used**
Charcoal				
Fuelwood				
Paraffin				

Crop residues				
Briquettes				
Other (specify)				

(b) Lighting (Kuwunikira)

Energy Source	**1= not used**	**2 = Rarely used**	**3=Sometimes used**	**4 = Always Used**
Electricity				
Candles				
Torch				
Fuelwood				
Solar				
Other (specify)				

5 (a) Which source of energy would you prefer for all your household's energy needs? (*Ndi njira ziti zimene mungakonde kugwiritsa ntchito pophikira/kuwunikira pakhomo pano)*

Charcoal ☐ Fuelwood ☐ Torch ☐ Solar ☐ Electricity ☐ Other: ………………….

(b) Why do you prefer this source of energy? (*Ndi chifukwa chani mungakonde njira mwatchulayi)*
Convenience ☐ Cheap ☐ Easily accessible ☐ No choice ☐ Safety ☐
Very reliable ☐ Other (specify): ……………………………………………………….

6. What is your average monthly energy needs in terms of the following?

Fuelwood (No. of head loads collected) ………………………………………...

Electricity (MK) ………………………………………...

Charcoal (No. of 50kg bags) ………………………………………...

Crop residues (Headload) ………………………………………...

Paraffin (litres) ………………………………………...

Other (specify) ………………………………………...

B. POPULATION VS LAND USE AND LAND COVER CHANGES

7(a). Do you think the population of your community has increased over the past 25 years? (*Kodi chiwerengero cha anthu chachuluka pakudutsa kwa zaka 25?)* Yes ☐ No ☐

(b) If **YES** what do you think have caused the population increase? (*Nde mukuganiza kuti chiwerengero cha anthu chikuchuluka chifukwa chiyani?)*
High Birth rate ☐ Immigration ☐ Reduced mortality rate ☐ Other (Specify): …….

8 (a). Do you think that more land will be needed as your family grows (*Kodi mukuganiza kuti malo ambiri azakhala akufunikila pamene banja lanu likukula?)* Yes ☐ No ☐

(b) If **YES**, how much extra land do you think you will need when you have a new family member? (*Ndi malo ochuluka bwanji amene m'banja mwanu mungaonjezere pamene banja lanu lakula)*

0.5 acres		1 acre		2 acres		> 2 acres		Don't know	

9. What kind of land would you clear for settlement when your family size increases? (*Kodi ndi mtundu wanji wa malo umene mungatsegule kuti mumangepo chifukwa chakuchulukana?)*
   Forest ☐ Fallow land ☐ Grazing land ☐ Other (specify)

C. AGRICULTURE vs LAND USE AND LAND COVER CHANGES

10. List the major crops easily grown in your community? (Start with the most important crops) (Tchulani mbeu zimene mumalima m'dera lanu?)

    (i) ……………………………………… (ii) …………………………………….
    (iii) ……………………………………... (iv) ……………………………………

11. Indicate the number of farms you have and their size, purpose and distance from home? *(Kodi muli ndi minda ingati, kukula kwawo, i, ntchito yake, komanso mtunda kuchokera pakhomo pano?)*

Farm land	**1= Owned 2= rented**	**Size (acres)**	**Purpose/Use (consumption, sale or both) include crop**	**Distance from home**
Farm 1				
Farm 2				
Farm 3				
Farm 4				
Farm 5				
Total				

12 (a). Has the crop production declined or increased over the past 25 years in your community? (*Kodi kakololedwe ka mbeu mdera lanu katsika/kakwera pa zaka 25 zapitazi?)*

Declined		Increased (**Go to 12c**)		Stayed the same		No idea	

(b) If the crop production has declined, in your opinion, what are the **FIVE** main reasons for decline? (**Rank on a scale of 1 - 5)** *(Ngati kakololedwe katsika mukuganiza kuti ndichifukwa chani?)*

Reason	**1**	**2**	**3**	**4**	**5**
Soil infertility					
Unreliable rainfall					
Pests and diseases					
Limited/inadequate land					
Lack of agricultural inputs					
Lack of improved seeds					

Inadequate labour/					
Low marketing prices of crops					
Lack of money for inputs					
High cost of agricultural inputs					
Poor access to subsidy programme					
Other (specify)					

(c) What do you think are the **FIVE** most important things to do to improve crop production in your community? (**Rank on a scale of 1 - 5)** *(Ndi njira ziti zimene zomwe mungagwiritse ntchito kuti ulimi upite patsogolo mdera lanu)*

What to do	**1**	**2**	**3**	**4**	**5**
Use of improved seeds					
Improved Access to loan					
Use of chemicals to control pests and diseases					
Have adequate land					
Increase the market prices of the crops					
Access to agricultural inputs					
Access to subsidy programmes					
Improve Soil fertility					
Practice crop rotation					
Use of modern farm implements					
Other (specify)					

13. What has happened to the size of the land you use for crop production? *(Kodi mukuona kusintha kotani kwa malo olima amene mukugwiritsa ntchito panopa?)* It has …
Increased ☐ Decreased ☐ No change ☐

14. (a) What have you done in the past when the crop production level on your land dropped *(Munapangapo chani pamene zokolola zanu zachepa?)*
Look for additional land ☐ Improve the fertility of the land ☐ Fallow ☐
Others (specify): ……………………………………………………………………………

(b). What will you do in the future if the crop production level on the land declines? (Mtsoolo muno ngati *zokolora za m'munda mwanu zachepa, mudzatani?)*
Look for additional land ☐ Improve the fertility of the land ☐ Fallow ☐
Others (specify): ……………………………………………………………………………

(c). If you look for additional land for crop production, what kind of land will you look for? (*Kodi ndi mtundu wanji wa malo umene mungatsegule pamene mukufuna kuonjezera malo olima?)*
Forest ☐ Fallow land ☐ Farm land ☐ Grazing land ☐
Other (specify):…….. ………………………………

15. How do you prepare your land for crop production? (*Kodi minda yanu mumasosa bwanji?)*
Burning ☐ Clearing with hand hoes ☐ Use of farm implements like tractors etc ☐
Others(specify: ……………………………………………………………………………………

16. Have ever cleared a new land for crop production? When? What kind of land did you clear? *(Kodi munayambapo mwatsegulako malo atsopano? Nanga ndi liti? Nanga mtundu wanji wa malo?)*

……
……
……

17a. Do you practice shift cultivation in your household? *(Kodi mumachita ulimi wosintha malo mdera lanu?)* Yes ☐ No ☐

b. If YES, please explain how this shift or rotation activity work? (*Ngati EYA, fotokozani kuti kusintha kwa malo anu kumatenga nthawi yayitali bwanji?*)

……
……
……

18 (a). Do you have animals on your farm or at your household? (*Kodi muli ndi ziweto pakhomo pano)* Yes ☐ No ☐

(b). If yes, what kind of animals and how many (*Ndi ziweto zanji ndipo zilipo zingati?)*

Animal	**No. of animals**
Cattle	
Sheep	
Pigs	
Rabbits	

Animal	**No. of animals**
Goats	
Donkeys	
Chicken	
Other (specify)	

D. LAND TENURE AND RIGHTS

19. Who has the right to own land in your household? (*Amene ali ndi umwini wamalo ndi ndani mnyumba mwanu?*) Men ☐ Women ☐ Both ☐

20. (a) Do you own land? (*Muli ndi malo anu anu?)* Yes ☐ No ☐

(b) If you own land, how did you get it? (*Nanga munawapeza bwanji*)
Bought it ☐ Inherited it ☐ Donation/gift ☐ Received as a payment ☐
Given by local leaders ☐ Given by the government ☐ Other (specify): ……………

(c). If **YES** to **Q20a**, What user-rights do you have on land? (*Ndi zinthu ziti zomwe mumaloledwa kupanga nawo malowo?)*. **(CHECK ALL THAT APPLIES)**

User-Right	**Tick**
Right to sell	
Right to lease out	
Right to donate/give out	
Right to farm	
Right to graze	
Right to use for religious purposes	
Right to develop	
Other (specify):	

(c) If **NO** to **Q20a**, Why?………………………………………………………………………………
………
………..
………..

21. How do people in the community generally get to own land? *(Kodi dera lino anthu amapeza bwanji malo?)*
Purchasing ☐ Inheriting ☐ Gift/ Donation ☐ Given by local leaders ☐
Forceful acquisition ☐ Other (specify): ……………………………………………

22. Who are the most important people/institutions making decisions about land ownership in your community? *Ndigulu litu la anthu kapena mabungwe amene ali ofunikira kwambiri opanga ziganizo zaumwini wa malo m'dera lanu?)*
Government ☐ Local leaders ☐ Religious leaders ☐ Politicians ☐
Other (specify): …………………………………………………………………………

23 (a). Is there communal/customary land in this community? (*Kodi muli ndi malo a m'mudzi mdera lanu?)* Yes ☐ No ☐

(b) Who controls access to the /communal/customary land? *(Kodi amene amapereka chilolezo kumalo a m'mudzi ndani?)*
Government ☐ Local leaders ☐ Religious leaders ☐
Other (specify): ……………………………………………………………………………

(c). Do you think that there should be land under communal/customary control? *(Mukuona kwanu mukuganiza kuti malo a m'mudzi ndofunika akhalepo?)* Yes ☐ No ☐

(d). If YES in **Q23c**, what in your opinion is the use of communal/customary land? (*Mukuona kuti malo a m'mudzi akhoza kugwiritsidwa ntchito bwanji?)*
Communal grazing land ☐ New settlements ☐ Communal water source ☐
To build public facilities ☐ Other (specify): ……………………………………………

24 (a). Are women allowed to own land in your community? (*Kodi amai amaloledwa kukhala ndi umwini wa malo mdera lanu?)* Yes ☐ No ☐

(b) If women are **NOT** allowed to own land, what are the reasons provided? (*Ngati* ***AYI****, Chifukwa chani?*)

They are not allowed to inherit		They are economically disadvantaged	
They are represented by male family members		They are not willing to own land	
Other (specify):			

25. Which group in the community is the most affected by land ownership issues? **CHOOSE ONE THAT APPLIES** (*Magulu nditchulewa, ndi ati amene amaponderezedwa pa umwini wa malo mdera lanu)*
Minority clans ☐ The poor ☐ Women ☐ Children ☐ The migrants ☐

The disabled ☐ Other (specify): ………………………………………………………

26. Why do you think this group is the most affected? *(Ndi chifukwa chiani kagulu kameneka amaponderezedwa)* ……………………………………………………………………..

27 (a). Do you know any rules and laws that are in place for the transfer, use and management of land in this area? (*Kodi mukudziwapo malamulo aliwonse pa kagwiritsidwe ntchito ka malo*)
Yes ☐ No ☐

(b). If **YES**,
(i) are these rules and laws being practiced in your community? *Malamulo amenewa, amagwira ntchito mdera lanu lino)* Yes ☐ No ☐

(ii)Who makes sure that these rules and laws are being practiced? *Ndani amaonetsetsa kuti malamulowa akutsatidwa mwandondomeko yake)*
…………………………………………………………………………………………………
…………………………………………………………………………………………………
(iii) What are some of the challenges you can think of with following these rules and laws? *(Ndi mavuto ati amene mukuganiza kuti mutha kukumana nawo potsatira malamulowa)*
…………………………………………………………………………………………………
…………………………………………………………………………………………………

E. FOREST vs LAND USE AND LAND COVER CHANGES

28. Name any government and community forest that you know in your area? *(Tchulani nkhalango imodzi yaboma ndi imodzi yammudzi zimene mukuzidziwa mdera lanu lino ndi mtundu wake: natural or man-made?)*

	Name of the forest	**Type: (man-made or natural)**
Government Forest		
Community Forest		

29. How has the forest cover changed in your community over the past few years? *(Munzaka zochepa zapitazi, kodi nkhalango zamdera lanu zasintha bwanji)*
Increased ☐ Declined ☐ No change ☐

30. Do you think that there is an increase in the rate of deforestation? *Kodi mukuganiza kuti pali kunsintha kuli konse pakuwonongeka kwa mitengo mnkhalango za mdera lanu* Y☐ No ☐

30. What do you think are the drivers/causes of increased deforestation rate in your area? **Rank them on a scale of 1 to 5 to indicate their level of severity** (*Mukuganiza kuti ndi zinthu ziti zikupangitsa kuonongeka kwa nkhalango mdera lino? Ndipo muziyike pa mulingo wa 1 mpakana 5*)

(a) Proximate/Direct Causes

Proximate cause	**1**	**2**	**3**	**4**	**5**
Firewood collection/domestic use					
Tobacco farming					
Construction					
Charcoal production					
Settlement					
Mining					
Agriculture expansion					
Shifting cultivation					
Timber					
Tradition medicine					
Bush fires					

Other (specify)					

(b) Underlying/Indirect Causes

Underlying cause	**1**	**2**	**3**	**4**	**5**
Poverty					
Population growth					
Urbanization					
Lack of law enforcement					
High cost of agriculture inputs					
Poor access to alternative energy supply					
Weak policies from government					
Weak leadership at all levels					
Demand for timber					
Lack of financial resources					
Poor marketing structures					
Political interference					
Other(Specify):					

31. What do you think should be done to reduce the rate of deforestation in your community (**Mention only 5**)? Please rank the importance of the activities from 1-5 (1=not very important and 5= very important). (*Kodi mukuganiza kuti ndi njira ziti timene tingachite pofuna kuchepetsa mchitidwe wowononga nkhalango*) Ndandalikani kufunika kwake pa mlingo wa 1-5

What to do	**1**	**2**	**3**	**4**	**5**
Law enforcement					
Promote tree planting					
Sustainable use of forest resources					
Use of alternative sources of energy					
Control of forest fires					
Improved ownership					
High penalties					
Other (Specify)					

32. What are the FIVE major impacts of deforestation in your community? Please rank the impacts in terms of importance (1=not very important and 5= Most important) *(Kodi ndi mavuto ati amene abwera chifukwa cha kuonongeka kwa nkhalango/mitengo mdera lanu) Ndandalikani kufunika kwa mavutowa pa mlingo wa 1-5*

Impacts	**1**	**2**	**3**	**4**	**5**
Lack of firewood					
Lack of wood for construction					
Floods and droughts					
Depletion of water resources					
Decline in scenic value					
Loss of soil fertility					
Other (Specify)					

33. Do you think that even more trees will be cleared from the forest in the near future? (*Kodi mukuganiza kuti kuwonongeka kwa nkhalango kukhala kukupitilira mdera lanu mtsogolomu*
Yes ☐ No ☐

34 (a). Do you think The Department of Forestry is doing enough in managing forests and checking illegal activities in the forests around you? *Kodi mukuganiza kuti nthambi yoyang'anira za nkhalango/aforesti ikukwaniritsa kupereka upangiri oteteza nkhalango mdera lanu kudzera mwa langizi awo Yes* ☐ *No* ☐

(b). If **NO**, Why not? If **YES**, Why do you think they are doing enough? *(Fotokozani yankho lanu mu (a)* ……………………………………………………………………………………
…………………………………………………………………………………………………
…………………………………………………………………………………………………
…………………………………………………………………………………………………

35 (a) Do you think it is necessary to plant trees in your community? *(Kodi mukuganiza kuti kudzala mitengo mdera lanu mkofunika) Yes* ☐ *No* ☐

(b) Please explain your answer. Why do you think there is/is not a need to replant trees in your community? *Fotokozani yankho lanu mu (a)*
…………………………………………………………………………………………………
…………………………………………………………………………………………………

36. (a) Do you own-planted trees?(*Kodi inuyo muli ndi umwini wa mitengo yodzalidwa)*
Yes ☐ No ☐

(b) If **YES** , do you make an income from selling the products (fruit/leaved) from the trees*? Kodi mumapeza phindu lina lililonse pogulitsako zokolora kuchokera ku mitengo yodzalidwayi*
Yes ☐ No ☐

(c) What are the forest produce and products that your sell?
…………………………………………………………………………………………………
…………………………………………………………………………………………………

37. What are the most important products you get from the forest and how important are these forest products to your household? Please rank the importance of these products from 1-5 (1=not very important and 5= very important). *(Tchulani zinthu zimene mungakonde mukumakololakuchokera ku nkhalango, ndipo mupereke kufunika kwake pa mlingo wa 1-5)*

Product	**1**	**2**	**3**	**4**	**5**
Firewood					
Charcoal					
Timber					
Medicine					
Honey					
Grass for thatching houses					
Poles					
Mushroom					
Wild fruits					
Reeds					

38. Please indicate what you use these products for? *(Pazinthu zomwe mwatchulazi perekani kugwiritsa ntchito kwake)*

Product	**HH consumption**	**Sale**	**Both**
Firewood			
Charcoal			
Timber			
Medicine			
Poles			
Thatching grass			
Honey			
Mushroom			
Wild fruits			
Reeds			

39. Where do you get wood for construction? *Kodi mitengo ya milimo mumaipeza bwanji?*
Own-planted trees ☐ Buy from community forests ☐ Buy from private Owners ☐
Market/Business men ☐ Buy from government forests ☐
Collect from the surroundings ☐ Other (specify): ………………………………

40 (a). Do you participate in any forestry management activities? *Kodi mumatenga nawo mbali pantchito zosamalira nkhalango?* Yes ☐ No ☐

(b) If **YES**,
(i) Please indicate in which programmes or activities you participate? **(Check Only The Relevant Options)** *Ngati ndi choncho, ndi ntchito ziti zimene mumatenga nawo mbali?*
Tree planting ☐ Bee keeping ☐ Fire fighting ☐ Forest patrols ☐
Weeding ☐ Nursery operations ☐ Other (specify)

(ii) Please indicate at which forest or woodlot you participate in these forest activities? *Ntchito zimenezi mumagwira mnkhalango yiti?*
Own forest land ☐ Community forests ☐ Govt. forests ☐ Other (specify: ……..

41. (a) Do you or any member of your household belong to a forest group or institutions? *Kodi m'banja mwanu alipo amatenga nawo mbali mmakomiti osamalira za nkhalango*
Yes ☐ No ☐

(b) If YES, please indicate which of the following forestry groups or organisations you or your family members belong to: *(Tchulani gululi/committee ya mu (a)*
Block Mgt committee ☐ VNRMC ☐ LFMB ☐ Other (specify

42(a). Do you know of any rules or laws in place to protect the forests around you? *Kodi mukudziwako malamulo aliwonse othandizira kuteteze nkhalango mdera lanu*
Yes ☐ No ☐

(b) If **YES**, please indicate the laws you are aware of *(Tchulani malamulo amene mukuwadziwawa)*

Type of laws	**Yes**	**No**
Forest Act and policy (Malamulo a boma oyendetsera nkhalango)		
Co-management agreement (Mgwirizano wa pakati paboma ndi akumudzi pofuna kuyendetsa nkhalango)		
Community by-laws (Malamulo oyendetsera nkhalango a kumudzi)		

43. Which type of activities are allowed in the forests around or close to your community*? Kodi ndi ntchito ziti zoloredwa kuchitika mnkhalango ya mdera lanu?*

Activities allowed	**Government**	**Community Forest**
Logging		
Charcoal production		
Clearing for crop production		
Collection of firewood		
Other (specify)		

44 (a). How has the distance to the collection of forest produce and products changed over the years? *Kodi mtunda wokakolora za mnkhalango wasintha bwanji mzaka zapitazi*

Increased ☐ Decreased ☐ Constant ☐

(b)If you indicated that distances that has to be travelled to collect forest products have increased, what do you think could be the **FIVE** reasons? Please rank the importance of the reasons from 1-5 (1=not very important and 5= very important*). Ngati mtundawu waonjezereka, mukuganiza kuti ndi chifukwa chiani?*

Reason	**1**	**2**	**3**	**4**	**5**
Increase in adjacent agricultural activities					
Increase in population					
Increased demand for forest resources					
Damage by other factors such as wind					
Forest fires					
Other (Specify)					

F. HOUSEHOLD ACCESS TO INFRASTRUCTURE AND SERVICES

45. Indicate the whether the distance over the past 25 years has changed from residence to the nearest infrastructure? *Tchulani ngati pali kusinthamu zaka 25 zapitazi kwa mtunda qochokera kunyumba kwanu kupita ku malo awa nditchulewa)*

Infrastructure	**Increased**	**Decreased**	**Constant**
Market			
Health Centre			
School			
Portable drinking water			
Water source (e.g. river/ stream)			
Main Roads			
Bus stop			

Town			

G. SHOCKS, VULNERABILITY AND COPING STRATEGIES/MECHANISMS

46(a) Are you happy with the current way of life? *Kodi ndinu wosangalala ndi mmene moyo wanu ulili panopa* Yes ☐ No ☐

(b) If **NO**, why not? Ngati sindinu wosangalala, ndi chifukwa chiyani?

High commodity prices		Unemployment	
Diseases		Lack of income	
Poor governance		Limited access to farm inputs	
Lack of market for crops		Other (Specify)	

(c) If YES, Explain……………………………………………………………………………….
…………………………………………………………………………………………………
…………………………………………………………………………………………………
…………………………………………………………………………………………………

47. Compare the following with what the situation was for you a few years ago? (Rank 1= Much Worse, 2= Worse, 3= No change for better, 4 = Better, 5 = Much better*) Pa zinthu zomwe nditchulezi, tasiyanitsani mmene zasinthila poyerekeza ndi zaka za mbuyozo*

Situation	**1**	**2**	**3**	**4**	**5**
Crop production *(Zokolora)*					
Soil fertility (					
Livestock production *(Ulimi wa Ziweto)*					
Fuelwood availability *(Kapezedwe ka nkhuni)*					
Timber availability					
Economic situation *Nkhani ya za chuma*					
Soil erosion					
Water availability					
External income *(Chithandizo/chuma cha kunja kwa khomo lanu*					

48. Over the past few years, what are the five major shocks or challenges you have experienced? (1=*1st Most important challenge experienced*, 2= *2nd Most important challenge experienced, 3rd Most important challenge experienced, 4th Most important challenge experienced and 5th Most important challenge experienced) Mu zaka zapitazi, tchulani ngozi zogwa mwadzidzi zokwana zisanu zimene mwakumana nazo m'banja mwanu*

Shock	**1**	**2**	**3**	**4**	**5**
Fire					
Drought					
Irregular rainfall pattern (too late, too early, heavy, low,)					
Increase in Price of Inputs					
Great Loss of crops/ crop damages					
Great loss/death of livestock					
Theft/Robbery and other Violence					
Local Unrest/Violence					
Floods					
Food shortage					
Price Raise of Food Items					

Illness of Household Member					
Death of Household Member					
Loss of Non-farm Jobs of Household Member					
Displacement due to government projects					
Other (specify)					

49. How did you cope with the shocks you have mentioned above shocks? **RANK ON THE SCALE OF 1 TO 5** *(Kodi ndi njira ziti zimene munagwiritsa ntchito pothana ndi mavuto odza ndi ngozi za dzidzi mwanena pamwambapo)*

Coping mechanism	**1**	**2**	**3**	**4**	**5**
Participated in piece works					
Received food aid (unconditional help from government)					
Relied on own-savings					
Obtained credit					
Reduced food consumption					
Household Members Migrated					
Reduced Expenditures					
Sold Agricultural Assets					
Sold forest products					
Received unconditional aid from relatives					
Sold livestock					
Sold crop stock					
Sold Land / Buildings					
Received Unconditional from NGOs					
Sold Durable Assets					
Sent Children to Live elsewhere					
Other (specify)					

50. (a) Were you able to recover from these shocks? *Kodi munakwanitsa kudutsa mmasautsa amenewa?* Yes ☐ ☐lo

(b) If, YES to Q 63(a), how long did it take you to recover from these challenges/shocks? *Zinakutengerani nthawi yaitali bwanji kuti mubwererenso ku moyo wanu wa tsiku ndi tsiku* ____

51. What are the effects of these shocks to your livelihood? *Kodi ngozi zimenezi zinakhudza bwanji moyo wanu wa tsiku ndi tsiku?*

Decline in crop yield ☐ Loss of assets ☐ Food insecurity/shortage ☐

Loss of income ☐ Other (specify): …………………………………………………………..

H. GENERAL LULC: PROXIMATE AND UNDERLYING CAUSES (DRIVERS) OF LULC CHANGES

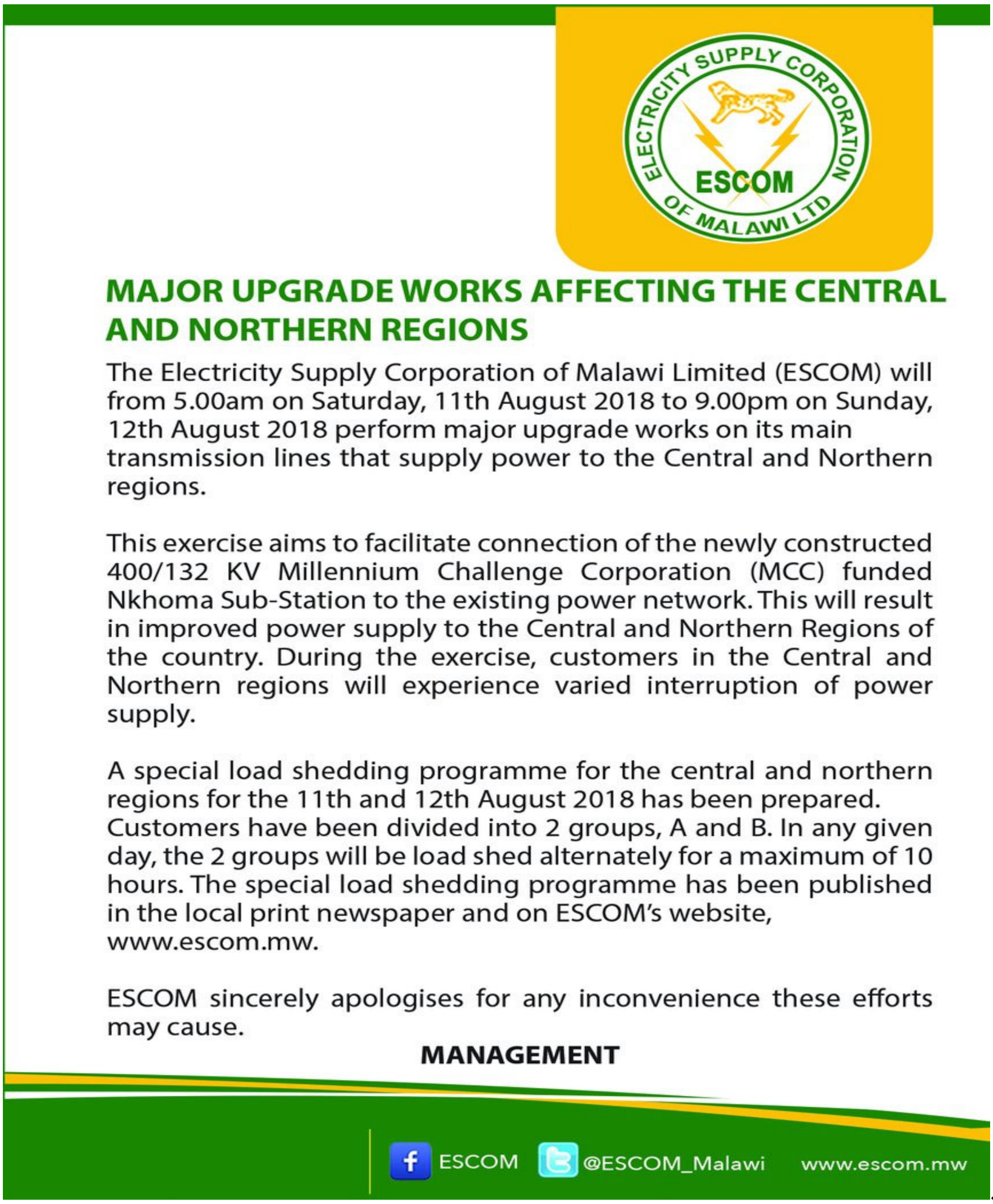
52. What do you think are the causes of land-use and land-cover changes in your area **(RANK ON A SCALE OF 1 TO 5**; 5 = least important and 1 = most important).

Proximate cause	**Rank**				
	1	**2**	**3**	**4**	**5**
Firewood					
Charcoal production					
Timber					
Construction					
Agriculture expansion					
Bush fires					
Settlements					
Firewood					
Others (Specify)					
Underlying Causes	**Rank**				
	1	**2**	**3**	**4**	**5**
Poverty					
Population growth					
Lack of financial resources					
Lack of law enforcement					
Demand for timber					
Others (Specify)					

Thank you for your time!

Thank you for participating in this study

Appendix 2: Example of Load Shedding by ESCOM in Malawi



ELECTRICITY SUPPLY CORPORATION OF MALAWI LTD
ESCOM

MAJOR UPGRADE WORKS AFFECTING THE CENTRAL AND NORTHERN REGIONS

The Electricity Supply Corporation of Malawi Limited (ESCOM) will from 5.00am on Saturday, 11th August 2018 to 9.00pm on Sunday, 12th August 2018 perform major upgrade works on its main transmission lines that supply power to the Central and Northern regions.

This exercise aims to facilitate connection of the newly constructed 400/132 KV Millennium Challenge Corporation (MCC) funded Nkhoma Sub-Station to the existing power network. This will result in improved power supply to the Central and Northern Regions of the country. During the exercise, customers in the Central and Northern regions will experience varied interruption of power supply.

A special load shedding programme for the central and northern regions for the 11th and 12th August 2018 has been prepared. Customers have been divided into 2 groups, A and B. In any given day, the 2 groups will be load shed alternately for a maximum of 10 hours. The special load shedding programme has been published in the local print newspaper and on ESCOM's website, www.escom.mw.

ESCOM sincerely apologises for any inconvenience these efforts may cause.

MANAGEMENT

ESCOM @ESCOM_Malawi www.escom.mw

Appendix 3: Ethical clearance approval letter

UNIVERSITEIT VAN PRETORIA
UNIVERSITY OF PRETORIA
YUNIBESITHI YA PRETORIA

Faculty of Natural and Agricultural Sciences
Ethics Committee

E-mail: ethics.nas@up.ac.za

Date: 14/08/2017

ETHICS SUBMISSION: LETTER OF APPROVAL

Ms MG Munthali
Department of Geography, Geoinformatics and Metereology
Faculty of Natural and Agricultural Sciences
University of Pretoria

Reference number: EC170513-116
Project title: Analysis of land use and land use cover changes and their implications on natural resources in Dedza District, Malawi

Dear Ms Munthali,

We are pleased to inform you that your submission conforms to the requirements of the Faculty of Natural and Agricultural Sciences Ethics committee.

Please note that you are required to submit annual progress reports (no later than two months after the anniversary of this approval) until the project is completed. Completion will be when the data has been analysed and documented in a postgraduate student's thesis or dissertation, or in a paper or a report for publication. The progress report document is accessible of the NAS faculty's website: Research/Ethics Committee.

If you wish to submit an amendment to the application, you can also obtain the amendment form on the NAS faculty's website: Research/Ethics Committee.

The digital archiving of data is a requirement of the University of Pretoria. The data should be accessible in the event of an enquiry or further analysis of the data.

Yours sincerely,

Chairperson: NAS Ethics Committee