INVESTIGATING THE IMPACT OF THE LAND REFORM POLICY ON LAND USE AND LAND COVER CHANGES, IN NGAKA MODIRI MOLEMA DISTRICT OF THE NORTH WEST PROVINCE.

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DECLARATION

I, Molebogeng Precious Mmangoedi, do hereby declare that this research report is my own work. It is being submitted for the Degree of Master of Science in Geographical Information Systems and Remote Sensing at the University of the Witwatersrand, Johannesburg. It has not previously been submitted for assessment or completion of any postgraduate qualification to another University or for another qualification.

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Molebogeng Precious Mmangoedi

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my brother Toney Bogatsu

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List of Acronyms

ANC	‘African National Congress’
CPAs	‘Communal Property Associations’
DRDLR	‘Department of Rural Development and Land Reform’
ESTA	‘Extension of Security of Tenure Act’
ETM	‘Enhanced Thematic Mapper’
FLAASH	‘Fast Line-of-sight Atmospheric Analysis of Hypercubes’
GIS	‘Geographic Information Systems’
LULC	‘Land use and land cover’
LULCC	‘Land use and land cover change’
MODTRAN	‘Moderate Resolution Atmospheric Transfer code’
MSS	‘Multi-spectral scanner’
NDP	‘National Development Plan’
NMMDM	‘Ngaka Modiri Molema District Municipality’
OLI	‘Operational Land Imager’
RF	‘Random Forest’
RMSE	‘Root Mean Square Error’
RS	‘Remote Sensing’
TIRS	‘Thermal Infrared Sensor’
TM	‘Thematic Mapper’
TOA	‘Top of Atmosphere’
USGS	‘United States Geological Survey’
USGS	‘United States Geological Survey’
UTM	‘Universal Transverse Mercator’
WGS	‘World Geodetic System’

ABSTRACT

The purpose of this study was to assess how land reform policies affected changes in land use and land cover in the province of North West's Ngaka Modiri Molema district municipality. The study employed remote sensing technologies to analyse changes in land use and land cover (LULC) resulting from the implementation of land reform programs between 1985 and 2015.

The primary objective of the research was to systematically map Land Use and Land Cover types across five-year intervals spanning from 1985 to 2024, leveraging Landsat earth observation data in conjunction with a random forest classifier. These methodologies were employed to facilitate the identification of spatial patterns and trends associated with the implementation of land reform policies within the study area.

Furthermore, the study utilized Landsat data and advanced change detection algorithms to quantitatively assess LULC changes over the specified timeframes. Through the application of spatial analysis techniques, the research aimed to elucidate the relationship between the implementation of land reform measures and corresponding shifts in LULC patterns across the research study area.

The findings of the investigation indicated a noticeable expansion in built-up areas between the years 1985 and 2024 which was approximately 10.86%. This expansion was primarily attributed to the growth experienced by the municipality during this period. Additionally, more opportunities might have risen from the agricultural farming activities and also from the land reform policy being implemented. However, as the ownership changed due to land redistribution and more land was being acquired by black people through the land reform policy, agricultural farming decreased slightly throughout the years. The reduction was due to the factors that arose from inefficient policy implementation. The study also recommends that remote sensing techniques should be utilised to carry out studies to determine LULC changes that derive from land policies aiming at dealing with socio-economic factors and urbanisation.

An incorporated agrarian reform sustainable programme has vast potential in cultivating the production of the projects, particularly if it involves packages in rural infrastructure, support services, and co-operatives. The major role of such an approach should be in the trainings conducted for the farmers, obtaining, and distributing agricultural resources and equipment to

agrarian reform or beneficiaries of the land reform projects. Additionally, there should be an allowance for special grants which will be useful in supporting the government's efforts.

CHAPTER ONE

INTRODUCTION

1.1 General Introduction

According to Moyo (2021), land stands out as a pivotal natural resource, bearing significant importance. It serves as a fundamental substrate that sustains all living organisms, encompassing human beings and their existence. Many human activities which include; producing food, developing infrastructure, and shelter and extracting natural resources, are dependent on land to be performed (Foley, 2005). Globally, land is becoming progressively scarce because of the continuous poor land management (Pillay, 2009). The LULC changes in South Africa have been attributed to several factors including urbanization, population growth, land policies, and land management which relate differently in different patio-temporal settings. (Briassoulis, 2000). Nonetheless, LULC changes have been resulting in significant environmental problems. Some of the environmental problems include loss in biodiversity, water population, influx in emergence of deserts and soil erosion. Additionally, LULC changes have a huge impact on the food security of several households as well as vulnerability especially in Africa (Govender, 2017).

The process of colonization in South Africa precipitated considerable disparities in land ownership, utilization, and administration. Predominantly, ownership of land was concentrated among foreign entities, with black individuals holding significantly smaller land parcels (Cousins, 2018). This inequality was exacerbated by legislative enactments such as the 'Natives Land Act of 1913', which confined land ownership for black individuals to about 7% of the total land area (South African Government, 2022). Later amendments, such as the '1936 Native Trust and Land Act', somewhat increased this allocation to thirteen per cent, but continued to prevent Black people from owning land.

The apartheid regime perpetuated these disparities by orchestrating widespread relocations of black communities to underdeveloped homelands and inadequately serviced townships, compelling them to pursue employment opportunities far from their places of residence (Bundy, 2014). This displacement contributed to socio-economic issues such as landlessness, poverty, and inequality within the South African economy. In order to rectify these disparities, the ‘Abolition of Racially Based Land Measures Act of 1991’ eliminated earlier discriminatory land legislation (Mahlati, 2009).

To create a fair and unbiased land distribution system, South Africa launched a land reform program in the 1990s (Hall, 2018). Legislative actions and programs were introduced to systematically progress land reform with the 1994 election of a new government (Visser, 1996). In order to achieve the goals of land reform, the African National Congress (ANC) created the ‘Reconstruction and Development Programme (RDP) in 1994 (Marais, 2013).’ Land reform was presented in the White Paper on South African Land Policy as a means of achieving equitable land distribution, reducing poverty, and improving the standard of living for those who benefitted (Rungasamy, 2011).

Land redistribution, land tenure reform, and land restitution are the three main pillars of the land reform program, which aims to improve access to land for historically underprivileged people and address racially discriminatory land ownership patterns (Walker, 2010). Key objectives include securing land tenure rights and restoring land rights to those previously dispossessed, including women (Claassens, 2014). These modifications are designed to foster sustainable development through collaborative endeavours involving the government, beneficiaries, and stakeholders, leveraging existing resources (Pienaar, 2004). The Vision 2030 and National Development Plan (NDP) recognize land reform as a catalyst for a dynamic agricultural sector that can generate employment and drive economic growth (National Planning Commission, 2020).

The NDP bases land reform on aspects that include, enabling the quick transfer of agricultural land to recipients who are Black (Aliber and Cousins, 2013). The redistribution of land is done in a way that minimizes the impact on business confidence in the agriculture sector and removes distortion of land markets (Lahiff, 2020). By guaranteeing that human abilities take precedence over land transfer through the use of incubators, mentorship programs, apprenticeships, and improved training in the field of agricultural sciences, such changes encouraged sustainable production on the redistributed land (Mahlati, 2019). An additional factor is establishing institutions for monitoring land utilization and protecting the land markets from opportunists, possible corrupt activities, and speculation. This is to be able to bring the targets of the land transfer to be aligned with the fiscal and economic realities. Such approaches have the potential to make the transfer of land successfully and to provide white commercial farmers as well as the industry bodies opportunity to be able to contribute towards the success of black farmers. Preferential procurement, chain integration, mentorship programs, and efficient skill development can all be used to take advantage of the prospects (Mahlati, 2019). In South Africa, land reform typically results in changes to the original LULC. These are mostly the result of changes in land ownership, which in turn affects the type of land use. Land laws and tenure systems that are in place at any particular time or place often influence the spatial patterns of LULC. Therefore, it is essential to set aside time to investigate how land tenure regulations affect changes in land cover (Sibanda et al., 2016).

Land reform presents a number of difficulties, with an emphasis on how to maintain land values and productivity sustainability once the reform is put into place. In a recent study, 71% of South Africa's impoverished people live in rural areas (Statistics South Africa, 2021). Rural communities deal with extremely distorted, tiny, or absent agricultural markets, and the situation is unlikely to improve very soon in the future (Deininger and Byerlee, 2011). The current patterns of access to land are also skewed due to the previous racialized land control system, as are the rights to water and irrigation (Hall, 2021). Even at this early stage, it is obvious that simply transferring assets or property would not guarantee a higher standard of living (Aliber and Cousins, 2013). Additionally, acquiring more land won't inevitably boost output or agricultural earnings (Lahiff, 2020). To solve this issue, focused governmental actions that specifically address market opportunities may be required (Moyo, 2021).

Inadequate knowledge of the local way of life, insufficient appraisal of the natural resources at hand, and insufficient awareness of the range of soil types all contributed to the abandonment of projects in these locations (May and Vaughan, 2000, Scholes and Biggs, 2021). When high-potential land is mismanaged, marginal land has to bear an intolerable extra weight to compensate for the underproduction, which negatively impacts the surrounding area as well. It is very important that land is transferred, or the resettlement of people is done after the installation has been completed. (Pienaar, 2004). Disadvantaged or no proper infrastructure in rural areas (e.g. bad roads and road networks, insufficient water and electricity supply, unreachable markets, insufficient credit facilities and unsatisfactory health and education services) may directly affect the success rate or failure rate of agricultural projects. Many aspects in rural areas have an influence on the extent of sustainability of land usage. This is usually because of the presence of extreme poverty which exists in a community and the limited access to sufficient natural resources. (Hofmeyr, 2002).

While addressing historical injustices and inequality is a significant aspect of land reform, it is essential to recognize that its impact extends beyond mere restitution. Land reform also plays a crucial role in poverty alleviation and providing sustainable livelihoods, which can profoundly reshape the agrarian economy and patterns of inequality (Bennett, 1996). However, poorly planned or executed land reform initiatives may have adverse effects on agriculture and food provision. Simply making land available is insufficient; it must be utilized in a viable and sustainable manner to have a meaningful impact on people's lives on a daily basis (Pienaar, 2004).

Established in 2006, the 'Proactive Land Acquisition Strategy (PLAS)' aims to address shortcomings observed in previous land reform initiatives, such as inadequate beneficiary selection, slow land acquisition processes, and inefficient land use on farms acquired (Gandidzanwa et al., 2021). Although beneficiary selection criteria prioritize a pro-poor approach and encompass evaluations of skills and wealth, it has become apparent that these criteria alone are inadequate or inconsistently applied. Additional factors, such as farmers' capacity to access suitable markets and integrate into value chains, also exert a substantial influence on their success (Pienaar, 2004). There is a huge opportunity to make use of the initiatives as a way of supporting LULC. To enhance the quality of data gathering for the purposes of supporting LULC analysis, remote sensing can be used.

Remote sensing technology offers significant advantages for land use and land cover (LULC) analysis by providing extensive and precise data collection capabilities. Key opportunities include:

- **Extensive Area Coverage:** Remote sensing enables the monitoring of large and remote regions, which is particularly useful for comprehensive environmental assessments (Pettorelli et al., 2014).
- **Temporal Change Analysis**: The ability to access historical and continuous satellite imagery allows for the analysis of temporal changes in LULC, helping to identify trends and patterns over time (Cohen and Goward, 2004)
- **High-Resolution Imaging**: Modern satellite technologies offer high spatial resolution images, which are essential for detailed mapping and classification of land cover types (Turner et al., 2015).

- **Agricultural Resource Management**: In precision agriculture, remote sensing supports monitoring crop health and estimating yields, which promotes efficient resource use and improves productivity (Mulla, 2013).

It becomes clear that remote sensing is a vital tool for tracking and analysing changes in LULC, especially when used in conjunction with land reform initiatives. The process of obtaining data on things, regions, or phenomena by analysing information obtained by devices that are not in close proximity to the object of interest is known as remote sensing (Lillesand, 2008). Compared to conventional aerial imaging, it offers improved resolution, increased spatial accuracy, and a wider spatial coverage (Richards and Richards, 1999; Rogan and Chen, 2004; Xiao et al., 2006).

This research focuses on using remote sensing to monitor and analyse LULC changes resulting from land reform projects in the Ngaka Modiri Molema District Municipality. Specifically, it employs change detection techniques in remote sensing to analyse transformations in LULC resulting from land reform initiatives.

1.2 Problem Statement

Significant differences in land ownership and entrenched poverty in rural areas were brought about by the historical land dispossession that occurred throughout South Africa's colonial and apartheid periods. South Africa launched a land reform initiative in 1994 after electing a new democratic government with the goal of correcting historical wrongs and promoting rural development (Aliber, 2004). This initiative sought to rectify the inequalities in land ownership that were perpetuated by the apartheid regime, with a particular focus on restitution, tenure reform, and redistribution as its core pillars (Palamuleni, 2012; Jacobs, 2003). Restitution aimed to address historical land rights issues, while tenure reform sought to reform land-holding structures. Conversely, land redistribution aimed to transform land ownership patterns across racial lines, with the potential to significantly improve rural livelihoods and contribute to economic development (Van Zyl, 1996). However, as land reform policies were implemented, unexpected environmental effects became apparent (Lidzhegu, Z. & Palamuleni, L., 2012).

Growing awareness of the potential of land reform to reduce poverty and structural inequality has led to a recognition of the need for a new approach to this issue (National Planning Commission, 2012). Nevertheless, it is acknowledged that land reform alone may not be sufficient to address rural poverty. The focus should also be on creating non-farm employment and income opportunities for both urban and rural populations (Cousins, 2016). A targeted land reform program, coupled with infrastructure development such as new irrigation schemes, could significantly improve household well-being, and generate employment opportunities.

There is a deficiency of study on the scope and implications of land use and cover changes in the Ngaka Modiri Molema district, particularly when using remote sensing imagery, despite a number of studies looking at these changes. Therefore, the aim of this research is to evaluate the extent to which the land reform policy has affected changes in LULC in the district. It also attempts to investigate how changes in land usage and land cover have been impacted by changes in land ownership resulting from the land reform initiative.

1.3 Aims and Objectives

The research's overall aim can be summarised as follows:

To investigate the impact of the land reform policy and implementation on LULC changes in the Ngaka Modiri Molema district over the period between 1985 to 2024 using multi-temporal remote sensing imageries.

Objectives:

1. To map the LULC types between the periods of 1985 to 2024 with five-year intervals using Landsat Earth observation data and random forest classifier.
2. To identify the spatial pattern and trends of the implementation of the Land Reform Policy in the study area using spatial analysis techniques.
3. To quantify the LULC changes between the periods of 1985 to 2024 with five-year intervals using Landsat data and change detection techniques.
4. To establish the relationship between the implementation of the Land Reform Policy and LULC changes in the study area using spatial analysis techniques.

1.4 Research Outline

The study was organized into five distinct chapters, each fulfilling a specific purpose and contributing to the main objectives of the research. The outline of the research is as follows:

<u>Chapter One: Introduction and Background</u>

The first chapter offers a comprehensive background to the study, presenting the research problem, aims, and overall objectives. It lays the foundation for the subsequent chapters and provides a framework for understanding the research context.

Chapter Two: Literature Review

Chapter Two provides a brief review of the relevant literature pertinent to the research topic. It encompasses discussions on concepts and theories concerning land ownership in Southern Africa’s context, the outline of some selected initiatives of land reform, the significance of remote sensing in detecting changes in LULC, as well as challenges inherent in utilizing remote sensing for LULC analysis. The arguments and discussions within this chapter are aligned with the research objectives, thereby steering the direction of the study.

Chapter Three: Research Methodology

This chapter provides the research methodology adopted in the study. It delineates the study area and elaborates on the remote sensing techniques employed to fulfil the research objectives. Furthermore, the chapter underscores the importance of remote sensing as a timely and cost-effective approach for acquiring precise spatial information concerning LULC.

Chapter Four: Presentation and Analysis of Findings

Chapter Four is dedicated to presenting and analysing the results of the investigations carried out. It elucidates the major findings obtained from the applied methodologies and provides an in-depth discussion of the study's outcomes.

Chapter Five: Conclusions and Recommendations

The final chapter offers conclusions drawn from the study's findings and provides evidence-based recommendations. The research findings, particularly regarding the nexus between land reform and LULC changes using remote sensing techniques, offer valuable insights that can inform the implementation of land reform programs in South Africa. The recommendations presented are grounded in the evidence derived from the study's outcomes.

CHAPTER TWO

LITERATURE REVIEW

The chapter explores the important issues surrounding land reform and changes in land use and cover, clarifying how remote sensing methods can be used to track LULC changes. It elaborates on the ideas underlying LULC modifications and offers insights into the background of land tenure and management in South Africa. Additionally, it examines the repercussions of colonization on land tenure and management practices. Furthermore, the chapter explores the interconnection between poverty and land access, the execution of land reform policies, and the encountered implementation challenges. The discourse on remote sensing and LULC changes serves as the concluding segment of the chapter.

2.1 Conceptual Issues: Land use and land cover changes (LULCC)

The LULC terminology encompasses various explanations. According to one interpretation, land cover is the visible biophysical characteristics that cover the surface of the Earth., including features such as grasslands, agricultural areas, forests, recreational areas, or built-up regions (Lambin, 2006). Alternatively, land use can be delineated by the inputs and methods employed to produce, alter, or maintain specific land cover types (Briassoulis, 2000).

In broader terms, LULCC refers to computable modifications observed within the aerial landscape, involving the decrease or increase in specific land uses or covers (Briassoulis, 2000). Furthermore, LULCC can be broadly divided into two groups: modification and conversion (Stolbovoi, 2002). Transitions from one type of cover or use to another, like turning a forest into pastureland, are referred to as conversions. On the other hand, modification entails changing the form and characteristics of the land while preserving the general land cover or use type (Duadze, 2004).

2.2 The history of land tenure and management in South Africa

The implementation of the ‘Group Areas Act of 1950’ swiftly followed the ascension of the National Party to power in South Africa. This legislation, enacted as part of the apartheid regime's agenda, facilitated the forced removal of black individuals from areas designated as "white," thereby intensifying racial segregation. Additionally, "coloured" and Indian populations were also uprooted from these designated white areas (Rugege, 2004).

Group Areas Act forced the removal of many successful Black landowners who had escaped the ‘1913 Land Act's restrictions’ on their land because they had title deeds, under the guise of "cleaning up" so-called "black spots." These "black spots" typically referred to fertile lands, whereas the areas to which people were relocated, namely the Bantustans, were characterized by overcrowding, overgrazing, and subsequent overcultivation (Rugege, 2004).

The ‘Prevention of Illegal Squatting Act of 1951’ empowered the eviction of people without formal land rights, thereby supporting the ‘Group Areas Act’ and other land laws that discriminated against people of colour. This law gave state agencies and private landowners the authority to evict people and destroy their homes without following the proper legal channels. Consequently, numerous individuals who were evicted, who had previously resided on the land with the consent of landowners, were classified as squatters and subjected to forced eviction (O'Regan, 2004). These displaced individuals were resettled in overcrowded Bantustans or homelands, while others were relocated to temporary vacant lands until these areas were required for alternative purposes, perpetuating further cycles of eviction. Between 1960 and 1983, an estimated three and a half million individuals were forcibly relocated due to different apartheid laws. (Walker, 1985).

Following 1994, South Africa started implementing land reform programmes to address the significant land inequality in the country. As much as eighty-seven percent of the land was owned by the white minority, who made up fourteen percent of the population at that time. The Land Reform Programme aimed to provide historically underprivileged Black people with land in order to improve living conditions, stimulate the local economy by redistributing land, provide compensation for land that was wrongfully taken during the apartheid era, and stabilise land access through tenure reform. (McCusker, 2004).

2.3 The impact of Colonization on land tenure and land management

The impact of colonization on land tenure and management in South Africa was profound. It resulted in a dual system of land tenure characterized by extensive commercial farming areas alongside communal lands. The communal areas were marked by a lack of structure, fragmentation, and poor planning, thus exacerbating spatial inequalities within the country. Prior to colonization, land tenure in South Africa was overseen by Amakhosi and traditional councils. However, the arrival of colonizers introduced political, social, cultural, and environmental influences that reshaped land tenure and management practices (Hoffman, 2014).

Hoffman (2014) noted that following the enactment of the 'Native Land Act of 1913', Namaqualand exhibited either sustained or augmented vegetation cover, whereas the Little Karoo region experienced substantial degradation and a notable decline in ecological integrity. Specifically, the Nama-Karoo biome underwent a noticeable rise in grassiness subsequent to a reduction in livestock numbers.

Colonization created a huge divide between private farms and the communal land area. The communal land area where the majority of the blacks were forced to stay following the 'Native Land Act of 1913' witnessed a significant in the cover and vegetation of the ecosystem. Specifically, the environmental conditions defining the communal area have been deteriorating. Several factors have been attributed to these changes and these include demographic and economic pressures, poor government support of land users and over-use of land (Hoffman, 2014). The amount of vegetation in the small area where most black people were compelled to live saw a sharp decrease. This resulted from crop cultivation, overgrazing, and wildfires. Over time, the land cover changed as a result of all these activities.

2.4 Poverty and Access to land resource in South Africa

In the discourse surrounding poverty alleviation, land reform emerges as a crucial factor with the potential to mitigate poverty while simultaneously fostering economic growth and job creation within South Africa (Sibanda, 2001; DRDLR, 2016). This hinges on the establishment of an effective pre- and post-transfer support program, wherein the government, commodity organisations, financial institutions, and organised agriculture can play pivotal roles in providing a comprehensive range of support services to new black commercial farmers. Furthermore, the implementation of sound business practices is imperative to enhance production and explore additional opportunities within the agricultural value chain. Additionally, involving traditional leaders of communities as custodians of tribal lands can be beneficial (Bernstein, A., McCarthy, J., and Dagut, S. (2008).

Nevertheless, poverty rates have remained persistently high in South Africa even after land reform programmes were put into place. A panel report on land reform highlights that the efforts in land reform have yielded limited success in alleviating poverty among households, as well as among small-scale and commercial black farmers. The primary causes of this predicament are the lack of a working land tenure system and an insufficient mechanism for giving beneficiaries access to land deeds when they purchase land parcels (Hall and Kepe, 2017; Cousins, 2013).

2.5 The land reform policy and implementation

The land reform policy in South Africa is underpinned by three key pillars: redistribution of land, reform of land tenure, and land restitution (Mostert, 2010). These pillars are designed to address the historical disparities in land ownership by facilitating increased access to agricultural land for historically disadvantaged individuals. Additionally, they aim to ensure the security of land rights and to restore land to those who were previously deprived of it due to racial laws or similar practices, as well as to individuals who never had land rights. The collaborative efforts of the government, stakeholders, and land beneficiaries are intended to implement these reforms in a manner that promotes sustainable development while maximizing available resources (Pienaar, 2004).

2.6 The challenges of land reform policy implementation

When South Africa began its democratic transition in 1994, one of the biggest challenges it faced was the equitable redistribution of land after racial disparities in ownership (DRDLR, 2016). Initiatives for land reform included things like tenure reform, redistribution, and land restitution. The post-apartheid government faced considerable anticipation regarding its ability to enact substantial transformations aimed at rectifying the historical injustices related to land dispossession. During the twenty years that Land Reform Programme was implemented, there has been multiple changes in the strategies, the creation of various instruments aimed at supporting land redistribution, and lately, a Recapitalisation and Development Programme aimed at supporting the production exhibited on the farms (DRDLR, 2016).

However, the implemented land reforms did not manage to achieve the expectations and multiple newly settled black farmers unfortunately became worse off than before upon obtaining access to the land (Rugege, 2004). Several factors contributed to this outcome, primarily stemming from the coordinated efforts of both pre- and post-settlement support services suggested by the government and the agricultural sector. Despite numerous proactive initiatives introduced by the government to coordinate pre- and post-transfer activities through partnerships with various stakeholders, these challenges have persisted. (Jacobs, 2003).

In communal areas, land tenure reforms faced numerous obstacles, particularly stemming from the Second-Class status assigned to black land rights under the law. Before 1994, South African legislation inadequately acknowledged the rights of occupation and use within black rural communities. Black residents were granted limited rights through conditional permits, essentially providing permission to hold a certificate of ownership. Another significant challenge impeding the implementation of land policies was the weak legal status compounded by overcrowding in communal areas. Moreover, the presence of forced overlapping rights resulting from historical forced removals and evictions during the era of segregation and apartheid exacerbated the situation. Furthermore, the partial breakdown of communal tenure systems, fuelled by the lack of legal recognition and diminishing administrative support, further complicated the implementation of land reform policies. Consequently, these challenges fostered corruption among traditionalists as they grappled with these issues.

2.7 The LULC changes as indicators of the land reform policy implementation

The process of detecting changes in a phenomenon's state by tracking it over various time periods is known as change detection (Singh, 1989). Change detection is defined by Hsiung Huang and Ju Hsiao (2000) as the analysis and distinction of multi-temporal images of a specific geographic region, accomplished by applying image-processing methods to examine changes in the terrain over different time periods (Hsiung Huang, 2000).

The significance of change detection is that it can be used to track Earth's natural resources by looking at the geographic distribution of pertinent populations. Essential components of change detection crucial for natural resource monitoring include identifying changes, understanding their characteristics, determining their extent, and analysing their spatial arrangement (Macleod, 1998). These elements form the foundation for assessing alterations in land cover, land use, and other environmental variables over time, enabling informed decision-making and sustainable management of natural resources. Applications for change detection include land cover analysis, tracking urban development, monitoring agricultural patterns, evaluating deforestation, managing natural disasters like floods in real time, and monitoring the environment (Bottomley, 1998).

Over the past two decades, various techniques for change detection have been developed. Lu et al. (2004) categorized these methods into seven groups: visual analysis, advanced modelling, transformation-based, algebraic, advanced modelling, and miscellaneous methods. Change detection analysis, as noted by Ernani and Gabriels (2006), encompasses a range of methods aimed at identifying, describing, and measuring differences between images of the same scene captured at different times or under different conditions. Lu et al. (2004) emphasizes the importance of selecting an appropriate change detection method tailored to specific application domains.

Commonly used methods for change detection include principal component analysis, post-classification comparison, and image differencing (Lu, 2004). Post-classification comparison provides detailed information on changes from one state to another, while image differencing and principal component analysis reveal changes or the absence thereof (Pillay, 2009).

2.8 Remote sensing for monitoring land use and cover changes

In order to analyse changes in LULC, remote sensing (RS) is essential in providing comprehensive observations of the entire Earth's surface that are frequently not possible with ground-based techniques alone (Lillesand, 2000). RS makes it possible to obtain satellite imagery and aerial photos by using RADAR, LiDAR sensors, multi-spectral scanners, and cameras installed on aircraft and satellite platforms. This allows for thorough analysis (Ellis, 2013). Because resources are highly reflective across different electromagnetic spectrum regions that are captured by different sensors, RS techniques provide distinct advantages in resource management. As a result, LULC mapping is an essential component of modern satellite sensor technology (Duadze, 2004). Furthermore, RS techniques prove invaluable in mapping LULC, particularly in inaccessible areas or where traditional mapping methods encounter challenges (Tucker, 2000).

Spatial information is imperative for effective land reform, ensuring sustainable development and garnering economic and political support (Bullard, 2001). Land use maps created from digital data, topographic maps for development planning, cadastral surveys for defining legal boundaries, and remote sensing imagery are examples of this type of information (Bullard, 2001). Proposals for land reform often hinge on two key questions: whether land should be privately owned or state-owned with specified usage rights, and how to establish a comprehensive national land information system to identify parcel location, size, and characteristics along with associated legal rights (McEwen, 2000). While technological tools like GPS, GIS, and remote sensing offer potential solutions, their efficacy relies on a supportive legal framework, institutional infrastructure, and financial backing to ensure long-term viability (McEwen, 2000).

Remote sensing techniques have been pivotal in studying land reform impacts, particularly through LULC mapping (Lidzhegu, Z. & Palamuleni, L., 2012). For instance, studies analysing LULC maps have shed light on the consequences of land reform policies, such as in South Africa's Makotopong region, where remote sensing techniques revealed changes in land cover post-reform (Lidzhegu, Z. & Palamuleni, L., 2012). Similarly, studies in Ethiopia have employed remote sensing alongside socio-economic data to monitor LULC changes, attributing shifts to factors like the 1975 land reform, which spurred forest conversion to cropland and settlements (Mengistu, 2008).

Furthermore, remote sensing methods have been instrumental in assessing agricultural land use change post-land reform programs, as demonstrated in Zimbabwe (Hentze, 2016). While traditional methods like phenology-based land use classification have limitations, innovative approaches using MODIS data have enhanced understanding (Hentze, 2016). Similarly, in Chipinge district, Zimbabwe, remote sensing techniques coupled with advanced analysis methods like Support Vector Machine (SVM) and Markov Chain Analysis (MCA) have facilitated quantification of LULC changes and predictive modelling (Jombo, 2016).

Overall, remote sensing techniques offer valuable insights into the complexities of land reform and LULC changes, providing a robust framework for monitoring and implementing policies ((Lidzhegu, Z. & Palamuleni, L., 2012). The literature underscores the global relevance of land reform challenges and emphasizes the importance of cross-country learning and collaboration in addressing these issues.

2.9 Image Classification and Change Detection

Image Classification is a crucial process in remote sensing, involving the categorization of pixels into predefined classes based on their spectral characteristics. Classification techniques are generally categorized into three main approaches: supervised, unsupervised, and object-oriented classification.

Supervised Classification involves training a classifier using labelled data to identify features within an image. This method requires ground truth data to train algorithms such as Support Vector Machines (SVM), Random Forests, and Neural Networks (Zhu et al., 2017). Supervised techniques are advantageous for their accuracy and precision in classifying complex land cover types.

Unsupervised Classification, on the other hand, does not require labelled data. Instead, algorithms like K-means clustering and ISODATA (Iterative Self-Organizing Data Analysis Technique) group pixels into clusters based on their spectral similarity (Jia et al., 2019). This method is beneficial when prior knowledge is limited but may require subsequent manual interpretation to label the clusters accurately.

Object-Oriented Classification involves segmenting an image into meaningful objects based on both spectral and spatial characteristics. This approach leverages image segmentation to delineate objects before classifying them using algorithms such as eCognition and OBIA (Object-Based Image Analysis) (Blaschke et al., 2014). Object-oriented classification is particularly effective for heterogeneous landscapes and provides context-based analysis, which enhances classification accuracy.

Classification Algorithms play a vital role in these processes. Modern algorithms like Deep Learning Convolutional Neural Networks (CNNs) have shown remarkable improvements in classification accuracy by learning complex patterns and features from large datasets (Zhang et al., 2021). Traditional algorithms, including Decision Trees and Maximum Likelihood, are still widely used due to their simplicity and robustness in various applications (Foody, 2018).

Change Detection involves analysing temporal imagery to identify and quantify changes in land cover or land use. Techniques such as post-classification comparison, image differencing, and change vector analysis are commonly employed to assess changes over time (Lu et al., 2018). Change detection is critical for monitoring environmental changes, urban expansion, and disaster impacts.

Prediction in remote sensing often involves forecasting future land cover changes based on historical data and trends. Techniques like cellular automata, Markov models, and machine learning approaches are used to predict future land use patterns and assess the potential impacts of various scenarios (Pontius et al., 2020). Predictive modelling supports strategic planning and management by providing insights into possible future scenarios.

CHAPTER THREE

METHODOLOGY

3.1 The study area

One of the four district municipalities in the North West Province is the Ngaka Modiri Molema District Municipality (NMMDM) (refer to Figure 1). Ngaka Modiri Molema District is positioned at the province's central nexus, and it is close to the international borders of Botswana. The district comprises of five local municipalities which are;

1. Mahikeng;
2. Ditsobotla;
3. Ramotshere Moiloa;
4. Ratlou; and
5. Tswaing.

district municipality serves as a significant administrative entity within the region. NMMDM has an estimated extent of twenty-eight thousand, two hundred and six square kilometres (28 206 km^2) with an overall population estimate of nine hundred thirty-seven thousand, seven hundred twenty-three (937 723) people as indicated by Ngaka Modiri Molema District Municipality (DC38) (NMMDM Annual Report 2022). The topography of NMMDM can mainly be classified as flat, with over two-thirds of the area falling into this category. Of the remaining third, approximately half can be classified as mountainous (to the north of the district in Ramotshere Moiloa), whilst the remaining area can be classified as rolling (DRDLR, 2016). The topography of the area is directly linked to land use for agricultural purposes, the kinds of crops that can be grown on a piece of land can vary depending on the slope (Harris et al., 2021).

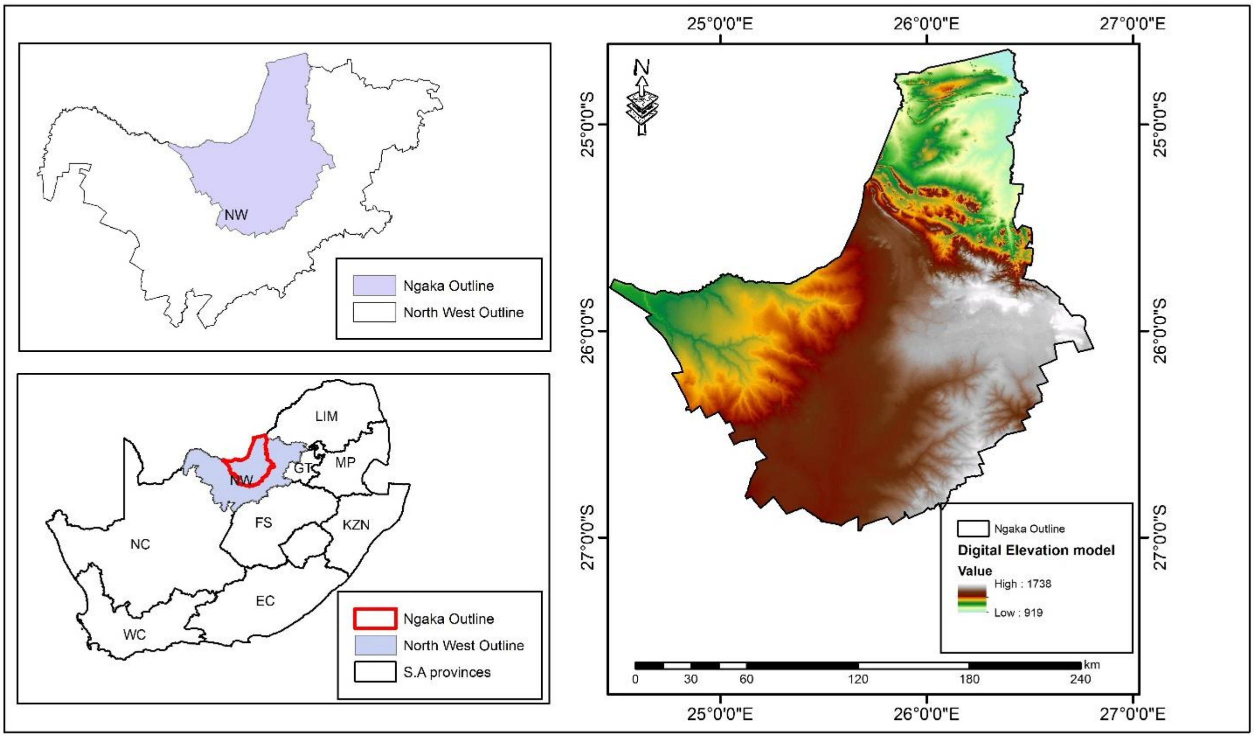


Figure 1**:** A location map showing the NMMDM in the Northwest Province, created from ArcMap.

3.1.1 The LULC in NMMDM

In the NMMDM of the North West province, the predominant natural vegetation comprises savannah, while grassland is prevalent in the southeast. The province's eastern region experiences semi-arid climatic conditions, contrasting with the aridity observed in the western half. Within NMMDM, grazing lands support sheep, game, and dairy cattle across the majority of the terrain (Masike and Urich, 2008). The landscape of the North West province is characterized by expansive flat savannahs and grasslands, fostering diverse biodiversity and agricultural activities, with hills and ridges interspersed throughout.

Potential land use categories in the area encompass Mining, Bare areas, Crop cultivation, Natural veld, Grazing lands, Forested areas, Plantations, Urban development, Built-up areas, Water bodies, and Wetlands. There is also some mining activity in the district, the Kalahari Group's most recent sand deposits cover the Ngaka Modiri Molema district. There are also a few outcrops of sedimentary rocks from various Supergroups and Groups. It is also possible that dolomite exists beneath the Kalahari sands. In a region like Ditsobotla, which is primarily dolomitic, minerals like shale, dolomite, limestone, feldspar, and diamond are mined. The majority of cement manufacturing companies are located in Ditsobotla, which is a local municipality in NMMDM (DMR, 2022).

Agricultural land in the District is formed mostly from crop and cattle farming. Wheat and maize farming predominate in the province's central and southern regions. The province produces almost any kind of crop, but the most important ones in terms of economic impact are groundnuts, maize, sunflower seeds, and wheat. Approximately one-third of the nation's maize is produced in the North West.

3.1.2 Population and the main activities in NMMDM

The NMMDM spans an area of 28,206 square kilometres within the North West Province (NWP). It hosts a population of 937,723 based on the published census results of the 2022 Ngaka Modiri Molema District Municipality (DC38) report. It comprises five Local Municipalities (LMs): Mahikeng LM, Tswaing LM, Ditsobotla LM, Ramotshere Moiloa LM, and Ratlou LM, with Mahikeng serving as the provincial capital. The district shares borders with Botswana to the north, the Northern Cape Province to the southwest, and Limpopo Province to the northeast, positioning it centrally within the NWP alongside neighbouring district municipalities.

In 2019, the population of NMMDM was approximately 961,960, representing around 1.6% of South Africa's total population or 23.3% of the North West Province's total population. Population growth rates between 2008 and 2018 averaged 1.33% annually, slightly lower than the provincial and national averages. Notably, the Ditsobotla Local Municipality experienced the highest population growth rate at 1.7%, followed by the Mafikeng Local Municipality, while the Ratlou Local Municipality had the lowest growth rate at 0.55%. However, the recent study shows that the population of NMMDM was 937,723 in 2022.

Projections based on current demographic trends anticipated that NMMDM's population to rise at an average annual rate of 1.6%, reaching 1.02 million by 2023. The economic landscape of the district is primarily driven by agriculture, encompassing both livestock and crop farming, alongside sectors of arts, culture, tourism, and mining, predominantly in remote areas.

Strategically located development corridors such as the N18 Western Frontier Corridor and the Platinum Corridor (N4) present promising opportunities for economic growth. Mahikeng, as the district's largest centre, is expected to play a pivotal role in economic development initiatives, notably through the Mahikeng Renewal and Rebranding project. While spatial planning responsibilities are not shared across NMMDM and its Local Municipalities, the District's Town Planning unit actively engages in key planning endeavours.

The district boasts underutilized tourism infrastructure and serves as a major transportation artery, with routes like N4 and R508 facilitating access to Botswana. Agriculture, tourism, and mining, including informal activities such as diamond and slurry mining, are the main economic drivers in the district. Leveraging its strategic location and development corridors, NMMDM aims to capitalize on its economic potential to alleviate poverty and create employment opportunities within the region.

3.1.3 History of land ownership in the NMMDM

Since the enactment of South Africa's land policy in 1995, the ‘Department of Land Affairs (DLA)’ has been pivotal in establishing the policy framework for land redistribution, achieving considerable success in allocating land to disadvantaged households and marginalized communities that have experienced land dispossession. Approximately 2,078,385 hectares of land have been distributed to beneficiaries since 1995 (DLA, 2008).

However, the DLA has proposed a new plan to address challenges related to the Community Property Association (CPA) membership, aiming to minimize or restrict membership numbers (DLA, 2008). This decision stems from concerns that some registered CPA members have received land acquisition grants without effectively utilizing the acquired land. Additionally, the incapacity of certain CPAs to deliver tangible benefits exacerbates the challenges faced by the DLA.

The government's land reform policy, outlined in the ‘Land Reform (Labour Tenants) Act of 1996’, introduced three key elements: redistribution, tenure reform, and restitution. This policy aims to increase black ownership of rural land, improve tenure security for rural and peri-urban dwellers, and provide restitution for those who were dispossessed under apartheid. Reaffirming its commitment to redistributing 30% of agricultural land to black individuals, as outlined in the ‘Reconstruction and Development Plan (RDP) of 1994’, the government extended the target date to 2014 in May 2001 (DLA, 2008). This target is considered the overarching objective of land reform, encompassing land transfers under the ‘Land Redistribution, Land Restitution, and Land Tenure programs.’

The NMMDM of the Northwest Province faces significant challenges in its land reform initiatives, particularly regarding the systemic failure of post-settlement support. This challenge has contributed to an estimated 50% failure rate of new land reform projects

(Antwi et al., 2014). Despite these shortcomings, both national and local governments are under considerable political pressure to accelerate land reform efforts to meet predefined targets. As a result, proactive land acquisition strategies (PLAS) are being implemented.

Despite the challenges, the NMMDM has made progress in its land claim procedures, with 85.5% of filed claims resolved and the majority of the remaining claims partially completed. The district is predominantly rural, consisting of 198 villages, twenty-one townships, eight towns, and one hundred and three wards. Ninety percent of the population resides in traditional authority areas, overseen by twenty-two traditional leaders.

However, despite possessing tourist attractions and agricultural land with significant potential, NMMDM faces socioeconomic disparities that contribute to high poverty rates. Addressing these disparities and improving post-settlement support will be essential for the success of land reform initiatives in the district. The land reform and restitution areas within the district municipality are illustrated in Figure 2 (DRDLR, 2016). Considering the multitude of land reform projects within its jurisdiction, the NMMDM has been chosen as the focal area for this study. In order to investigate how land reform initiatives affect LULC, this study uses remote sensing techniques.

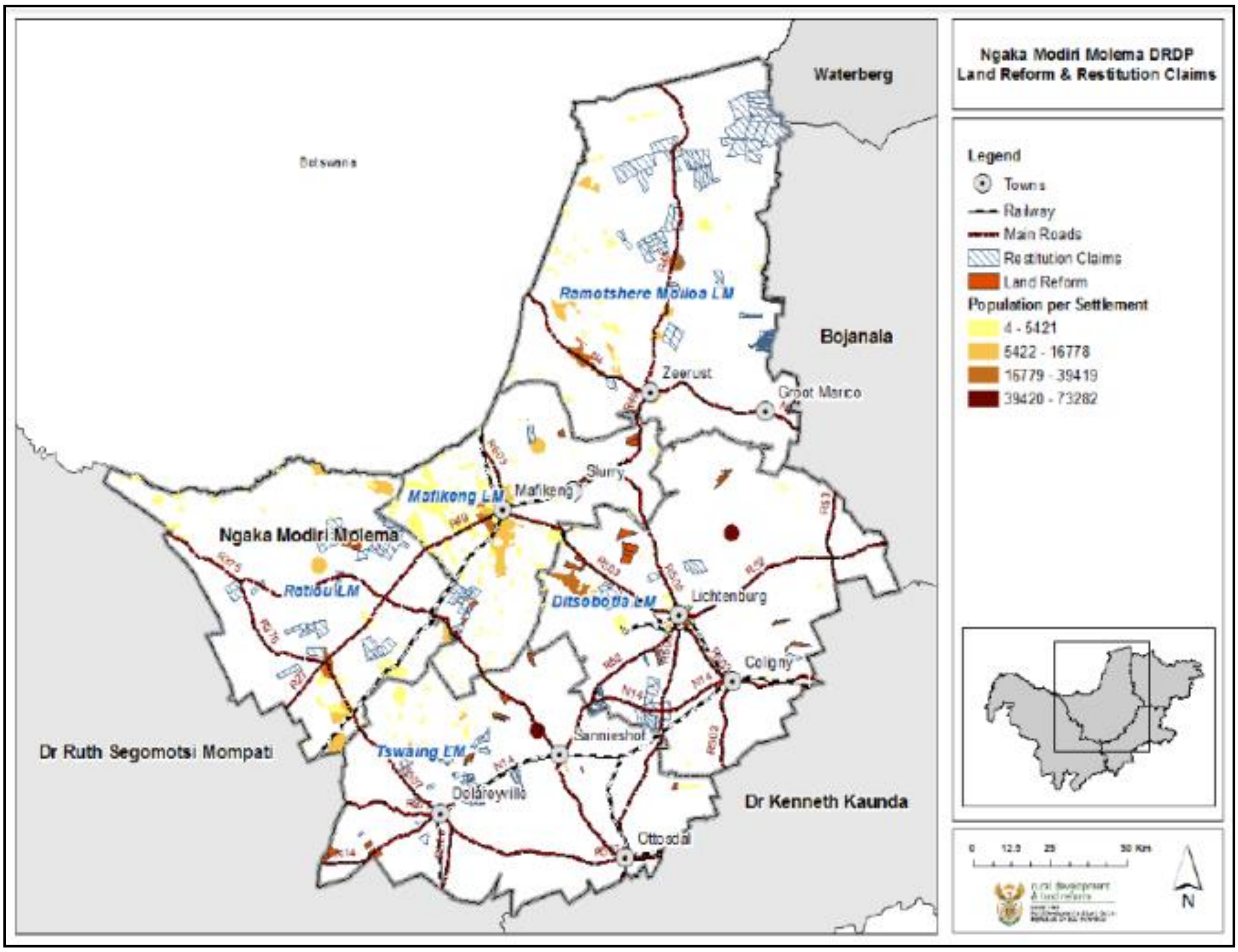


Figure 2: Map obtained from the NMMDM Rural Development Plan: Northwest Province (March 2016).

3.2 Materials and Methods

3.2.1. Remote Sensing Data

The study utilized Landsat satellite imagery spanning from 1985 to 2024, encompassing the years 1985, 1990, 1995, 2000, 2005, 2010, and 2015, as outlined in Table 1. The 1985 image was sourced from Landsat 5 TM, while subsequent years also used Landsat 5 TM until 2010 and Landsat 8 OLI/TIRS in 2015. The sensor and spectral range of these images varied. Since it has a high spatial resolution and affordability, Landsat imagery was chosen, especially for mapping LULC in smaller areas (Hu et al., 2013). Furthermore, the United States Geological Survey (USGS) Earth Science Data Interface provides free access to valuable and ongoing Landsat observations of the Earth's surface (USGS, 2014; Chander et al., 2009).

The satellite images utilized in this study were obtained from specific path and row coordinates within the NMMDM, sourced from the USGS. These images were mosaicked and clipped to the boundary. All satellite images used in the study had a consistent spatial resolution of 30 meters, providing detailed observations of the Earth's surface. This resolution is well-suited for distinguishing various land cover types and monitoring subtle changes in land use. The temporal resolution of the imagery was 16 days, meaning that each image was captured at intervals of 16 days within the satellite’s orbit, offering a frequent and consistent view of the study area.

The acquisition dates for these images ranged from March to May each year, spanning the period from 1985 to 2024. This timing was strategically chosen to correspond with the growing season in the Northern Hemisphere, which maximizes the visibility of vegetation and other land cover types. By selecting these dates, the study ensured that seasonal variations did not significantly impact the consistency of the data.

To effectively monitor and analyse land use and land cover (LULC) changes over time, images were collected at five-year intervals. This approach allowed for a comprehensive assessment of LULC trends and patterns, providing a clear picture of how land use has evolved over the 30-year period. The five-year interval strikes a balance between capturing meaningful changes and avoiding excessive data, enabling robust analysis of temporal dynamics and trends in land cover.

For the analysis of LULC change in the study area, cloud-free Landsat scenes from Landsat 5, 7, and 8 missions were utilized, covering different periods with suitable spatial resolutions. Landsat data's extensive archive and consistency with previous missions enable long-term assessment of regional and global LULC changes (Irons et al., 2012). Given Landsat data's durability and applicability for LULC mapping in smaller regions, it was deemed suitable for this study's objectives (Hu et al., 2013). In summary, the Landsat satellite imagery spanning from 1985 to 2024 provided the foundation for assessing LULC changes in the NMMDM, leveraging its high spatial resolution, cost-effectiveness, and extensive data archive.

Table 1: Landsat data source, dates and resolution (USGS, 2014).

Acquisition date	Sensor	Path/row	Spatial Resolution (meter)	Temporal Resolution
09 May 1985	Landsat 4-5 TM	172/077 172/078 172/079 171/078	30	16
23 April 1990	Landsat 4-5 TM	172/077 172/078 172/079 171/078	30	16
20 April 1995	Landsat 4-5 TM	172/077 172/078 172/079 171/078	30	16
30 March 2000	Landsat 7 ETM	172/077 172/078 172/079 171/078	30	16
29 April 2005	Landsat 5 TM	172/077 172/078 172/079 171/078	30	16
05 April 2010	Landsat 5 TM	172/077 172/078 172/079 171/078	30	16
13 March 2015	Landsat 8 OLI/TIRS	172/077 172/078 172/079 171/078	30	16

3.2.2 Reference data for image classification

The ground truth data encompassed all classes utilized in the study. Ground truthing involved utilizing Google Earth and digitizing points to generate classified maps. Table 2 displays the count of both training and test data points utilized for image classification. Regions of Interest (ROIs) were employed to extract image spectra from agricultural land and various common LULC classes. Subsequently, the ground reference data were randomly partitioned into two sets: a training dataset comprising 70% of the samples and a validation dataset comprising the remaining 30% (see Table 2).

Table 2: Training and validation data set for the LULC classes.

Land cover classes	Code	Training	Test	Total
Waterbodies	**WB**	180	77	257
Bare surface	**BS**	180	77	257
Built-up	**BU**	294	126	420
Agricultural land	**AL**	515	221	736
Woody vegetation	**WV**	186	79	265
Grassland	**G**	214	91	305

3.2.3 Farms Ownership Data

The transformation of land ownership among farmers in the NMMDM is illustrated in Figure 3. This ownership dataset was utilized to examine the changes in LULC resulting from the land tenure reforms implemented through various land reform projects. Legislation introduced post-1994 aimed to grant the security of tenure to individuals, particularly farm workers and labour tenants, over the residences and land they inhabit and cultivate.

Different forms of land tenure exist, including private ownership, communal ownership through communal property associations (CPAs), and renting arrangements. Private ownership entails an individual or business owning the land or property, with a title deed serving as legal documentation. Communal ownership allows groups to own land collectively through CPAs, a common occurrence in the NMMDM due to numerous land claims awarded to CPAs. Renting involves leasing homes or land from private landowners, companies, local authorities, or institutions.

The 'Land Reform Act 3 of 1996' protects the civil rights of labour tenants living on farms and engaged in agricultural activities, prohibiting their eviction without a court order or if they are aged over 65. Historical land ownership data were sourced from the DRDLR in the North West province, encompassing farms allocated under the land reform policy from 1996 to 2017. This data was compiled into an Excel spreadsheet after successful land claims, ensuring comprehensive documentation and preservation for future reference. The farmer ownership data from the NMMDM facilitated the identification of shifts in ownership from white individuals to black individuals (see Figure 3).

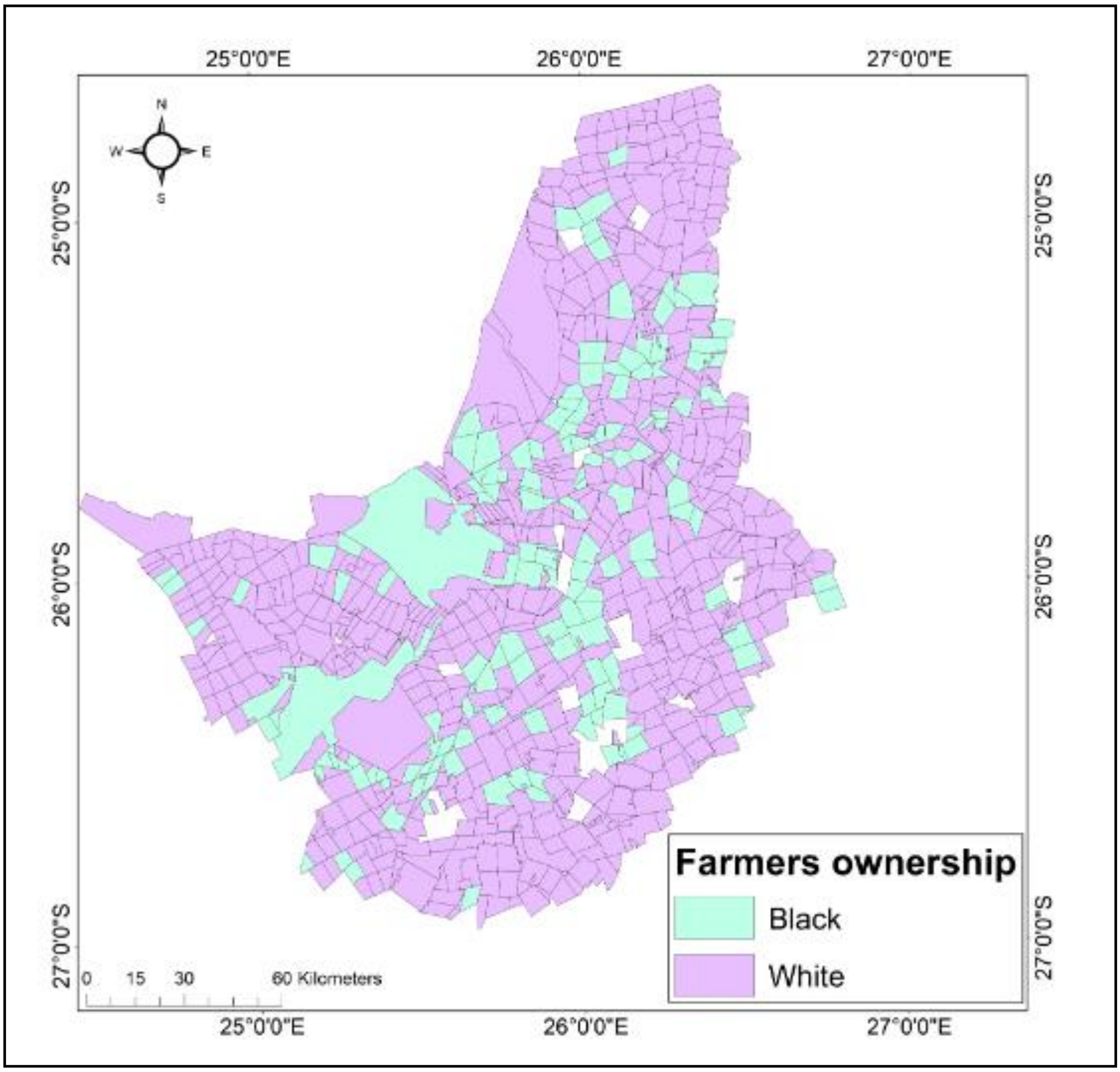


Figure 0: Farmers within NMMDM showing the Black and White ownership distribution from 1996-2015.

3.3 The LULC Mapping

The mapping of the LULC in the NMMDM of the North-West province took place over the course of several stages of the study. These phases included image pre-processing, acquiring reference data, classifying images, and computing the accuracy assessment.

3.3.1 Data pre-processing

Prior to being used in this study, Landsat images underwent pre-processing procedures. Ensuring high levels of geometric precision, radiometric accuracy, and atmospheric correction is essential for both historical and contemporary mapping endeavours (Lu et al., 2004). Numerous factors such as solar-earth distance, zenith and view angles, topography, atmospheric conditions, and temporal changes in target features can introduce anomalies in satellite imagery, thereby impacting LULCC mapping outcomes (Chandra, 2012).

To facilitate visual interpretation in true colour, the study employed specific combinations of sensor bands for different years. These combinations included bands 3, 2, and 1 for 1985, 1990, 1995, and 2000 images; bands 3, 2, and 1 for 2005 and 2010 images; and bands 4, 3, and 2 for the 2015 image. Spectral ranges for the sensors were provided, with bands ranging from 0.45 to 1.10 µm for the MSS, 0.45 to 12.50 µm for the TM and ETM+ sensors, and 0.43 to 12.52 µm for the OLI and TIRS sensors (USGS, 2014).

Radiometric calibration was performed using radiometric calibration coefficients to convert Landsat images to TOA radiance. The FLAASH module in ENVI 5.5 was utilized for radiance calibration, which also facilitated atmospheric correction and removal of noise and sensor errors (Lu et al., 2004). Using the nearest neighbour method, resampling was done while preserving the original pixel brightness values for matching the Landsat images spatial resolution. To perform geometric correction, the RMSE was utilised, ensuring an RMSE value of less than 0.5 for accurate rectification (Barreto and Howland, 2006). Image-to-image registration in ENVI 5.5 Classic was employed to geometrically correct images from 1985 to 2010 to match the 2015 image. Ground Control Points from the 2015 image were used as references, with warp GCPs for the remaining images. All images were rectified to Universal Transverse Mercator (UTM) projection, World Geodetic System (WGS) 1984, and Zone 36 South to ensure accuracy in analysis (Jensen, 1996).

3.4 The LULC class definition and sampling

The LULC types of nomenclature (refer to Table 3) adheres to the land cover classification scheme proposed by Thompson (1996). For each image spanning from 1985 to 2024, Google Earth Imagery and available national land cover data were utilized to establish ground truth data per LULC class for the Random Forest (RF) algorithm of supervised classification. The 30/70 rule was employed for training and validation data allocation. To produce meaningful geographic features, image classification entails identifying pixels and statistically classifying them based on whether or not they have the same digital numbers and spatial orientation (Mesev, 2010). This process compares the pixels to aggregate pixels into classes that represent information relevant to researchers or land managers (Mas, 1999).

The acquired Landsat images were used to identify the different forms of LULC. Training and validation samples were collected for supervised classification, which was utilised to create an effective classifier. Representative samples were chosen for each LULC class based on the satellite images. The training samples that were collected included areas with built-up areas, water bodies, woody vegetation, and bare surfaces. To increase the classification efficiency, each class has eighty or more training examples. Details on the LULC classification scheme and characteristics are given in Table 3 below.

Table 3: The LULC classification scheme

CLASS	**DESCRIPTION**
Water bodies	Dams, reservoirs, rivers, streams, and ponds
Woody vegetation	An area dominated by scattered tall trees with grasses
Grassland	An area dominated by grasses and other herbaceous plants
Agriculture land	Large-scale area with soil tilled for agricultural purposes
Bare surface	Non-vegetated land (excluding agricultural fields and open-cast mines)
Built-up	An area that consists of factories, industrial, residential, commercial structures, excluding my infrastructures.

The spectral signatures identified in the training set were used to classify representative samples for LULC. The approach used reference data that were derived from images, covering the years 1985, 1990, 1995, 2000, 2005, 2010, and 2015, covering the NMMDM. These images were sourced from Google EarthTM (*http://earth.google.com*) to serve as ground-truth data for LULC classification (Knorn et al., 2009; Han et al., 2014).

3.4.1 Random Forest classification

The Random Forest (RF) classifier, initially introduced by Breiman in 2001, constructs multiple classification trees by generating several bootstrap samples from the primary training dataset through replacement. Each tree is grown independently to its full size without pruning, resulting in a sophisticated composite classifier. Utilizing a random subset of candidate features (mtry) to identify the optimal split at each node introduces randomness into the classification process. The final classification is determined by the majority vote of the individual classification trees, with each tree having access to out-of-bag (OOB) data, approximately 33 percent of the main dataset, for validation purposes.

In this research study, the Random Forest algorithm was employed for classification. This ensemble classifier builds numerous decision trees using random samples from the training set. The user specifies the number of variables to be considered at each node split and the quantity of trees to be generated from the training sample. A portion of the training data is reserved as the out-of-bag sample for algorithmic validation, while a bootstrap sample from the training data is used for training. Additionally, Random Forest offers insights into the significance of variables for optimizing the classification process.

Given that Landsat images from five different sensors were utilized in the study, discrepancies in spectral responses and band configurations were observed. Despite challenges in obtaining reference data for past images, such as MSS data, an OLI-based classifier was developed for each Landsat image used. Disparities in sensor properties between OLI and other sensors, including wavelengths and spectral sensitivities, were addressed by employing an empirical line approach to adjust for differences in atmospherically adjusted surface reflectance. The direct relationship between OLI and other Landsat images (TM and ETM+ SLC on) was established using the surface reflectance of the OLI image in 2014 as a reference, thereby calculating the relationship for each band.

3.5 Accuracy Assessment

Remote sensing-based land cover maps require quantitative accuracy assessment to ensure the statistical significance of their results (Jensen, 1996). This evaluation is particularly crucial for post-classification change detection analysis. Accuracy assessment involves comparing classified maps with reference test data, typically organized in an error matrix with referenced data in columns and classed data in rows. It measures the agreement between ground reference samples collected during fieldwork and the satellite image classification (Palamuleni, 2012).

In this study, accuracy assessment was conducted based on the outcomes of Random Forest (RF) classification applied to Landsat 8 images. The aim was to evaluate the quality of classifications and identify errors in the final maps. Metrics such as overall accuracy, kappa coefficient, and user and producer accuracies were utilized to gauge the accuracy and reliability of LULC maps. The confusion matrix, generated using post-classification tools in ENVI 5.5 software, utilized ground truth Regions of Interest (ROIs).

Challenges arise when incorporating old or historical photos into LULC change analysis due to a lack of ground reference data (Witmer, 2008). Spectral confusion, noise, and flaws in classification methods can lead to errors in identified images (Liu and Cai, 2012). The primary objective was to determine the effectiveness of categorizing pixels within the study area into relevant feature classes using quantitative methods. To evaluate the accuracy of the LULC maps derived from Landsat data, stratified random pixels were generated from each map. This evaluation encompassed images from different years, and metrics such as the kappa statistic, overall accuracy, and producer and user accuracies were computed using the confusion matrix and ground truth ROIs (Cohen, 1960; Congalton and Green, 2008; Adam et al., 2014). Overall accuracy reflects the probability that a randomly selected point will be correctly classified on the LULC map (Richards, 2012).

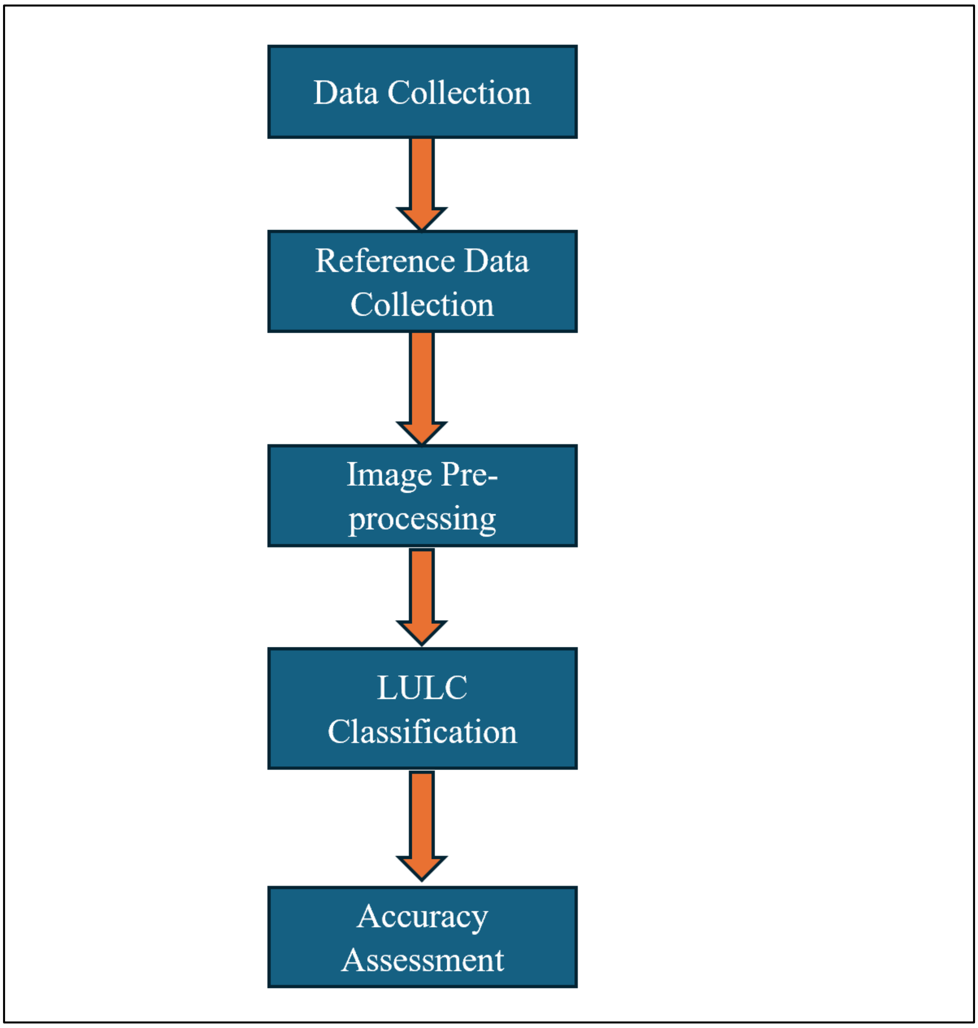
Methodology Outline

1. **Data Collection**
    - **Satellite Imagery**: Landsat 5 TM (1985-2010) and Landsat 8 OLI/TIRS (2015) images obtained from USGS for specific path and row coordinates within NMMDM.
    - **Temporal Range**: 1985, 1990, 1995, 2000, 2005, 2010, 2015.
    - **Spatial Resolution**: 30 meters.
    - **Temporal Resolution**: 16 days.
    - **Acquisition Dates**: March to May each year.
2. **Reference Data Collection**
    - **Ground Truth Data**: Obtained via Google Earth, digitizing points for classified maps.
    - **Regions of Interest (ROIs)**: Extract image spectra for various LULC classes.
    - **Data Partitioning**: 70% training dataset, 30% validation dataset.
3. **Image Pre-processing**
    - **Radiometric Calibration**: Convert images to TOA radiance using radiometric calibration coefficients.
    - **Atmospheric Correction**: Using FLAASH module in ENVI 5.5.

- **Geometric Correction**: RMSE value < 0.5 for rectification, images registered to UTM projection, WGS 1984, Zone 36 South.
- **Band Combinations for Visual Interpretation**:
    - 1985, 1990, 1995, 2000: Bands 3, 2, 1
    - 2005, 2010: Bands 3, 2, 1
    - 2015: Bands 4, 3, 2

4. **LULC Classification**
    - **Classification Scheme**: Based on Thompson (1996).
    - **Supervised Classification**: Random Forest algorithm.
    - **Training and Validation Samples**: 30/70 rule.
5. **Accuracy Assessment**
    - Assess classification accuracy using the validation dataset.

Flowchart 1 summarizes the methodology used and major steps followed in this research.



Flowchart 1: The summary of the methodology followed

3.6 Change Detection

In this investigation, the Change Detection Statistics method was applied to assess the status of land cover within the NMMDM region. The primary objective was to identify areas where changes have occurred to fulfil the research aims and objectives. To examine the relationship between the implementation of the Land Reform Policy and LULC changes in the study area using spatial analysis techniques, an overlay technique in ArcMap was employed. This technique involved overlaying land ownership data with the LULC data of the study area. By doing so, the evolution of land use types over time in relation to changes in land ownership was analysed. This analysis provided insights into the types of land-use changes that have occurred over time and their association with specific land ownership patterns.

3.6.1 Change detection statistics

In this research, the Change Detection Statistics method was utilized to evaluate the status of land cover within the NMMDM region. The primary aim was to pinpoint areas where alterations have occurred, aligning with the research objectives. By employing the change detection statistics feature in ENVI 5.5 software, a detailed analysis of LULC changes between two classified images was conducted. This statistical analysis enabled the identification of variations in classes between the initial and final state classified images, highlighting areas where pixel modifications occurred in the latter image. These changes were quantified in terms of pixel counts, percentages, and hectares, providing insights into the evolving landscape.

The Change Detection Statistics method was integral for evaluating land cover changes over time. This algorithm involved the following critical steps:

1. **Data Preparation and Classification**:
    - Landsat images from different years were pre-processed and classified into various LULC categories using a supervised classification method (the Random Forest algorithm).
    - Ground truth data used to train and validate the classification model, ensuring high accuracy.
2. **Image Comparison**:
    - Classified images from different time points compared using the change detection statistics feature in ENVI 5.5.
    - This comparison highlights areas where changes in land cover have occurred.
3. **Quantification of Changes**:
    - Changes quantified by calculating the number of pixels that have transitioned from one class to another between the two images.
    - These pixel changes are then converted into percentages and areas (hectares) to provide a more intuitive understanding of the changes.
4. **Spatial Overlay Analysis**:
    - To understand the impact of land reform policies, a spatial overlay analysis is performed in ArcMap.
    - This involves overlaying land ownership data with LULC data to identify correlations between policy implementation and land cover changes.

5. **Interpretation and Insights**:
    - The results from the change detection analysis are interpreted to identify trends and patterns in land cover changes.
    - These insights help inform land resource planning and policymaking, ensuring sustainable land management practices.

To explore the relationship between the implementation of the Land Reform Policy and LULC changes in the study area, a spatial analysis technique involving an overlay method in ArcMap was applied. This approach entailed overlaying land ownership data with LULC data to discern trends in land use types over time corresponding to changes in land ownership. Through change detection, the study aimed to detect, characterize, and quantify differences between classified images captured at different time points. This facilitated the observation of changes occurring over the study period, spanning from 1985 to 2024. The generated change detection statistics offered valuable insights into the dynamics of LULC changes, providing essential information for land resource planning, regulation, and management.

CHAPTER FOUR

RESULTS

4.1 The LULC Mapping

The LULC map for the year 1985, depicted in Figure 1, illustrates the distribution of various land cover classes in the NMMDM. According to the histogram provided, approximately 11.66% of the municipality consisted of bare surfaces. The majority of the land area, about 35.79%, was covered by grassland, followed by woody vegetation covering 26.44%, agricultural land covering 22.01%, built-up areas covering 1.09%, and water bodies covering 2.99%. The distribution of agricultural land was predominantly observed in the southern and western parts of the municipality, as indicated in the classified map (Figure 4).

In 1990, significant alterations in land cover patterns were observed within the NMMDM. The proportion of bare surfaces decreased to 6.73%, while agricultural land expanded to cover 23.62% of the area. Notably, grassland coverage increased from 35.79% in 1985 to 39.14% in 1990, indicating a substantial rise. Moreover, slight variations were noted in the coverage of built-up areas, woody vegetation, and water bodies. The accuracy assessment conducted for 1990 revealed an overall accuracy of 72.90%, with the error matrix depicted in Table 5.

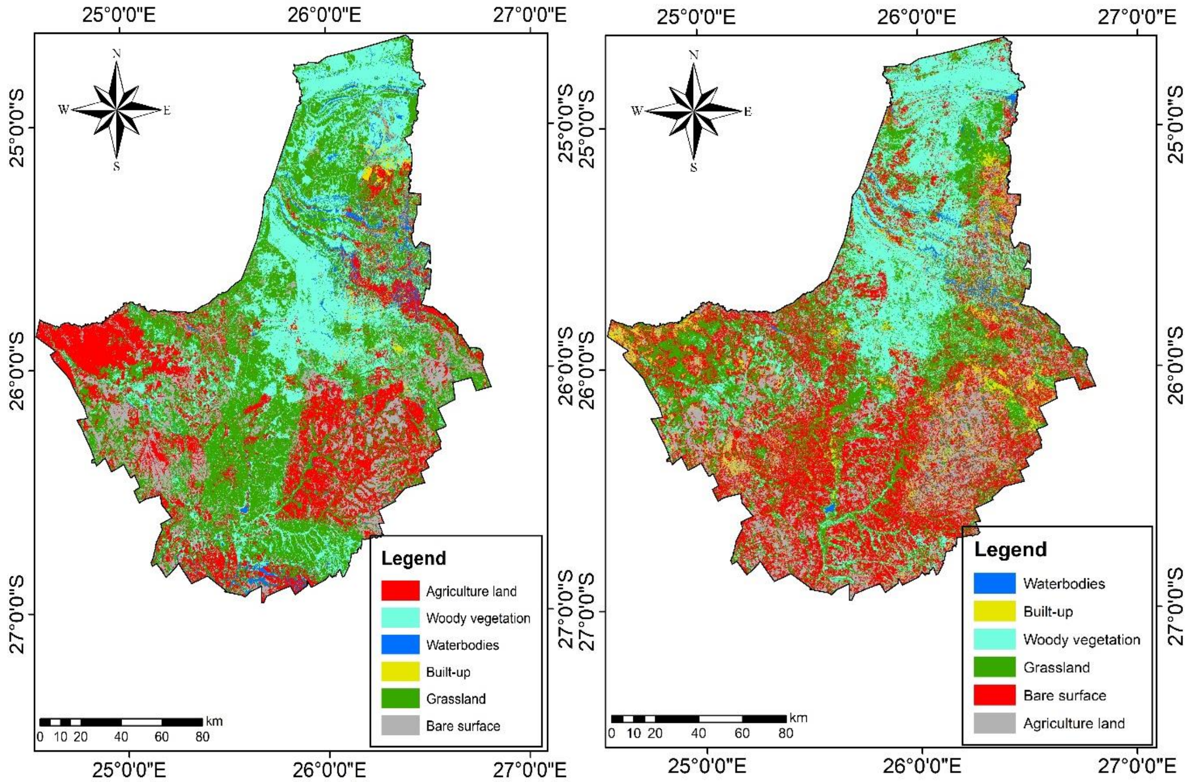


Figure 3: The LULC maps for NMMDM in 1985 and 1990.

The LULC map for the year 1995, depicted in Figure 5, reveals changes in the distribution of land cover classes within the NMMDM. During this period, the proportion of bare surfaces increased to 13.17%, indicating a notable rise compared to the 6.73% from 1990. Agricultural land use expanded further, covering 31.16% of the land area, while woody vegetation accounted for 23.86%. Built-up areas and water bodies occupied 2.96% and 2.16% of the municipality, respectively.

The increase in bare surfaces from 1990 to 1995 suggests potential land degradation or changes in land management practices. Despite this increase, agricultural land use also experienced growth, signifying ongoing agricultural activities or expansion. The accuracy assessment for the year 1995 yielded a reliability of 74.0%, as detailed in Table 2c, along with the confusion matrix error.

The LULC map for the year 2000 is depicted in Figure 4, and the histogram (Figure 5) displays the area of coverage as a percentage. It is shown that agricultural farms made up 23.33% of the municipality's land, while the remaining 11.73%, 20.16%, 38.31, 4.79%, and 1.63% were made up of bare land, wooded land, grassland, built-up areas, and waterbodies. In 1995, the land surrounding agricultural land was comparable and had more grassland since some parts had not been ploughed, leaving them covered in grassland. As some agricultural land became bare land, the area of bare surface increased from 13.17% in 1995 to 11.73% in 2000 as some agricultural land was now turned into bare surface. Table 2d shows the accuracy of 2000 as 75.1 % and the confusion matrix error is shown in Table 7.

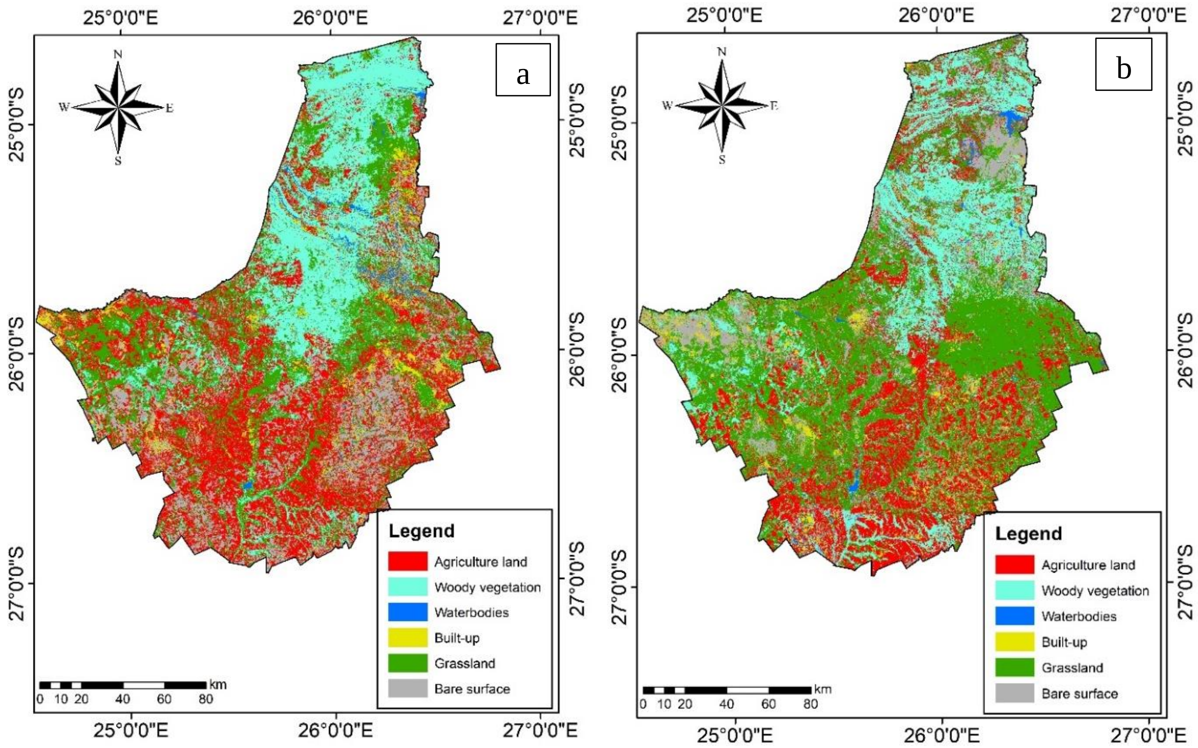


Figure 4: The LULC maps for NMMDM in a) 1995 and b) 2000.

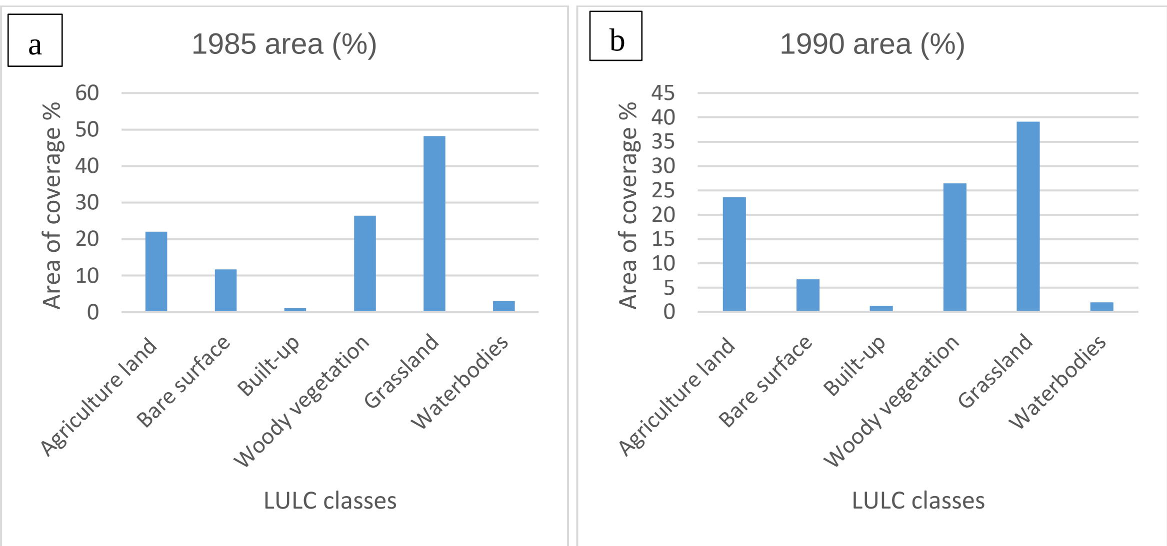


Figure 5: Histograms of LULC for (a) 1985 and (b) 1990 in percentage area.

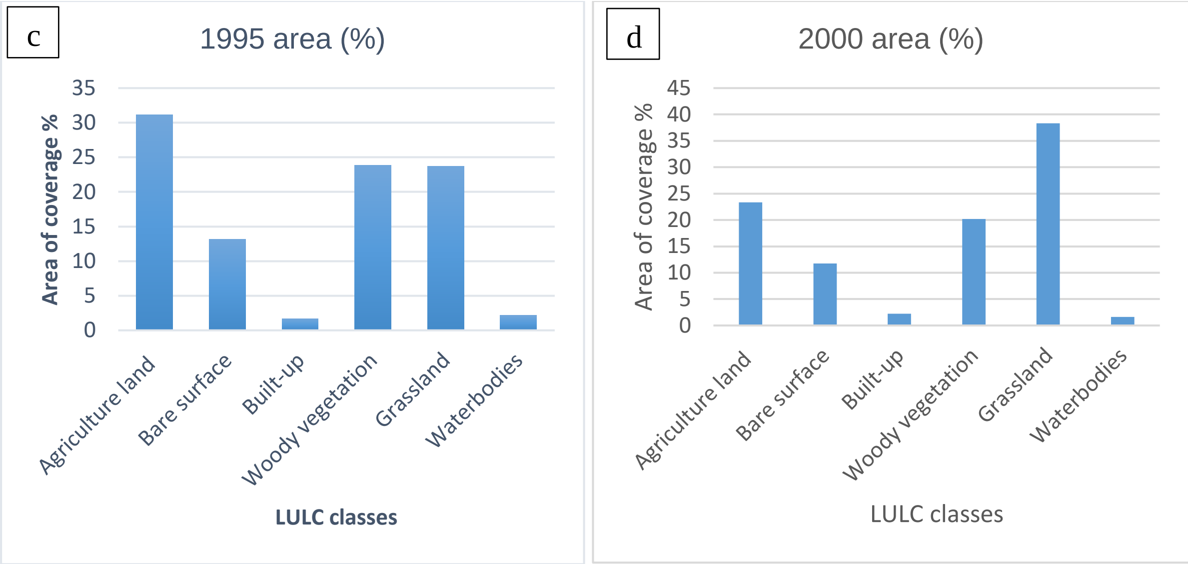


Figure 6: Histograms for LULC for (c) 1995 and (d) 2000 in percentage area.

The LULC map for the year 2005, as illustrated in Figure 4, provides insights into the changing landscape of the Ngaka Modiri Molema municipality. During this period, agricultural fields accounted for 17.51% of the total area, marking a significant decrease from the previous years. This decline in agricultural land use may be attributed to factors such as reduced farming activities and drought conditions, which affected the region's agricultural productivity.

Grassland emerged as the dominant land cover class, covering 47.07% of the municipality, indicating a shift towards natural vegetation or pastureland. Additionally, the proportion of woody vegetation increased to 20.16%, suggesting potential afforestation or natural regeneration of vegetation cover. The rise in built-up areas to 3.6% reflects urban expansion or infrastructure development driven by population growth within the district.

Water bodies and bare surfaces accounted for 1.63% and 11.73% of the land area, respectively. The increase in built-up areas and the decline in agricultural land highlight the dynamic nature of land use changes influenced by socio-economic factors and environmental conditions.

Table 2e shows the accuracy of 2005 as 76.0 % and the confusion matrix error is shown in Table 8. The LULC map for 2010 and Figure 9's histogram of the LULC coverage demonstrate that 6.5% of Ngaka municipality was undeveloped in 2010. Farmland made up 21.12% of the total area, followed by waterbodies (1.67%), built-up areas (4.79%), woody vegetation (32.5%), and grassland (36.4%). According to the map's depiction of LULC classes (Figure 6), agricultural farms were primarily distributed in the municipalities southwest. However, it is also obvious that there were built-up regions in the municipality's northwest. The accuracy for 2010 is displayed in Table 2f as being 79.18%, and the confusion matrix error is displayed in Table 9.

The LULC map for 2015 and Figure 10 histogram of the LULC coverage demonstrate that 6.4% of Ngaka municipality was undeveloped in 2015. Farmland occupied 19.41% of the land, followed by 0.88% of waterbodies, 5.93% of built-up areas, 11.27% of wooded areas, and 48.22% of grassland. According to the map's depiction of LULC classes (Figure 4), agricultural land was primarily distributed in the municipality's southeast and southwest regions. However, it is also obvious that there were built-up regions in the municipality's northwest. The of the municipality North west province, known for its dense population, aligns with neighbourhoods where farmworkers residing on redistributed farms predominantly dwell. The escalation in built-up areas can also be attributed to the population surge within the district, encompassing households and residential settlements. According to Table 2g, the accuracy of the classification for the year 2015 stands at 82.7%, with the corresponding confusion matrix errors detailed in Table 10.

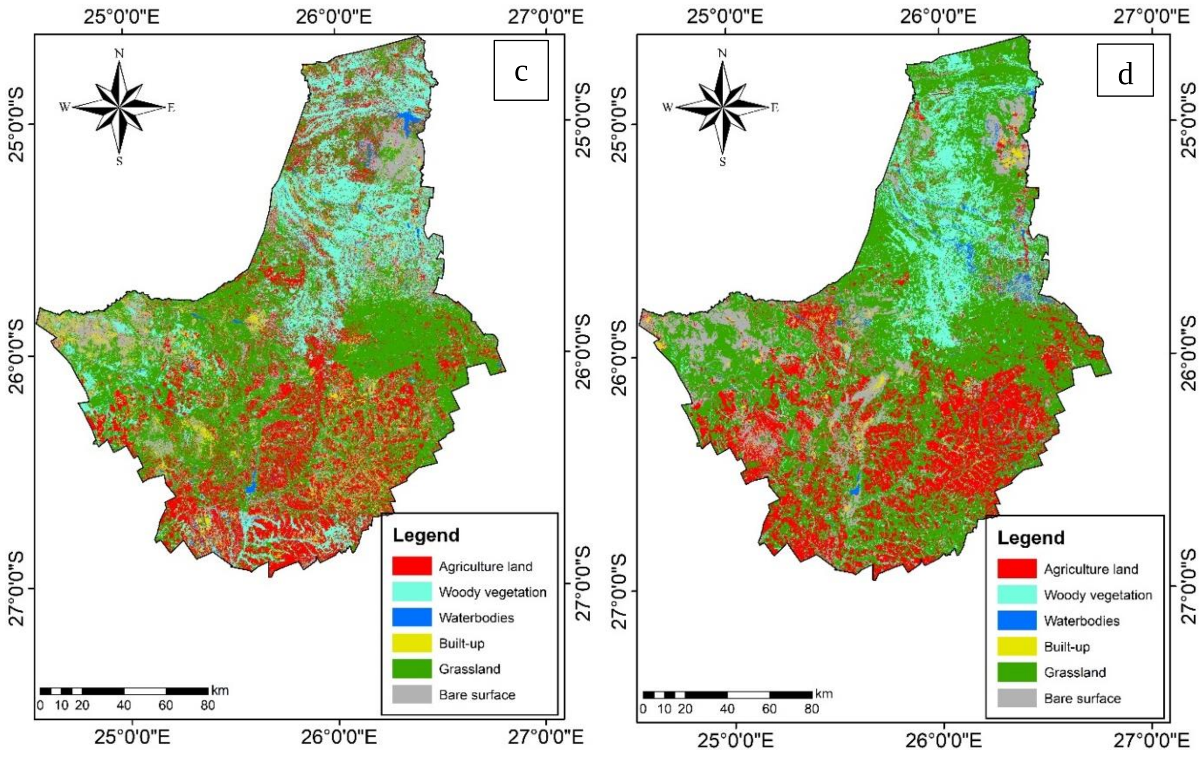


Figure 7: LULC maps for NMMDM in c) 2005 and d) 2010.

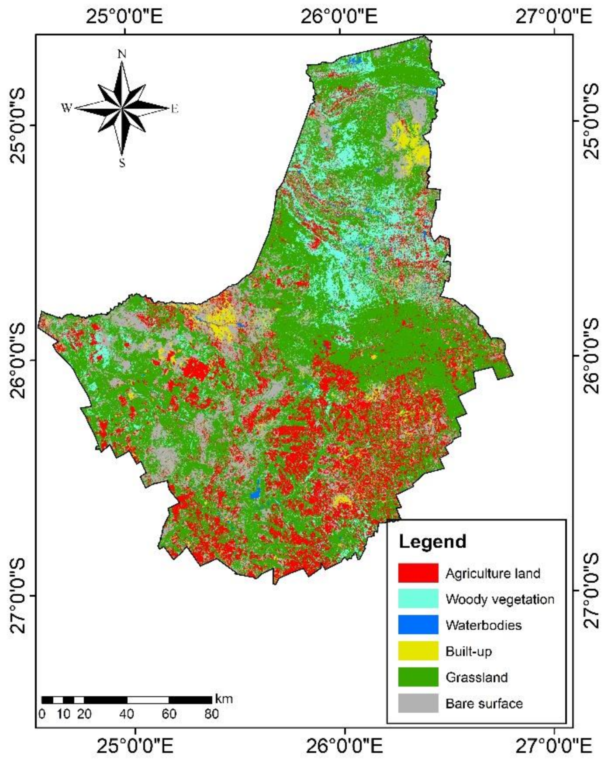


Figure 8: LULC map for NMMDM in 2015.

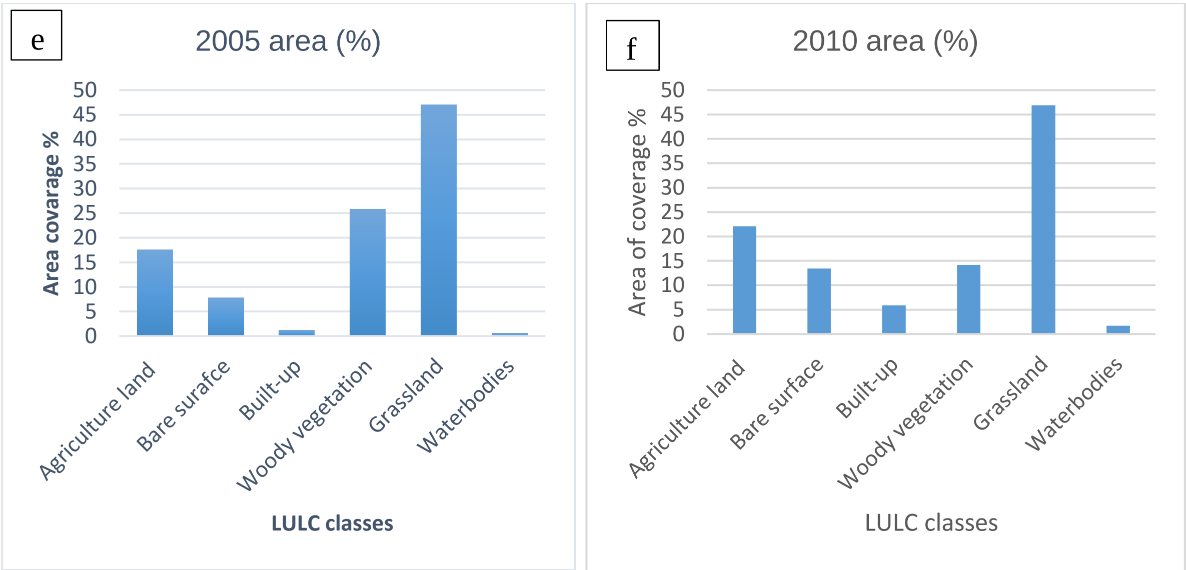


Figure 9: Histograms of LULC coverage for e) 2005 and f) 2010.

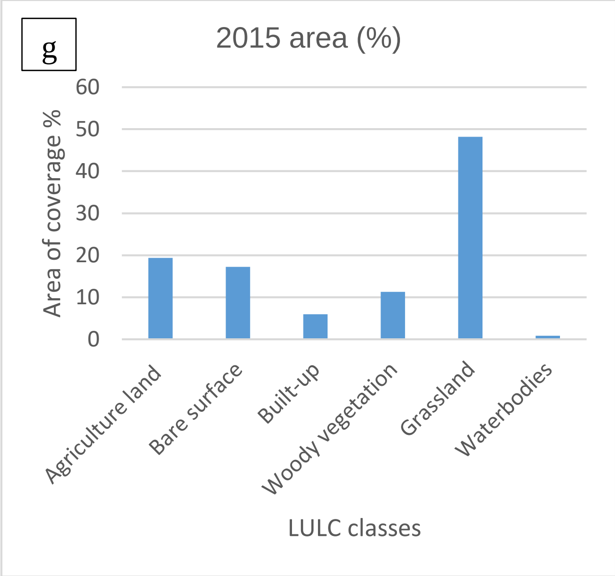


Figure 10: Histograms of LULC coverage for g) 2015.

4.2 Maps showing the overlay of the change of ownership of the land having an impact on the agriculture of the NMMDM from 1985 to 2024.

The analysis of the relationship between changes in land ownership and agricultural land is depicted in Figures 11 and 12. These figures illustrate a notable trend wherein the area of fluctuating land ownership has increased over time, accompanied by a corresponding decrease in agricultural land. This pattern suggests a dynamic shift in land use and ownership dynamics within the Ngaka Modiri Molema municipality.

Specifically, the most significant changes in agricultural land area occurred between the years 2005 and 2010, as well as between 2010 and 2015. During these periods, there was a pronounced decline in agricultural land use, indicating potential challenges or shifts in farming practices or land management strategies. Further examination of Figures 12 and 14 reinforces the observed decrease in agricultural land over time. Significant declines in agricultural land area were observed between the years 1985 and 1990, 1990 and 1995, and between 2010 and 2015. These findings highlight the necessity for a more comprehensive understanding of the factors influencing changes in agricultural land use and their potential implications for food security and rural livelihoods.

Moreover, the analysis reveals that grassland has been the land use class encroaching upon agricultural space over the years, indicating potential land conversion or natural succession processes. Table 4 provides summary statistics of agricultural land dynamics over the study period, offering insights into the magnitude and direction of changes in agricultural land use within the municipality.

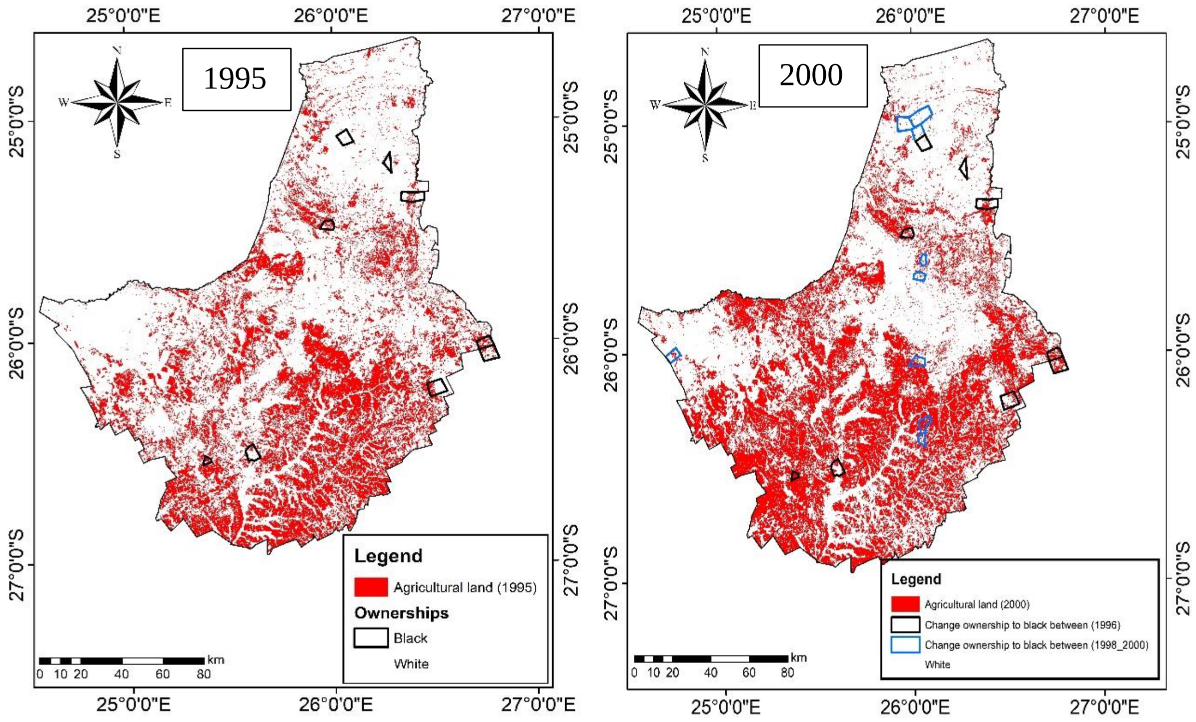


Figure 11: Maps showing the agricultural land and land ownership overlay in the NMMDM for the years 1995 and 2000.

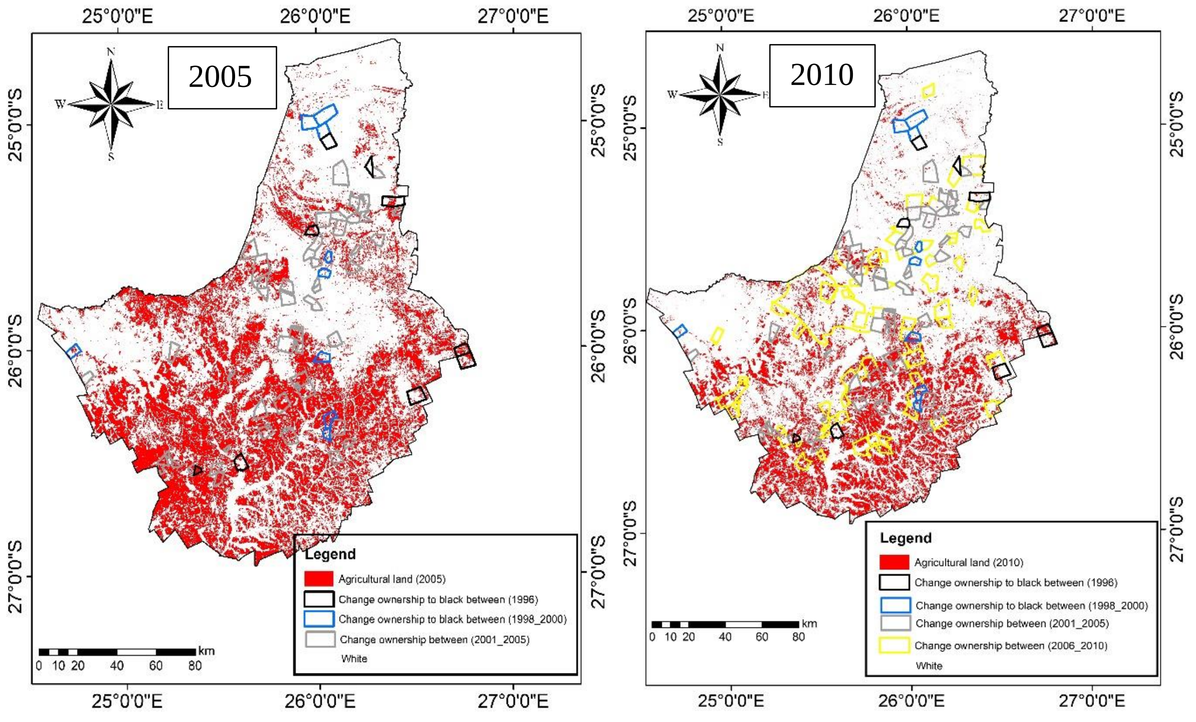


Figure 12: Maps showing the agricultural land and land ownership overlay in the NMMDM for the years 2005 and 2010.

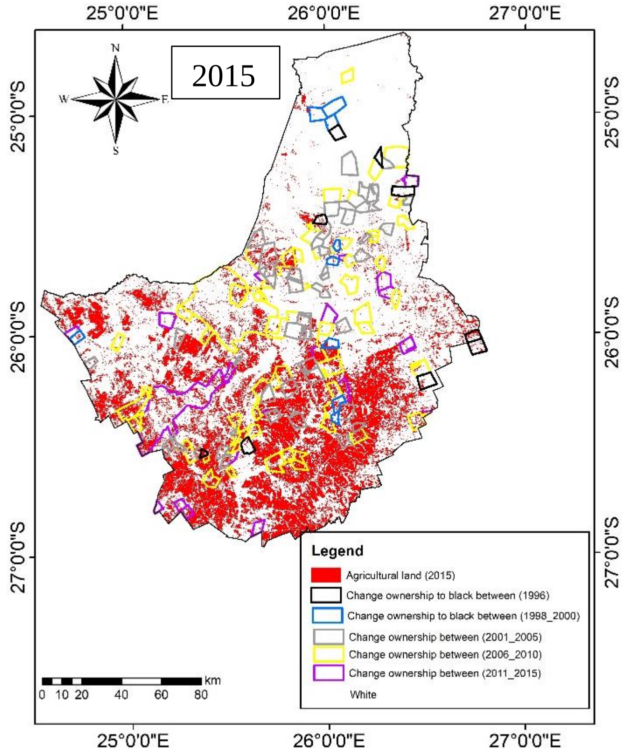


Figure 13: Maps showing the agricultural land and land ownership overlay in the NMMDM for the year 2015.

Table 4: Statistical information of the agricultural land area for each year.

Class	1985	1990	1995	2000	2005	2010	2015
Agricultural land	22.01	23.62	31.16	23.33	17.51	22.12	19.41

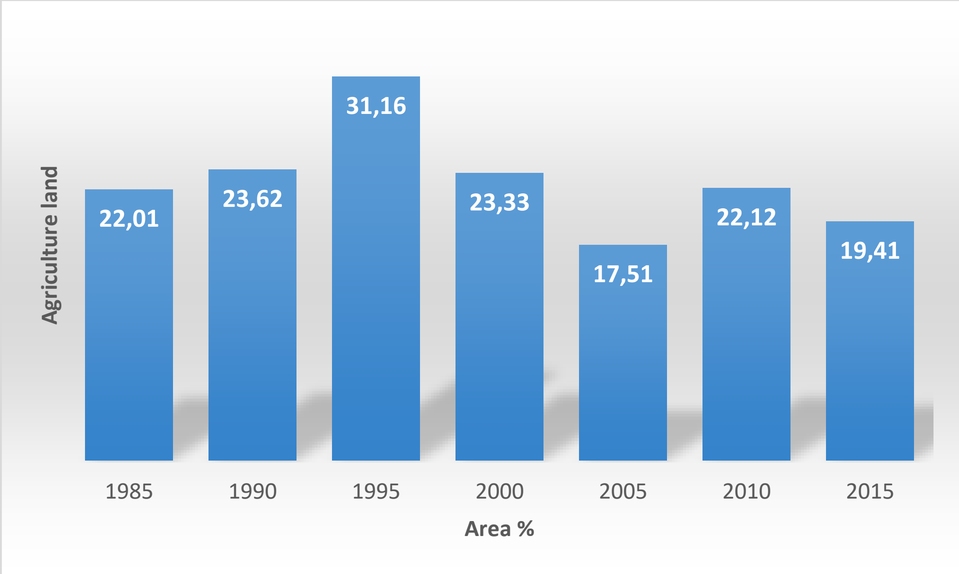


Figure 14: Agriculture land coverage for 1985, 1990, 1995, 2000, 2005, 2010 and 2015.

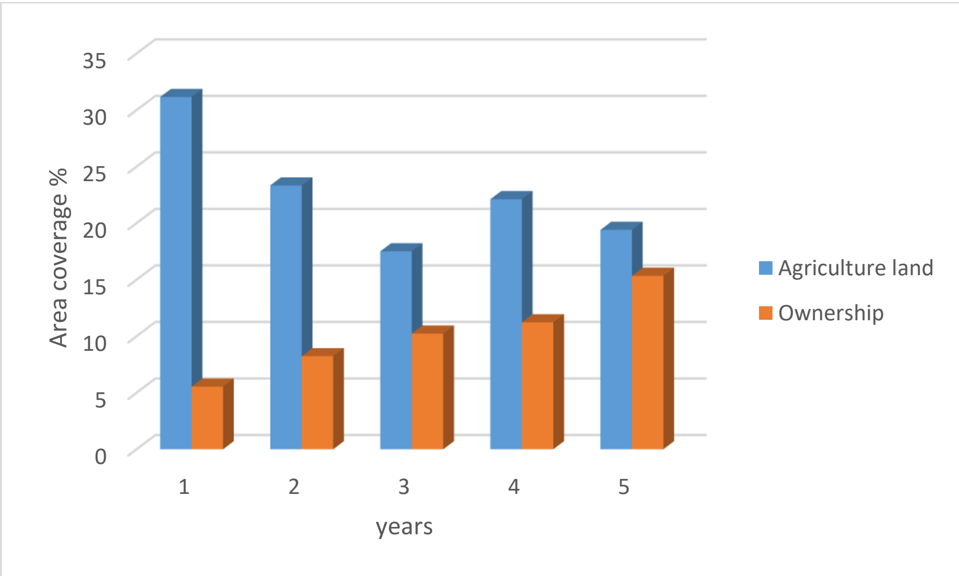


Figure 15: Histogram illustrating the relationship between agriculture and black ownership.

Spatial analysis techniques were used in ArcMap to map and overlay the land ownership data, which changed from white owners to black owners due to the Land Reform Policy. The ownership data used in this study was obtained from the Land Reform Branch in the Northwest Province of the Department of Rural Development and Land Reform. The maps above show the pattern of the agricultural land in the district, as the land ownership changes from white owners to black owners.

The first map for the year 1985 depicts the ownership in the district before the implementation of the land reform policy. On the 1990 map, we can see there is a slight increase in agricultural land, and this was also before the implementation of the land reform policy. In 1994 South Africa became a democratic country under a new ruling party and new laws were being implemented. On the 1995 map, ownership data was used from 1996 when the land reform policy came into effect in the district, there were a few changes in the ownership of land from white owners to black owners. The agricultural land also slightly increased in the years 1995-1996. On the 2000 map, we can see a slight increase in black ownership as well as an increase in the agricultural land of the district.

On the 2005 map, black ownership started increasing rapidly as the land reform was being implemented, but the agricultural land was starting to decrease. These can be due to many factors such as owners who are acquiring the land not having the adequate training to carry out the usual agricultural or farming activities that were performed on the land previously by white-owned experienced farmers. On the 2010 map, as the black land beneficiaries of the land increased, we can see a decrease in the agricultural land. This can be due to various reasons as some beneficiaries of the land did not have training or background about how to maintain the agricultural land in terms of animal and crop farming. On the last map for 2015, there was still an increase in the black beneficiaries as the policy was being implemented, but we can see a decrease in the agricultural land. As the land reform was implemented on the NMMDM, we can see a trend of the growth of the black owners from the white owners, but there is a decrease in the agricultural land as the years pass by.

4.3 Accuracy Assessment

Table 2 presents a comparative analysis of user and producer accuracies for various LULC classes over the study years. Notably, the water body class consistently demonstrates higher accuracy compared to other classes, indicating greater precision in its classification. For example, in 1985, the built-up class exhibited the lowest producer's accuracy at 50.0%, while the grassland class had the lowest user's accuracy at 40.5%. These lower accuracies may stem from spectral similarities among certain land cover types, such as grassland, bare surface, and agricultural land. These similarities could result in misclassification of pixels, leading to reduced accuracy metrics for these classes.

Furthermore, compared to previous years, the overall accuracy of the 1985 Landsat imagery was inferior, possibly as a result of the image being resampled from 60 metres to 30 metres resolution to maintain consistency with other images. The accuracy of the categorization may have been impacted by distortions or mistakes produced during the resampling procedure. The kappa coefficient, which indicates the degree of agreement between the categorised maps and ground truth data, is shown in Table 3 for the classification maps for each year. This coefficient helps evaluate the categorization findings' consistency and dependability over time.

Overall, the accuracy assessment underscores the importance of considering spectral characteristics, resolution, and data preprocessing steps in remote sensing classification analyses to ensure robust and reliable land cover mapping results.

Table 3 Comparison between the classification's accuracy for land cover

Imagery	Kappa Accuracy
1985	0.70
1990	0.76
1995	0.73
2000	0.79
2005	0.75
2010	0.74
2015	0.85

4.4 Confusion Matrix Assessment

The confusion matrix of classification error obtained for discrimination Agriculture land (AF) and other land cover types, including water bodies (W), Bare surface (BS), Built-up (BU), Grassland (G), and WV=Woody vegetation. Please refer to Appendix B for the Confusion Matrix assessments.

4.5 Summary of LULC Classes

The LULC maps depicting the LULC of NMMDM were produced for the seven years examined in this investigation: 1985, 1990, 1995, 2000, 2005, 2010, and 2015. The classification of LULC classes and their corresponding change statistics for each of these seven years are condensed and presented in Tables 11 through 16 below. The stable distribution of LULC for each year under study was determined from the thematic maps generated through RF classification.

The agriculture land extent and its proportion for the year 1985 - 1990 in the Ngaka municipality was 807207, 97 hectares. The class increased to 4.17 % in the year 1990. The woody vegetation extent for the year 1985 was 21, 76% of the total area. Its cover extent and its proportion increased to (36,07 %)14, 31% in the year 1990. The grassland extent for the year 1985 was 36,60% of the total area. Its cover extent and its proportion decreased to (23,61 %) 12,94% in the year 1990. Localised decreases in grassland land corresponded to agricultural land that did not have crops in 1985, which explains the increase in agricultural land from 24,63% in the year 1985 to 28,80% in the year 1990 (Table 11).

As shown in Table 11, the image difference for bare surface and agricultural land increased by 258653,72 and 807207, 96 ha, respectively. The table also illustrates those waterbodies, built-up, and grassland decreased by 5860, 42, 258653, 72, 3580,99 and 661662, 65 ha, respectively.

As indicated in Table 11, the agricultural land class encompassed a total area of 690,005.48 hectares (48.63%) by 1985, with a subsequent alteration of 4.17% by 1990. Notably, a substantial portion of grassland underwent conversion into woody vegetation, constituting 1,011,007.83 hectares (36.07%). Similarly, agricultural land exhibited significant transitions to other LULC classes, amounting to 807,207.97 hectares (28.80%).

Out of the initial 373,521.93 hectares of bare land in 1985, only 258,653.72 hectares remained unchanged by 1990. Remarkably, the bare surface underwent considerable transformations, with 90.77% transitioning into various LULC classes. Predominantly, bare land converted into agricultural land, comprising 690,005.48 hectares (24.63%), and forested land, accounting for 1,011,007.83 hectares (11.60%). Additionally, transformations led to grassland and water bodies, covering 258,653.72 hectares (9.23%) and 5,860.42 hectares (0.21%), respectively.

The built-up areas totalled 74,910.61 hectares (2.67%), with 54,934.33 hectares (1.96%) remaining unchanged between 1985 and 1990. Noteworthy alterations involved conversions of built-up land into bare land, grassland, water bodies, and agricultural land, comprising 258,653.72 hectares (9.23%), 661,662.65 hectares (23.61%), 5,860.42 hectares (0.21%), and 807,207.97 hectares (28.80%), respectively. A substantial transformation of built-up land primarily occurred into grassland, amounting to 1,011,007.83 hectares (36.07%), while minimal changes were observed into other surfaces, totalling 3,580.99 hectares (0.13%).

Water bodies covered an area of 9,900.42 hectares (0.35%) in 1985, with 5,860.42 hectares (0.21%) remaining unchanged by 1990.

Table 5: Statistics of LULC classification were determined from Landsat data between 1985 and 1990.

Land Cover type	LULC 1985		LULC 1990		Change in % from 1985 to 1990
	Area (Ha)	% of Area	Area (Ha)	% of Area	
Agriculture land	690005,48	24,63	807207,97	28,80	4.17
Bare surface	373521,93	13,33	258653,72	9,23	-4.11
Built-up	74910,61	2,67	54934,33	1,96	-0.72
Woody vegetation	609760,80	21,76	1011007,83	36,07	14,31
Grassland	1025655,48	36,60	661662,65	23,61	-12.94
Waterbodies	9900,42	0,35	5860,42	0,21	-0.14
	2801955,087	**100**	**2802907,921**	**100**	**0.00**

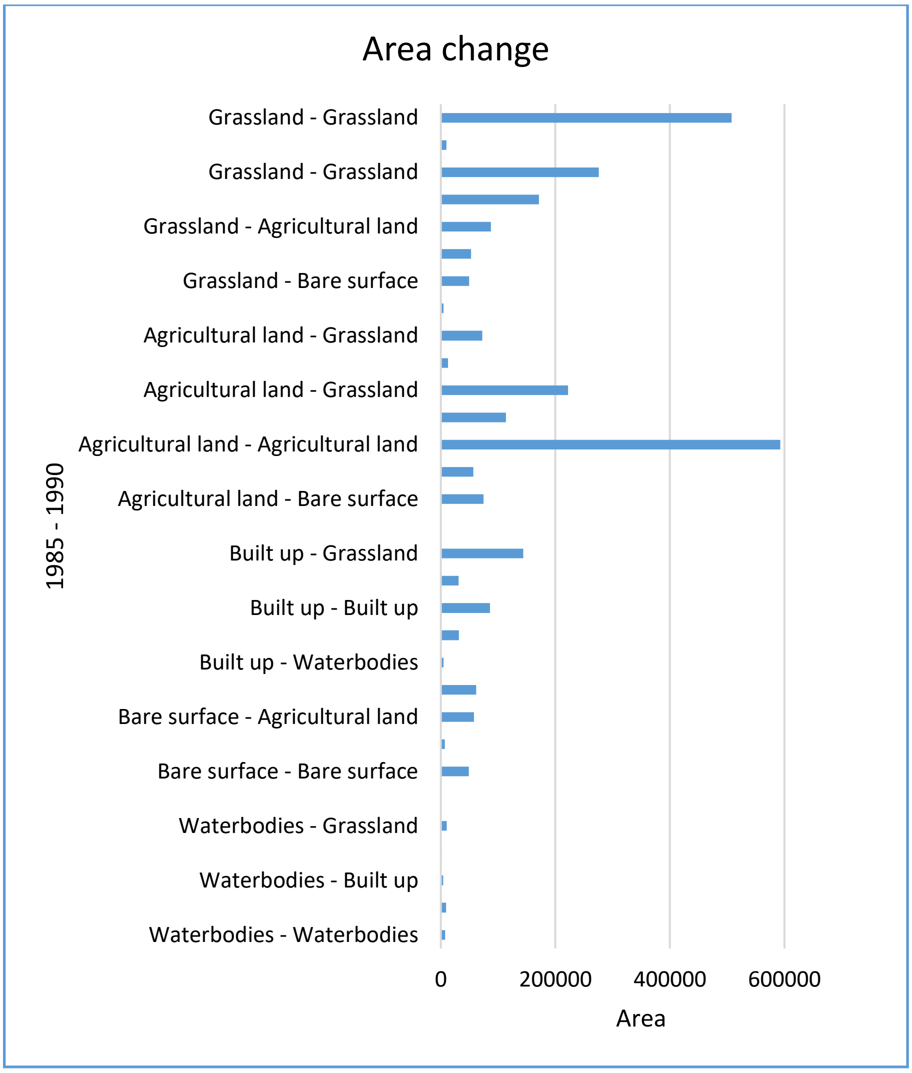


Figure 16: Ngaka LULC changes statistics in Hectares between 1985 and 1990.

The agricultural land extent and its proportion for the year 1990 - 1995 in the Ngaka municipality was 807207,97 ha, which increased to 0.83 % in the year 1995. The grassland extent for the year 1995 was 595097,22 (21.23%) of the total area. Its cover extent and its proportion increased to 21.23 % in the year 1995. Localised increases in both agricultural lands corresponded to farmlands that did not have crops in 1990, which explains the significant increase in grassland from 23,61% in the year 1990 to 21,23% in the year 1995 (Figure 10) (Table 12).

The changes in LULC types between 1990 and 1995 are displayed in Table 12. Table 12 demonstrates the rise in bare surface by 258653,72 ha (9,23%) and 309973,53 ha (11,06%) with a decrease of agricultural land by 807207,97 ha (28,80%) respectively. Waterbodies, Bare surface, and built-up land increased by 7559,36 ha, 309973,53 ha, 4218,14 ha and

58049,17 ha. Table 12 shows that most agricultural land transformed into grassland. This suggests that a significant area of bare surface turned into grassland, whilst the least transformation was from built-up and water bodies between the period of 1990 and 1995.

Table 6: Statistics of LULC classification determined from Landsat data between 1990 and 1995.

Land Cover type	LULC 1990		LULC 1995		Change in % from 1990 to 1995
	Area (Ha)	% of Area	Area (Ha)	% of Area	
Agricultural land	807207,97	28,80	830247,18	29,62	0.83
Bare surface	258653,72	9,23	309973,53	11,06	1.83
Built-up	54934,33	1,96	58049,17	2,07	0.05
Woody vegetation	1011007,84	36,07	997764,70	35,60	-0.48
Grassland	661662,65	23,61	595097,22	21,23	-2.37
Waterbodies	5860,42	0,21	7559,36	0,27	0.06
	2802907,921	**100**	**2802909,303**	**100**	**0.00**

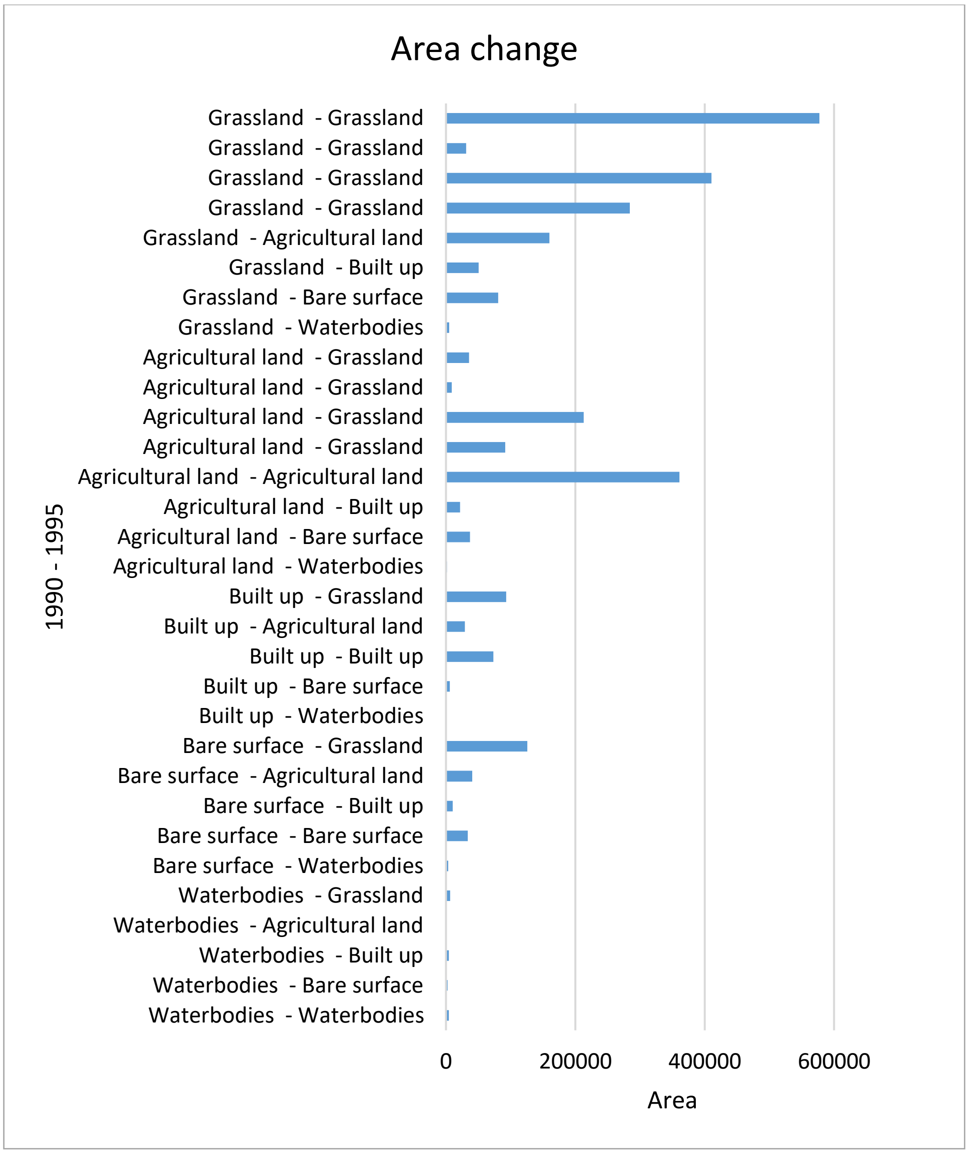


Figure 17: Ngaka LULC change statistics in Hectares between 1990 and 1995.

Table 13 presents the changes in LULC types between the years 1995 and 2000. It reveals that woody vegetation and agricultural land decreased by 997,764.70 hectares and 830,247.18 hectares, respectively. These decreases are also represented in percentages, with bare surfaces showing a decline of 1.57% and water bodies decreasing by 0.18%. Conversely, agricultural land and grassland experienced increases of 1,039,556.15 hectares (37.09%) and 623,864.69 hectares (22.26%), respectively.

Table 7: Statistics of LULC classification determined from Landsat data between 1995 and 2000.

Land Cover type	LULC 1995		LULC 2000		Change in % from 1995 to 2000
	Area (Ha)	% of Area	Area (Ha)	% of Area	
Agriculture land	830247,18	29,62	6169321201	22.01	-7.61
Bare surface	309973,53	11,06	3269369181	11.66	0.6
Built-up	58049,17	2,07	306618699.8	1.09	-0.98
Woody vegetation	997764,70	35,60	7411356792	26.44	-9.16
Grassland	595097,22	21,23	10033199032	35.80	14.57
Waterbodies	7559,36	0,27	838863482.4	2.99	2.72
	2804877.20	**100**	2802904,591	100	**0.00**

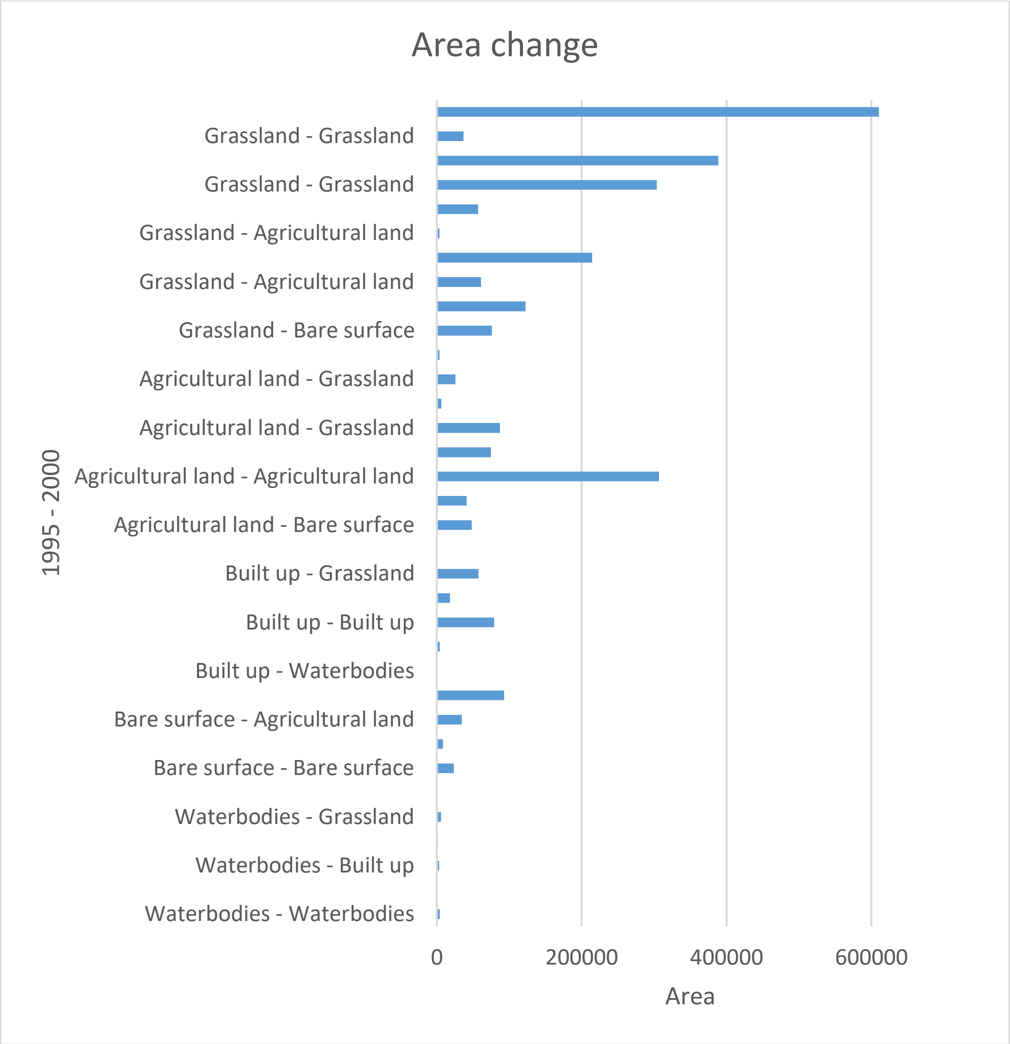


Figure 18: Ngaka LULC changes statistics in Hectares between 1995 and 2000.

The agriculture land extent between the years 2000 and 2005 further decreased to 953697,44 ha (34,03%) of the total area in the municipality (Table 4), with the decrease corresponding with a further substantial increase in grassland to 473282,00 ha (16,89%) of the total area. During this same period, there was a decrease in built-up areas from 43134,19 ha (1,54%) to 46154,84 (1,65%) of the total area. Between 2000 and 2005 there were moderate changes in the different land cover types.

Table 4 illustrates the transitions in LULC types between the years 2000 and 2005, presenting both the absolute changes and their respective percentages. Notably, water bodies and woody vegetation experienced decreases of 838,863.4824 hectares (0.35%) and 7,411,356.792 hectares (10.19%) respectively. Conversely, bare surface, built-up areas, and grassland witnessed increases of 285,556.65 hectares (10.19%), 46,154.84 hectares (1.65%), and

1,037,508.74 hectares (7.61%) respectively. Furthermore, a notable transformation occurred where a significant portion of grassland converted into woody vegetation, totalling 1,037,508.74 hectares (37.02%).

These findings highlight a substantial conversion of agricultural land into grassland, with minimal transformations observed from built-up areas to water bodies during the period spanning 2000 to 2005.

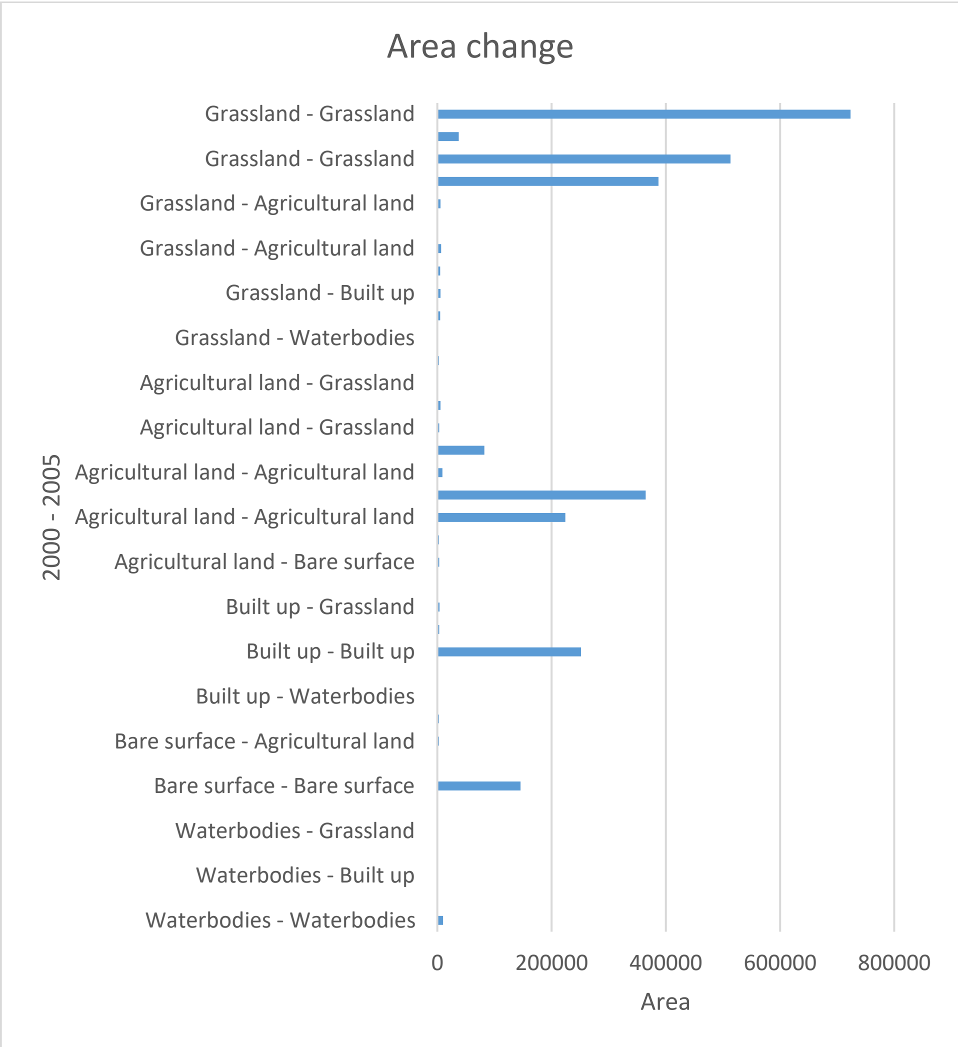


Figure 19: Ngaka LULC change statistics in Hectares between 2000 and 2005.

The agricultural land extent between the years 2005 and 2010 recovered well, with an increase from 4909964442 (34,03%) % to 594429,67 ha (21,21%) of the total area. There was also a decrease in bare surface from 10,19 % to 6,49 % and waterbodies from 0,09% to 0.23 % of the total area. This meant that there was a significant decrease in grassland from 60.16% to 47.43% of the total area in the municipality (Table 15). Between the years 2005 and 2010, only agricultural land was hugely impacted by deterioration from 473282,01 (16,89%) 1019992,99 ha to (36.39%) of the total area (Table 15) (Figure 13).

Table 15 illustrates how the LULC categories changed from 2000 to 2005. The conversion in hectares and % is displayed in Table 15. Waterbodies rose by 6510,84 ha (0.23 %), 21839,22 ha (0.78%), and 1019992,99 ha (36.39 %), respectively, as Table 15 demonstrates. The majority of agricultural land converted to grassland, as shown in Table 15, with a value of 1019992,99 (36,39%).

Table 8**: Statistics of LULC classification determined from Landsat data between 2005 and 2010.**

Land Cover type	**LULC 2005**		**LULC 2010**		**Change in % from 2005 to 2010**
	Area (Ha)	**% of Area**	**Area (Ha)**	**% of Area**	
Agriculture land	4909964442	17.52	6199129703	22.12	4.6
Bare surface	2186308364	7.80	3762538286	13.43	5.63
Built-up	348333142	1.24	479480288.2	1.71	0.47
Woody vegetation	7237376519	25.82	13142214657	14.16	-11.66
Grassland	13194900853	47.08	1019992,99	46.91	-0.16
Waterbodies	152597459.4	0.54	3966448559	1.67	1.17
	28029480779	**100**	**2802907,555**	**100**	**0.00**

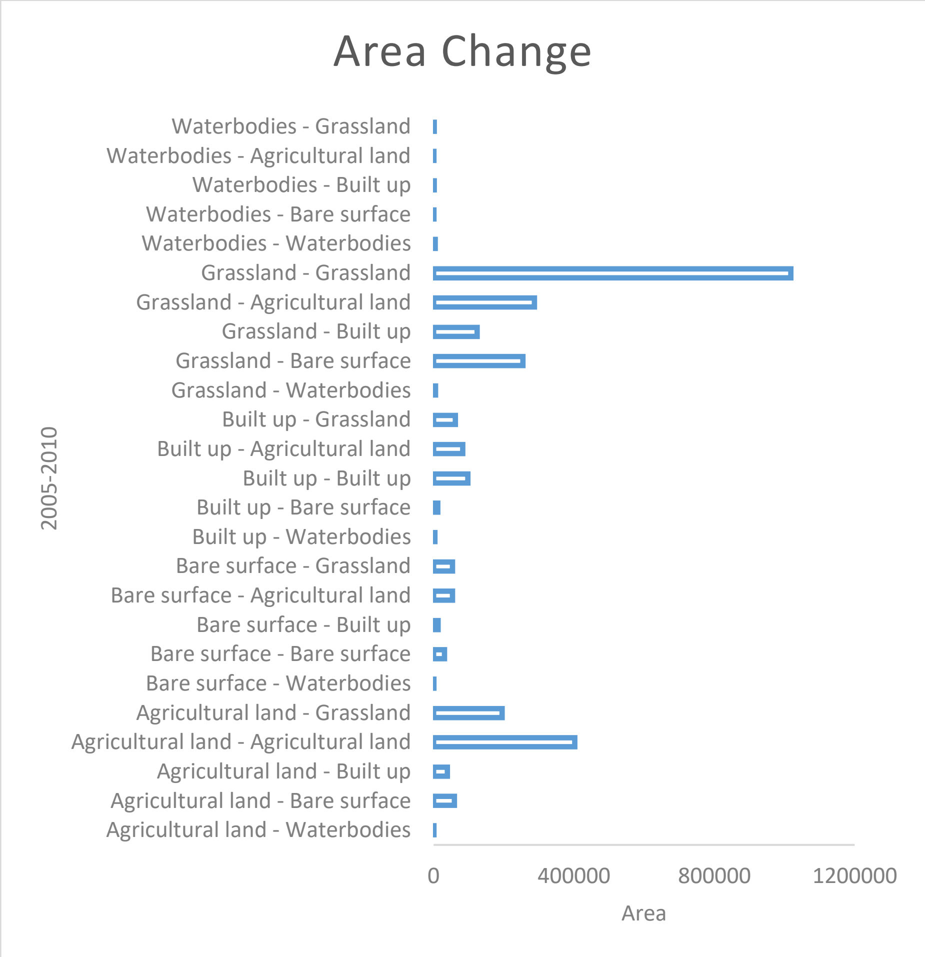


Figure 20: Ngaka LULC changes statistics in Hectares between 2005 and 2010.

Table 16 illustrates that the agricultural land class remained relatively stable between 2010 and 2015, with a total of 594429,67 ha (21,21%). The majority of grassland areas were converted to agricultural land, as evidenced by the value of 983428,2162 hectares (35,09%). For the whole study period, the grassland extent, and its proportion for the year 2015 in the municipality was 1185576.78 ha (42.21 %) of the total area (Table 16). Some of the decrease in agricultural land may be attributed to new built-up developments. The grassland has had a significant increase from the year 1985 and 2015 from 23.61% to 35.09 % of the total area. The built-up areas through new development have increased between 1985 and 2015, from 2,09 % to 2.67% of the total area (Figure 21).

Table 9: Statistics of LULC classification determined from Landsat data between 2010 and 2015.

Land Cover type	LULC 2010		LULC 2015		Change in % from 2010 to 2015
	Area (Ha)	% of Area	Area (Ha)	% of Area	
Agriculture land	6199129703	22.12	5442755400	19.42	-2.7
Bare surface	3762538286	13.43	4832989200	17.24	3.81
Built-up	479480288.2	1.71	830595600	2.96	1.25
Woody vegetation	13142214657	14.16	3160150200	11.27	-2.89
Grassland	1019992,99	46.91	13516126200	48.22	1.31
Waterbodies	3966448559	1.67	246970800	0.88	-0.79
	2802907,555	**100**	**28029587400**	**100**	**0.00**

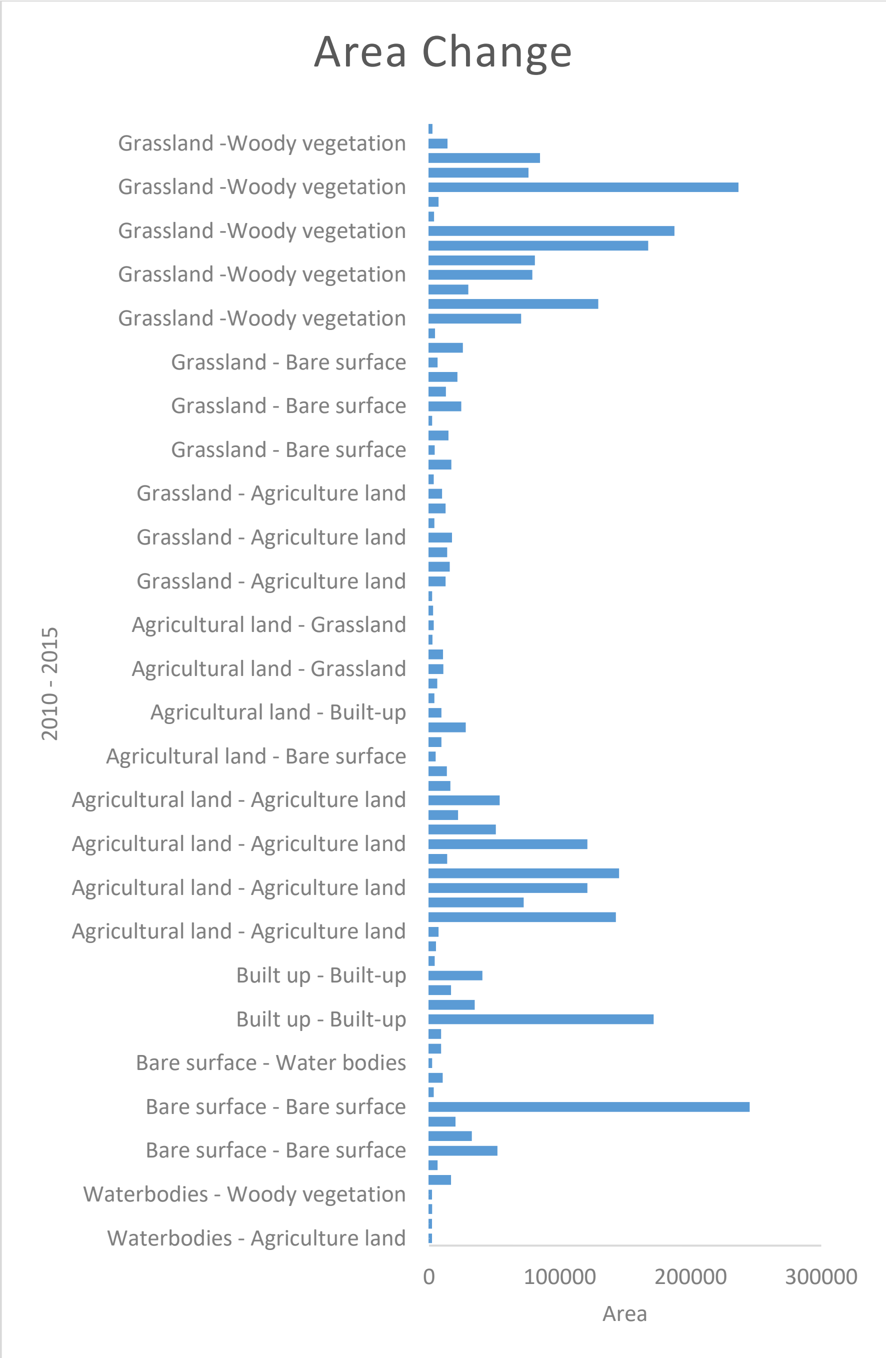


Figure 21: Ngaka LULC changes statistics in Hectares between 2005 and 2010.

Between 2010 and 2015, there was a significant decrease in agricultural farmland size within the NMMDM. As outlined in Table 16, agricultural land decreased by 5.48% during this period, following declines of 9.58% from 2005 to 2010 and 2.29% from 2000 to 2015. Simultaneously, there was an uptick in bare surface coverage during periods of agricultural land decline, with increases of 13.07% from 2000 to 2005 and 3.55% from 2010 to 2015.

Estates' coverage area in the district has declined since the onset of land reform, with reductions of 4.89% from 2010 to 2015, 2.35% from 2000 to 2005, and 0.21% from 2005 to 2010. The decrease in agricultural farm coverage can be attributed to several factors, including farm disturbances, shortages of farm workers, and inputs in newly resettled farms. These factors have contributed to an increase in bare land within the district, as indicated in Table 16.

Furthermore, the decline in agricultural farm coverage has been influenced by reduced farming activities due to insufficient knowledge and machinery among newly resettled farmers for cultivating cash crops, which previously occupied extensive areas before the 2000 reform. Instead, subsistence farming has become more prevalent, covering smaller areas compared to cash crops grown before the reform.

Since 2000, there has been a noticeable increase in built-up areas, as indicated in Table 16. Built-up areas expanded by 0.73% from 2000 to 2006, 5.58% from 2006 to 2011, and 5.64% from 2011 to 2014, potentially leading to a reduction in agricultural land during these periods. This increase in built-up areas is attributed to population growth, resulting in more housing construction, including structures in newly resettled farms.

The forested area increased until 2010 following the land reform's initiation. However, deforestation became evident afterward, particularly between 2011 and 2014, due to various factors such as expansion of arable land, demand for fuelwood, urban expansion, and other human activities, including farming and construction. The land covered by water bodies decreased until 2015, possibly due to farming practices leading to river siltation, stemming from poor farming methods and conservation practices among newly resettled farmers. This indicates that the land reform had significant implications for LULC in Ngaka district, aligning with prior studies highlighting declines in agricultural cropland due to land reform initiatives.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

This chapter encapsulates the comprehensive findings of the research study, encompassing conclusions, limitations, and recommendations derived from the investigation. Through the analysis of Landsat imagery, significant insights were gained regarding the effects of the Land Reform policy within the NMMDM. This analysis facilitated a nuanced comprehension of LULC alterations within the district municipality, shedding light on how these changes have influenced agricultural practices and land ownership dynamics.

5.1 Discussion

This discussion is grounded in change detection statistics obtained from the analysis of two classified images spanning from 1985 to 2024, specifically: 1985–1990, 1990–1995, 1995–2000, 2000–2005, 2005–2010, and 2010–2015. The outcomes of the change detection analysis conducted on these seven Landsat images unveil notable LULC alterations within Ngaka municipality over the specified period.

Tables provided in the preceding text illustrate both positive and negative changes in LULC classes, with positive signs indicating increases and negative signs indicating decreases within the specified time frames. For instance, Table 11 highlights an increase in agricultural land area by 4.17% from 1985 to 1990, whereas grassland, bare surface, built-up areas, and water bodies witnessed declines of -4.11%, -0.72%, -12.94%, -0.51%, and -0.14% respectively during the same period.

From 1990 to 1995, there was a notable decrease in grassland, with declines of -2.37% and -5.37% between 1990–1995 and 1995–2000, as shown in Table 13. However, grassland increased by 21.46% between 1995–2000 and further by 22.26% from 2000–2005, as demonstrated in Table 16. Concurrently, agricultural land increased by 29.48% during 2005–2010 but decreased in 2010–2015, as depicted in Table 16. This decline in agricultural land was offset by increases in bare surface, grassland, and built-up areas, possibly due to reduced agricultural activity during this period.

The increase in built-up areas during this time can be attributed to population growth, leading to increased housing construction within the district. Furthermore, the decrease in agricultural land and grassland may have been influenced by the 1994 Land Acquisition Act, which altered land acquisition dynamics in the country, potentially resulting in the transformation of grassland and water bodies within the municipality. Additionally, restrictions on building permanent residences for resettled individuals under the 'Land Apportionment Act' may have contributed to the decline in built-up areas.

Further to the southwest of the study it is covered by agricultural land. Looking at later years' images from 1985 – 2015 agricultural land varies being mostly grassland. For example, agricultural land on the 1985 map is different from the 2015 map due to the grassland. The reason for the change during 1985 -2015 in Ngaka could be due to the change of ownership or no crops. Comparing the LULC for the seven observation periods, differences in the LULC were observed. The vegetation in 1995 grew. Between the seven years, the reason for the agriculture is not clear. If it is due to the change of ownership or is due to the grown grassland, no crops.

This study was conducted in alignment with previous research investigating the quantifiable impacts of the Land Reform Programme on LULC changes in Ngaka District, North West, utilizing Landsat observations. The primary objective of this study was to assess the extent to which the land reform program influenced LULC changes within the Ngaka District, North West.

The results found from this research shows that the LULC class of agricultural land, which is land used for animal and crop farming as well as other agricultural activities, has decreased from the year 1985 by 5,21%. This is visible from table 11 which shows that in 1985 the percentage of area was 24,63 % and in 2015 table 17 shows that the area percentage of agriculture was 19,42%. A lot of factors may be contributors to the decreasing change of agricultural land between the years 1985 and 2015. The decline in agricultural activity on land during the specified years can be attributed to several primary factors. These include farmers' low levels of education, which hinder their comprehension of agricultural dynamics, poor management practices, insufficient farming skills, limited access to formal and profitable markets, high transportation costs to reach these markets, inadequate market information, and a lack of government assistance and services.

A significant portion of the agricultural land cover class has evidently undergone conversion into grassland, bare surface, or built-up area land cover types. This transformation is clearly depicted in the land cover maps generated for the years 1985 and 2015 (Figures 4 and 8). It was further demonstrated by Google Earth imagery that the majority of the agricultural land has been transformed into other land classes throughout the years.

The bare surface land cover class includes land types such as degraded land, exposed rocks and unvegetated land. This land cover type accounted for approximately 13,3% area percentage of the study area's total land cover (Table 11). By 2015, there had been a slight increase in the bare surface land cover class by 3,91% leaving the total land cover area percentage to 17,24% in 2015 (Table 17). We can deduce from the results of the LULC maps that the bare surface land has increased due to the decrease in agricultural land throughout the years. One possible explanation for this could be the widespread use of human activities, which has led to widespread soil erosion and degradation (Egoh & Reyers, 2011).
Land degradation lowers the amount of productive soil that is available for farming, even though it is recognised as a global ecological problem that reduces the availability of organic soil (Dlamini & Chivenge, 2014). The quantity of arable land that exists for subsistence farming, commercial farming and food production has decreased due to the increased occurrence of barren lands, which is one of the main causes of the land competition (Grobler C, 2006).

The built-up area land cover class within the NMMDM exhibits a diverse range of settlement types, including both formal and informal settlements, villages, as well as residential and commercial areas. In 1985, this land cover class accounted for approximately 2.67% of the total land extent in the study area, as depicted in Table 11. By 2015, there was a significant increase of 0.29%, bringing the built-up area to occupy 2.96% of the total land extent. This expansion can be attributed to the district's growing population and the consequent rise in housing demands, leading to the expansion of residential areas. Despite being predominantly rural, the district holds significant potential for primary sectoral goods production, particularly in crop farming and mining, which positively impact the district's socio-economic status (Oduniyi and Tekana, 2020).

The woody vegetation land cover type comprises trees found in residential areas, along roadsides, near farms, as well as in reserved and protected forests. It constituted the second largest percentage of land coverage in the district. In 1985, the woody vegetation class covered an area of 609,760.80 hectares (21.76%), as illustrated in Table 11 and Figure 1. However, by 2015, there was a decrease in its extent by 10.49%, resulting in a reduced coverage of 316,015.02 hectares (11.27%) (Table 17). This shift towards a significantly reduced woody vegetation land type is evident in land cover maps from 1985 to 2024 (Figures 1 and 4). The transformation, prominently observed as a conversion to grassland cover, is attributed to the growing demands for food, energy, building materials, and shelter, leading to deforestation and land conversion activities common in rural areas (Palamuleni, 2012).

The grassland class emerges as the most dominant land cover class in the study area, covering 1,025,655.48 hectares (36.60%) of land in 1985 (Table 11). Despite experiencing a rapid increase of 11.62% in 2015, reaching a total coverage of 1,331,612.62 hectares (20.26%), it remained the largest land cover class in the district. The land cover maps from 1985 to 2024 (Figures 1 and 4) reveal that areas previously classified as agricultural land and woody vegetation in 1985 have transitioned to grassland by 2015. This increase in grassland benefits animal farming, a major agricultural activity in the district, providing grazing areas for cattle and other livestock, as well as resources for traditional medicinal purposes.

There was a significant increase in the waterbodies from the year 1985 to the year 2015. In 1985, the waterbodies land cover type had an area of 9900,42 ha (0,35%), which increased by 0,53% resulting in an area change of 24697,08 ha (0,88 %) by 2015. We can see from the LULC maps that the study area has very little waterbodies and the increase throughout the years from 1985 to 2024 may be due to factors such as increasing storms and heavy rainfall which may also have an impact of causing floods.

The findings of the study effectively met the research aim of examining the influence of the land reform policy and its implementation on LULC changes in the NMMDM from 1985 to 2024, utilizing multi-temporal remote sensing imagery. By leveraging remote sensing techniques and employing the random forest algorithm classifier, the study successfully identified and characterized various land cover classes over the study period, facilitating a comprehensive exploration of LULC dynamics within the district.

The implementation of the land reform policy had a discernible impact on the decline in agricultural land over the study period. This effect is evident in maps from Figure 7 to Figure 9, which illustrate the transition of land ownership from white farmland owners to black and communal landowners. The observed pattern indicates that as the land reform policy unfolded in South Africa, changes in land tenure within the district commenced around 1996, as per data obtained from the Department of Rural Development and Land Reform (DRDLR). Utilizing land reform data from the department, changes in ownership were mapped against agricultural land class in the district across the years to assess its impact on agricultural land, a primary socio-economic activity within the district municipality.

However, the study's findings reveal that changes in land cover were observed across all land cover classes during the study period. Additionally, population growth (manifested as an increase in the built-up area) and environmental changes or ecological succession (including changes in woody vegetation, grassland, bare surface, and waterbodies) were identified as the primary factors driving changes in land cover across all other land cover classes in the NMMDM, excluding agricultural land cover classes. The most significant LULC change observed in the study area, directly linked to the unintended consequences of land reform policy implementation, was the reduction in agricultural land activities and productivity. The findings demonstrate a rapid decline in agricultural productivity following the adoption of the land reform policy in the district.

In order to investigate historical changes in LULC patterns, it is crucial to use historical records, such as satellite images analysed using remote sensing techniques. This will allow researchers to clearly understand the nature of changes and effectively identify the factors causing the changes that have been detected. Additionally, the study offered techniques that were helpful in examining the type of landscape change that occurred after the land was returned.

Change detection procedures coupled with remote sensing techniques proved to be invaluable for mapping the landscape transformations resulting from the implementation of the land reform policy and for analysing the seven Landsat images. However, it's important to note that the specific research objectives played a crucial role in guiding the analysis of remotely sensed data to achieve the study's primary goal.

The objectives of the research below were achieved from the study methodology and results obtained.

-To map the LULC types between the periods of 1985 to 2024 with five years intervals using Landsat earth observation data and random forest classifier.

The collection of spatiotemporal data for LULC classification was facilitated in this study by the effective application of remote sensing image classification. Investigating the effects of various socioeconomic and environmental factors on the surface of the Earth was made easier by mapping LULC changes. This research presented an algorithm for analysing LULC change using time-series data from Landsat. Utilising imagery from Landsat 5, 7, and 8 for the years 1985 to 2024, the application of the Random Forest (RF) classifier, a robust classification technique was done on the ENVI 5.5 software.

- *To identify the spatial pattern and trends of the implementation of Land Reform Policy in the study area using spatial analysis techniques.*

The spatial patterns and trends were identified in the study by using spatial analysis techniques in ArcMap, when an overlay was created on the maps from the years of the study, to determine the relationship between the change of ownership throughout the years after the land reform policy implementation with the impact that it had on the agricultural land. The NMMDM LULC changes between 1985 and 2015 were found to be reasonably well investigated through the application of GIS and remote sensing techniques. Change detection techniques were employed to identify LULC changes, and spatiotemporal LULC dynamics were observed through analysis. The process and pattern of prominent changes in LULC can be ascertained with the use of LULC change detection techniques that make use of satellite imagery as well as the analytical functions and algorithms found in the GIS environment.

- *To quantify the LULC changes between the periods of 1985 to 2024 with five years interval using Landsat data and change detection techniques.*

The study's assumptions regarding the quantification of LULC changes using Landsat earth observations were corroborated by previous research. For instance, (Jombo S. S., 2016) utilized Landsat imagery spanning from 1992 to 2014 to assess the impact of the Fast Track Land Reform Program (FTLRP) on LULC changes in Chipinge District, Zimbabwe. Their findings, which highlighted the significance of Landsat observations in quantifying LULCC resulting from Zimbabwe's land reform policy, align with the results obtained in our study.

Similarly, (Palamuleni, 2012) employed remote sensing techniques and Landsat data to detect LULC changes and investigate the consequences of the South African land reform program. Although different classifiers were utilized in these studies, such as Support Vector Machine (SVM) by (Jombo S. S., 2016) and Maximum Likelihood classification by (Palamuleni, 2012), the outcomes underscored the value and applicability of Landsat imagery in understanding the effects of land reform policies on LULC dynamics.

In the study, the implementation of the random forest classifier yielded significant results, contributing to the comprehensive analysis of LULC changes over time. While various classification methods were employed across different studies, the consistent findings underscore the robustness and versatility of Landsat data in elucidating the impacts of land reform policies on LULC dynamics.

- *To establish the relationship between the implementation of Land Reform Policy and LULC changes in the study area using spatial analysis techniques.*

The study successfully established a relationship between the implementation of the land reform policy, characterized by the shift in land ownership from white to black landowners, and changes in agricultural land from 1985 to 2024. The findings indicated a significant decrease in agricultural land over the years, attributed to shifts in land tenure and ownership. Through the use of remote sensing techniques and analysis of satellite images, the study generated accurate maps of the landscape and provided statistical findings, elucidating the impact of the South African land reform policy on land use and LULC changes on restituted land.

Furthermore, the study offered insights into the types of landscape transformations occurring both before and after land restitution. By examining LULC changes on restituted land, the research shed light on the broader impacts of land reform policies on landscape dynamics. The findings underscored the value of remote sensing as a valuable tool for estimating and understanding LULC changes, highlighting its utility in assessing the effects of land management policies and informing land use planning decisions.

Implications of Detected Changes on Land Reform Policy

The change detection analysis reveals several important implications for the land reform policy in Ngaka District:

1. <u>Reduction in Agricultural Land:</u>

The observed 5.21% decrease in agricultural land from 1985 to 2015 suggests that the land reform policies may not have provided sufficient support and training for new landowners, which could negatively impact agricultural productivity and food security. Effective training and resources for sustainable farming practices are essential for the success of land reform.

2. <u>Increase in Grassland and Bare Surfaces:</u>

The conversion of agricultural land into grassland and bare surfaces indicates potential shortcomings in the sustainable management of newly acquired lands. This shift underscores the need for land reform programs to include comprehensive environmental and land management education to prevent land degradation and promote sustainable practices.

3. Expansion of Built-up Areas:

The growth in built-up areas, driven by increasing housing demands due to population growth, highlights the challenge of balancing urban development with the preservation of agricultural and natural lands. Effective land use planning and zoning regulations are crucial to managing this growth sustainably.

4. Impact of Land Reform Legislation:

Specific legislative acts, such as the 1994 Land Acquisition Act, appear to have significantly influenced land use patterns. The decline in agricultural and grassland areas may be linked to these acts, suggesting that policies should focus not only on transferring land ownership but also on supporting its effective and sustainable use.

5. Decline in Woody Vegetation:

The reduction in woody vegetation points to environmental impacts, such as deforestation and land conversion activities, associated with land reform policies. Integrating conservation measures into land reform initiatives is vital to protect and restore forested areas, which are essential for ecological balance and biodiversity.

6. Need for Policy Adjustments:

The findings indicate that land reform policies require adjustments to better support sustainable land use and management practices. Providing education, resources, and ongoing support to new landowners is crucial to maintaining or enhancing land productivity and environmental health.

7. Long-term Monitoring and Support:

The dynamic changes in LULC classes over the studied period highlight the necessity for continuous monitoring and support for land reform beneficiaries. Adaptive management strategies and ongoing assessment are essential to address emerging challenges and ensure that land reform objectives are achieved effectively.

Understanding these implications allows policymakers to refine land reform strategies to promote sustainable land use, support agricultural productivity, and balance development needs with environmental conservation.

5.2 Relations of the Results and Existing Literature

a) Changes in LULC Classes

The findings from this study, which indicate fluctuations in agricultural land and grassland, are consistent with previous research. Studies such as those by Jombo et al. (2016) and Palamuleni (2012) have documented similar patterns of land use change driven by socio-economic and policy influences. These fluctuations in Ngaka District reflect broader trends observed in other regions.

b) Impact of Land Reform Policies

The decrease in agricultural land and the subsequent increase in other land cover types, like grassland and built-up areas, can be directly linked to the impact of land reform policies. Similar trends were observed by Jombo et al. (2016) in Zimbabwe, where land reforms resulted in significant alterations to agricultural landscapes.

c) Population Growth and Urban Expansion

The study's observation of increased built-up areas due to population growth is consistent with findings by Oduniyi and Tekana (2020), who explored the socio-economic impacts of population increases on land use in South Africa. The rising demand for housing and expansion of residential areas in NMMDM aligns with these broader patterns.

d) Transformation of Agricultural Land

The conversion of agricultural land to grassland, bare surfaces, and other land cover types aligns with Grobler (2006), who highlighted the impact of land degradation and conversion on agricultural productivity. This study's findings of decreased agricultural land due to soil erosion and human activities echo these concerns.

e) Bare Surface Increase and Degradation

The increase in bare surfaces observed in this study, driven by soil erosion and human activities, is supported by research from Egoh and Reyers (2011) and Dlamini and Chivenge (2014). These studies also identified land degradation as a significant factor in changing land cover patterns.

f) Decline in Woody Vegetation

The reduction in woody vegetation due to deforestation and land conversion activities is consistent with Palamuleni (2012), who noted similar declines in forested areas due to increased demands for resources in rural regions.

g) Dominance of Grasslands

This study found that grasslands remained the dominant land cover type, supporting livestock and local livelihoods, which aligns with other research emphasizing the critical role of grasslands for grazing and traditional uses.

h) Increase in Water Bodies

The increase in water bodies from 1985 to 2015, attributed to climatic factors like storms and heavy rainfall, is consistent with other studies linking extreme weather events to changes in land cover, highlighting the importance of considering climate variability in land use analyses.

i) Remote Sensing and Change Detection

The effective use of remote sensing techniques and change detection analysis in this study is validated by similar methodologies used in another research. Jombo et al. (2016) and Palamuleni (2012) also employed these techniques to map and understand LULC changes, reinforcing their utility in policy impact assessments.

j) Land Reform Policy and LULC Changes

The relationship established between land reform policies and LULC changes in this study mirrors findings from other regions. Jombo et al. (2016) demonstrated the impact of land reforms on LULC changes in Zimbabwe, while Palamuleni (2012) explored similar impacts in South Africa, indicating that the influence of land reforms on land use patterns is a common phenomenon.

5.3 Conclusion

The primary aim of this research was to evaluate the impact of the land reform policy on LULC dynamics within the NMMDM of South Africa's North West province. Leveraging seven Landsat images, our study delved into the ramifications of the land reform policy on LULC changes within the NMMDM. Employing Landsat earth observation data alongside Geographic Information Systems (GIS) and remote sensing methodologies, we scrutinized shifts in LULC from 1985 to 2024 within the district municipality. Change detection methodologies were applied to pinpoint alterations in LULC, followed by spatial analyses to discern prevailing patterns and trends subsequent to the land reform policy's implementation.

The random forest classifier was harnessed for image classification of Landsat images at five-year intervals, facilitating the detection of LULC changes. Our analysis of Landsat observations centred on elucidating land patterns and transitions over a three-decade span (1985–2015). Furthermore, an overlay spatial analysis technique in ArcMap was employed to establish the relationship between changes in agricultural land post the land reform policy's enactment. Our findings uncovered a correlation between the rise in black farm ownership and the decline in agricultural land, potentially attributable to factors such as inadequate training or knowledge among new landholders, alongside challenges in farm maintenance.

An additional objective of our study was to map LULC types pre and post the land reform policy and ascertain alterations between these periods. Outcomes revealed substantial increments in built-up areas and grassland, with the latter primarily stemming from a reduction in agricultural land, likely influenced by shifts in land ownership. Our investigation underscores the significance of harnessing historical records, such as satellite imagery analysed through remote sensing methodologies, to probe historical shifts in LULC patterns. This approach empowers researchers to gain deeper insights into the nature of changes and effectively discern the driving factors behind detected land alterations. Furthermore, our study deployed techniques to scrutinize landscape modifications following the implementation of the land reform policy. Change detection procedures utilizing remote sensing methodologies emerged as potent tools for analysing the seven Landsat images.

5.4 Recommendations

- The findings of this study highlight the importance of utilizing LULC changes as indicators for assessing the effectiveness of land reform initiatives. Therefore, integrating spatial data analysis through remote sensing techniques is essential for planning, monitoring, and evaluating land reform projects in South Africa.
- Adequate training provided by the government to land claimants or beneficiaries is crucial for enabling effective utilization of agricultural land.
- A challenge encountered during the study was the limited availability of aerial photos covering the entire region for gathering training samples. Consequently, Google Earth emerged as the primary reliable data source. However, intermittent gaps in data

availability on Google Earth posed difficulties in visual interpretation and gathering training samples, potentially impacting the classification process.

- Ensuring consistency in data formats consumed a significant amount of time during the study due to discrepancies between Landsat images and the local datum. This underscores the importance of meticulous data management practices to mitigate such discrepancies and ensure the accuracy of analyses.

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APPENDICES

APPENDIX A

Table 2: Producer, user and overall accuracies.

a) Producers' accuracy, users and overall accuracy for 1985.

Class Name	Producer's Accuracy %	User's Accuracy %	Overall Accuracy%
Woody vegetation	84.81	68.57	71,49%
Grassland	82.41	80.54	
Agriculture land	80.13	91.26	
Bare surface	87.01	56.52	
Built-up	50.00	86.36	
Waterbodies	100.00	83.58	

b) Producer accuracy, user and overall accuracy for 1990.

Class Name	Producer's Accuracy %	User's Accuracy %	Overall Accuracy%
Woody vegetation	81.67	62.69	73.76%
Grassland	83.33	73.21	
Agriculture land	82.81	89.83	
Bare surface	66.67	61.11	
Built-up	79.22	88.40	
Waterbodies	94.5	87.5	

c) Producer accuracy, user and overall accuracy for 1995.

Class Name	Producer's Accuracy %	User's Accuracy %	Overall Accuracy %
Woody vegetation	82.27	75.86	75.85%
Grassland	79.17	70.37	

Agriculture land	92.06	85.29	
Bare surface	62.50	45.45	
Built-up	50.00	76.00	
Waterbodies	87.50	91.30	

d) Producers' accuracy, users and overall accuracy 2000

Class Name	Producer's Accuracy %	User's Accuracy %	Overall Accuracy %
Woody vegetation	63.64	77.78	79.11%
Grassland	70.83	53.13	
Agriculture land	92.19	85.51	
Bare surface	70.83	56.67	
Built-up	68.42	89.66	
Waterbodies	79.17	100.00	

e) Producers' accuracy, users and overall accuracy for 2005.

Class Name	Producer's Accuracy %	User's Accuracy %	Overall Accuracy %
Woody vegetation	83.48	81.48	79.01%
Grassland	79.17	63.33	
Agriculture land	89.06	84.43	
Bare surface	65.38	62.96	
Built-up	61.11	88.00	
Waterbodies	89.61	100.00	

f) Producer accuracy, users and overall accuracy for 2010.

Class Name	Producer's Accuracy %	User's Accuracy %	Overall Accuracy %
Woody vegetation	77.79	73.49	80.18%
Grassland	83.33	76.14	
Agriculture land	81.25	92.86	
Bare surface	81.58	73.81	
Built-up	69.84	85.71	
Waterbodies	100.00	72.22	

g) Producers, users and overall accuracy for 2015.

Class Name	Producer's Accuracy %	User's Accuracy %	Overall Accuracy %
Woody vegetation	85.29	72.5	81.80%
Grassland	83.33	66.67	
Agriculture land	88.89	86.15	
Bare surface	74.41	79.17	
Built-up	76.32	93.55	
Waterbodies	86.96	100.00	

APPENDIX B

Table 4: Confusion matrix of LULC types in Ngaka municipality 1985.

Classes	WV	BU	G	AF	BS	WT	Total
WV	67	5	13	5	3	19	112
BU	0	65	0	1	1	0	49
G	7	18	75	68	5	2	175
AF	1	8	0	94	0	0	103
BS	1	27	3	49	67	0	165
WT	3	3	0	4	1	56	67
Total	79	126	91	221	77	77	671

Note: WT= Waterbodies, BS = Bare surface, BU = Built-up, G= Grassland, AF = Agriculture land, WV= Woody vegetation.

Table 10: Confusion matrix of LULC types in Ngaka municipality 1990.

Classes	WV	BU	G	AF	BS	WT	Total
WV	79	0	5	11	24	7	126
BU	0	61	1	3	0	4	69
G	0	16	82	14	0	0	112
AF	0	0	1	153	13	4	171
BS	0	0	2	31	77	5	115
WT	0	0	0	9	12	57	78
Total	79	77	91	221	126	77	671

Note: WT= Waterbodies, BS = Bare surface, BU = Built-up, G= Grassland, AF = Agriculture land, WV= Woody vegetation.

Table 11: Confusion matrix of LULC types in Ngaka municipality 1995.

Classes	WV	BU	G	AF	BU	WT	Total
WV	65	8	0	1	0	14	88
BU	0	47	2	12	6	1	68
G	10	18	59	5	17	16	125
AF	2	18	28	149	17	5	219
BS	1	27	1	10	30	8	77
WT	1	8	1	44	7	33	94
Total	79	126	91	221	77	77	671

Note: WT= Waterbodies, BS = Bare surface, BU = Built-up, G= Grassland, AF = Agriculture land, WV= Woody vegetation.

Table 12: Confusion matrix of LULC types in Ngaka municipality 2000.

Classes	WV	BU	G	AF	BS	WT	Total
WV	78	0	2	14	1	0	95
BU	0	65	3	5	0	20	93
G	0	17	77	37	11	5	147
AF	1	1	0	148	1	2	153
BS	0	38	3	16	59	3	119
WT	0	5	6	1	5	47	64
Total	79	126	91	221	77	77	671

Note: WT= Waterbodies, BS = Bare land, BU = Built-up, G= Grassland, AF = Agriculture land, WV= Woody vegetation.

Table 13: Confusion matrix of LULC types in Ngaka municipality 2005

Classes	WV	BU	G	AF	BS	WT	Total
WV	66	0	1	14	0		81
BU	0	72	20	1	1	6	100
G	0	25	64	13	5	2	109
AF	0	21	0	141	5	0	167
BS	11	6	1	47	60	0	125
WT	2	2	5	5	6	69	89
Total	79	126	91	221	77	77	671

Note: WT= Waterbodies, BS = Bare surface, BU = Built-up, G= Grassland, AF = Agriculture land, WV= Woody vegetation.

Table 14: Confusion matrix of LULC types in Ngaka municipality 2010.

Classes	WV	BU	G	AF	BS	WT	Total
WV	61	2	1	3	15	1	83
BU	0	88	0	2	0	6	96
G	0	1	82	14	6	4	107
AF	17	6	2	140	12	9	186
BS	1	27	3	4	38	15	88
WT	0	2	3	58	6	42	111
Total	79	126	91	221	77	77	671

Note: WT= Waterbodies, BS = Bare surface, BU = Built-up, G= Grassland, AF = Agriculture land, WV= Woody vegetation.

Table 15: Confusion matrix of LULC types in Ngaka municipality 2015.

Classes	WV	BU	G	AF	BS	WT	Total
WV	58	12	11	6	1	4	92
BU	0	88	0	0	29	1	118
G	3	6	66	33	0	7	115
AF	13	6	6	175	5	3	208
BS	4	14	7	5	36	4	70
WT	1	0	1	2	6	58	68
Total		79	126	91	221	77	77

Note: WT= Waterbodies, BS = Bare land, BU = Built-up, G= Grassland, AF = Agriculture land, WV= Woody vegetation.