INVESTIGATING CHANGES IN PINEAPPLE (*ANANAS COMOSUS*) CULTIVATION IN THE EASTERN CAPE, SOUTH AFRICA, FROM 1984 TO 2020

A thesis submitted in fulfilment of
the requirements for the degree of
MASTER OF SCIENCE

at

Rhodes University

July 2023

By

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Abstract

Land use and land cover change (LULCC) resulting from agricultural activities have significantly impacted landscape transformation and fragmentation. The Albany Thicket Biome in the Eastern Cape Province stands out for its exceptional vegetation diversity and remarkable rates of species endemism. However, the relationship between agricultural activities and the Albany Thicket Biome has not received sufficient attention in the literature, creating a significant gap in understanding the extent of landscape transformation and the vegetation's recovery rate. This study aims to address this gap by utilising remote sensing technologies to investigate the LULCC specifically caused by pineapple cultivation in the Lower Albany area between 1984 and 2020. Analysis, using remotely sensed imagery and spatial analytical tools, provide accurate identification of pineapple fields and enable monitoring of their effects on LULCC dynamics across a wide spatial and temporal scale. Complementary field assessments examined the impacts of pineapple cultivation on land use and cover. Twelve image classifiers were tested to identify the most appropriate technique for mapping pineapple fields, and the Supervised Pixel-based Support Vector Machine (SVM) image classifier was found to be the most suitable. Utilising Landsat 4, 5, 7, and 8 satellite imagery, 27 land cover maps were created, spanning the period from 1984 to 2020. Additionally, field verification was conducted at 59 randomly generated sites to validate the findings. Spatial analysis of the data revealed that the pineapple industry in the study area has expanded by 733 hectares since 1984. Significant land use changes were observed, including converting land to wildlife ranches, grazing areas, and alternative agricultural practices. The land cover analysis identified the emergence of pioneer species in former pineapple fields, suggesting the potential for Albany Thicket regrowth if appropriately managed. This research contributes to a better understanding of the impacts of pineapple cultivation on the Albany Thicket Biome and provides valuable insights for land use planning and monitoring efforts. A comprehensive assessment of LULCC dynamics can be achieved by utilising remote sensing techniques, informing sustainable land management practices in the study area and beyond.

Acknowledgements

I would like to express my sincere gratitude to all those who have supported and guided me throughout the journey of completing this research study. First and foremost, I extend my deepest appreciation to my supervisor, Prof. Ian Meiklejohn, whose invaluable expertise, continuous encouragement, and unwavering support have been instrumental in shaping this research work. Your insightful feedback and constructive criticism have played a pivotal role in refining the quality of this dissertation.

I would also like to extend my thanks to the Department of Geography at Rhodes University for providing me with a stimulating academic environment and necessary resources to carry out this research. The department's commitment to excellence in teaching and research has been an inspiration to me, and I am grateful for the opportunities I have received to grow and develop as a scholar. I owe a special debt of gratitude to Gillian McGregor, whose invaluable guidance and insightful discussions were instrumental in shaping the conceptualisation of my research project.

I would like to express my deepest gratitude to my parents, Ross and Angela Marriner, for their unwavering love, support, and belief in me throughout this academic journey. Your constant encouragement, understanding, and sacrifices have been the driving force behind my accomplishments, and I am truly grateful for your unwavering presence in my life.

Furthermore, I extend my heartfelt appreciation to the pineapple farmers who graciously agreed to be a part of this study. Their willingness to share their knowledge, experiences, and valuable insights have enriched this research significantly. Their expertise and cooperation have been indispensable in understanding the intricacies of the pineapple farming industry, and I am grateful for their contributions.

Last but certainly not least I want to extend a heartfelt message of gratitude to Robyn Flanegan. Your unwavering support, understanding, and love have been my rock throughout this journey. Your patience and encouragement, especially during the challenging times, have meant the world to me. I appreciate your belief in me and your willingness to stand by my side as I pursued my academic goals.

To all those mentioned above and to everyone else who has played a role in shaping this dissertation, I am forever indebted to your guidance and assistance. This work would not have been possible without your support, and I am truly grateful for the opportunities and knowledge I have gained from this experience.

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Abbreviations

BCE	-	Before the Common Era
C0CA	-	Census of Commercial Agriculture
CARA	-	Conservation of Agricultural Resources Act
CART	-	Classification and Regression Trees
CD: NGI	-	Chef Directorate: National Geospatial Institute
DAFF	-	Department: Agriculture, Forestry and Fisheries
DALRRD	-	Department of Agriculture, Land Reform and Rural Development
DEA	-	Department of Environmental Affairs
DEM	-	Digital Elevation Model
DRDAR	-	Department of Rural Development and Agrarian Reform
EIA	-	Environmental Impact Assessment
EMS	-	Electromagnetic Spectrum
ESRI	-	Environmental Systems Research Institute
ETM+	-	Enhanced Thematic Mapper Plus
EVI	-	Enhanced Vegetation Index
FAO	-	Food and Agriculture Organisation
GEE	-	Google Earth Engine
GIS	-	Geographic Information System
GPS	-	Global Positioning System
IC	-	ISO-Cluster
IR	-	Infrared
KNN	-	K-Nearest Neighbour
LiDAR	-	Light Detection and Ranging
LULC	-	Land use and land cover
LULCC	-	Land use and land cover change
MDB	-	Municipal Demarcation Board
ML	-	Maximum Likelihood
NASA	-	National Aeronautics and Space Administration
NDVI	-	Normalised Difference Vegetation Index
NEMA	-	National Environmental Management Act
NOAA	-	National Oceanic and Atmospheric Administration
NPCI	-	Normalised Pigment Chlorophyll Ratio Index

OLI - Operational Land Imager
PGA - Pineapple Growers Association
PSRI - Plant Senescence Reflectance Index
RT - Random Trees
SANBI - South African National Biodiversity Institute
SANLC - South African National Land Cover
SAVI - Soil-Adjusted Vegetative Index
StatsSA - Statistics South Africa
STEP - Subtropical Thicket Ecosystem Planning Project
STRM - Shuttle Radar Topography Mission
SVM - Support Vector Machine
TIRS - Thermal Infrared Sensor
TM - Thematic Mapper
UAV - Unmanned Aerial Vehicle
USGS - United States Geological Survey
UTM - Universal Transverse Mercator
VI - Vegetation Indices
WWF - World Wildlife Foundation

Data Disclaimer

All Landsat satellite imagery (Landsat 4, 5, 7, and 8) is courtesy of the United States Geological Survey (USGS) and was downloaded from the USGS '*Earth Explorer*' webpage. The following base maps were used for aesthetic purposes for the maps created in ArcGIS Pro:

- Imagery: Earthstar Geographics, Maxar
- Topographic: ESRI, HERE, Garmin, FAO, NOAA, USGS,
- Human Geography: ESRI, HERE, Garmin, FAO, NOAA, USGS

The following Geographic Information System (GIS) data layers were used for creating the maps in this research study:

- South African vegetation (2006), obtained from the Rhodes University Geography Department. (Source: Mucina and Rutherford, 2006).
- South African geology (1:250000), obtained from the Rhodes University Geography Department. Geological Survey of South Africa. (Source: Council for Geoscience, n.d.).
- Five-metre elevation lines: obtained from the CD: NGI Geospatial Portal.
- Wildlife ranch dataset: Obtained from Dr. William Fowlds.
- South African vector datasets: provinces, municipalities, wards, roads, and rivers. Obtained from the CD: NGI Geospatial Portal and MDB.
- World countries vector dataset: Obtained from ESRI.
- South African National Land Cover datasets (1990, 2013-2014, 2018, 2020): 35 – 72 land cover classes, reprojected UTM 27 south. Obtained from the Department of Environmental Affairs (DEA) GIS data downloads webpage. (Source: DEA, 2016).
- Shuttle Radar Topography Mission (STRM) 30m: Obtained from the United States Geological Survey (USGS) 'Earth Explorer' webpage.

CHAPTER 1: INTRODUCTION

1.1. Background

Approximately 22% of the natural landscape in South Africa has been altered and lost since the arrival of European settlers in the 1700s and 1800s (Skowno *et al.*, 2019; Carvalho *et al.*, 2022). Landscape degradation results from land use and land cover (LULC) transformations. Land use refers to the practical usage of land on the Earth's surface, such as agriculture, urban, or industrial use, while land cover refers to the physical characteristics of land on the Earth's surface, such as forests, wetlands, or grasslands (Fairbanks *et al.*, 2000). Agriculture is the most significant driver of land use and land cover change (LULCC) (Lambin, & Meyfroidt, 2011), resulting in extensive fragmentation and transformation of the landscape. An analysis of LULCC resulting from agricultural activities can provide insights into the interaction between human land use practices and the environment. Agricultural activities, such as cultivation, irrigation, and expansion of agricultural lands, profoundly impact land cover patterns and ecosystem dynamics at local, regional, and global scales. Understanding the LULCC dynamics resulting from agricultural agrarian activities provides valuable information for land managers, policymakers, and stakeholders involved in sustainable land management and agricultural planning (Lloyd *et al.*, 2002; Carvalho *et al.*, 2022). Moreover, assessing the spatial and temporal dynamics of agricultural land use changes helps identify areas of land degradation, land use conflicts, and potential opportunities for improved land use practices (Rouget *et al.*, 2003).

The unique and floristically diverse Albany Thicket Biome in the Eastern Cape province of South Africa has been exposed to large-scale degradation (Lubke *et al.*, 1986; Palmer *et al.*, 2006), resulting in extensive fragmentation and transformation of the landscape (Carvalho *et al.*, 2022). The Subtropical Thicket Ecosystem Planning Project (STEP), started in 2000, identified that more than 70% of vegetation units within the Albany Thicket are moderately to severely degraded due to LULCC (Lloyd *et al.*, 2002). Recent studies categorised a further 40%- 60% decrease in the Thicket division delimited by the STEP project as degraded, transformed, or lost to anthropogenic activities (Carvalho *et al.*, 2022). Globally, and specifically within the Albany Thicket Biome, agriculture is the primary driver of LULCC, through the clearing of natural vegetation for crops or herbivory by domestic livestock (Hoffman and Everard, 1987; La Cock *et al.*, 1990; Lloyd *et al.*, 2002; Carvalho *et al.*, 2022).

Understanding the dynamics of LULCC resulting from crop cultivation is crucial for effective land management and sustainable development (Fairbanks, 2000). Traditional methods of monitoring land use change, such as field surveys and manual mapping, are often time-consuming, labour-intensive, and limited in spatial and temporal coverage (Fairbanks, 2000; Alshari, & Gawali, 2021). Remote sensing technologies, particularly satellite imagery, offer an efficient and consistent approach to investigating and monitoring large-scale land cover changes over extended periods (Lillesand *et al.*, 2015). "Remote sensing is the science of extracting information about an object without being in physical contact with it" (Roy *et al.,* 2013: 77). It is instrumental in investigating LULCC resulting from agricultural activities (Lillesand *et al.*, 2015). Landsat, a freely available satellite imagery enterprise operating since 1972 (NASA, 2023a), provides valuable data for assessing land cover dynamics. Using image classification techniques, it becomes possible to identify and map different land cover types, including crop fields, to assess their spatial-temporal impact on the landscape over time.

1.2. Motivation

The Ndlambe Municipality in the Eastern Cape province, where the Albany Thicket Biome is located, is the leading national producer of pineapples, accounting for over 60% of the country's yield (StatsSA, 2021). While pineapple farming has become an important economic activity in the region, the associated LULCC dynamics and their implications have received limited attention in scientific research. No studies have attempted to examine the extent to which the pineapple industry has affected the landscape within this biome. Furthermore, there is neither a holistic conceptualisation of the South African pineapple industry nor an assessment of the global, national, political, or socio-economic forces that have influenced the industry in the past.

Remote sensing has been used to identify specific crop types from satellite imagery, including sugarcane (Zhou *et al.*, 2015; Chen *et al.*, 2020; Virnodkar *et al.*, 2020), corn (Hatfield, & Prueger, 2010), rice (Motohka *et al.*, 2010), soybean (Hatfield, & Prueger, 2010), wheat (Hatfield, & Prueger, 2010), and canola (Hatfield, & Prueger, 2010). To date, remote sensing has not been utilised to identify the spatial-temporal changes of pineapple fields through medium-resolution and freely available satellite imagery. The use of remote sensing on pineapples is limited to using unmanned aerial vehicles (UAVs) for fruit counting (Grounds *et al.*, 2008; Hobbs *et al.*, 2021; Shiu *et al.*, 2023; Syazwani *et al.*, 2022) and disease detection (Balasundram *et al.*, 2013). Furthermore, remote sensing has been used to identify LULCC in diverse landscapes (Aboel Ghar *et al.*, 2004; Kumar, & Agrawal, 2019; Ngcofe *et al.*, 2019; Rawat, & Kumar, 2015). Thus, there is significant potential to build upon existing research on LULCC to identify and assess the LULCC of pineapple cultivation through medium-resolution and freely available satellite imagery. Remote sensing-based approaches can provide a comprehensive and objective assessment of land cover dynamics, enabling a deeper understanding of the spatiotemporal patterns of pineapple cultivation and its associated land use changes.

By addressing these knowledge gaps, this study seeks to contribute to understanding pineapple cultivation by investigating past land use changes, current effects on the land cover, and patterns and trends that have influenced the industry. Furthermore, examining the patterns and trends of the pineapple industry from its origins to the present and reviewing the subsequent limitations and successes will enable a holistic conceptualisation of the industry's future.

1.3. Aims and Objectives

This research study aims to utilise remote sensing technologies to investigate the LULCC that have resulted from pineapple cultivation in the Lower Albany Area between 1984 and 2020.

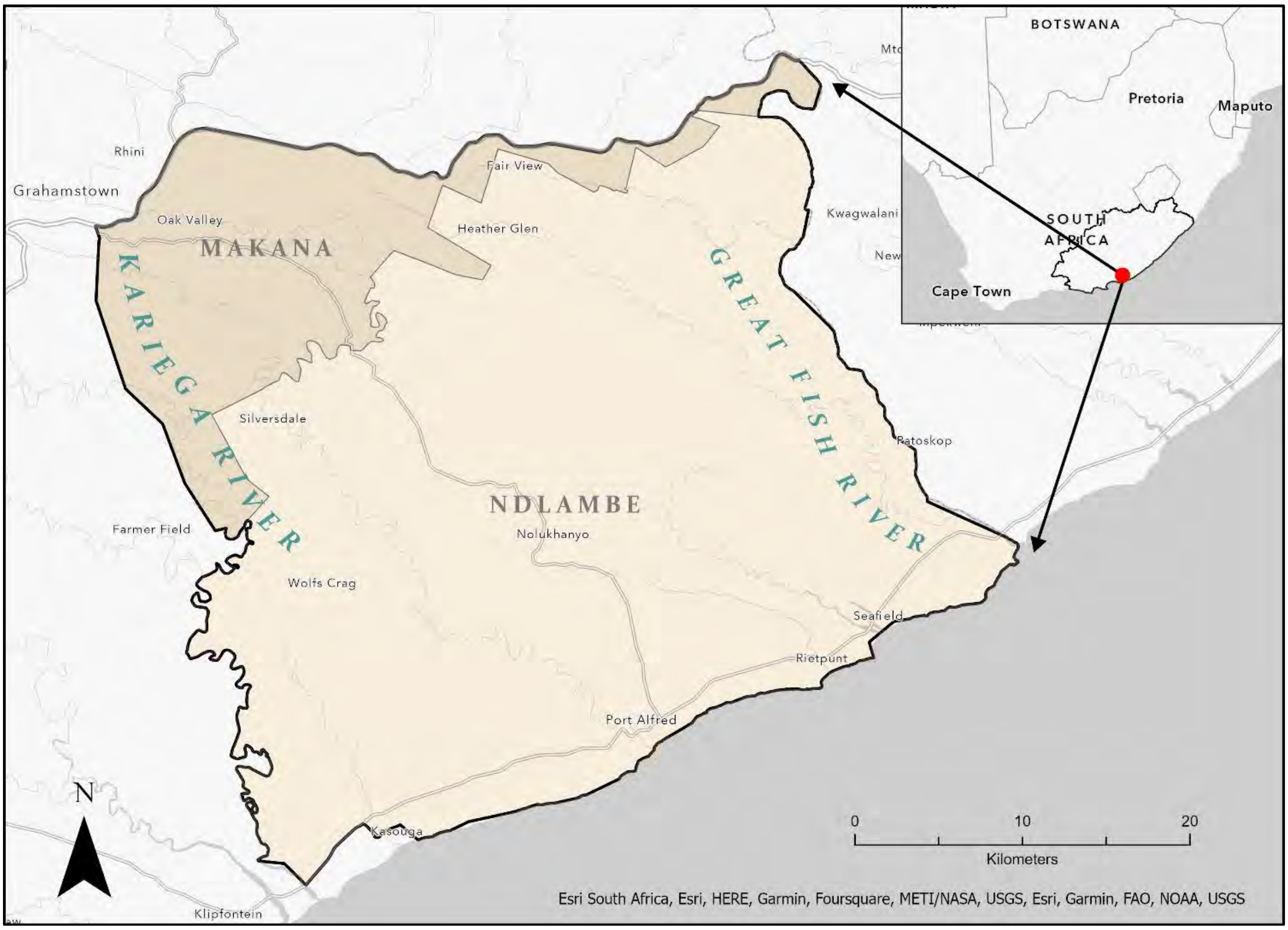
To achieve the aim of this research study, the following objectives were followed:

1. To examine the information pertinent to the evolution of the pineapple industry.
2. To determine the optimal methodology for mapping the spatial and temporal boundaries of pineapple cultivation.
3. To perform a comprehensive spatial analysis of LULCC induced by pineapple farming activities.
4. To develop a conceptual framework illustrating the LULCC patterns occurring from pineapple cultivation.

CHAPTER 2: STUDY AREA

2.1. Setting

The study area for this research is restricted to a 156,939-hectare region in the lower Albany area, situated within the Ndlambe and Makana Municipalities and the Cacadu and Sarah Baartman Districts, respectively. The extent of the study area and location within the municipalities is illustrated in Figure 1. The Kariega River represents the eastern extent of the study area, while the Great Fish River represents the western extent. The town of Makhanda delimits the northern extent, which follows the N2 road westwards until it crosses the Great Fish River. The southern extent of the study area follows the coastal zone until the juncture of the easterly Kariega and westerly Great Fish Rivers. This area produces approximately two-thirds of the country's pineapples (StatsSA, 2021), making it an ideal location to research changes within the industry and the subsequent effects on the landscape. The study area boasts a wide diversity of vegetation, geology and socio-economic characteristics, discussed in the subsequent sections.



Esri South Africa, Esri, HERE, Garmin, Foursquare, METI/NASA, USGS, Esri, Garmin, FAO, NOAA, USGS

Figure 1: Locality map of the study area.

2.2. Vegetation

Albany Thicket, in which pineapples are grown in the study area, is almost exclusively found in the southwest region of the Eastern Cape, with fragments stretching into the southeast region of the Western Cape (Mucina, & Rutherford, 2006). Albany Thicket has recently been accepted as a distinct biome, described by Hoare *et al.* (2006), due to the climatic uniqueness of the region and the subsequent unusual vegetation structures, which include remarkable flora diversity and highly localised endemism (van Wyk, & Smith, 2001; Hoare *et al.*, 2006). Previously, Acocks (1988) described the peculiar dominant vegetation of the semi-arid river valleys along the eastern coast of South Africa as Valley Bushveld, defined as "a semi-succulent thorny shrub 2-3 metres in height" (Acocks, 1988). Furthermore, Rutherford, & Westfall (1986) classified the region's vegetation into the widespread Savanna Biome. The top life-form combinations and climatic features in the region correlated with their criteria for the Savanna Biome (Rutherford, & Westfall, 1986). Rutherford, & Westfall (1986) noted that the region's vegetation displayed a variety of life-form combinations, which could, with future research, be classified into a distinct biome. Scholes (1997) classified the region's vegetation as part of the broad-leafed Savanna vegetation class.

On the other hand, Moll and White (1978) and Cowling (1983) provided evidence for the classification of the region's vegetation as a separate physical and floristic unit, which assisted Low and Rebelo (1998) in justifying the classification of the vegetation into the Subtropical Transitional Thicket Biome. This vegetation class extended from the Kei River to the southwestern Cape (Vlok *et al.*, 2003). Fairly recently, the STEP project, initiated in 2000 (Cowling *et al.*, 2003), recognised the region as comprising a distinct biome due to the unique climatic conditions, vegetation structures and diversity, and exceptionally high regional endemism (Hoare *et al.*, 2006). Hoare *et al.* (2006) formally adopted the term Albany Thicket Biome, a term recognised by the World Wildlife Foundation (WWF), for the peculiar vegetation structure and unique climatic patterns found exclusively in the southeast region of the Eastern Cape, with fragments stretching into the southwestern part of the Western Cape (Hoare *et al.*, 2006).

This biome's region is called the Albany Centre of Endemism because of its high endemism and biodiversity (van Wyk, & Smith, 2001). Numerous studies have attempted to identify the overall number of plant and endemic species within the Albany Thicket Biome. Lubke *et al.* (1986) identified 205 endemic species in the region, and additionally, Cowling and Hilton-Taylor (1994) identified 200 local endemic species and a substantial 2 000 taxa within the biome. Threatened species in the biome comprise at least 180 species limited to a considerably narrow distribution range (Victor, & Dold, 2003). The Albany Thicket Biome represents an estimated 10% of species endemism (Hoare *et al.*, 2006). The region also boasts a significant portion of near-endemic species, especially succulents, with the most notable research conducted by van Wyk and Smith (2001), which significantly identified 365 endemic/near-endemic succulents within the Albany Centre of Endemism, suggesting that the 10% of endemics recorded is probably underestimated (Hoare *et al.*, 2006).

The Albany Thicket Biome consists of two primary vegetation groups, Dune Thicket and Mainland Thicket (Carvalho *et al.*, 2022). Furthermore, the vegetation of these two groups is classified into Solid and Mosaic classes depending on the structural density of the vegetation (Lloyd *et al.*, 2002). The Solid and Mosaic Thicket classes comprise four vegetation types: Coastal Dune Thicket, Valley Thicket, Arid Thicket, and Mainland Montane Thicket, more recently referred to as Mesic Thicket (Hoare *et al.*, 2006). Solid Thicket is structurally comprised of intact thicket representing each vegetation type. In contrast, Mosaic Thicket represents a sparse distribution of thicket mosaiced with vegetation from adjacent biomes such as Fynbos, Grassland, or Forest (Lloyd *et al.*, 2002). The unique vegetation groups are spatially distributed across the various geological contexts found in the region and are characterised by the presence of specific species (Hoare *et al.*, 2006). Coastal Dune Thicket is restricted to the sandy soils along the coastal regions (Hoare *et al.*, 2006). It is most dense in dune slacks and depressions in the dunes, where the vegetation is well-protected against the high salt-concentrated winds and periodic fires (Lloyd *et al.*, 2002). Valley Thicket is found along the steep valleys, a characteristic geological feature of the southeastern coastline (Hoare *et al.*, 2006). Arid Thicket is found along the low-elevation river basins, where the climate and topography contribute to an arid environment (Lloyd *et al.*, 2002). Mesic Thicket is structurally similar to Valley Thicket; however, the more prominent mesic conditions drive the structural difference between the two vegetation groups (Lloyd *et al.*, 2002).

Figure 2 illustrates the vegetation units found within the extent of the study area. The vegetation in the study area is dominated by Albany Thicket, with the addition of small fragments of the Fynbos, Savanna, and Forest Biomes. A diverse mosaic of vegetation units of the Albany Thicket Biome is found in the region. The predominant unit of Albany Thicket in the region is the Grahamstown Grassland Thicket, which dominates the higher altitude plain surfaces (Hoare *et al.*, 2006). The Albany Mesic and Valley Thickets are also found along the well-watered valley regions (Hoare *et al.*, 2006). The Nanaga Savanna Thicket, characterised by short grasses with a mosaic of bush clumps, is found along the study area's western portion, with more moderate and gentle slopes (Hoare *et al.*, 2006). The eastern border of the study is in dramatic contrast to the west, with the mosaic combination of the Fish Valley, Mesic and Arid Thicket types found coexisting with the steeper and more frequent valley slopes. Finally, the southern coastal border of the study area is dominated by the Kasouga Dune Thicket vegetation unit with the presence of Cape Seashore Vegetation types.

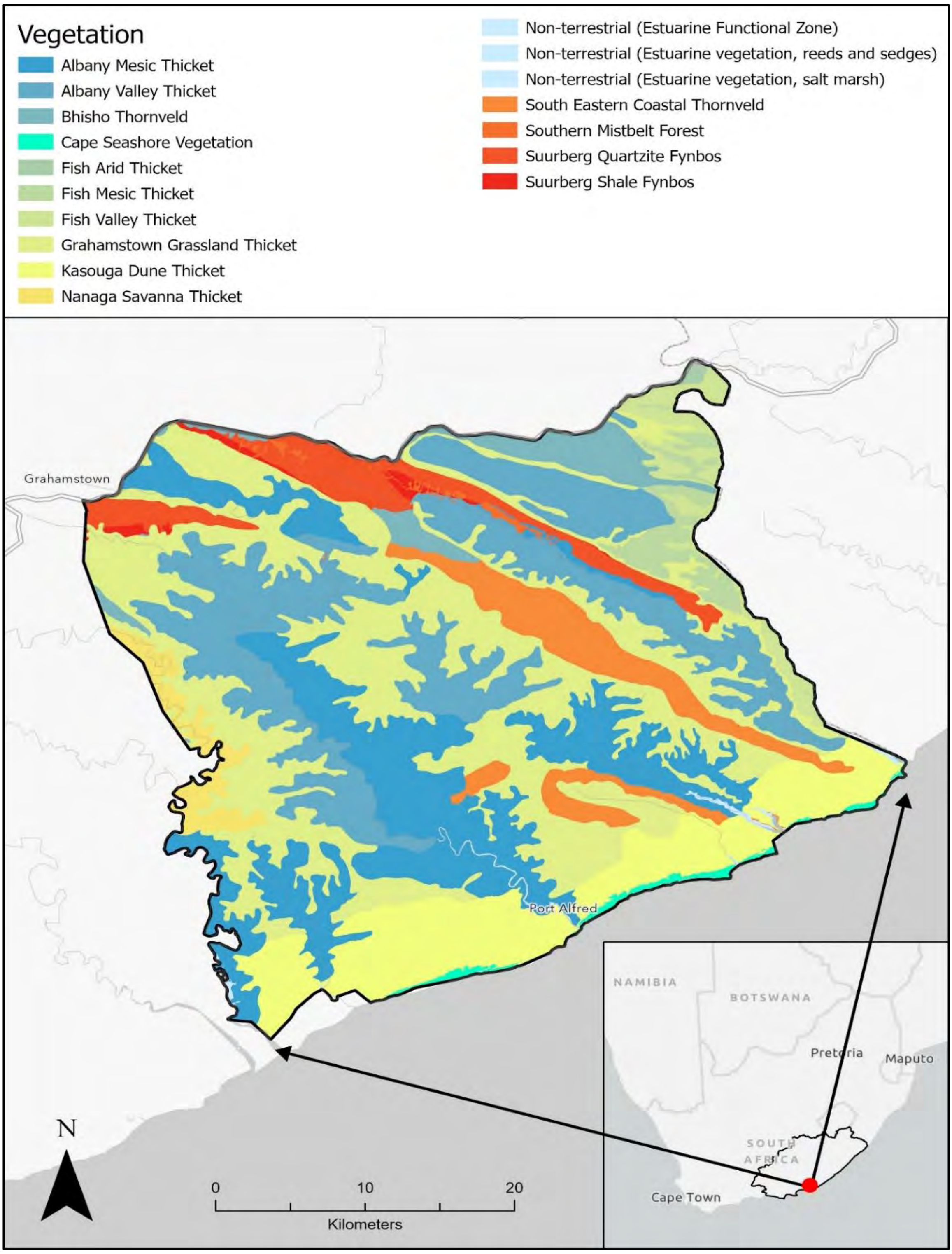


Figure 2: Vegetation of the study area. (Source: SANBI, 2012) (https://www.sanbi.org/).

2.3. Landscape and Geology

The study area presents diverse geological lithologies with two prominent groups: the Cape and Karoo Supergroups, as illustrated in Figure 3. The location of the study area is positioned at the easterly extent of the Cape Supergroup, resulting in a more abundant presence of the younger Karoo Supergroup geologies found in the region (Mpofu *et al.*, 2020). The Cape Supergroup formations developed approximately 250 million years ago (Norman, & Whitfield, 2006). Of the Cape Supergroup geologies found in the study area, the Bokkeveld Group, composed of sandstones and shales, is the oldest, with a small portion of the formation located in the southwest corner of the study area (Norman, & Whitfield, 2006). The Witteberg Group is also abundantly spread throughout the study area. The Witteberg Group is the youngest formation of the Cape Supergroup and comprises numerous formations, including the widespread Weltevrede and Witpoort formations throughout the study area (Booth, 1999). The Witteberg Group, including the Weltevrede and Witpoort formations, comprises quartz-rich sandstones and shales, and displays extensive folding (Norman, & Whitfield, 2006; Buttner *et al.*, 2015). The Karoo Supergroup was deposited approximately sixty million years ago (McCarthy, & Rubidge, 2013). The Dwyka and Ecca Groups of the Karoo Supergroup are present in the study area. The Dwyka Group is the oldest, comprised of tillite rocks.

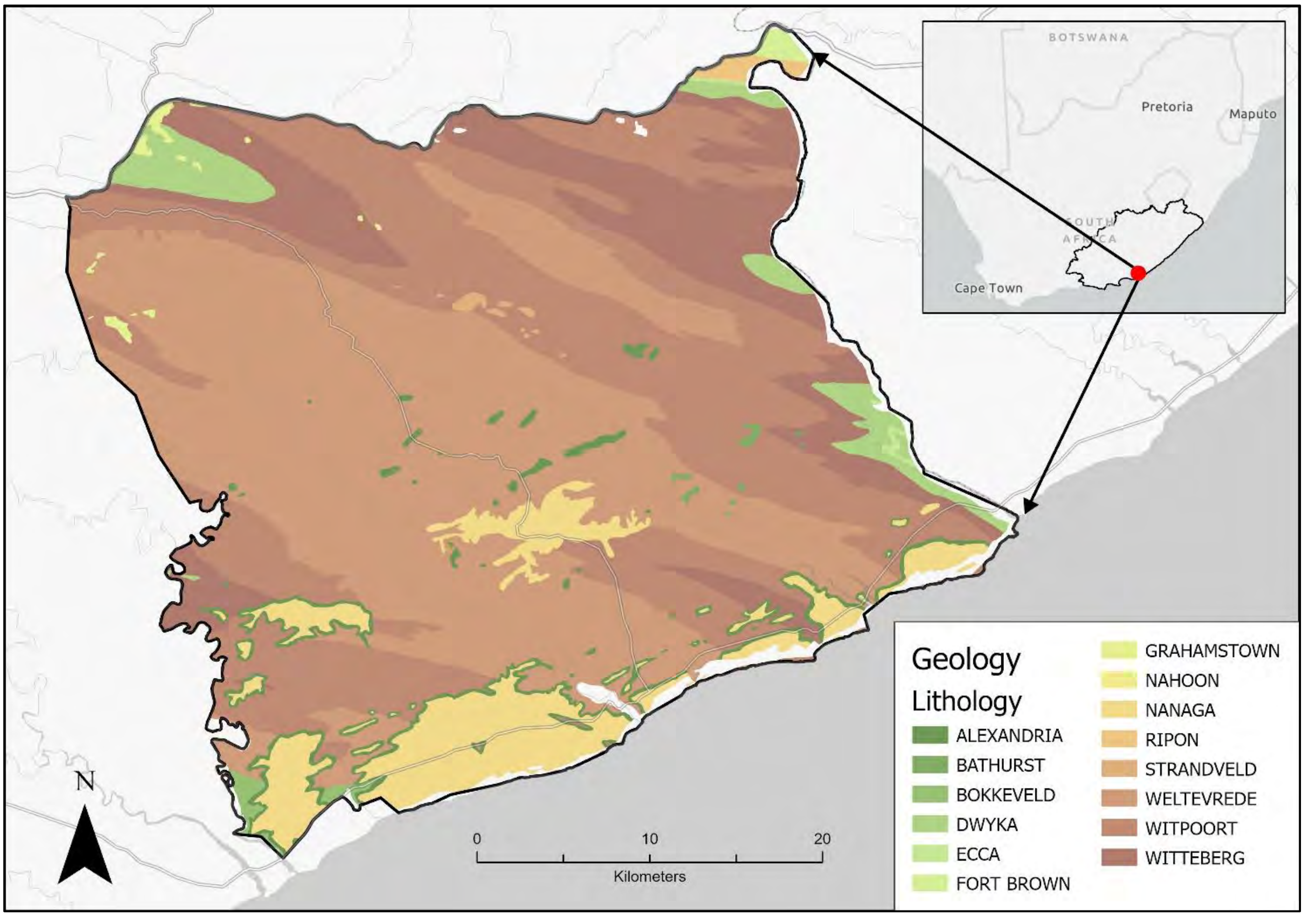


Figure 3: Geology of the study area (Source: Council for Geoscience, n.d.) (https://www.geoscience.org.za/).

The Ecca Group is formed of sandstones and shales resulting from millions of years of deposition. Numerous younger formations are present in the study area, including the Alexandria, Bathurst, Fort Brown, Grahamstown, Nahoon, Nanaga, Ripon and Strandveld formations, deposited approximately forty million years ago (Norman, & Whitfield, 2006). These formations were deposited more recently than the Cape Supergroup and are found above the underlying supergroups. The rich diversity of geology in this study area provides a variety of soil combinations to support the various life forms (Hoare *et al.*, 2006). The soil structure in the study area varies due to the wide variety of geological features. The well-defined Cape Fold Belt features provide a structured frame of steep valleys where the quartz sand establishes coarse and unstructured soils (Hoare *et al.*, 2006). On the other hand, the fine-textured soils derived from the Karoo Supergroup formations provide suitable locations for plant succession (Hoare *et al.*, 2006).

The study area contains a landscape characterised by steep river valleys and grassland plateaus created by the complex arrangement of the geological formations (Hoare *et al.*, 2006). The elevation of the study area varies from sea level in the southern region to a high of 870 metres along the northern boundary (Figure 4). Rivers have carved valleys in the region, resulting in steep slopes which

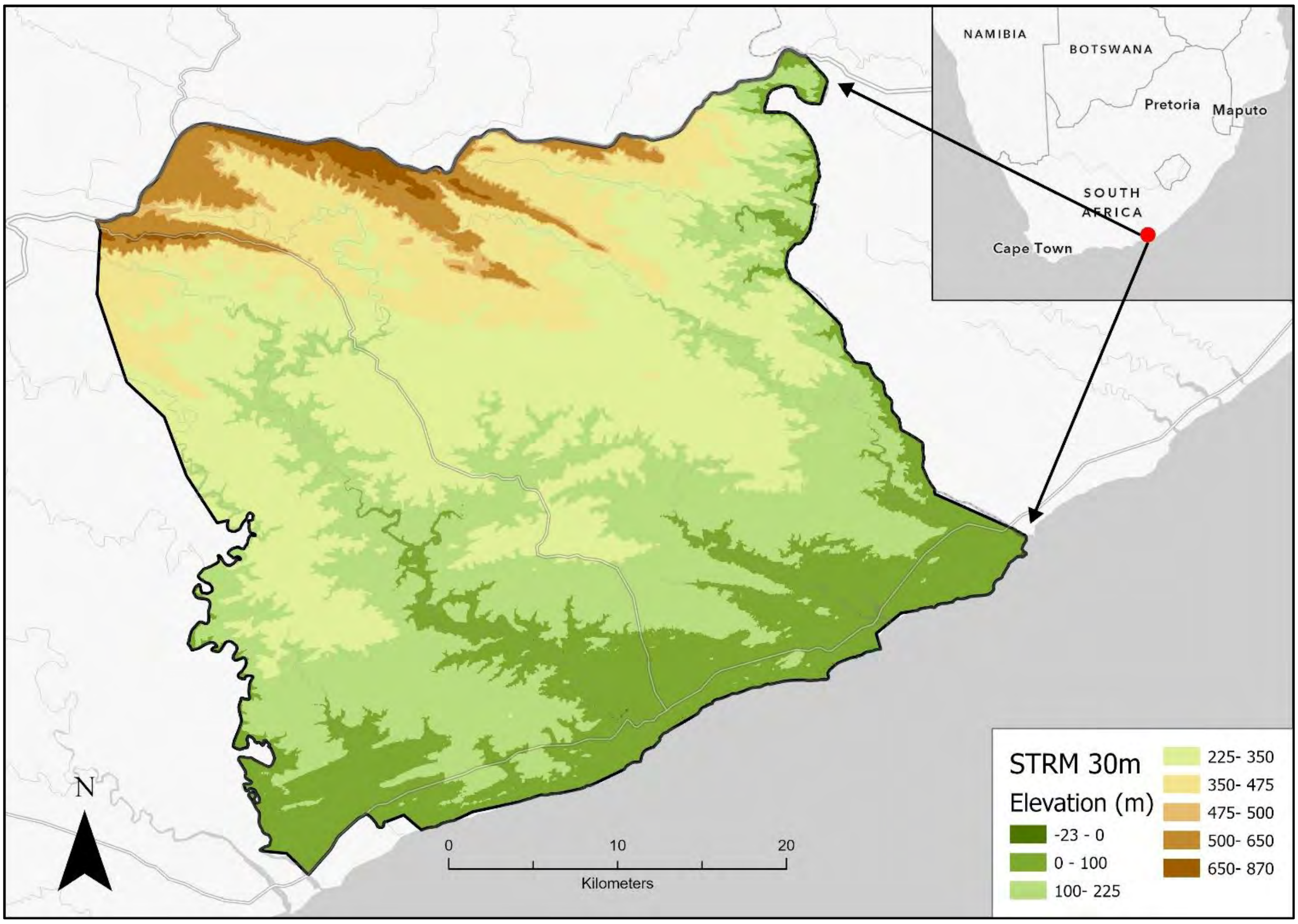


Figure 4: Digital Elevation Model (DEM) of the study area (Source: USGS Earth Explorer, 2023) (https://earthexplorer.usgs.gov/).

limit the land suitable for agriculture (Figure 5, A). Additionally, the region contains various slope orientations resulting from the geological formations (Figure 5, B).

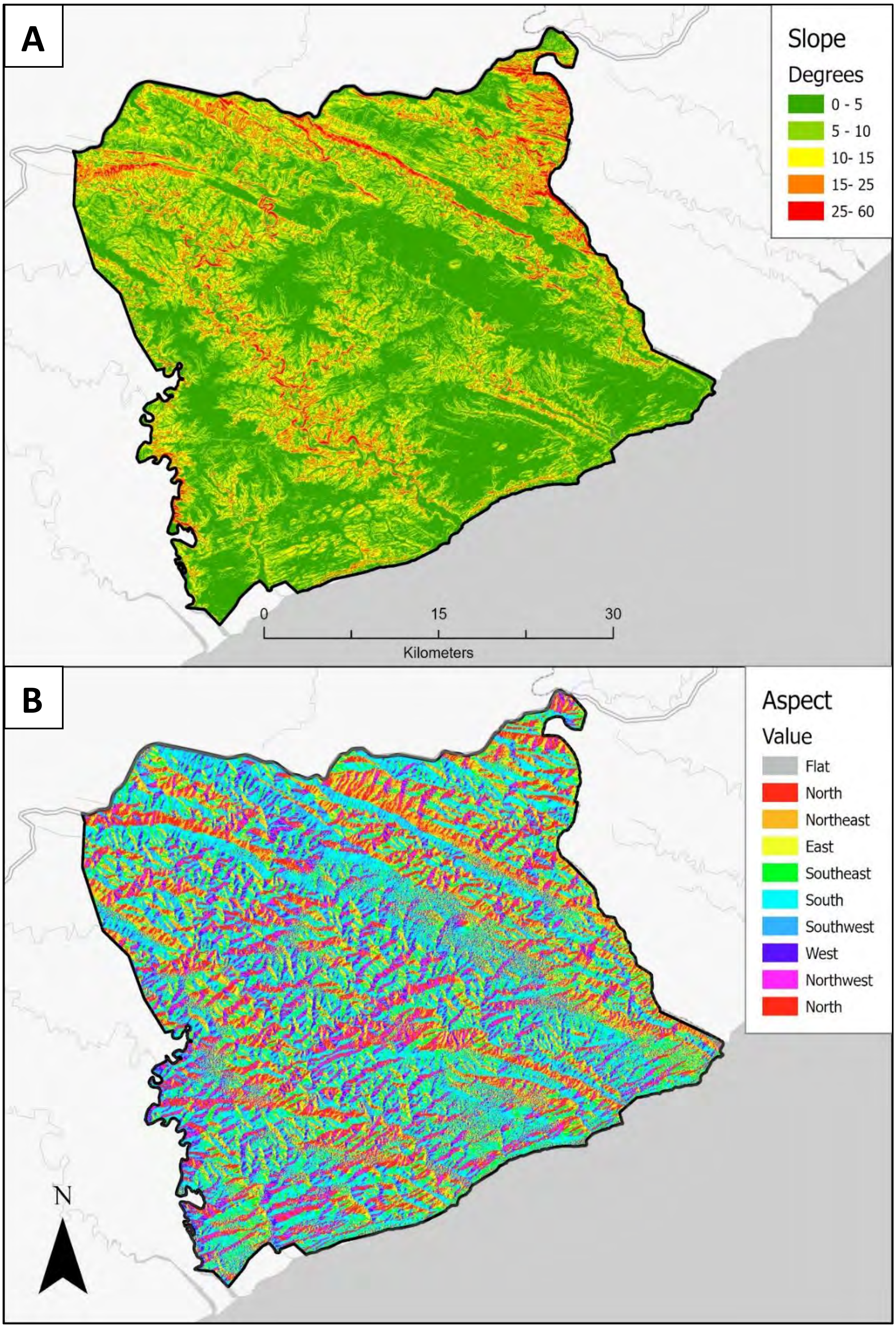
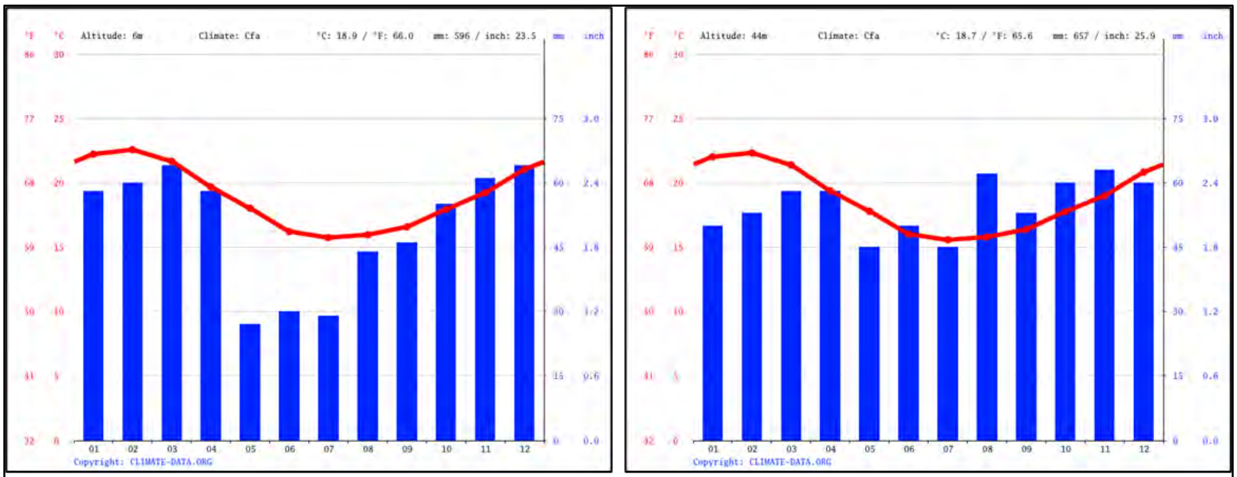


Figure 5: Slope (A) and Aspect (B) models (Source: USGS Earth Explorer, 2023) (https://earthexplorer.usgs.gov/).

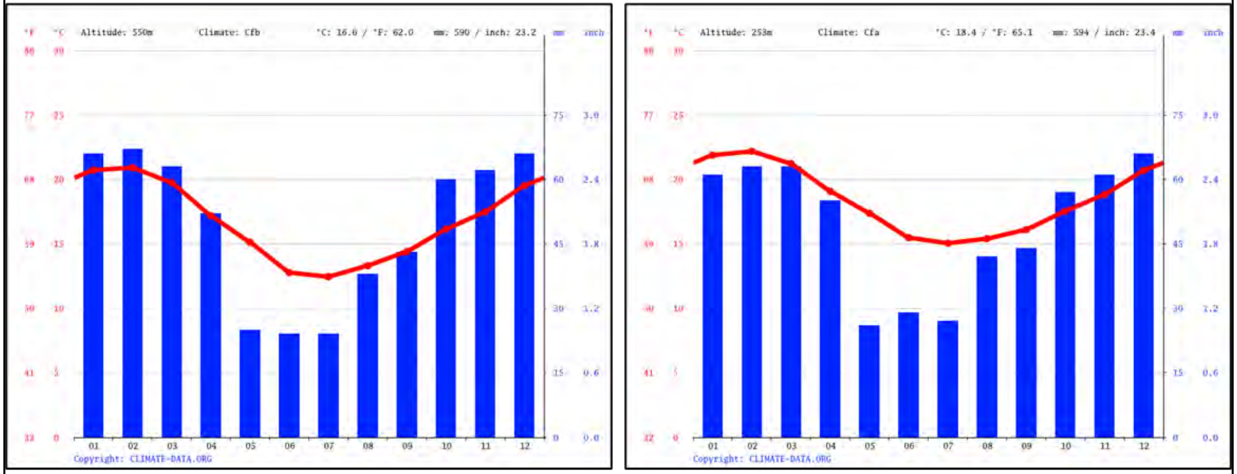
2.4. Climate

The study area is positioned between the two dominant climatic patterns in South Africa, creating an interesting climatic system (Hoare *et al.*, 2006). The climate of the study area is derived from the Climographs of four major towns. According to Figure 6, the region receives all-year rainfall from the southwest climatic system and summer rainfall from the northeast climatic system (Hoare *et al.*, 2006). However, rainfall is unreliable and unpredictable, resulting in common droughts for extended periods (Hoare *et al.*, 2006). The region receives 600 mm of rainfall annually, most during summer (Palmer *et al.*, 2010). The area experiences a mean annual temperature of 17°C, reaching 30°C in the summer months and dropping to less than 10°C in winter (Hoare *et al.*, 2006).



1) Port Alfred

2) Kenton-on-Sea



3) Makhanda (Grahamstown)

4) Bathurst

Figure 6: Climographs for the four towns in the study area (Source: Climate-Data.org, 2023) (https://en.climate-data.org/).

2.5. Socio-economic characteristics

The study area contains diverse socio-economic characteristics, overlapping two municipalities and containing, or in proximity to, several economically active towns. The study area lies primarily within the Ndlambe Municipality, with the northwestern portion occupied by the Makana Municipality. Both municipalities are characterised by a rural landscape, with agriculture and tourism controlling the economy. Four towns are located in the region of the study area. Port Alfred is situated along the southern border, Kenton-on-Sea at the southwestern corner, Makhanda along the northern border, and Bathurst in the centre of the study area. As stated earlier, the Ndlambe Municipality is the largest producer of pineapples in the country, contributing to over two-thirds of the country's yield (StatsSA, 2021). Biodiversity-related tourism significantly contributes to the area's economy, with numerous wildlife ranches in both municipalities. Within the study area, Port Alfred and Bathurst are the two dominant economically active towns situated within the Ndlambe Municipality. Kenton-on-Sea and Makhanda are economically active towns near the study area, along the southwestern and northern borders.

Municipalities contain wards, which are individual governing bodies that report to the municipal authorities. Each ward provides information regarding the human population captured by the national census (StatsSA, 2012). The region has six Ndlambe municipal-level wards: ward numbers 5, 6, 7, 8, 9 and 10, and one Makana municipal-level ward: ward 13 (Figure 7). The socio-economic characteristics of these are discussed below.

- Ward 5 includes the town of Bathurst, a quaint touristic village with a developing agricultural sector. It covers 7,724 hectares of the study area. Ward 5 has a total population of 6,318, with 1,806 households and an average annual household income of R29,400. Approximately 1,953 people are employed, and 33.2% of individuals are older than fifteen.
- Ward 6 is the largest in the study area, covering 118,284 hectares. This ward has a population of 8,990 people, 1,871 households, and an average annual income of R29,400. Approximately 55.8% (3343) of the inhabitants of fifteen years of age or older are employed.
- Wards 7, 8 and 9 are associated with the community of Nemato (Nelson Mandela Township), situated on the outskirts of Port Alfred.
    - Ward 7 covers 83 hectares, has a population of 5,393 people, 2,058 households, with an average annual income of R14,600 per household, and an employment rate of 33.7%.

  - Ward 8 covers 137 hectares, has a population of 4,332 people, 940 households, with an average annual income of R29,400 per household, and an employment rate of 38.8%.
  - Ward 9 covers 131 hectares, has a population of 6,385 people, 3,316 households, with an average annual income of R14,600 per household, and an employment rate of 39.8%.
- Ward 10 is associated with the town of Port Alfred, contributing 1,045 hectares of the study area. This ward's total population is 5,415, with 1,723 households earning an annual average income of R115,100. Approximately 54.8% of people able to work are employed.
- Lastly, ward 13 of the Makana Municipality is present in the northern region of the study area and contributes 29,534 hectares to the study area (Figure 7). This large ward has a population of 6,494, with 1,806 households earning an average annual income of R29,400 per household. Approximately 45.6% of individuals above 15 years of age are employed.

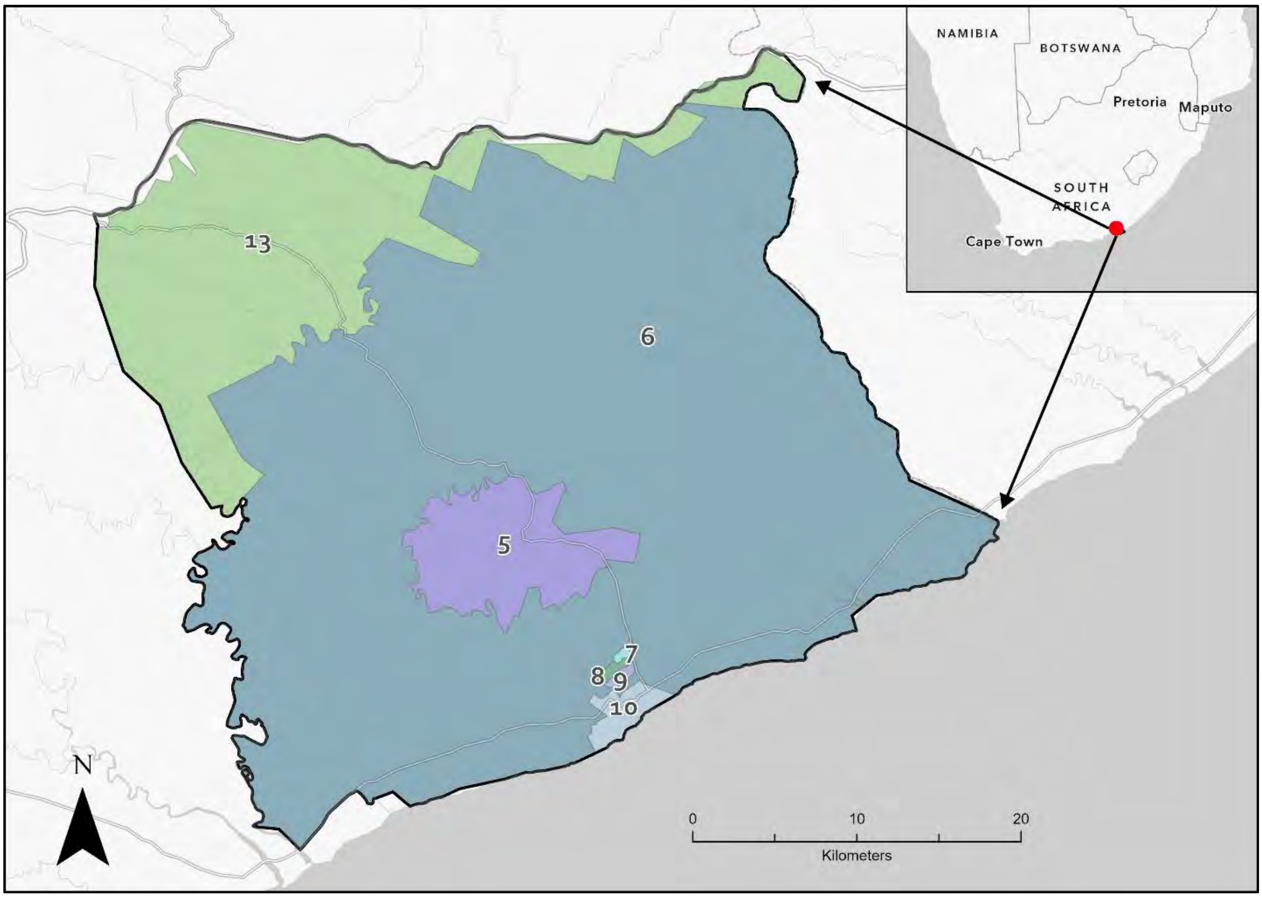


Figure 7: Ward number and location within the study area. Supporting information including population, household, employment, and income are presented for each ward. Tabulated data downloaded from the 2011 National Census (Source: StatsSA, 2012).

2.6. Pineapple production

The Ndlambe Municipality in the Eastern Cape province, where this study is located, is the leading producer of pineapples in South Africa, accounting for over 60% of the country's yield (StatsSA, 2021). The National Landcover (SANLC) (DEA, 2016) dataset is a raster-based GIS layer that displays a pixel-level identification of the land cover features throughout the country. The different land cover types are classified into unique and exceptionally detailed classes. "Cultivated commercial and permanent pineapple" fields are classified into a single class within the broader agricultural class. According to the SANLC dataset, in 2020 the study area contained 9,747 hectares of pineapple fields, 48% of the pineapple fields identified throughout the whole country (20,156.66 ha) (Figure 8). Furthermore, pineapple fields account for 6% of the study area's land cover.

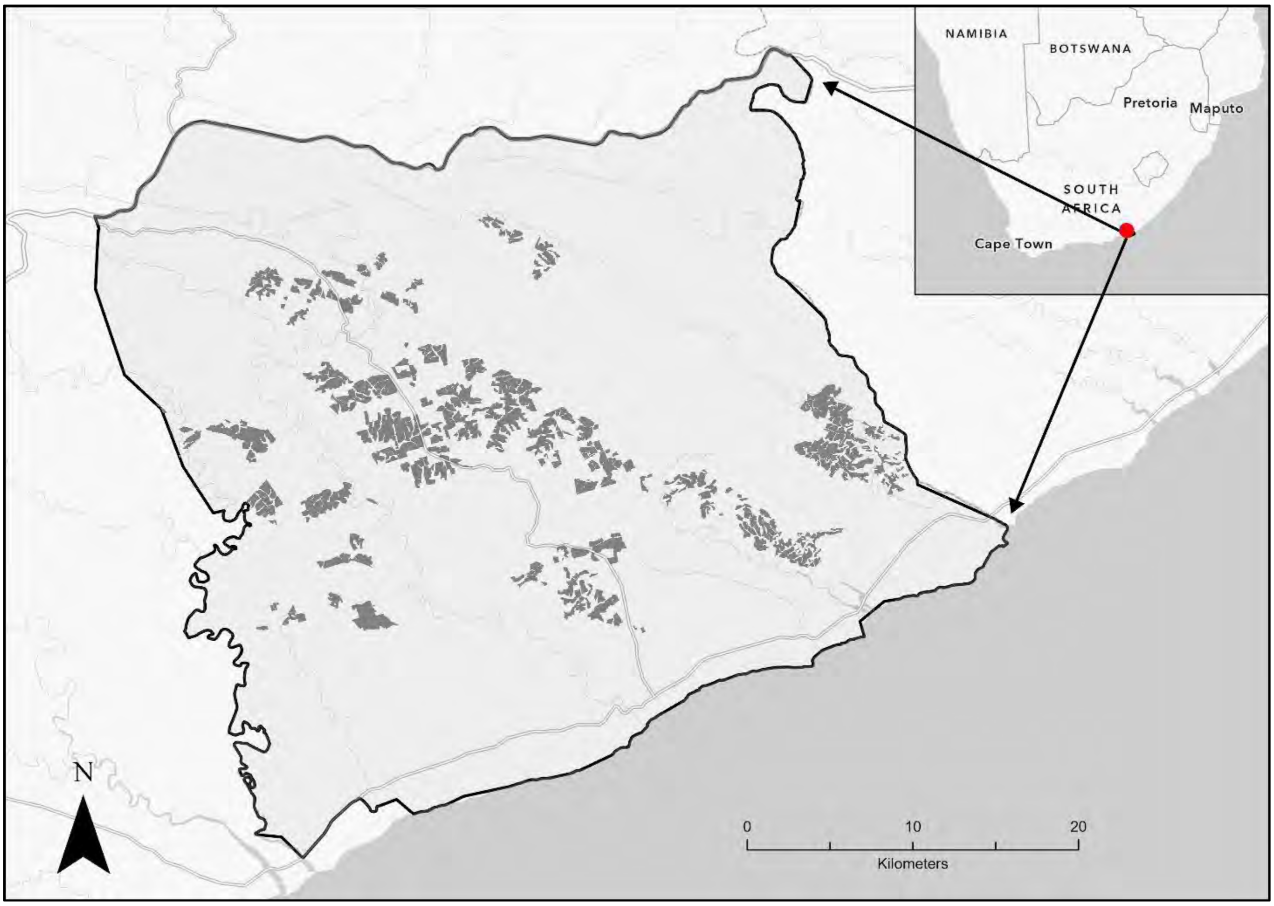


Figure 8: Extent of pineapple farms within the study area. Pineapple location data extracted from the 2020 National Landcover (SANLC) (Source: DEA, 2016).

2.7. Summary

The area for this research study encompasses a landscape containing essential relationships between the diverse vegetation, complex geology, unique climate, and various social factors and economic activities. Each factor cannot be investigated independently, as the actions of each factor influence the functionality of the entire system. Furthermore, the functions of each factor are influenced by global and historical actions. The geological features present in the study area are as a result of millions of years of tectonic activity. The unusual climate of the study area is the result of national climate systems influenced by global ocean currents. A combination of geological formations and the abnormal climatic systems in the study area enabled the development of the Albany Thicket Biome, a unique biome with remarkable vegetation characteristics. In addition, the unique combination of all these factors - geology, vegetation, and climate - created a haven for the successful production of pineapples. Pineapples are responsible for numerous employment opportunities for residents in the rural landscape. However, a disruption to the socio-ecological system can negatively impact the productive functionality of all factors within the system. Therefore, it is essential to examine the role of the pineapple industry within the socio-ecological system of the study area.

Following the discussion of the specific characteristics of the study area, a literature review has been conducted that investigates the global, national, and regional factors that have influenced the pineapple industry on a larger scale, and explores how the pineapple industry has, in turn, influenced the landscape. Examining the study area's political, economic, and social aspects is vital for establishing a holistic understanding of the past trends and patterns of pineapple cultivation, and the successes and limitations within. Furthermore, methodologies in the literature are reviewed to investigate the applications of remote sensing in assessing the intricate relationship between pineapple cultivation and the socio-ecological landscape.

CHAPTER 3: LITERATURE REVIEW

3.1. Introduction

To achieve the aims and objectives of this research study, a comprehensive examination of existing literature is presented in the subsequent sections. This literature review is divided into six parts:

1) An overview of the global pineapple industry, examining the origins and spread of pineapple cultivation across the world and the identification of the leading nations in production of the fruit.
2) A historical overview of the South African pineapple industry, investigating the introduction of pineapples to South Africa, the spread of pineapples within the country, and the growth of the national pineapple industry.
3) The factors that have influenced the South African pineapple industry, including examining the political, economic, and spatial transformations and obstacles.
4) The environmental consequences of pineapple farming, the literature surrounding its sustainability and its effects on the landscape.
5) LULCC patterns and trends in Africa, examining the patterns within the African context, with particular emphasis on the unique and floristically distinct Albany Thicket Biome.
6) GIS/remote sensing applications in analysing LULCC, including an in-depth evaluation of appropriate Remote Sensing methodologies well-suited for studying LULCC within an agricultural framework.

This comprehensive literature review lays the groundwork for a holistic and insightful exploration of the global and national factors that have caused a change in the pineapple industry, the relationship between pineapple cultivation and LULCC, and the identification of appropriate Remote Sensing methodologies to capture and analyse the change.

3.2. Overview of the global pineapple industry

The pineapple, known scientifically as *Ananas Microstachys*, originated in the tropical Brazilian rainforests (Strauss, 1960; Hossain, 2016). *Ananas Microstachys* was discovered by the Tupi Guarani Indians of the Amazonia region, who are considered the pioneers of pineapple domestication (Beauman, 2006). It is believed that the transition from the wild to the domesticated pineapple occurred around 2000 BCE, when the Amazonian tribes adopted a stable village lifestyle (Beauman, 2006), thus making the cultivation of pineapples a 4000-year-old practice.

Initially restricted to South and Central America, the pineapple remained unknown to the Old World until 1493, when Christopher Columbus encountered the fruit on the Caribbean island of Guadeloupe, during his second voyage (Beauman, 2006; O'Connor, 2013; MacEwen, nd). Columbus presented the pineapple to the King and Queen of Spain upon his return in 1496 (Beauman, 2006). The King expressed a preference for the fruit, leading to its association with royalty and the title "King of Fruits" (Beauman, 2006; MacEwen, nd).

After Columbus's encounter, Spanish and Portuguese fleets spread the pineapple to their colonies in the tropical and sub-tropical regions during the 16th and 17th centuries (MacEwan, nd). An illustration of the spread of pineapples by Spanish, Portuguese and Dutch sailors is presented in Figure 9 (Joy, & Anjana, 2016; Jiang, 2021). Portuguese explorers introduced pineapples to St. Helena, Madagascar, India, China, and West Africa between 1505 and 1602 (Jiang, 2021). Spanish voyages spread pineapples to East Asian countries, including the Philippines, Indonesia, Singapore, Taiwan, and Thailand, from 1565 to 1700, and eventually to Hawaii in 1813 (Jiang, 2021). In the 1660s, the Dutch introduced the fruit to South Africa (Jiang, 2021), a notable event which is discussed further in the following section.

The global cultivation of pineapples expanded rapidly due to these early introductions. Pineapples are produced across the globe in regions that experience tropical and sub-tropical climatic conditions (Hossain, 2016) in regions between latitudes 30°N and 33°58'S (Figure 9) (Hossain, 2016). Pineapple production requires warm and humid climates, with temperatures between 20°C and 30°C (Hossain, 2016). Frost and excessive heat can damage the fruit. Pineapples thrive in well-drained, gently sloped, non-compacted, and slightly acidic soil (4.5 – 5.6 pH) and are sensitive to waterlogging (Hossain, 2016). The global area and yield of pineapple cultivation has doubled since the earliest recorded statistics, illustrated by Figure 11. In 1961, the pineapple industry accounted for 369.31 hectares of land under pineapple cultivation, globally, and in 2021, the area rose to 1,046.71 hectares (Figure 11). Furthermore, in 1961, 10.37 tons/hectare of pineapples were produced globally, increasing to 27.36 tons/hectare in 2021 (Figure 11).

As discussed earlier, the locations that support pineapple cultivation are restricted to tropical and subtropical climatic regions. Figure 10 provides a proportional illustration of the area under pineapple cultivation (in hectares) and the yield (in tons) of pineapples for each continent. The data is acquired from the Food and Agriculture Organisation of the United Nations (FAO) (FAO, 2022). In both instances, Asia is the leading continent in the cultivation and production of pineapples (FAO, 2022). Central and

South America produce the second-highest yield of pineapples, followed by Africa and Oceania (FAO, 2022). Conversely, Africa has the second-highest area under pineapple cultivation, followed by the Americas and Oceania (FAO, 2022).

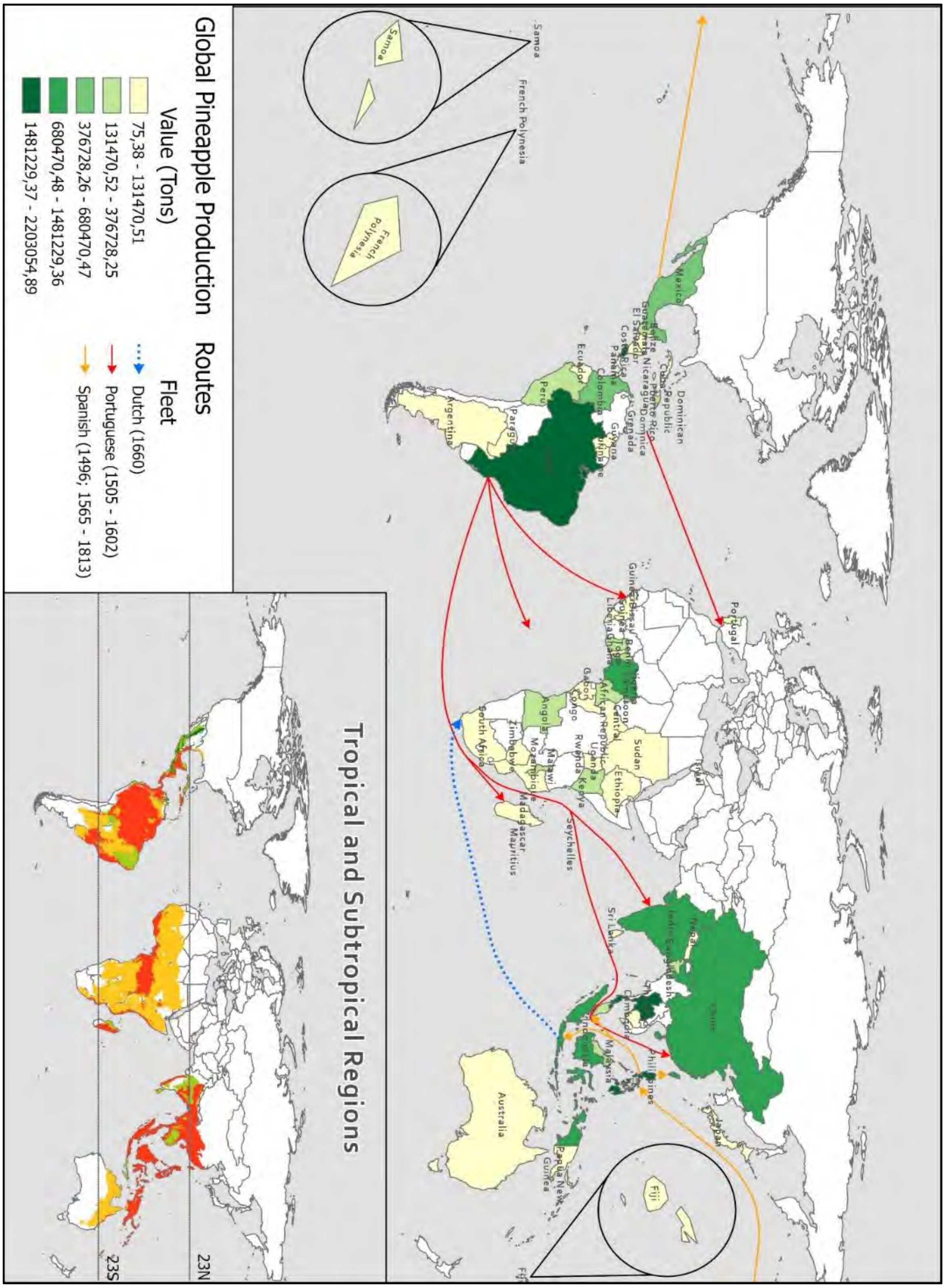


Figure 9: Global distribution of pineapples and the historic origins in each country (Data source: Jiang, 2021; FAO, 2022).

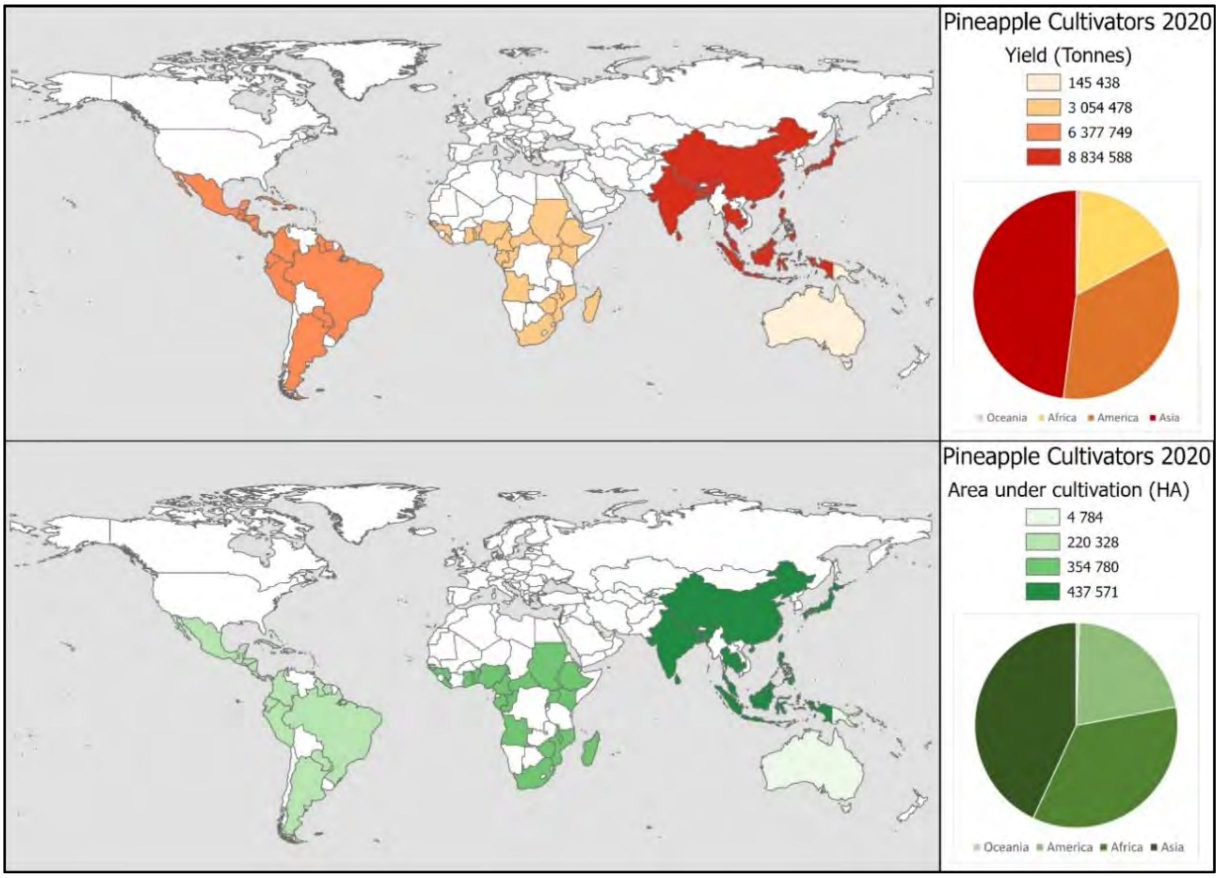


Figure 10: Global distribution of pineapples with associated yield and area statistics (Data source: FAO, 2022).

Figure 12 is an illustration of the top 10 pineapple-producing countries. Five Asian countries are in the Top Ten global pineapple-producing countries (FAO, 2022), including the Philippines, Indonesia, China, India, and Thailand. The Philippines is the global leader in the cultivation of pineapples, yielding a significant 2,702.55 tons in 2020, followed by Costa Rica, Brazil, Indonesia, China, India, Thailand, Nigeria, Mexico, and Colombia (FAO, 2022). Although Africa is competitive in the global pineapple trade, Nigeria is the only African country in the Top Ten list of pineapple-producing countries, as displayed in Figure 12 (FAO, 2022). South Africa is a relatively small pineapple-producing country in the global context, ranking 31st in pineapple production, yielding 87.96 tons in 2020 (FAO, 2022).

While South Africa’s contribution to the global pineapple industry is modest, the unique microclimate created by its southernmost cultivation point (33°58’S) yields distinct flavour profiles (Dean, 2018). The pineapple industry in South Africa plays a significant role in the country’s economy, generating international demand, providing employment opportunities, and stimulating local markets (Department of Agriculture, Land Reform and Rural Development (DALRRD) (DALRRD, 2019). The history of pineapple farming in South Africa has undergone significant economic, spatial, environmental, social and political changes since the arrival of the fruit. These aspects will be explored in subsequent sections.

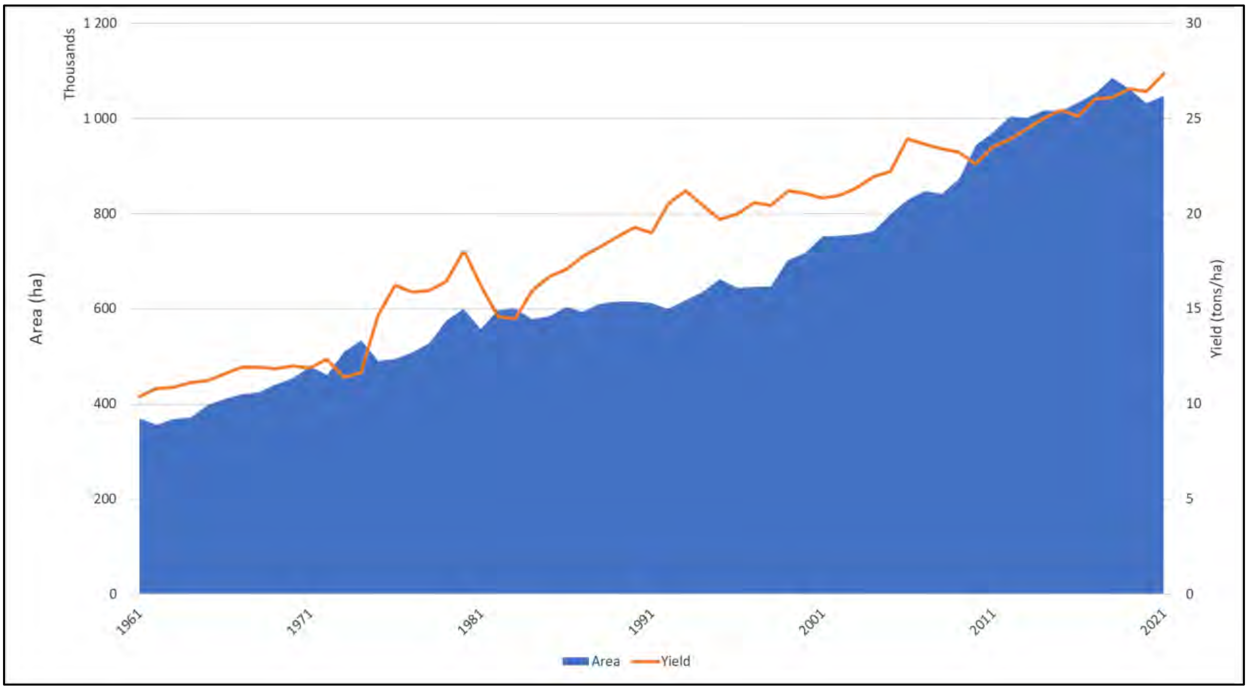


Figure 11: Global area (hectares) and yield (tons/hectare) of pineapple cultivation (Data source: FAO, 2022).

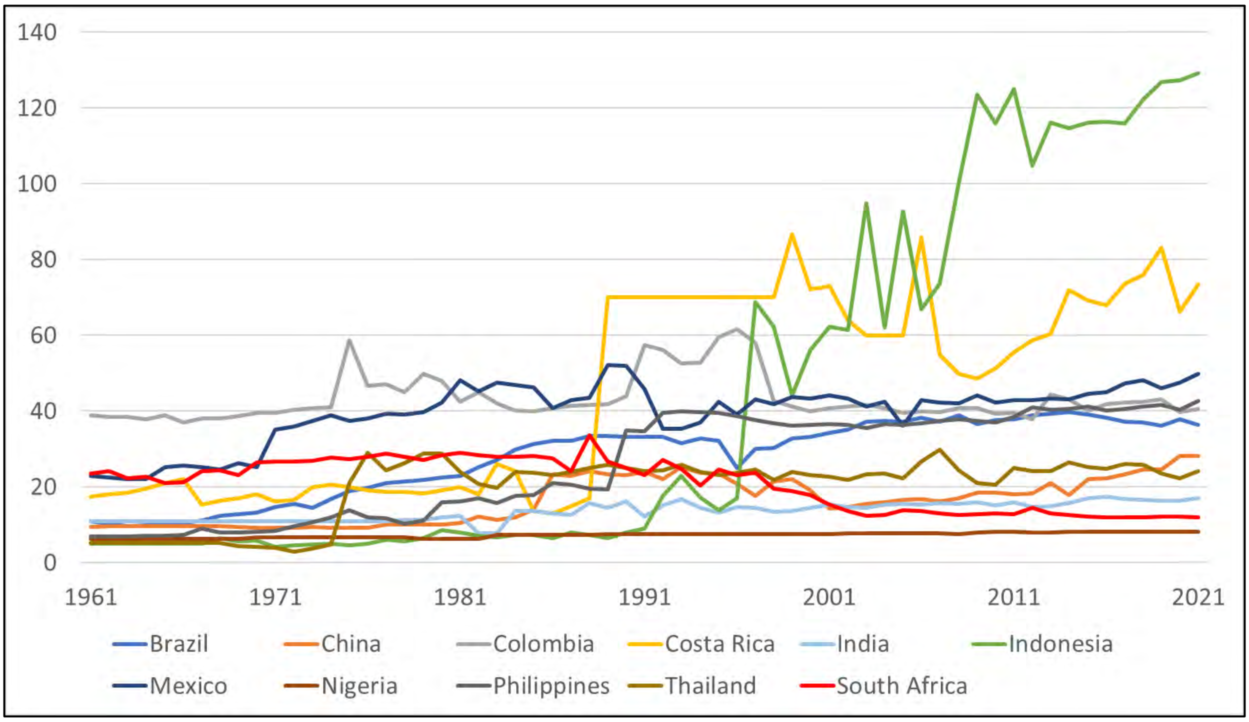


Figure 12: Line graph illustration of the Top Ten global pineapple producing nations in terms of tons produced. South Africa (31st) is added for reference (Data source: FAO, 2022).

3.3. A historical overview of the South African pineapple industry

Pineapple cultivation in South Africa has been an important agricultural activity for over a century. The origin of pineapples in the country can be traced back to the arrival of Jan van Riebeeck at the Cape of Good Hope in 1655 (Strauss, 1960). The subtropical plants were planted "in the shadow of Table Mountain" (Strauss, 1960; p. 4), a region that is incompatible with the cultivation of subtropical commodities. It was not until two centuries later, in 1865, that pineapples re-emerged in South Africa, finding more favourable conditions in the warm and humid climate of KwaZulu-Natal (Strauss, 1960; Boucher, 1991).

The successful introduction of pineapples in KwaZulu-Natal was facilitated by its ideal climate, characterised by high rainfall and moderate temperatures. This region became a thriving location for pineapple cultivation, allowing the subtropical plants to prosper and flourish (Strauss, 1960; Boucher, 1991). Following their successful domestication in KwaZulu-Natal, pineapples quickly spread to the Eastern Cape through trade exports (Strauss, 1960) and, in a modest barber shop in Makhanda (formerly Grahamstown), the most successful pineapple cultivation industry in South Africa was initiated.

Mr Charles Purdon, an influential figure in the pineapple industry, acquired several dozen Queen pineapple heads from a local barber shop in Makhanda (Strauss, 1960; Boucher, 1991). In 1865, Purdon planted these pineapple heads on a hillside at his farm in the Bathurst region, where they flourished (Strauss, 1960). Two decades later, in 1890, Charles Purdon's son, William Purdon, acquired the Cayenne pineapple variety from KwaZulu-Natal and focused on its production, marking an important milestone in the industry (Strauss, 1960). The Purdon family's pineapple production steadily increased over the years, leading them to supply neighbouring farmers with the necessary materials to cultivate pineapples (Strauss, 1960). This initiative kick-started today's large-scale and commercially active pineapple industry in the Bathurst district.

The Eastern Cape, specifically the Ndlambe Municipality encompassing Bathurst, has become the highest producer of pineapples in South Africa, accounting for more than 60% of the country's yield (DALRRD, 2019; StatsSA, 2021). The South African pineapple industry has evolved significantly since its introduction in the 1800s, influenced by various factors, as discussed in the subsequent sections of this literature review.

3.4. Factors influencing the South African pineapple industry

According to the literature, the South African pineapple industry has experienced significant volatility in production since the reintroduction of the fruit in the mid-1800s. Over time, the country has shifted from producing pineapples primarily for local consumption (Strauss, 1960) to becoming a competitive international exporter during the 1900s (Boucher, 1991). However, pineapple production in South Africa is modest, accounting for less than 1% of the country's agricultural output (StatsSA, 2021). Figure 13 illustrates the fluctuations in the yield of pineapples, processing, local markets, and international export trends, and the area under pineapple cultivation since 1984. The troughs and peaks of production can be attributed to significant political, economic, social, spatial, and environmental factors. In the following sections, the factors identified as significant elements in the literature during these pivotal moments in pineapple production are discussed.

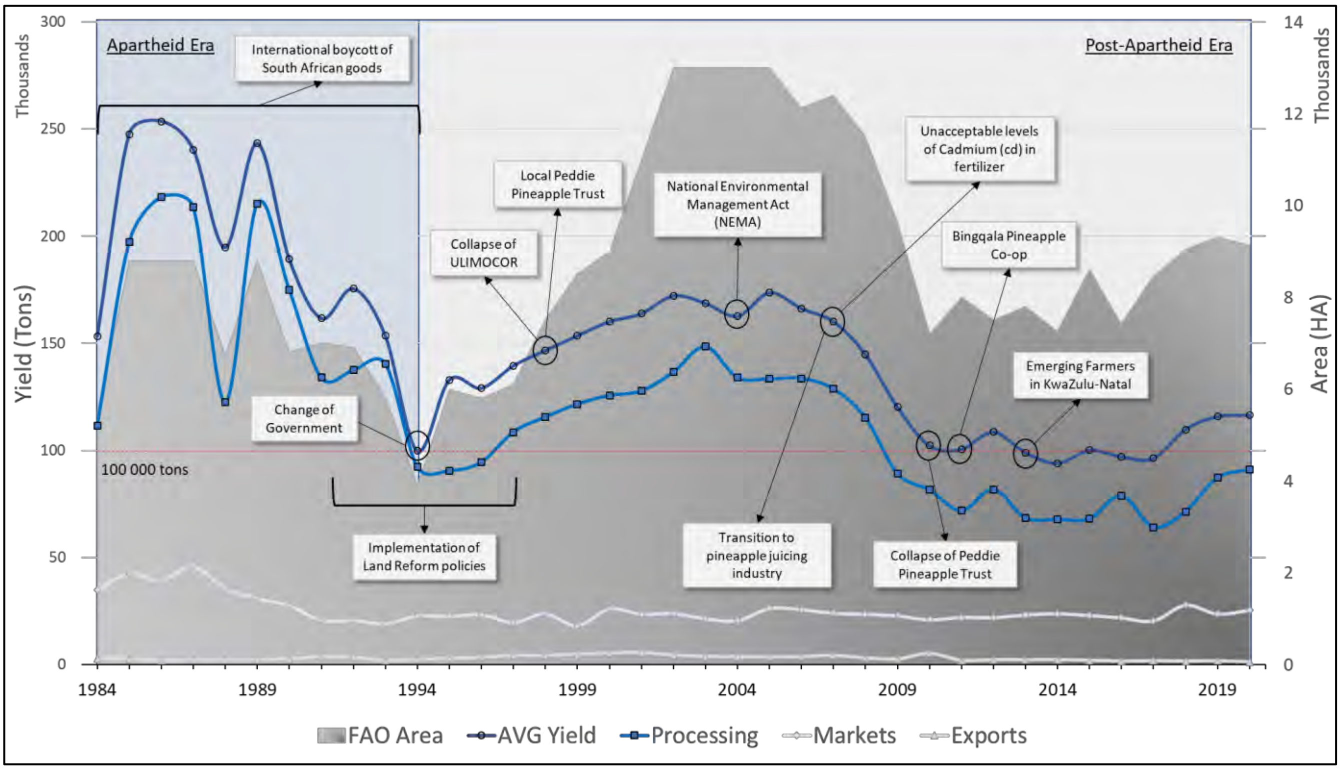


Figure 13: Yearly pineapple production in yield (tons) and area under cultivation (ha). Yield data created from the average between findings published by FAO (2022) and Abstract of agricultural statistics 2019 and 2022 (DAFF, 2021). Area under cultivation from FAO (2022). Processing, markets, and exports from Abstract of agricultural statistics 2019 and 2022 (Source: DAFF, 2021; FAO, 2022).

3.4.1. Political factors

Throughout the historical progression of South Africa, the nation has undergone numerous episodes of profound political transformation. The literature review in this section examines the pivotal political factors that have significantly influenced the pineapple industry, resulting in the troughs and peaks of the available cultivation (Figure 13). This analysis sheds light on the intricate relationship between these political factors and their consequential impact on pineapple production. The knock-on effects of the political scenarios on pineapple cultivation in the two distinct eras will be investigated, pivoting around the introduction of democracy in 1994. To illustrate these dynamics, specific case studies are presented, offering examples of the transformative shifts that have occurred over time.

3.4.1.1. The apartheid era (-1994)

This difficult period in South Africa's history profoundly impacted the country's political landscape. Apartheid was formally legislated in 1948, and abolished when South Africa became a democracy in 1994 (Figure 13). The apartheid era was characterised by widespread social and economic inequality in the agricultural sector, with white farmers controlling the commercial component through governmental support, and black farmers relying on subsistence farming due to significant barriers preventing entry and growth in the commercial markets (Aguera *et al.*, 2020). The government implemented policies to favour white farmers, who owned most of the land, and discriminated against black farmers.

Under the Group Areas Act of 1950, the government forcibly removed black farmers from their land and relocated them to designated "homelands" (Kloppers, & Pienaar, 2014). These areas were typically arid and unsuitable for farming, which led to a decline in agricultural productivity and increased poverty among black farmers (Kloppers, & Pienaar, 2014). Additionally, black farmers faced numerous obstacles in accessing resources and markets. They were often excluded from formal credit systems, had limited access to infrastructure, and faced discriminatory pricing and marketing practices (Kloppers, & Pienaar, 2014). Furthermore, the apartheid regime enacted laws that prohibited farm workers from organising trade unions and participating in collective bargaining practices, which led to poor working conditions and low wages (Aguera *et al.*, 2020).

The extreme inequality imposed by the apartheid laws prompted international boycotts against the South African government (Gurney, 2000). The anti-apartheid movement, which gained momentum in the 1970s and 1980s, aimed to end apartheid, and garnered support by mobilising international solidarity through extensive boycotts (Gurney, 2000). One of the anti-apartheid movement's key strategies was mobilising support for the international boycott of South African agricultural products. While the boycotts primarily targeted agricultural products such as citrus fruits and wine, their impact on the pineapple industry is evident in the fluctuations of pineapple production between 1961 and 1994, as illustrated in Figure 13. These boycotts significantly pressured the South African government to dismantle apartheid (Konieczna, & Skinner, 2019), and the international export markets became unpredictable during this period, resulting in economic instability in South Africa, as noted in the immense fluctuations in pineapple production (Figure 13).

In addition to the above, the Conservation of Agricultural Resources Act 43 of 1983 (CARA) was implemented by the South African government in 1983, which restricted the flexibility of South African farmers (de Villiers, 2007). The Act was established to conserve biodiversity, and provide erosion control and landscape management (Curtis, 2010). The Act stipulated that farmers required the necessary permission from authorities to clear virgin land which had not undergone anthropogenic transformation (de Villiers, 2007; Curtis, 2010). Furthermore, the Act encouraged farmers to protect cultivated lands against wind and water erosion and to ensure that the lands surrounding their premises were effectively protected. Curtis (2010) indicated that South African farmers were frustrated with the newly appointed legislation. However, the Act aimed to ensure the longevity of biodiversity and cultivated landscapes within the country (de Villiers, 2007).

Although the introduction of CARA restricted the flexibility of pineapple farmers in South Africa, the end of apartheid demonstrated a positive transformation in the pineapple industry following the change in government in 1994 (Figure 13). The transition to democracy initiated notable programmes, including land reform, to address historical inequalities. This shift towards equality marked a pivotal moment in South Africa’s agricultural sector, presenting opportunities for growth and development. The political changes affecting pineapple cultivation after the change of government in 1994 are discussed in the following section.

3.4.1.2. Post-apartheid era (1994-2020)

Since the end of apartheid in 1994, the South African government has implemented significant policy and legislative transformations to address the inequalities adopted by the previous government (Bhorat, & Kanbur, 2006). These new policies not only aimed to improve the livelihoods of previously disadvantaged people, but also to tackle economic and environmental issues, resulting in more consistent annual pineapple production (Figure 13).

One key initiative during this period was the land reform programme, which aimed to rectify the historical imbalances in land ownership and to promote social and economic justice (Kloppers, &

Pienaar, 2014). The programme consisted of three main components: land restitution, land redistribution, and land tenure reform (Walker, 2008; Kloppers, & Pienaar, 2014).

The land restitution programme focused on restoring land rights to individuals who had been dispossessed of their land under apartheid (Walker, 2008), including those individuals who had been forcibly removed from their land, subjected to discriminatory land laws, or had their land confiscated (Walker, 2008). The process involved either returning the land to the claimants or compensating them. In parallel, the land redistribution programme was introduced with the goal of transferring land from white landowners to black farmers to achieve a 30% transfer of agricultural land to black farmers by 2030 (Ntsebeza, 2007). This initiative involved the purchase of land from white farmers and its subsequent allocation to black farmers. However, the programme encountered several challenges, such as limited funding, capacity constraints, and difficulty in identifying suitable land for redistribution (Ntsebeza, 2007; Kloppers, & Pienaar, 2014). Another aspect of the land reform programme was tenure reform, which aimed at providing secure land tenure to individuals residing on communal land, including farm workers and people living in former homelands (Cousins, 2010). The objectives of this programme included the legal recognition of land rights, improved land administration, and increased access to resources and services (Cousins, 2010). However, the programme also faced challenges, such as a lack of political will, bureaucratic obstacles, and resistance from traditional leaders (Cousins, 2010; Kloppers, & Pienaar, 2014).

Despite various challenges, the implementation of these land reform policies has provided opportunities for historically disadvantaged individuals to acquire land and to establish their agricultural enterprises, an example of which is a small town in the former Ciskei homeland which has undergone numerous changes in ownership as a result of the land reform policies.

Initially excluded from the Ciskei homeland, Peddie was part of the former Cape Province (Igodan *et al.*, 1999). As the Ciskei homeland expanded through consolidation, Peddie's agricultural potential led to its inclusion within the Republic of South Africa. In 1984, the prosperous pineapple farms were acquired from white farmers and transferred to the Ciskei Agricultural Corporation, Ulimocor (Figure 13) (Zitshu, 2016). Peddie's already established and locally owned pineapple industry gained momentum, employing 400 local employees and joining international export markets (Igodan *et al.*, 1999). However, by 1995, the industry faced collapse due to a lack of financial, technological, and infrastructural support, resulting in the cessation of all agricultural operations by Ulimocor in 1997 (Zitshu, 2016).

Following the transition in governmental power, efforts were made to revitalise the pineapple industry in Peddie. In 1998, the Peddie Pineapple Trust was established with governmental aid and local stakeholder support (Figure 13) (Zitshu, 2016). The Census of Commercial Agriculture (CoCA) reported 375 hectares of pineapple fields in Peddie, and a production of 7,609 tons (StatsSA, 2003). However, corruption, insufficient governmental aid, and institutional weaknesses contributed to the downfall of the emerging pineapple industry (Zitshu, 2016). Subsequent statistics in 2007 showed a decline to only 12 hectares of pineapple fields, and a production of 430 tons (StatsSA, 2010). By 2017, the industry had collapsed entirely, with no yield produced that year (StatsSA, 2020).

The demise of the Peddie Pineapple Trust created an opportunity for business ventures in a town desperately in need of employment opportunities. Consequently, the Bingqala Pineapple Co-op was formed in 2011 by residents who had been severely affected by the collapse of Ulimocor (Figure 13) (Sitshinga, 2021). The cooperative successfully rejuvenated the dormant pineapple farms, aided by funding from the Department of Rural Development and Agrarian Reform (DRDAR) in 2014. This support revitalised an economically dynamic industry that currently employs over 30 residents (Sitshinga, 2021). Establishing the Bingqala Pineapple Co-op exemplifies the positive outcomes of government initiatives by promoting emerging black farmers in a traditionally white-dominated industry.

Although the change of government in 1994 initiated the move towards equality within the agricultural sector, a second environmental legislation act was established, further limiting the flexibility of farmers to clear virgin ground. In 1998, the National Environmental Management Act 107 of 1998 (NEMA) was established, adding to the groundwork implemented by CARA (De Villiers, 2007). The legislation within NEMA required farmers to undergo an Environmental Impact Assessment (EIA) before embarking upon the development of listed agricultural activities. Clearing of virgin land refers to "the transformation or removal of indigenous vegetation of 3ha or more, or of any size where the transformation or removal would occur within a critically endangered or an endangered ecosystem listed in terms of section 52 of the National Environmental Management: Biodiversity Act, 2004 (Act No. 10 of 2004)" (Government Gazette, 2004). Furthermore, an EIA is required for activities including the "Transformation or removal of indigenous vegetation on land that has been transformed over ten years ago…; Any phased transformation or removal of indigenous vegetation…; Removal or transformation of indigenous vegetation with, for example, a bulldozer to create firebreaks, roads or tracks…" (Government Gazette, 2004). NEMA aims to protect biodiversity and ensure that responsible agricultural activities occur within the environmental system (Curtis, 2010).

The historical period defined as the post-apartheid era saw South Africa undergo significant political transformation, benefiting previously disadvantaged societies and aiming to preserve the country's ecological integrity. In summary, the era is characterised by an attempt to restore social equality to the agricultural landscape, but also to restore ecological integrity, by ensuring responsible agricultural practices. The pineapple industry benefited from land reform and social equality programmes. However, the NEMA regulations constrained the growth of the pineapple industry. The economic factors affecting the pineapple industry are discussed in the following section.

3.4.2. Economic factors

The literature highlights that the overarching reason for the fluctuations in pineapple production is related to the influence of both global and local economic markets (Hossain, 2016; Dean, 2018). The theory of supply and demand drives the production of any agricultural commodity, specifically, in this instance, pineapple cultivation in South Africa. If the dominant pineapple-producing countries experience a productive season, the global supply of pineapples will outweigh the global demand, resulting in a decrease in the price of the fruit (Dean, 2018). Knowing that most South African pineapples are destined for the export market, as presented in Figure 13 earlier in the literature review, the production of pineapples in South Africa depends on the state of the global markets for the commodity (DALRRD, 2019, StatsSA, 2021).

A noteworthy example is the rise of pineapple production in South Africa due to World War II (Strauss, 1960). The dominant supply regions of pineapples, namely Malaysia and Taiwan, were negatively affected during the war (Strauss, 1960). With the resulting decline in the worldwide supply of pineapples, a significant gap was created for new and emerging pineapple industries to take advantage of the spike in the price for pineapples following the increased demand for the fruit. South Africa and Australia benefited greatly from this opportunity and became two of the primary suppliers of pineapples during that time (Strauss, 1960).

In South Africa, the pineapple industry expanded rapidly after the war. Prosperous farmers relocated to the Eastern Cape, cultivating intensely on previously established lands, and ploughing new lands to produce the fruit (Strauss, 1960). This was short-lived, however, as the price of pineapples settled due to the overproduction of pineapples by South Africa and Australia, along with the recovery of the Malaysian and Taiwanese industries post-war (Strauss, 1960). Many farmers in the Eastern Cape went bankrupt, and farm consolidation was initiated. In the 1950s, approximately 400 farmers were present in the Eastern Cape (Strauss, 1960). This number significantly decreased to 80 in the 1980s, and 23 in 2015 (Dean, 2018). Nonetheless, the South African pineapple industry has continued to produce processed and fresh fruits to contribute to the country’s overall economic sector (DALRRD, 2020). According to Boucher (1991), South Africa was ranked the eighth-largest producer of pineapples in the world during the 1990s. Today, however, South Africa is ranked the 31st most prominent producer of pineapples (FAO, 2022), indicating a significant rise in competition in the global market.

Conversely, unfavourable growing conditions may limit the global supply, increasing the demand and boosting the price of pineapples (Hossain, 2016). Additionally, changes in exchange rates and inflation may influence the annual price of exported commodities (Jaji *et al.*, 2018). Therefore, farmers continually operate based on the economics of scale theory, whereby the production rate depends on the return value with the outcome of earning a profit, factoring in the production, employment, processing, and export costs (Dean, 2018).

In addition to unfavourable growing conditions, uncontrollable factors can ruin even the most dominant agricultural industries. A significant incident occurred in 2004 during which a fertiliser, created in China and exported to farmers in South Africa, contained an exceedingly high level of the heavy metal toxin cadmium (Cd) (Hill *et al.*, 2012; Venter, 2016). The compromised fertiliser was sold to pineapple farmers in South Africa who unwittingly used the fertiliser on the crops (Figure 13). All crops exposed to this fertiliser were infected, and could not be sold (Hill *et al.*, 2012). If even one fruit in a yield was identified to contain an unacceptable level of Cd, the entire harvest was rejected, causing significant economic strain on the growers (Venter, 2016). Pineapple growers, processors, transporters, distributors, and other stakeholders suffered severe financial losses (Hill *et al.*, 2012).

However, the processing factories in South Africa coincidentally began the transition towards juice concentrate before identifying the toxin (Hill *et al.*, 2012). Fruits with varying levels of cadmium could be mixed to create a juice that displayed acceptable levels of Cd, resulting in it being suitable to sell in the global markets (Venter, 2016). The result of this single devastating scenario was a complete change to the South African pineapple industry, as the industry currently only exports juice concentrate. In some cases, however, several pineapple farms had to shut down as the burden of toxic fertiliser was too severe (Hill *et al.*, 2012; Venter, 2016).

In summary, various economic factors reshaped the South African pineapple industry and altered the spatial arrangement of cultivators in the country. As a result, South Africa has found a niche to compete against global competition with the world's most experienced and successful pineapple-producing countries. The following section will discuss how the South African pineapple industry has changed in a spatial context.

3.4.3. Spatial factors

The spatial distribution of pineapples in South Africa depends on numerous factors. The most notable factor is the climatic requirements of the fruit. As discussed previously in the literature review, pineapple cultivation requires warm and humid areas with temperatures of between 20°C and 30°C (Hossain, 2016). Temperatures below this range will result in constrained fruit growth and damage caused by frost (Hossain, 2016), while temperatures above this range will result in potential sunburn damage to the fruit (Hossain, 2016).

As previously discussed, pineapples were initially cultivated in parts of the Eastern Cape and KwaZulu-Natal provinces. According to Boucher (1991), South Africa's four prominent pineapple-producing areas were the Eastern Cape coastal belt, the Levubu region of Limpopo, and the Hluhluwe and Umkomaas regions of KwaZulu-Natal. However, the Eastern Cape and KwaZulu-Natal provinces are the only remaining productive pineapple-producing regions (DAFF, 2020). Figure 14 illustrates the national spatial variation of pineapple cultivation, based on data obtained from the National Land Cover datasets since 1990 (DEA, 2016).

The Eastern Cape and KwaZulu-Natal provinces are the only two provinces that contain pineapples as a land cover type in the four National Landcover datasets since 1990 (DEA, 2016). The Eastern Cape province is the dominant producer of pineapples in the country, accounting for over 70% of the country's yield (Figure 14) (DEA, 2016). The Smooth Cayenne pineapple is the primary variation grown in the Eastern Cape, accounting for 95% of production in the province (Boucher, 1991; Venter, 2016; Dean, 2018). This variation is well-suited for processing and canning (Hossain, 2016). In contrast, the KwaZulu-Natal province primarily grows the Queen pineapple variation, which is more suitable for fresh consumption in local markets, or for international exports (Dean, 2018; DALRRD, 2019).

The changes in the spatial distribution of pineapples are attributed to the political and economic factors discussed in the previous sections. Political interventions have influenced the nature of the farmers, and where pineapples can be cultivated, and the economic changes have influenced the extent to which pineapples are cultivated. A holistic discussion of the consequences of pineapple cultivation on the landscape, with respect to these factors, is presented in the following section.

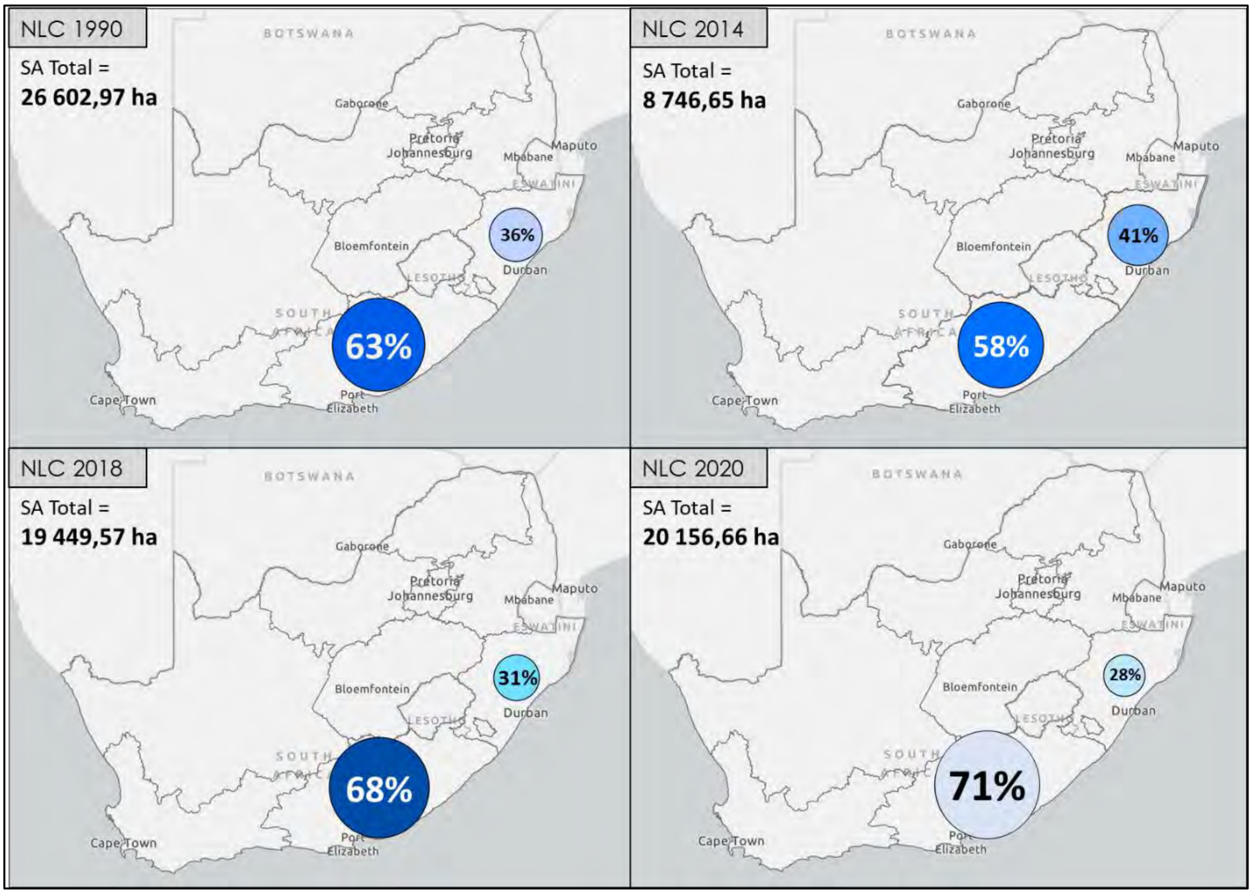


Figure 14: Geographic distribution of pineapple growing areas in South Africa. Pineapple classes extracted from the SANLC datasets for 1990, 2014, 2018 and 2020, and rounded off to the nearest whole number (Data source: DEA, 2016).

3.5. Environmental consequences of pineapple cultivation

The cultivation of pineapples has been scrutinised for promoting soil erosion, due to the land preparation and farming techniques adopted by pineapple growers, since the 1900s (Boucher, 1991). "Pineapple farmers are, therefore, by their cultivation practices, accelerating soil erosion" (Boucher, 1991, p. 25). According to Boucher (1991), soil erosion of pineapple farms is caused by a combination of several factors.

First, the ridges on which pineapples are grown may improve yield but can encourage soil loss due to the creation of "micro slopes". Water is concentrated in the furrows between the ridges, which subsequently causes a greater velocity of surface runoff than infiltration. Furthermore, pineapples are primarily grown on slopes, which further encourages surface runoff. Second, Boucher (1991) states that the leftover plant material is commonly burnt, after which the soil is mechanically broken down to a fine tilth, making the land more susceptible to erosion. Additionally, the consistent breakdown depletes vital nutrients in the soil which, therefore, requires more fertilisers to allow for future growth.

Third, Boucher (1991) explains that the pineapple lands are left exposed between the growing stages, and the subsequent lack of ground cover significantly encourages soil erosion.

In contrast to Boucher (1991), Strauss (1960) interviewed sixty-nine pineapple growers in the Eastern Cape and concluded that most plant pineapples "on sloping ground to ensure the best drainage and the layout is planned to eliminate soil erosion as much as possible" (Strauss, 1960 p. 54). However, pineapples are farmed differently today, with a greater focus on sustainability. In an interview with Dean (2018), Mark Harris, the largest producer of pineapples in the country, explained the growing practices that farmers adopt today. Instead of burning the leftover plant material after harvesting, as Boucher (1991) identified, the material is knocked down and worked back into the soil as mulch. This process requires less heavy mechanical equipment and external chemicals. Furthermore, pineapple growers constantly monitor the state of the soil with scientific stakeholders, to identify the resources that need to be replenished into the soil before replanting can begin (Dean, 2018). Collaborations with entomologists have decreased the need for chemical insecticides by 70% over the past ten years due to consistent monitoring of harmful pests (Dean, 2018).

The contrasting information in the literature concerning the consequences of pineapple cultivation initiated an in-depth examination of the LULCC prevalent in an African context. It is unclear to what extent the South African pineapple industry has reshaped the landscape, emphasising the relevance of this research study. To fill this knowledge gap, the patterns and trends of LULCC in an African context are discussed in the following section. Thereafter, the various Remote Sensing methodologies of LULCC identification in an agricultural context are discussed.

3.6. Land use and land cover change (LULCC)

The need for accurate and timely data of the Earth's surface is continuously growing, as this information is essential for decision-making in land-based applications (Assede *et al.*, 2023). Land on Earth is categorised into two types: land use and land cover. Land use refers to how humans utilise land for agriculture, urban development, or industrial purposes (Fairbanks *et al.*, 2000), while land cover refers to the physical characteristics of the Earth's surface, such as forests, wetlands, grasslands, or barren areas (Fairbanks *et al.*, 2000). Understanding the features and activities present at the landscape level at any given time enables researchers to investigate the changes between land covers and land use.

LULCC is a topic that refers to the modifications that occur on the Earth's surface, particularly regarding the transformation of natural landscapes into human-dominated environments. LULCC is a global phenomenon with significant implications for ecosystem services, biodiversity, and the provision of natural resources (Lambin, & Meyfroidt, 2011). It has been identified as a critical driver of environmental change, including climate change, habitat loss, and soil degradation (Lambin, & Meyfroidt, 2011). The impacts of LULCC are often complex and interrelated, with feedback mechanisms that amplify the effects of land use changes.

The patterns of LULCC vary across the globe and depend on the particular country's governance. The literature surrounding LULCC is growing in Africa, even as Africa is recognised as a global climate change hotspot (Fairbanks *et al.*, 2000; Assede *et al.*, 2023). Africa is home to diverse fauna and flora and boasts centres of exceptional endemism; however, it also holds areas with poor environmental management, often due to powerful global actors (Assede *et al.*, 2023). The drivers and trends of LULCC in an African context are discussed in the following section.

3.6.1. Patterns in Africa

Studies in Africa have identified land-use change as the most significant cause of biodiversity loss (Kindu *et al.*, 2015; Gondwe *et al.*, 2019; Assédé *et al.*, 2020). The most prominent consequence of land-use change in Africa is a decline in woody cover (Assede *et al.*, 2023). Biomes across the African continent have lost 21.6% of species richness, 42% of species abundance, a further 5.6% loss of species richness, and 12.3% loss of species abundance is projected by the year 2100 (Assede *et al.*, 2023). The subsequent effects of this transformation include soil erosion, nutrient cycling modification, hydrology changes, increased albedo, and greater greenhouse and aerosol gas concentrations (Lambin, & Meyfroidt, 2011).

Studies have been undertaken to identify the drivers of LULCC in the African context. A noteworthy review is that of Assede *et al.* (2023), who examine the trends and patterns of LULCC in African countries. The study highlighted that the most significant drivers of LULCC in Africa are changes in agricultural practices and population growth (Assede *et al.*, 2023), which complement the global drivers of LULCC (Lambin, & Meyfroidt, 2011). The relationship between these two drivers creates a negative feedback loop that initiates a continual downward spiral of landscape degradation (Lambin, & Meyfroidt, 2011). Therefore, it is vital to implement governance regulations into these socio-ecological systems to maintain food security while addressing biodiversity targets.

The patterns of LULCC are not uniform across African countries. In Africa's Sahelian Zone, Assede *et al.* (2023) noted an increase in forest cover and a promising recovery of vegetation and canopy cover. In West Africa, a significant decrease in vegetation cover was noted, resulting from the conversion to cropland (Assede *et al.*, 2023). Furthermore, Assede *et al.* (2023) presented a notable decrease in soil resources and quality in East Africa due to agricultural landscapes. Following the review of LULCC in Africa by Assede *et al.* (2023), the subsequent section will provide an in-depth discussion of the patterns and trends of LULCC in South Africa.

3.6.2. Patterns in South Africa

South Africa boasts a highly diverse landscape, including nine floristically distinct biomes: Albany Thicket, Desert, Forest, Fynbos, Grassland, Indian Ocean Coastal Belt, Nama-Karoo, Savanna, and Succulent Karoo (Mucina and Rutherford, 2006). The biodiversity in these biomes ranks South Africa as the third most diverse country in the world, containing three of the 34 global biodiversity hotspots (Skowno *et al.*, 2019). South Africa contains approximately 458 different ecosystem types, 80% endemic to the landmass (Skowno *et al.*, 2019). The biodiversity structure of each ecosystem is essential for the health and resilience of the system to produce functional ecosystem services. Ecosystem services provide direct and indirect benefits to humans, including water supply and purification, oxygen purification, ecotourism, recreation, nutrient cycling, and pest control (Skowno *et al.*, 2019), to name a few. Natural capital is a valuable resource in South Africa as its presence provides the direct and indirect resources needed for human well-being, and it also provides a sustainable platform for the longevity of the relationship between nature and humans.

Natural hotspots are fragmented within South Africa's diverse cultural landscape. Approximately 22% of South Africa's natural landscape has been altered or lost since the arrival of European settlers in the 1700s and 1800s (Skowno *et al.*, 2019; Carvalho *et al.,* 2022). Several studies have attempted to assess the LULCC in South Africa, the findings of which are presented below:

1. The SANLC land cover change dataset noted that between 1990 and 2020, mining areas increased by 161,169 hectares (58%), commercial pivot and irrigated cultivation increased by a significant 717,287 ha (297%), commercial cultivation increased by 1,498,816 ha (12%), urban areas increased by 886,359 (36%), and planted forests increased by 596,012 ha (31%) (DFFE, 2023).

2. Wynberg (2002) identified that in the 1990s, 16.5% of the country's landscape was transformed, and 10.1% was degraded.
3. Schoeman *et al.* (2013) identified that between 1994 and 2005, a 1.2% increase was seen in transformed land associated with urbanisation, cultivation, plantation forestry, and mining, from 14.5% in 1994 to 15.7% in 2005.

4. Ngcofe *et al.* (2019) identified, between 2013 and 2017, a 341.71 hectare (0.15%) decrease in natural wooded land, a 788.42 hectare (0.85%) decrease in shrublands, a 490.74 hectare (3.61%) increase in wetlands, a 1042.38 hectare (2.68%) increase in built-up areas, and a 140.66 hectare (3.83%) increase in mines.

Land cover changes resulting from land use activities vary regarding the historical, political, and socio-economic influences experienced in the region (Palmer *et al.*, 2010). The transformation rate is not uniform across the country as different factors affect regions. The Ndlambe Municipality in the Eastern Cape, where this study is focused, is home to a mosaic of different land use activities that have fragmented the unique and endemic Albany Thicket Biome. The following section will discuss the literature surrounding LULC in the Albany Thicket Biome.

3.6.3. Patterns in the Albany Thicket Biome

The Albany Thicket Biome has experienced significant levels of degradation, causing noticeable landscape fragmentation (Lloyd *et al.*, 2002; Vlok *et al.*, 2003; Hoare *et al.*, 2006; Carvalho *et al.*, 2022). Large-scale vegetation clearing for crop production, and the unsustainable browsing of domestic livestock, are the primary drivers of vegetation degradation in the Albany Thicket Biome (Skowno *et al.*, 2019; Carvalho *et al.*, 2022).

Before the arrival of European settlers in the 1700 and 1800s, human populations in the region were sparse, with most activities concentrated along the Sundays River Valley (Hoare *et al.*, 2006; Skowno *et al.*, 2019; Carvalho *et al.*, 2022). The region presented a harmonious socio-ecological relationship between the sparse human populations and the indigenous herbivores, ranging from duiker to elephant. The historically indigenous species are biologically crucial as they support the growth, structure, and evolution of the Albany Thicket Biome (Cowling and Kerley, 2002). Due to the introduction of pastoralism, the delineation of farms in the region fragmented the habitats of the ecologically important herbivores. Additionally, increased hunting significantly reduced the indigenous herbivores' populations in the biome (Hoare *et al.*, 2006).

The most well-documented form of degradation in literature surrounds the effects of herbivory by goats on the Albany Thicket Biome (Lloyd *et al.*, 2002; Lechmere-Oertel, 2003). Goats are seen as the most successful domestic livestock at browsing the high biomass of Albany Thicket (Lloyd *et al.*, 2002; Hoare *et al.*, 2006). Vegetation comprising Albany Thicket has not developed resilience to the unsustainable browsing of goats (Hoare *et al.*, 2006). Albany Thicket is slow growing, with low annual production that displays a false perception of forage available for animal production (Hoare *et al.*, 2006). Additionally, Albany Thicket is found to recover very slowly, with research showing that it can take up to 18 months for the vegetation to recover from 50% defoliation by goats (Hoare *et al.*, 2006). Goats differ significantly from indigenous herbivores in terms of feeding strategies; they are gregarious, meaning that they browse individual plants or patches of vegetation in groups, which significantly increases localised damage (Lechmere-Oertel, 2003).

Complementary to the introduction of domestic livestock and the removal of indigenous herbivores, large-scale clearing of natural vegetation for crop production further fragmented the Albany Thicket Biome. During the 1800s, pineapple cultivation in this region expanded rapidly, resulting in the clearing of natural vegetation to create appropriate fields for cultivation. Today, the region is the largest producer of pineapples in South Africa, accounting for over two-thirds of the country's yield (Skowno *et al.*, 2019). Former productive pineapple fields have transitioned to alternative commercial agricultural options (Hill *et al.*, 2012) or transformed into wildlife ranching (Palmer *et al.*, 2010), a common industry in the Eastern Cape. In South Africa, in protected areas, national parks and private reserves, wildlife ranching generates a significant R14 billion annually through tourism-related activities (Skowno *et al.*, 2019), providing unique income opportunities through nature-based services.

Numerous studies have attempted to quantify how the Albany Thicket Biome has degraded. The STEP project aimed to identify and assess the extent of the transformation and degradation of the various Thicket types found within the biome region (Lloyd *et al.*, 2002). Using Remote Sensing techniques, Lloyd *et al.* (2002) identified that more than 70% of the Thicket Biome vegetation units were classified as moderately to severely degraded. The Solid Thicket type displayed over 42% as severely degraded or transformed; similarly, over 77% of the Mosaic Thicket type was affected (Lloyd *et al.*, 2002). Various degradation forces were identified, including urbanisation, herbivory, and cropland cultivation (Lloyd *et al.*, 2002). More recently, a 40%-60% decrease in the Thicket division delimited by the STEP project was identified as degraded, transformed, or lost to anthropogenic activities (Carvalho *et al.*, 2022).

The literature indicates that the significant deterioration of the Albany Thicket Biome calls for immediate attention and conservation for the longevity of the endemic biome (Mills *et al.*, 2007). LULCC is a complex and multifaceted issue that requires an interdisciplinary approach to be fully addressed. Remote sensing, modelling, and field surveys have been used to study the drivers and impacts of LULCC. At the same time, policy interventions and community-based approaches have been implemented to address the adverse effects of LULCC and to promote sustainable land use practices.

The following section will discuss the relevant literature surrounding the Remote Sensing methodologies to assess the extent of LULCC in an agricultural context.

3.7. Remote sensing applications

Remote Sensing and GIS technologies are becoming increasingly vital methods for the detection and quantification of LULCC due to human-induced landscape alteration (Lillesand *et al.*, 2015; Rawat, & Kumar, 2015; Kumar, & Agrawal, 2019). Satellite imagery collected through remote sensing technologies is the basis for LULC interpretation and change analysis (Attri *et al.*, 2015; Lillesand *et al.,* 2015). LULC classification is helpful in numerous studies to monitor spatio-temporal change, including that of agriculture (Weiss *et al.*, 2020), environment (Alshari, & Gawali, 2021), and urbanisation (Kumar, & Agrawal, 2019). The following sections will discuss the theory of remote sensing, followed by a review of the current applications of remote sensing, and the application of remote sensing in detecting LULCC.

3.7.1. The theory of remote sensing

Satellite images capture the Earth's landscape from an aerial perspective, acquiring information which cannot be visualised with the naked eye (Lillesand *et al.*, 2015). Satellites are fitted with sensitive cameras and sensors that capture light in the electromagnetic spectrum (EMS) (Figure 15). At its very core, light is made up of photons (NASA, 2023a), which move at the speed of light (300,000 km/sec) in waves, much like how waves move through the ocean (Horning, 2019). The energy of a photon will determine the frequency or size of the wave, which will influence the visibility of its light on Earth. The light in the EMS is divided into categories based on these wavelengths.

Short wavelengths comprise high-frequency and short waves, including x-rays (Figure 15). These wavelengths range from approximately 1 nanometre (nm) to about 0.36 nanometres (Horning, 2019). The longer wavelengths include microwave and radio waves (Figure 15) (Horning, 2019; NASA, 2023a). Microwaves range from 1 millimetre (mm) to 1 metre (m), whereas radio waves, the longest wavelength with the lowest frequency, are measured beyond 1 metre (NASA, 2023a). Visible wavelengths (red, green, and blue) are measured in the middle of the EMS, between 0.4 and 0.7

micrometres (µm), or 400 to 700 nm (NASA, 2023a). The infrared (IR) region, a beneficial wavelength in remote sensing applications, spans between 0.7 and 100 micrometres (NASA, 2023a).

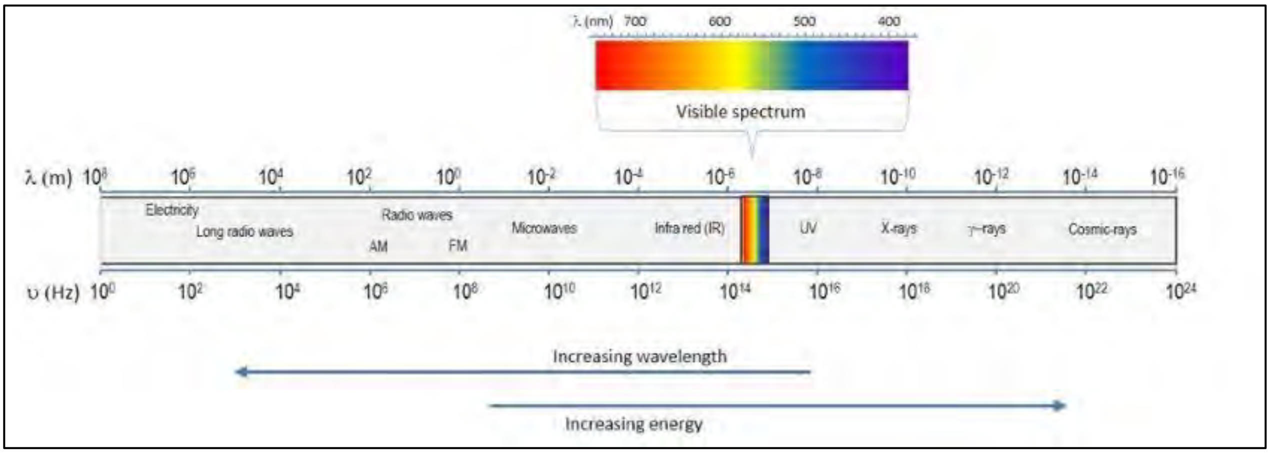


Figure 15: Electromagnetic spectrum (Source: Engineering Toolbox, 2016). (https://www.engineeringtoolbox.com/electromagnetic-spectrum-d_1929.html) [Accessed: 01 July 2023].

Light in the EMS reaches the Earth and is absorbed or reflected by the features on the ground (Horning, 2019). For example, plants appear green because they reflect the green portion of the EMS and absorb blue and red-light energy to fuel photosynthesis and create chlorophyll (Lillesand *et al.*, 2015). The cameras attached to the satellites have specific sensors to capture light reflected from the earth in different wavelength frequencies. The wavelengths are presented in the form of bands (NASA, 2023a). Landsat 9, an American Earth Observation satellite launched by NASA and the USGS in 2021, captures light in 11 bands of wavelengths (NASA, 2023a). Each band is sensitive to capturing light within a specific wavelength range. For example, the green band captures light between 0.53 and 0.59 micrometres (NASA, 2023a).

Each land cover type on Earth reflects a unique combination of wavelengths across the EMS, called spectral reflectance patterns (Horning, 2019). Plants are green because they reflect green light, but they also reflect near-infrared radiation based on the amount of chlorophyll the plant contains (Lillesand *et al.*, 2015). Furthermore, the health of plants can be diagnosed by satellites based on the frequency of the near-infrared radiation that the plant reflects (Horning, 2019). Every land cover type on Earth projects a spectral reflectance pattern that can be converted into a LULC map using GIS software.

3.7.2. Current trends of remote sensing

Remote sensing has been a cornerstone of scientific research and data collection for decades, enabling an understanding of the environment in ways previously unimaginable (Lillesand *et al.*, 2015). In recent years, the emergence of high-resolution aerial imagery, through small satellites and UAVs, have revolutionised the field of remote sensing (Toro, & Tsourdos, 2018; Zhang *et al.*, 2020). These versatile devices have the potential to provide unprecedented levels of spatial and temporal data, offering cost-effective and accessible solutions for agricultural mapping (Mogili, & Deepak, 2018).

Small satellites, also known as nanosatellites or CubeSats, have gained significant popularity due to their compact size, low cost, and rapid development cycle (Zhang *et al.*, 2020). These satellites are equipped with remote sensing instruments capable of capturing high-resolution imagery, enabling the monitoring of large-scale agricultural areas. The use of small satellites has democratised remote sensing, allowing researchers, organisations, and farmers to access valuable data for informed decision-making (Zhang *et al.*, 2020). To date, numerous low-orbiting small satellites provide high resolution imagery for researchers, including key technologies such as Maxar Technologies (Laradji *et al.*, 2020), PlanetScope (Zhang *et al.*, 2020), Sentinel-2 (Phiri *et al.*, 2020), Landsat (Wulder *et al.*, 2019), and UAVs (Mogili, & Deepak, 2018; Toro, & Tsourdos, 2018).

Maxar Technologies is a leading provider of advanced space technology solutions, offering high-resolution imagery through its satellite constellations, including WorldView and GeoEye (Laradji *et al.*, 2020). These satellites capture multispectral imagery that aids in detailed agricultural mapping. The WorldView satellite constellation offers high-resolution imagery with pixel resolutions ranging from 30 centimetres to 50 centimetres, depending on the specific satellite and sensor used (Laradji *et al.*, 2020; Maxar Technologies, 2023). By leveraging their data, stakeholders can monitor crop health, identify stress factors, and assess the effectiveness of various agricultural practices (Laradji *et al.*, 2020). Maxar's satellite imagery has been instrumental in supporting precision agriculture, enabling farmers to optimise inputs, reduce costs, and maximise yields.

PlanetScope, operated by Planet Labs, is a constellation of small satellites designed for global daily monitoring (PlanetScope, 2023). These satellites capture high-frequency imagery with moderate resolution, making them ideal for monitoring dynamic agricultural landscapes. The PlanetScope constellation of small satellites captures imagery with a pixel resolution of approximately 3 to 5 meters (Zhang *et al.*, 2020; PlanetScope, 2023). While not as high-resolution as some other satellites, PlanetScope's advantage lies in its frequent revisit times and global coverage, allowing for regular monitoring and assessment of agricultural areas (Zhang *et al.*, 2020). PlanetScope's imaging capabilities provide valuable insights into crop phenology, land use changes, and vegetation indices (Zhang *et al.*, 2020).

Sentinel-2, part of the European Space Agency's Copernicus programme, is a constellation of satellites designed specifically for land monitoring (European Space Agency, 2023). With its multispectral capabilities, Sentinel-2 captures high-resolution imagery across the visible, near-infrared, and shortwave infrared regions of the electromagnetic spectrum (Phiri *et al.*, 2020). The Sentinel-2 satellites provide imagery with pixel resolutions ranging from 10 metres to 20 metres, depending on the spectral band (Phiri *et al.*, 2020; European Space Agency, 2023). These data are particularly useful for monitoring vegetation health, crop health, and water stress (Phiri *et al.*, 2020). Sentinel-2's frequent revisit times enable the tracking of seasonal changes and the detection of crop variability within a single growing season.

The Landsat programme, jointly operated by NASA and the United States Geological Survey (USGS), has been a cornerstone of remote sensing for several decades (NASA, 2023b). Landsat satellites provide a continuous record of the Earth's surface, allowing for the long-term analysis of agricultural landscapes (Wulder *et al.*, 2019). The Landsat satellites offer a pixel resolution of 30 metres, which is suitable for regional-scale agricultural monitoring and analysis (Wulder *et al.*, 2019; NASA, 2023b). Despite the coarser resolution compared to some other satellites, Landsat's long-standing record and availability of historical data make it valuable for studying agricultural trends and long-term land management (Wulder *et al.*, 2019). The multispectral data acquired by Landsat sensors helps assess vegetation conditions, monitor land use patterns, and quantify crop productivity (Wulder *et al.*, 2019). Landsat's historical archive enables researchers to analyse trends, study the impact of land management practices, and evaluate the effectiveness of agricultural policies.

Unmanned aerial vehicles, commonly known as drones, have emerged as versatile tools for agricultural remote sensing. Equipped with imaging sensors, UAVs can capture high-resolution imagery at a localised level. The pixel resolution of imagery captured by UAVs can vary depending on the specific drone and sensor used. However, advancements in technology have enabled UAVs to capture imagery with pixel resolutions ranging from a few centimetres to several metres (Mogili, & Deepak, 2018). This flexibility allows for high-resolution mapping of localised agricultural areas, providing detailed information for precision agriculture and site-specific management (Pajares, 2015). UAVs equipped with sensors like LiDAR (Light Detection and Ranging) and thermal cameras enable accurate yield mapping and crop estimation (Toro, & Tsourdos, 2018). LiDAR technology allows for the creation of detailed 3D models of crop canopies, facilitating the estimation of plant height, biomass, and canopy density (Salamí *et al.*, 2014). Thermal cameras detect temperature variations, aiding in the identification of water stress, disease hotspots, and crop maturity (Mogili, & Deepak, 2018; Toro, & Tsourdos, 2018). By combining these data with satellite imagery and ground-truthing, farmers can generate precise yield maps, predict crop yields, and make informed decisions regarding harvesting and marketing strategies (Mogili, & Deepak, 2018; Toro, & Tsourdos, 2018). UAVs play a crucial role in the precise application of agricultural inputs. By integrating drones with sprayers or seeders, farmers can deliver fertilisers, herbicides, and seeds with high accuracy and efficiency (Faiçal *et al.*, 2014). Using GPS-guided systems and mapping technologies, drones can follow predetermined flight paths, ensuring uniform coverage and reducing chemical drift (Mogili, & Deepak, 2018). This not only minimises the environmental impact of agrochemicals, but also improves the cost-effectiveness of input applications. Farmers can treat specific areas or individual plants based on their requirements, optimising resource allocation and reducing chemical usage (Mogili, & Deepak, 2018). UAVs provide a flexible and cost-effective means of data acquisition, offering near-real-time information for timely interventions and decision-making (Toro, & Tsourdos, 2018).

Small satellites and UAVs have emerged as powerful tools for analysing LULCC. These innovative technologies provide researchers and scientists with cost-effective and efficient means to collect high-resolution spatial and temporal data on the Earth's surface (Mogili, & Deepak, 2018). By combining the capabilities of small satellites and UAVs, researchers can gain a comprehensive understanding of LULCC dynamics (Attri *et al.*, 2015). This integration of technology facilitates more accurate assessments, supports informed decision-making, and aids in developing sustainable land management strategies.

3.7.3. Image classification for LULCC

LULC maps are created through image classification, a process that assigns each pixel in a satellite image to a land cover assigned by the user (Li *et al.*, 2014). Supervised classification is the most popular and accurate form of image classification presented in the literature (Tuia *et al.*, 2011; Li *et al.*, 2014). Supervised classification requires the user to provide training samples of the spectral reflectance patterns of the land covers. The GIS software will then compute the classification over the entire defined area and produce a LULC map of the various land covers defined by the user. For mapping LULC, numerous appropriate and relevant studies are presented in the literature, including:

- Maximum Likelihood Classifier (ML) (Harris, 2003; Enderle, & Weih, 2005; Rawat, & Kumar, 2015; Herbei, & Sala, 2016; Esetlili *et al.,* 2018; Kumar, & Agrawal, 2019; Guliyeva, 2020),
- Random Trees Classifier (RT) (Guliyeva, 2020), and
- Support Vector Machine (SVM) (Esetlili *et al.,* 2018; Guliyeva, 2020).

The decision to use a particular classifier for LULCC depends on the chosen satellite used in the study. Satellites vary considerably regarding accessibility and resolution, making some more applicable than others. Three common open-sourced and medium to high-resolution satellites are commonly presented in the literature for uses in agricultural LULCC, including:

- Landsat (Aboel Ghar *et al.*, 2004; Enderle, & Weih, 2005; Herbei, & Sala, 2016),
- Sentinel-2 (Guliyeva, 2020; Basheer *et al.*, 2022), and
- Planet (Basheer *et al.*, 2022).

The classification methodologies involve gathering ground-tested training samples to assess the spectral reflectance patterns in order to accurately differentiate and map the various land covers in the landscape (Kumar, & Agrawal, 2019; Guliyeva, 2020). To differentiate these land covers, Vegetation Indices (VI) are created from the satellite images to accurately differentiate healthy vegetation from inanimate covers. Landsat and Sentinel-2 can create medium-resolution vegetation indices at 30 and 10 metres per pixel. Various VIs utilised for LULCC are presented in the literature, including:

- Normalised Difference Vegetation Index (NDVI) (Aboel Ghar *et al.*, 2004; Herbei, & Sala, 2016; Guliyeva, 2020).
- Soil-Adjusted Vegetative Index (SAVI) (Hatfield, & Prueger, 2010).
- Enhanced Vegetation Index (EVI) (Hatfield, & Prueger, 2010).
- Normalised Pigment Chlorophyll Ratio Index (NPCI) (Hatfield, & Prueger, 2010).
- Plant Senescence Reflectance Index (PSRI) (Hatfield, & Prueger, 2010).

The combination of VIs and medium-resolution satellite imagery can differentiate certain crops from surrounding land covers in the landscape. Noteworthy studies have used image classification techniques to identify specific crop types, including:

- Sugarcane (Zhou *et al.*, 2015; Chen *et al.*, 2020; Virnodkar *et al.*, 2020).
- Corn (Hatfield, & Prueger, 2010).
- Rice (Motohka *et al.*, 2008).
- Soybean (Hatfield, & Prueger, 2010).
- Wheat (Hatfield, & Prueger, 2010).
- Canola (Hatfield, & Prueger, 2010).

3.8. Summary

This literature review provides an in-depth examination of the global and South African pineapple industries, including the political, economic, and spatial factors affecting pineapple cultivation, the consequences of pineapple farming, trends, and an overview of the patterns of LULCC in Africa and RS applications for analysing LULCC in an agricultural landscape. The literature indicates that the cultivation of pineapples has been a common practice for thousands of years, with the initial domestication of the fruit originating in the Brazilian rainforests (Strauss, 1960; Hossain, 2016). However, the introduction of pineapples outside of South America has only occurred within the last few hundred years. Since the spread of the fruit by Christopher Columbus, pineapples have been cultivated in most nations within the tropical and subtropical climatic zones (Joy, & Anjana, 2016; Jiang, 2021).

Although the largest producers of pineapples are found in Asia and South America, the South African pineapple industry has managed to thrive since cultivation commenced on a commercial scale in 1865 (StatsSA, 2021). Pineapples grown in South Africa, specifically within the Ndlambe Municipality, are the most southerly grown pineapples globally, generating a unique taste which makes the fruit sought after internationally (Hossain, 2016). However, many political, economic, and spatial factors have caused changes to the South African pineapple industry. International boycotts (Gurney, 2000), governmental changes (Kloppers, & Pienaar, 2014), environmental laws (de Villiers, 2007), and fertiliser contaminations (Hill *et al.*, 2012) have either negatively or positively affected the industry.

Nonetheless, the pineapple industry has been scrutinised for accelerating environmental degradation through unsustainable farming practices (Boucher, 1991). The literature indicates that, in Africa, land transformation through agricultural activities is the most significant cause of environmental degradation (Lambin, & Meyfroidt, 2011). Furthermore, the literature indicates that image classification through remote sensing technologies is an accurate and successful method for identifying changes in land use and land cover, specifically to analyse the effects on the landscape of an agricultural activity (Basheer *et al.*, 2022).

Remote sensing technologies have improved the collection and interpretation of LULCC. Satellite imagery provides information into the spatial and temporal changes of land (Lillesand *et al.*, 2015). UAVs have revolutionised the functionality of LULCC through their usability, versatility, and high-resolution imagery (Mogili, & Deepak, 2018). The role of small satellites and UAVs in agriculture has dramatically improved the efficiency of farm managers' decision-making. Several studies have used small satellites or UAVs to identify pineapple fields, for purposes including disease detection (Balasundram *et al.*, 2013) and yield estimation (Grounds *et al.*, 2008; Hobbs *et al.*, 2021; Syazwani *et* *al.*, 2022; Shiu *et al.*, 2023;). Although the literature provides sufficient research into the identification of many crops using freely available medium-resolution satellite imagery, the detection of pineapple fields using satellite imagery is not well documented in the literature. This study aims to fill this research gap. The following chapter provides a methodology to identify the LULCC from pineapple fields, using Landsat satellite imagery in conjunction with a supervised classification technique.

CHAPTER 4: DATA AND METHODS

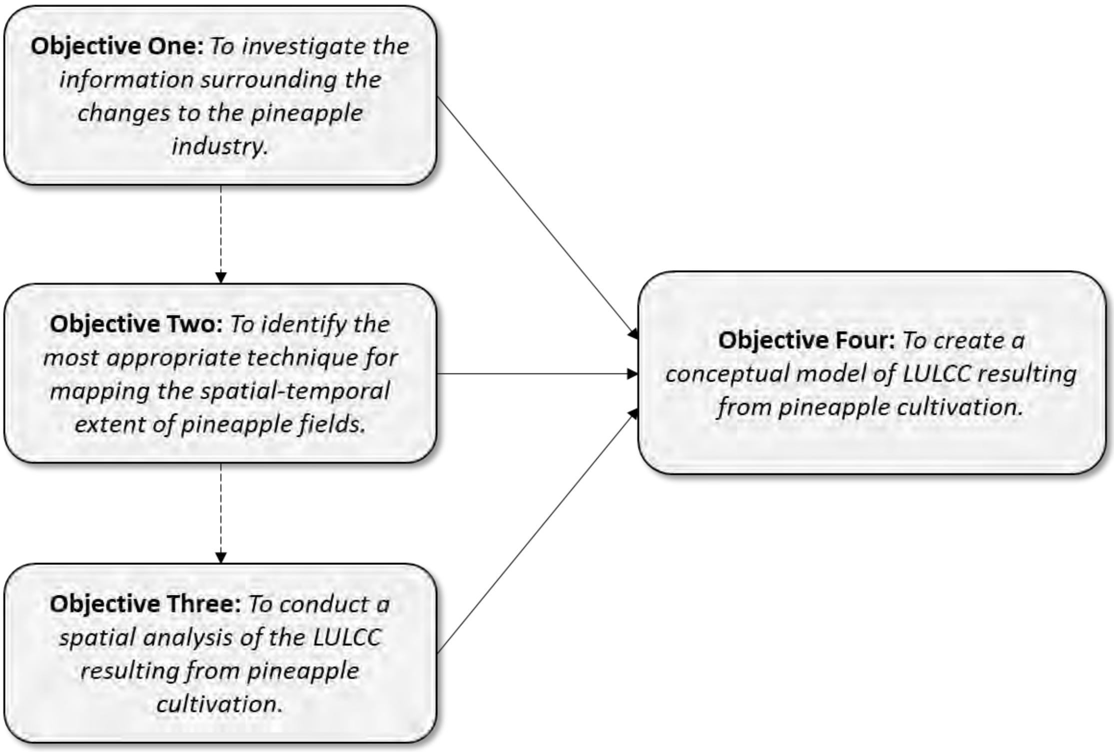
4.1. Introduction

The methods of this research study utilise various relevant and appropriate methodologies adopted from the literature to complete the research aim: *to use remote sensing to investigate the LULC changes that have resulted from pineapple cultivation in the Lower Albany area from 1984 until 2020*. The methodological frameworks highlighted in the literature indicate that the driving forces of LULCC are multifaceted and complex, requiring various approaches to be adopted (Verburg *et al.*, 2006). Therefore, this research study's methodologies incorporate quantitative and qualitative data collection methods to examine primary and secondary data sources. The methods section is divided into three parts: the methodologies for Objective One, Objective Two and Objective Three, which together enable the completion of Objective 4 (Figure 16).

- Objective One aims to examine the information surrounding the changes in the pineapple industry. Objective One followed a qualitative approach to collecting data from primary data sources and included interviews with five key stakeholders in the pineapple industry in the study area. Interviews with local pineapple farmers is essential for the conceptualisation of this research study as the participants provide valuable insights into the current and historic complexities of pineapple farming in the study area. Furthermore, the results of the interviews guided an in-depth review of the literature surrounding the topics discussed in the discussions. The results of Objective One guided the methodology for Objective Two.
- Objective Two aims to identify the most appropriate and accurate method for mapping pineapple fields. Objective Two incorporated a quantitative approach to produce primary data types. Relevant studies in the literature suggested the use of various satellite imagery providers, software applications and image classifiers, which were tested and compared to identify the most accurate and appropriate technique to map pineapple fields. The results of Objective Two enabled the implementation of Objective Three.
- Objective Three aims to analyse the spatial changes between pineapple fields. Objective Three incorporated a quantitative data collection approach to analyse primary data types. Satellite images captured between 1984 and 2020 were downloaded from the chosen satellite provider. Each image was classified using the identified image classifier. Thereafter, the pineapple cultivation area, and the spatial and land cover changes between the years, were analysed. Furthermore, sixty random sites were generated from the remote sensing analysis to guide a field verification process. This task aimed to investigate the actual land cover of each site through

ground-truthing, and as a critique of the accuracy of the remote sensing analysis in detecting pineapple fields using medium-resolution satellite imagery.

- Lastly, completing each objective mentioned above, and the subsequent results, enabled the completion of the final objective (Figure 16). Objective Four aimed to develop a conceptual model of LULC relating to pineapple cultivation in the Lower Albany Area from 1984-2020. The completion of Objective Four incorporates both qualitative and quantitative data types. Furthermore, primary and secondary data sources were analysed for this objective. The results of the previous three objectives were integrated to create a holistic conceptual model of the patterns and trends of the relationship between pineapple cultivation and LULC. The presentation of the conceptual model is discussed in Chapter 6. The specific methodologies for each objective are presented in the following sections.



Objective One: *To investigate the information surrounding the changes to the pineapple industry.*

Objective Two: *To identify the most appropriate technique for mapping the spatial-temporal extent of pineapple fields.*

Objective Three: *To conduct a spatial analysis of the LULCC resulting from pineapple cultivation.*

Objective Four: *To create a conceptual model of LULCC resulting from pineapple cultivation.*

Figure 16: A summarised model of the objectives for this research study. The following objectives are only possible after the completion of the previous objective.

4.2. Objective One: To investigate the information surrounding the changes in the pineapple industry

As mentioned above, investigating the perceptions of local stakeholders is critical to understanding the direct and indirect drivers of LULCC experienced by farmers in the pineapple industry. The methodologies for Objective One include a qualitative analysis of primary and secondary data sources to investigate the information surrounding the changes in the pineapple industry in South Africa and, more specifically, the Lower Albany area. Figure 17 illustrates the methodological framework created for Objective One. The methods used to complete Objective One included qualitative approaches, including five interviews with local pineapple farmers in the study area and an extensive review of the literature pertaining to the changes in the pineapple industry on global and local scales. An initial brief literature review created the foundation of knowledge on relevant topics to guide the interviews. The knowledge gained through the interviews then, in turn, guided the direction of an extensive review of the literature on global and local scales. It must be stated that the detection and analysis of pineapple fields through remote sensing technologies is the focal analysis of the study. The objective of the interviews and literature review was, first, to gain a greater understanding of the pineapple industry and the changes within, and second, to support or contrast the findings of the remote sensing analysis. The information obtained directly from farmers enabled a holistic interpretation of the study's findings. Furthermore, information regarding the nature of how pineapples are farmed was explored to assist the collection and interpretation of satellite imagery in the methodologies to follow. The details of the two approaches are described in the following sections.

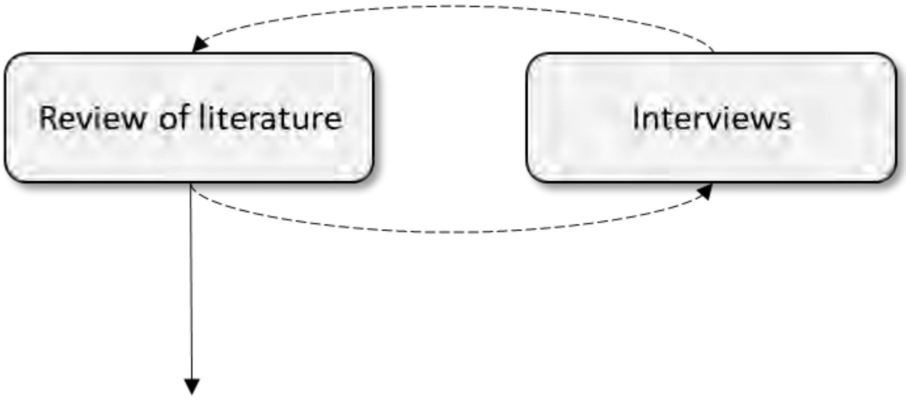


Figure 17: Simplified model of the methodologies followed by Objective One.

4.2.1. Introduction of the interview participants

The participants of the interview process are members of the Pineapple Growers Association (PGA) which is located in Bathurst (Figure 18). An introduction of each participant is presented below. It must be clearly stated that the interview participants provided consent to the use of their information in this research study. Given the historical nature of the research question, it is essential that the names and information of the participants are published to aid the narrative of pineapple farming in the Eastern Cape. Additionally, the farm location of each participant is presented in Figure 19.

a) Greg Pike

Greg Pike is a successful pineapple farmer in the Bathurst region and is the President of the Pineapple Growers Association for South Africa. Pike is deeply connected to the pineapple industry in the Bathurst region. He operates his pineapple venture on lands his family has owned since the early 1900s (Figure 19). He has run the business independently for 20 years. Pike's family-owned pineapple cultivation footprint has expanded since the establishment of the farm in the 1900s, through the consolidation of neighbouring fields. As President of the PGA, Pike organises meetings with surrounding farmers to ensure each farmer conducts responsible agricultural practices. Pike also uses the meetings to share information with other pineapple farmers regarding news in the industry.

b) Mark Harris

Mark Harris is a successful pineapple farmer in the Albany district, and the largest producer of pineapples in the country. According to fellow pineapple farmers, Harris is also the single largest individual pineapple producer in the world. Harris bought an established pineapple farm in the Bathurst region in 1982, after a successful career in the agricultural sector elsewhere in Africa. He has since expanded the operation's footprint by consolidating several neighbouring pineapple farms. According to the other participants, Harris is the "model farmer" as he operates the most extensive practice in the area and consistently produces quality fruits.

c) Nigel Arnold

Nigel Arnold is a generational pineapple farmer in the region, with his parents having been successful pineapple farmers on the same lands he farms today. Arnold owns a large and successful pineapple farm in the Langholm district of the Bathurst region. Arnold has witnessed the changes in the study area, making him an ideal candidate for this research study.

d) Richard Muir

Richard Muir is one of the newest pineapple farmers in the study area. Muir's parents farmed pineapples in the study area, and he grew up acquiring the necessary knowledge and experience of how to run a successful pineapple farm. However, in the 1980s, Muir's parents converted the pineapple farm into a cattle farm. In 2018, Muir returned to his childhood home and began pineapple farming once again. At the time of this research, Muir had completed his first harvest cycle and had begun to prepare the lands for the next cycle.

e) Brandon Handley

Brandon Handley is a young and energetic pineapple farmer in the study area. He is a local to the region, having grown up on a pineapple farm in the Bathurst region. Handley runs his family pineapple farm, an impressive feat for a young farmer in an industry dominated by more experienced farmers.

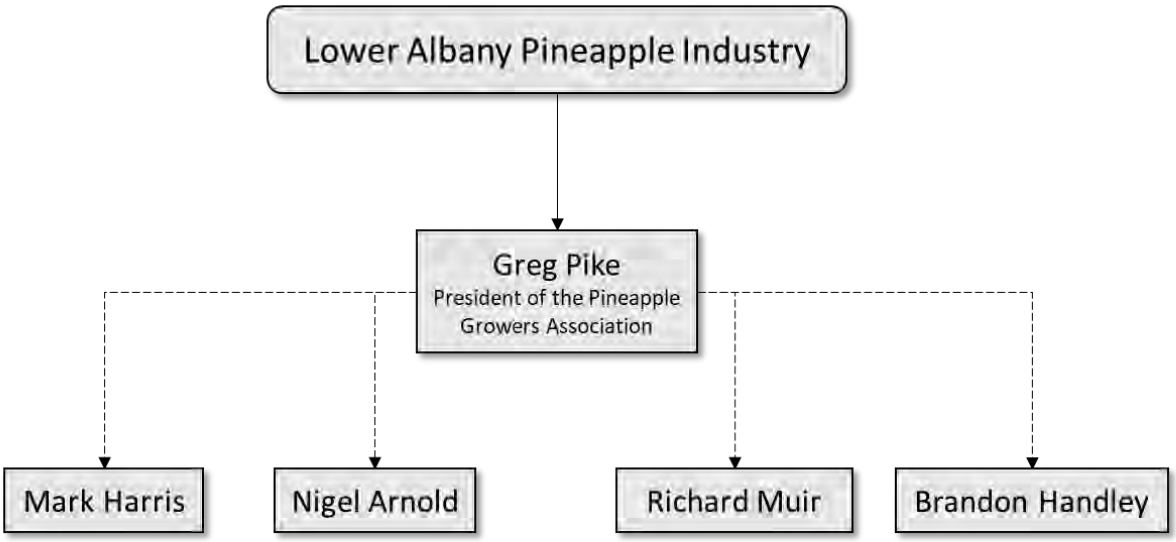


Figure 18: An organogram illustrating the connectivity of the participants interviewed for Objective One.

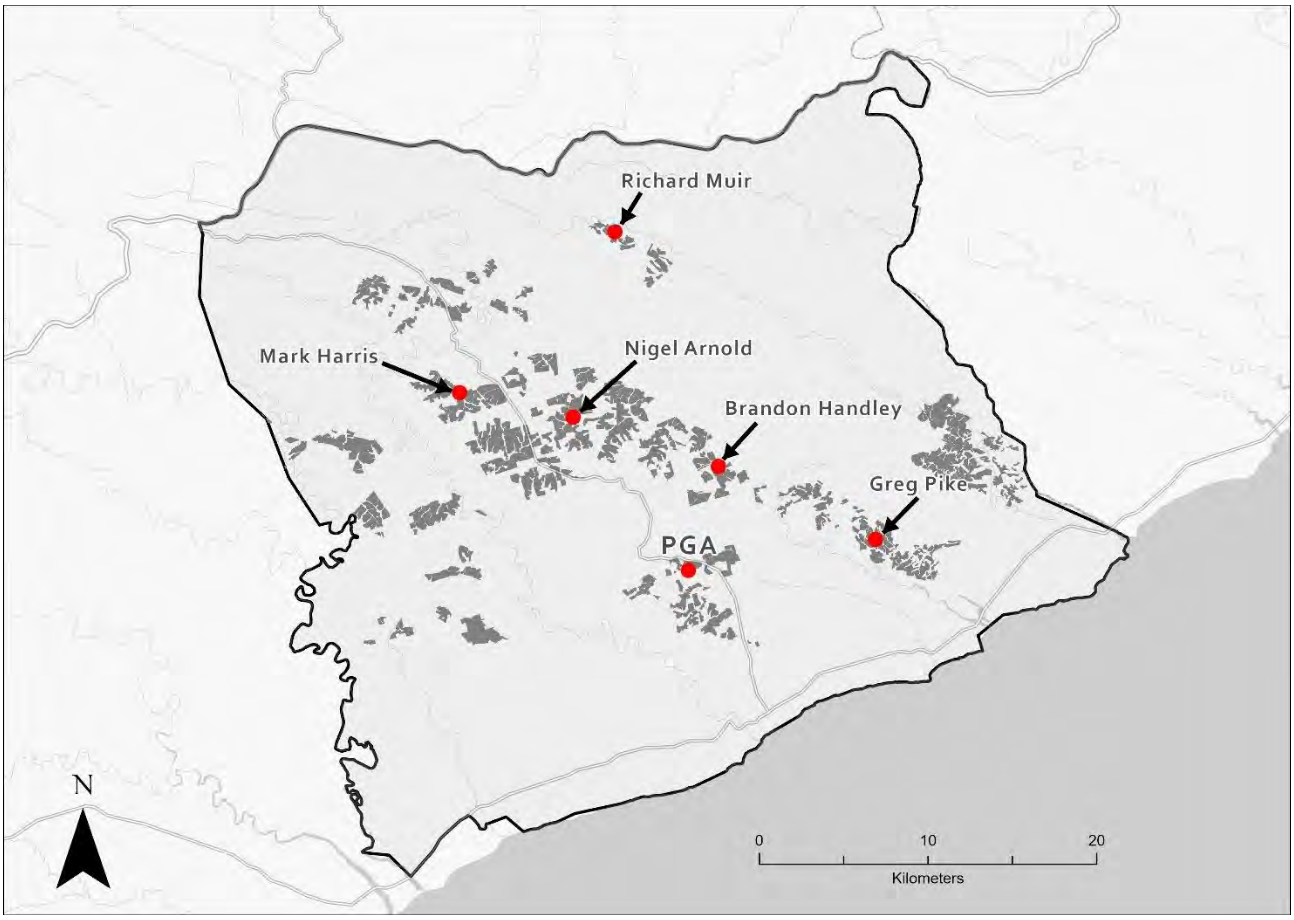


Figure 19: Locations of the interview participants' farms.

4.2.2. Interviews with pineapple farmers in the study area

Semi-structured interviews were conducted with five pineapple farmers who own commercial farms within the study area. The interviewees were nominated by a snowball effect, whereby one participant would recommend another candidate they believed was suitable for the study. The participants were required to be current pineapple growers, farming within the extent of the study area. The initial participant, an individual deeply established in the pineapple industry in the study area, was recommended by an associate. An email was sent to the candidate explaining the scope of the study and an explanation of the need for the interviews. Information regarding the ethical guidelines and the nature of the interview were emphasised in the email. The requirement for signing a participant consent document and the use of a voice-recording device was expressed in the email. If the candidate agreed to participate in the study, the interview date, time, and location were agreed upon. If the candidate did not agree to participate, recommendations of other suitable candidates were requested to continue the study.

Upon arrival at each interview location, each participant was asked again if a voice-recording device could be used to capture the content of the interview. If the participant agreed, the device was activated to capture the entire conversation. The next step requested the interviewee to sign the participant consent form with the approval of a witness (Appendix A). Once these steps were completed, the interview could begin.

The guiding structure of the interviews is presented in Table 1. These questions were the backbone of the interview; however, discussions surrounding each topic were encouraged. The questions aimed to investigate, from the perception of local pineapple farmers, how pineapple farms are acquired, the past and future changes and challenges of pineapple cultivation, the standard farming practices, and the spatial and geographic requirements for pineapple cultivation. The interviews ranged from one hour to one and a half hours. At the end of each interview, recommendations for other suitable pineapple growers were requested. The password-protected voice recordings of the interviews were saved in a cloud-based and secure location with the participant's name to ensure the information was easily accessible for analysis. The information from each interview was tabulated against each of the primary topics. Thereafter, the new knowledge that had been obtained was used to direct an extensive literature review, described in the following section. An explanation of each question is presented below:

Table 1: Interview questions.

1) How many years have you farmed pineapples at this farm?		
2) Did you buy the pineapple farm or was it already a pineapple farm?	*2.1) If you started the farm, what occurred at the farm before you bought it?*	*2.2) If it was already a farm, what products were farmed?*
3) What changes have taken place in the pineapple industry in the area?		
4) What happens to pineapple fields after harvesting? Are they replanted with pineapples? Or are they abandoned?	*4.1) If replanted with pineapples, is there a limit to how many cycles a single field can go through until it is no longer functional?*	*4.2) If not replanted, what happens to the lands?*
5) Where do you see the future of pineapple cultivation in the Bathurst area going?		
6) Why are pineapples only grown in certain areas within the study area?		
7) What are the geographic criteria for cultivating pineapples?		

- Question 1 investigated how many years the participant has farmed pineapples at the farm. The answer to this question was essential as it indicated how many years of pineapple cultivation had occurred on each farm, and how connected the current farmer was with the area's industry. It was also critical to gain information from participants with a wide range of experience to ensure the results can be interpreted holistically.
- Questions 2, 2.1, and 2.2 investigated whether a land use transition had occurred since the participant acquired the land. The answers to these questions provided valuable insights into the common trends of land use transitions resulting from pineapple cultivation, and indicated which previous land use practice supported the cultivation of pineapples. First, the questions sought to investigate whether the participants acquired an already functioning pineapple farm or whether they had established their pineapple farm themselves. If the farmers stated that they initiated the pineapple farm, they were asked what land use practices had occurred before their purchase (Question 2.1). If the participant stated that the prior land use was agricultural, the participant was asked which agricultural products had previously been cultivated on the land (Question 2.2). The answers to these questions guided a literature review investigating why specific land uses are transitioning in the study area. The answers contributed to the holistic examination of the changes to the pineapple industry in the study area.
- Question 3 challenged the participants to think about the changes to the pineapple industry before or during their involvement in the industry. Lengthy discussions surrounding the topic were encouraged in order to gain an extensive insight. The answers to this question guided the in-depth literature review of the changes highlighted by the local pineapple farmers.
- Questions 4, 4.1, and 4.2 aimed to investigate the standard farming practices of pineapple farmers in the study area. The initial literature review indicated a contrasting view regarding the sustainability of pineapple farming practices. These questions aimed to identify precisely how pineapple farmers plant and harvest pineapples, and how they prepare and rehabilitate pineapple fields, to address any misconceptions illustrated in the literature. Question 4.1 aimed to investigate how many cultivation cycles a single field can endure until the field is no longer productive. The answers to this question guided the final conceptualisation of the remote sensing analysis in determining the lifespan of a pineapple field. Question 4.2 investigated the common land use transitions resulting after the cultivation of pineapples. The answers to this question were cross-referenced with the remote sensing analysis findings to critique the accuracy of the analysis.

- Question 5 challenged the farmers to indicate the future trajectory of the pineapple industry within the study area. The answers to this question were vital as they were incorporated into the study's future analysis of the pineapple industry.
- Question 6 aimed to investigate why pineapples are only grown in certain areas within the study area. The answers to this question were integral in creating the final conceptual model as they provided reasons for the spatial variability of pineapple fields.
- Question 7 aimed to investigate the geographic and topographic requirements for suitable pineapple cultivation. Much like the answers to Question 6, the answers to Question 7 provided valuable evidence for the spatial changes observed within the study area.

4.2.3. Review of literature

The results of the interviews provided valuable insights into the national and local forces that directly affect local pineapple farmers. Moreover, the results of the interviews led to an extensive review of the literature to gain additional information on the topics highlighted by the participants. The literature review aimed to investigate further the national challenges highlighted by the participants, and to investigate the global forces that have influenced the functionality of the South African pineapple industry.

Firstly, an overview of the global pineapple industry was presented in Section 3.2 of Chapter 3. This section aimed to place the South African pineapple industry within the context of the global industry and to identify the ways in which the global pineapple industry influences the national industry. The global distribution of pineapples was examined. Furthermore, the production of pineapples on each continent was assessed. Additionally, the section examined statistics regarding the most productive pineapple-producing nations in terms of yield and land area under cultivation. Lastly, the Top Ten ranking pineapple-producing countries were identified and compared with South Africa.

Secondly, the literature review aimed to investigate the pineapple industry in South Africa from a historical context. The historical overview of the pineapple industry in South Africa, presented in Section 3.3 of Chapter 3, investigated the introduction and spread of pineapples in South Africa. The reasons for the changes in production over several decades were discussed. Additionally, the current context of the South African pineapple industry was discussed in Section 3.4 of Chapter 3. This section aimed to investigate the political, economic, and spatial factors affecting the functionality of the South African pineapple industry, specifically in the Ndlambe Municipality in the Eastern Cape province, where this study is situated. The review of the political factors included an examination of the two vastly different government administrations in South Africa since 1984, and the effects of each on the agricultural industry. The review of the economic factors included an investigation of the factors that influence the global and national theory of supply and demand with reference to the pineapple industry. Lastly, the review of the spatial factors included an in-depth examination of the reasons for the spatial variability observed in the country. The literature review regarding the factors causing changes in the South African pineapple industry provided valuable insights into the reasons for the changes observed in the study.

The extensive review of the global and national factors affecting pineapple cultivation in the study area, and the interviews with local pineapple farmers, enabled a holistic understanding of the global and local changes to the pineapple industry and the forces affecting the industry. Furthermore, the literature review provided various relevant techniques to map agricultural fields within a diverse landscape. The techniques guided the methodology for Objective Two, as discussed in the following section.

4.3. Objective Two: To identify the most appropriate technique for mapping the spatial-temporal extent of pineapple fields

Objective Two aimed to identify and produce the most accurate and relevant remote sensing technology to map the extent of pineapple fields in the Lower Albany area. Numerous studies in the literature have highlighted supervised image classification of open-sourced medium-resolution satellite imagery as an accurate method for identifying specific crop fields in a diverse landscape (Harris, 2003; Enderle, & Weih, 2005; Motohka *et al.*, 2008; Hatfield, & Prueger, 2010; Rawat, & Kumar, 2015; Zhou *et al.*, 2015; Herbei, & Sala, 2016; Esetlili *et al.*, 2018; Kumar, & Agrawal, 2019; Chen *et al.*, 2020; Guliyeva, 2020; Virnodkar *et al.*, 2020; Basheer *et al.*, 2022). The methodology outlined below is obtained from Basheer *et al.* (2022).

Two GIS-based software applications were incorporated in this research study; ArcGIS Pro and Google Earth Engine (GEE). Figures 20 and 21 illustrate the methodologies for image classification in ArcGIS Pro and GEE, extracted from Basheer *et al.* (2022). Only Landsat imagery was incorporated for the methods of this study due to the suitable temporal extent of the imagery. Image classification is not standardised, and the classifier used varies depending on the purpose of the study and the features present in the landscape. Therefore, the various image classifiers highlighted by Basheer *et al.* (2022) were tested and compared to identify the most appropriate approach for the specific needs of this research study. The steps in the following sections discuss the methods for image classification in ArcGIS Pro and GEE, including the collection of appropriate, cloud-free satellite images, the identification of land cover specific spectral reflectance patterns, the generation of training samples, the classification of satellite images, and the assessment of classifier accuracy (Figures 20, & 21).

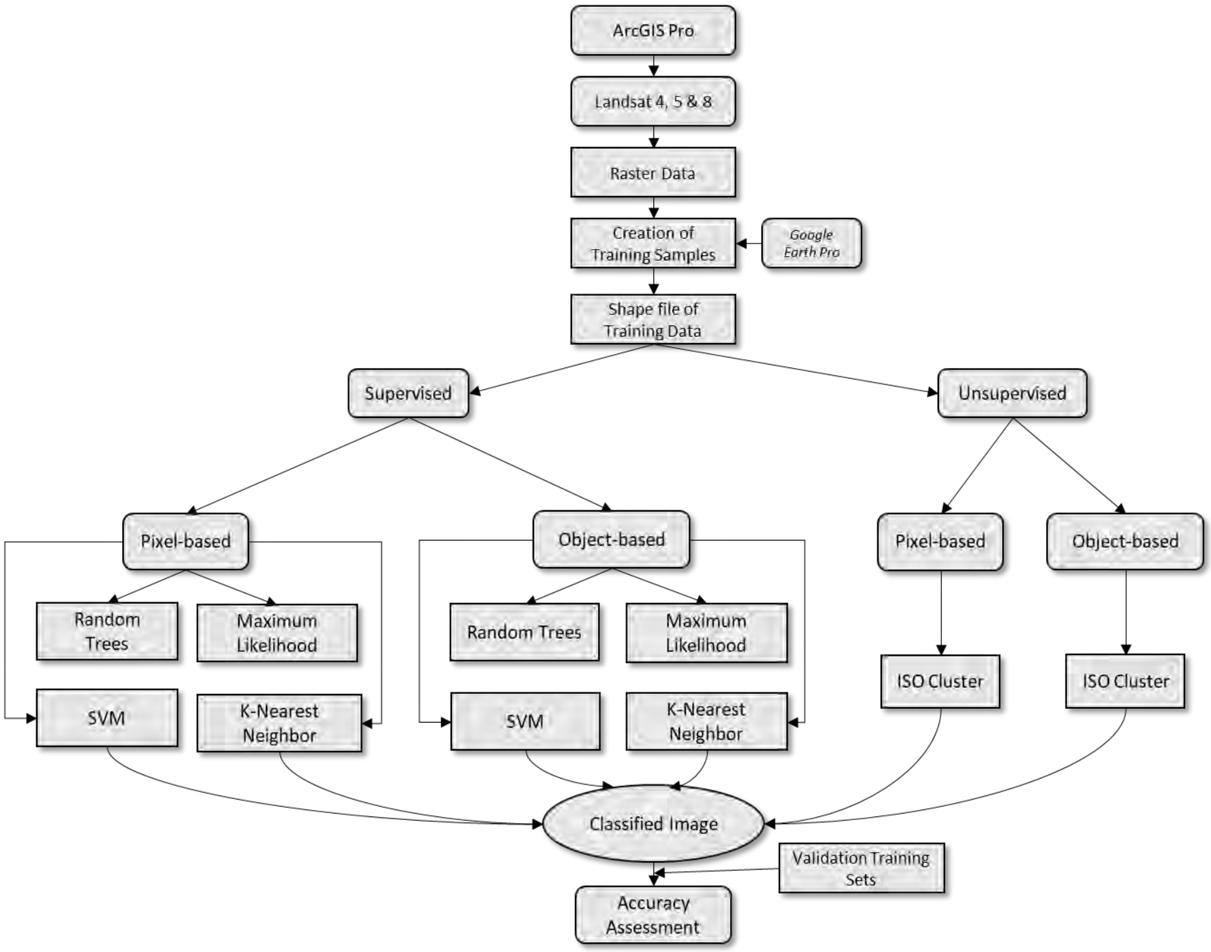


Figure 20: The methodological framework for the image classification process conducted in ArcGIS Pro. Ten image classifiers were created and compared. The methods were adapted from Basheer et al. (2022).

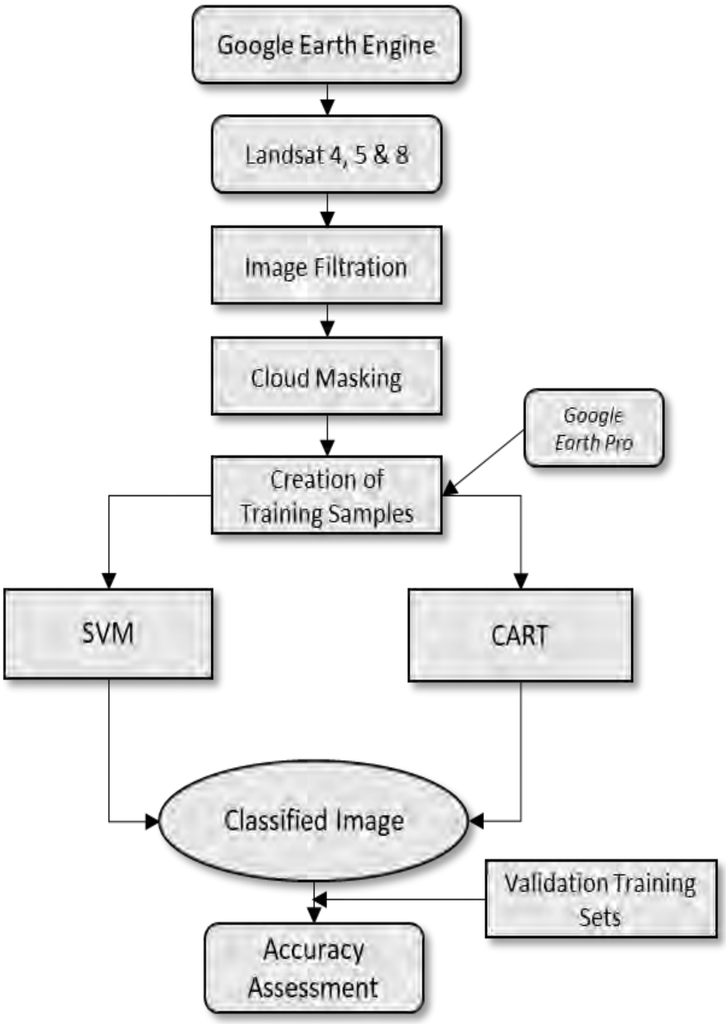


Figure 21: The methodological framework for the image classification process conducted in GEE. Two image classifiers were created and compared. The framework was adapted from Basheer et al. (2022).

4.3.1. Data preparation

The same Landsat satellite image and training samples were used to test the performance of image classifiers across two software applications. When using ArcGIS Pro, a cloud-free Landsat 8 satellite image (e.g., LC08_L2SP_170083_20200524_20200820_02_T1) was downloaded from the USGS Earth Explorer website (https://earthexplorer.usgs.gov/). Alternatively, when using GEE, the Landsat 8 image collection (LANDSAT/LC08/C01/T1_SR) was filtered to the same image as USGS Earth Explorer using ". filterDate(e.g., 24-05-2020)". A study area polygon was uploaded as an asset to GEE as stored under the name "Study_Area." The Landsat 8 image collection was filtered to the location of the study area using ".filterBounds(Study_Area)". Data preparation was concluded by identifying the unique spectral reflectance patterns of the land cover types to identify accurate training samples for the image classification process.

4.3.1.1. Spectral reflectance profiles

An assessment of the land covers in the study area was conducted to obtain suitable training samples. This included a comparison between the land covers presented in the SANLC and the Landsat 8 satellite image, as well as an analysis of the spectral reflectance patterns of each land cover for the image classification processes. According to the 2020 SANLC dataset, the study area includes six general land covers: Barren Land, Built-up, Cultivated, Forested Land, Grassland/Shrubland, and Waterbodies. On the other hand, the Landsat 8 satellite image displays several prominent land cover types, including Thicket, Grassland, Active Fields, Barren Fields, Waterbodies, Built-up, and Beach. In the SANLC 2020 dataset, the Beach, a prominent land cover in the study area, is categorised within the Barren field land cover class. To avoid confusion, the Beach was added as a separate land cover class for the study. Additionally, the Landsat 8 satellite image displayed significant variations in the areas identified as Cultivated by the SANLC. The spectral reflectance patterns vary considerably if the field is under cultivation or ploughed and bare. Therefore, fields that display distinct spectral patterns of crops were categorised as “Cultivated”, and ploughed fields were categorised as “Barren Fields”.

In total, seven different land covers were identified in the study area. Thicket, Grassland, Active Fields, Barren Fields, Waterbodies, Built-up, and Beach were the land covers used to identify the spectral reflectance patterns between each class. For the image classifier to accurately differentiate between the seven land covers, a spectral reflectance pattern of the seven land covers in the study area was created in ArcGIS Pro, using the “Spectral Profile” chart option of the Landsat 8 satellite image (Figure 22). Significant differences were present between several classes, most notably between Waterbodies and Beach. Due to the sparse alignment of water molecules, water absorbs nearly all the light with which it interacts. According to Figure 22, the light wave with the highest reflectance from water is green, at a mean value of 9,046, recorded by band 3 in the Landsat 8 satellite. On the other hand, beach sands were observed to reflect nearly all light waves with which they interact. Beach sands reflect Shortwave Infrared 1 light the highest, at a mean value of 27,649, recorded by band 6 of the Landsat 8 satellite.

A critical similarity can be observed between intact, healthy Thicket and productive pineapple fields. The two land covers produce similar reflectance values in the first four bands (coastal aerosol, blue, green, and red) and in the sixth and seventh bands (shortwave infrared 1 and 2). However, a significant difference is observed from the reflectance values of band 5 (near infrared) between the two vegetation land covers. According to the results in Figure 22, Thicket produced a reflectance value of 16,403, compared to Active Fields, which produced a value of 20,414. Although these land covers display healthy and productive vegetation systems, the critical difference is that Thicket is a natural system and relies on natural irrigation. Pineapple fields are managed and supplemented with added nutrients and irrigation schemes. Therefore, these two land covers are distinct enough for an accurate distinction to be made during the classification process.

The final land cover, Barren Field, is unique and distinct across the EMS. Barren Fields are characterised as bare soil with no vegetation cover. The light reflected from Barren Fields is exceptionally high in the near-infrared and shortwave infrared wavelengths recorded by bands 5, 6 and 7. Figure 23 clearly represents the spectral differences between the common land covers in the study area using bands 7, 5 and 3.

The results of the spectral signature of the land cover suggest that six of the seven land covers are suitable for accurate classification. The Urban land cover is too similar to Grasslands and was discarded from the classification process. A GIS polygon layer of the urban areas in the study area was used instead to display the spatial location and extent of urban areas in the final output.

Therefore, the six land cover classes used for the training samples are 1) Thicket, 2) Active field, 3) Barren field, 4) Grassland, 5) Beach, and 6) Waterbodies. The identified six land covers were used to guide the generation of training sample data.

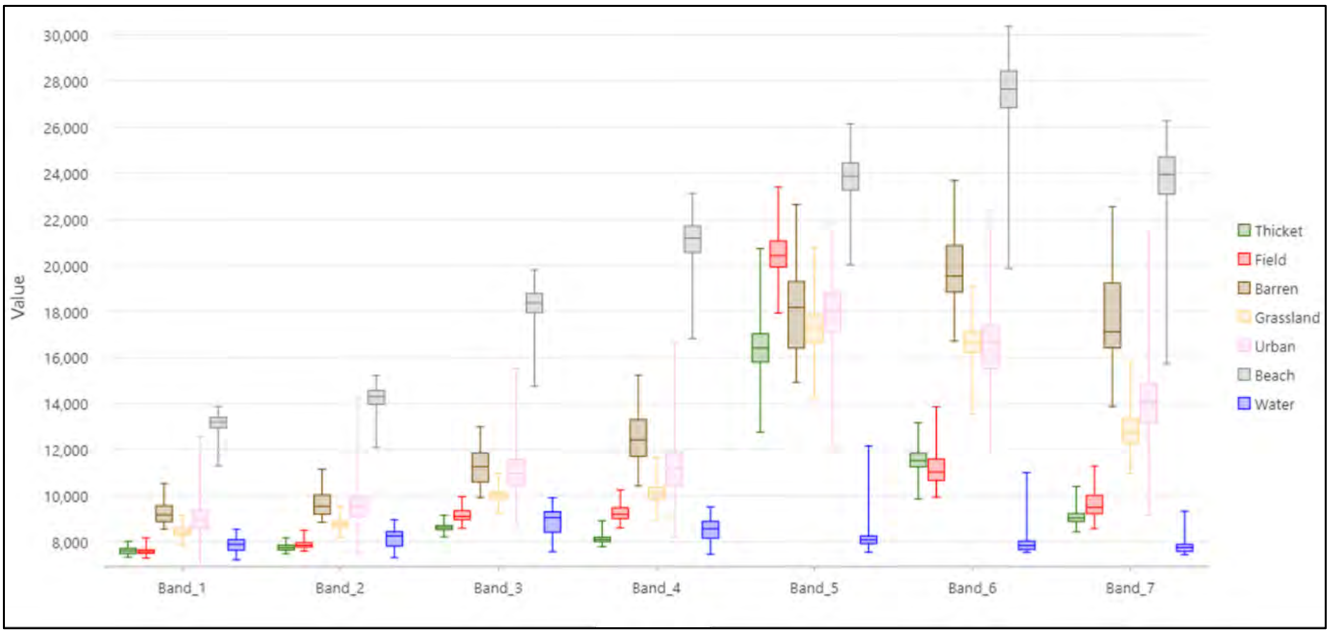


Figure 22: Spectral reflectance profiles for seven land covers in the study area over seven bands of the EMS.

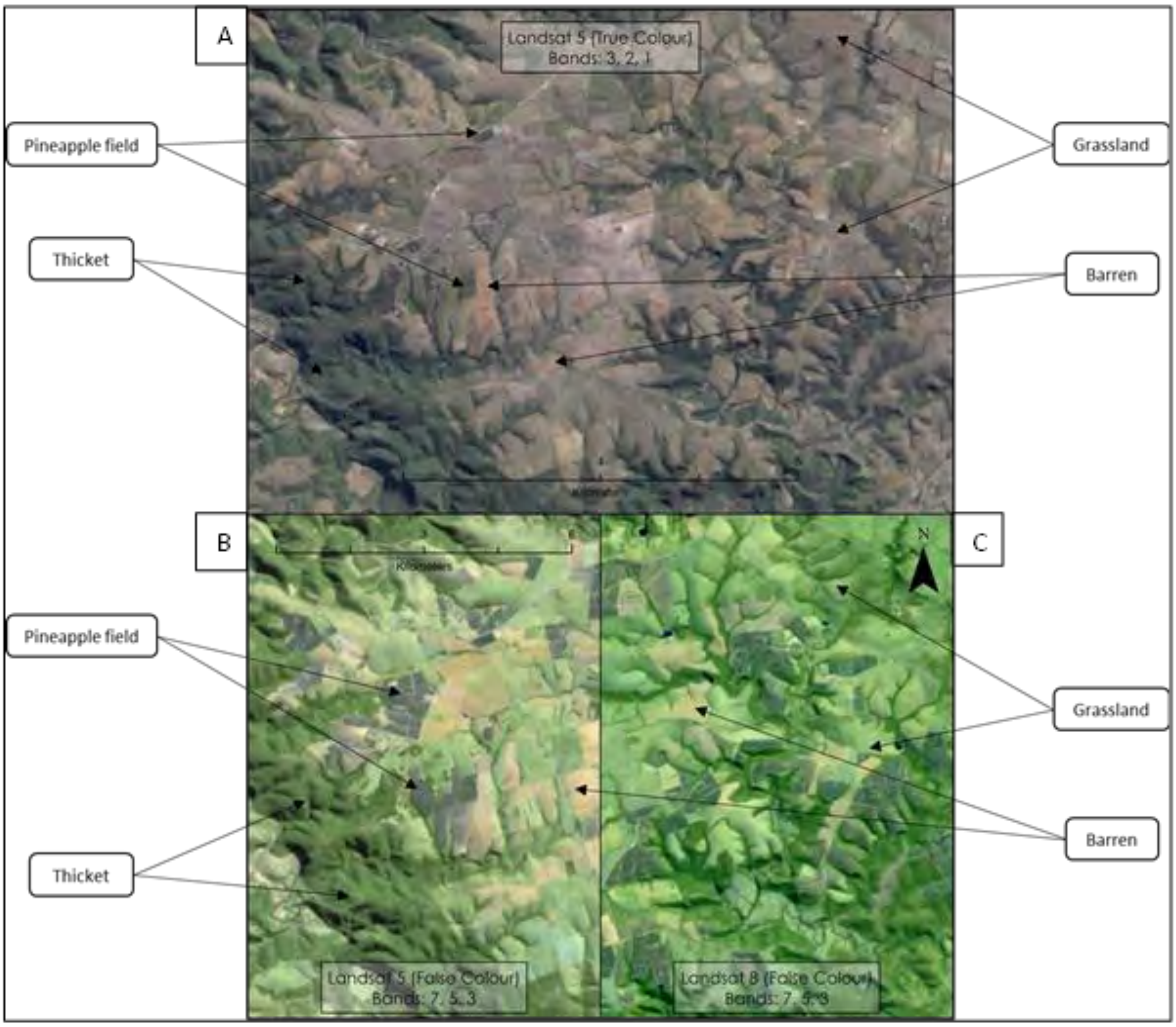


Figure 23: A visual representation of the study area's land covers in a; A) Landsat 5 True colour image, B) Landsat 5 False Colour Image, and C) Landsat 8 False Colour Image (Source: USGS Earth Explorer, 2023).

4.3.1.2. Training sample data

Training samples were created in ArcGIS Pro. A false colour image of the 2020 Landsat 8 satellite image was created using bands 7, 5, and 3 in the respective red, green, and blue channels. This band combination distinguishes natural vegetation (Thicket and Grassland) from active pineapple fields. A new feature class was created in ArcGIS Pro for each of the six land cover types. Fifty polygons per land cover class were created over areas representing the specific land cover (Basheer *et al.,* 2022). In total, three hundred training samples were created in ArcGIS Pro (Figure 24). Seventy per cent of the data was assigned to training, and the remaining thirty per cent was used for validation (Basheer, 2022). The polygons were saved as shapefiles and stored in a secure location. The polygon shapefiles were loaded into both ArcGIS Pro and GEE. The methods of image classification across the two platforms are described below.

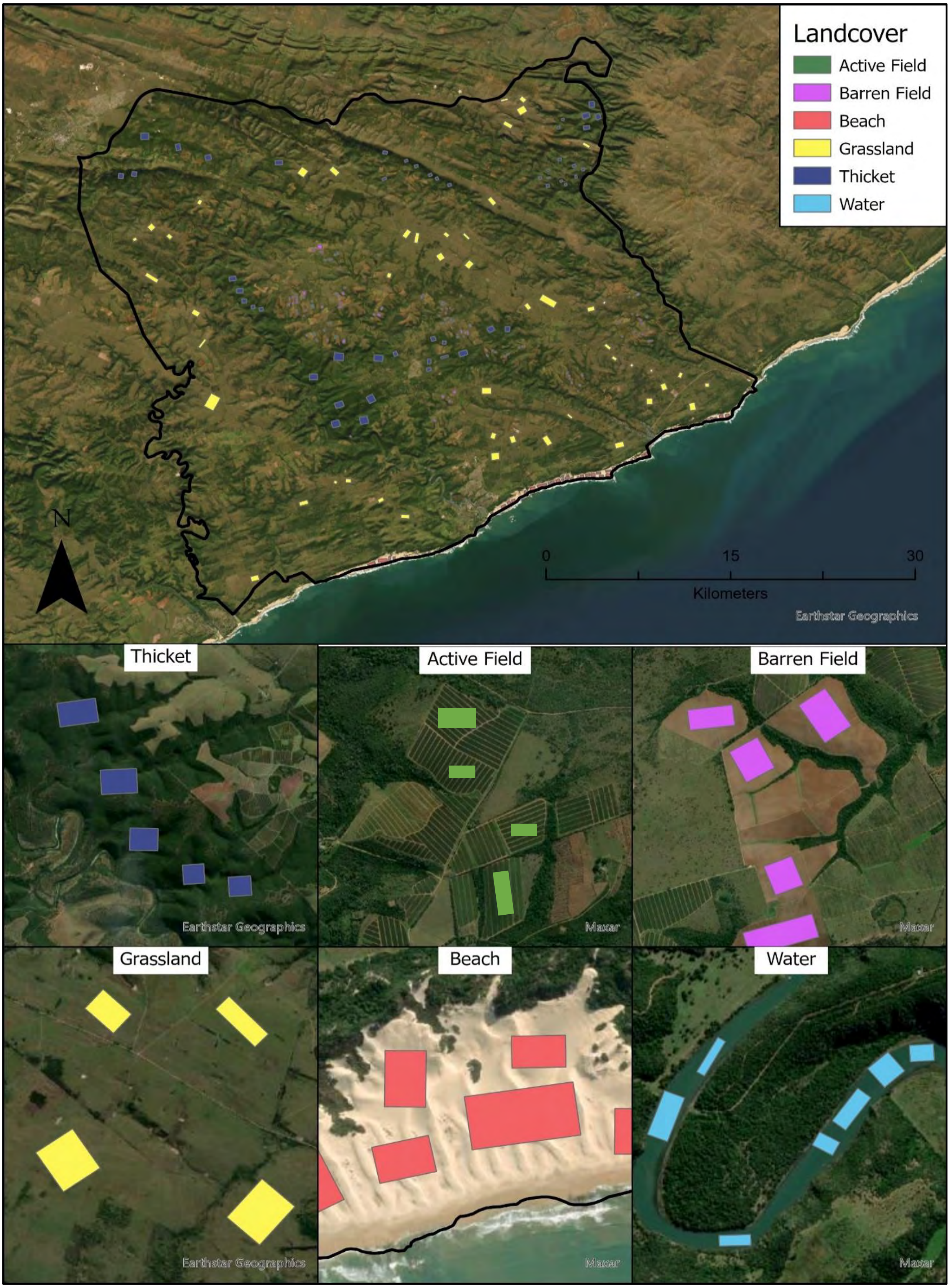


Figure 24: Illustration of the 300 Training samples. Thicket was dense vegetation with a high reflectance in the NIR portion of the EMS. Active Fields contained the distinct pineapple farming grid-like patterns and contained an even higher reflectance in the NIR portion of the EMS. Barren fields were dull in colour, bare of vegetation, and contained low values in the NIR portion of the EMS. Grasslands were not Thicket nor Barren Fields and contained medium values in the NIR portion of the EMS. Beach reflected as white with low values in the NIR portion of the EMS. And Water reflected as dark blue or black in a False colour image.

4.3.2. Data processing

In ArcGIS Pro, supervised and unsupervised image classification techniques were used to classify a Landsat 8 image (Figure 20). The cloud-free Landsat 8 satellite image was uploaded to a new map in ArcGIS Pro. The image was clipped to the extent of the study area using the "Extract by Mask" Spatial Analyst tool. With the image activated, the "Classification Wizard" was used to classify the Landsat 8 satellite image. A classification schema was created using the six land covers described in the previous section. The training sample polygons were added to the map and assigned as the training samples for each classification technique. The following ten image classifiers were created in ArcGIS Pro:

- Supervised Image Classification:
  a) Pixel-based:
    1. Support Vector Machine (SVM) – Maximum of 500 samples per class.
    2. Random Trees (RT) – Maximum of 50 random trees, maximum of 30 tree depth, and maximum of 1000 samples per class.
    3. Maximum Likelihood (ML)
    4. K-Nearest Neighbor (KNN)

  b) Object-based:
    1. Support Vector Machine (SVM) - Maximum of 500 samples per class.
    2. Random Trees (RT) - Maximum of 50 random trees, maximum of 30 tree depth, and maximum of 1000 samples per class.
    3. Maximum Likelihood (ML)
    4. K-Nearest Neighbor (KNN)

- Unsupervised Image Classification:
  a) Pixel-based:
    1. ISO-Cluster (IC) – Maximum of 5 classes, maximum of 20 iterations, maximum of 5 cluster merges per iteration, maximum of 0,5 merge distance, a minimum of 20 samples per cluster, and skip factor of 10.

  b) Object-based:
    1. ISO-Cluster (IC) - Maximum of 5 classes, maximum of 20 iterations, maximum of 5 cluster merges per iteration, maximum of 0,5 merge distance, a minimum of 20 samples per cluster, and skip factor of 10.

In GEE, supervised image classification techniques were assessed (Figure 21). The added land cover class shapefiles were stored as Feature Collections and named accordingly. The properties for each Feature Collection were assigned the property "landcover," and a unique value was assigned to each Feature Collection in chronological order. A script, adapted from Basheer (2022), was written to classify the Landsat 8 image in:

1. Support Vector Machine (SVM)
2. Classification and Regression Trees (CART)

```
var className =
thicket.merge(fields).merge(barren).merge(grassland).merge(water
).merge(beach);
var bands = ['B2', 'B3', 'B4', 'B5', 'B6', 'B7'];
var training = image.select(bands).sampleRegions({
  collection: classNames,
  properties: ["landcover"],
  scale: 30
});
var classifier = ee.Classifier.(libsvm().smileCart()).train({
  features: training,
  classProperty: "landcover",
  inputProperties: bands
});
var classified = image.select(bands).classify(classifier);
```

The twelve image classifier outputs underwent an accuracy assessment in both ArcGIS Pro and Google Earth Engine. The following section describes the methodology of the accuracy assessments.

4.3.3. Accuracy assessment

Accuracy assessments were conducted for the twelve image classifier outputs in ArcGIS Pro and GEE (Figures 20, & 21). The accuracy of an image classifier was affected by methods, procedures, time, and space. Assessing the accuracy of an image classifier was vital for the accuracy of the research study. Basheer (2022) found slight to significant variations in the accuracy of the various image classifiers used in ArcGIS Pro and GEE. The efficiency of the image classifiers used in this research study was assessed on their overall accuracy, identifying the percentage of correctly classified testing data.

In ArcGIS Pro, a dataset was generated using a stratified random sampling approach to generate the training samples from the verification samples (Basheer, 2022). Stratified sampling was used to categorise the dataset or population according to the characteristics of its attribute. The 30% validation datasets were added as the reference datasets to assess the accuracy of the ten image classifiers. Five hundred random points were generated for the accuracy assessments.

In GEE, the validation datasets were added to the project and named accordingly with the prefix “v” to differentiate between the testing and validation datasets. The datasets were stored as Feature Collections with the properties for each Feature Collection assigned the property “landcover,” a unique value was assigned to each Feature Collection in chronological order. A script, adapted from Basheer (2022), was written to assess the accuracy of the two image classifiers:

```
var valNames =
vThicket.merge(vFields).merge(vBarren).merge(vGrassland).merge(v
Water).merge(vBeach);
var validation = classified.sampleRegions({
  collection: valNames,
  properties: ["landcover"],
  scale: 30
});
var testAccuracy = validation.errorMatrix("landcover",
"classification");
print("Validation error matrix:", testAccuracy);
print("Validation overall accuracy:", testAccuracy.accuracy());
```

The results of the accuracy assessments were tabulated for comparative analysis (Table 12). The results of Objective Two initiated the implementation of Objective Three, the methodology of which is presented in the following sections.

4.4. Objective Three: To conduct a spatial analysis of the LULC changes resulting from pineapple cultivation

The methods for Objective Three included a yearly land cover classification of Landsat satellite imagery between 1984 and 2020, a spatial analysis of the LULCC, a selection of random pineapple fields, and a field verification of the LULC at each identified site. The Supervised Pixel-based SVM image classifier identified in the previous Objective was used to classify twenty-seven Landsat satellite images. Figures 25 and 26 illustrate the methodological framework for Objective Three.

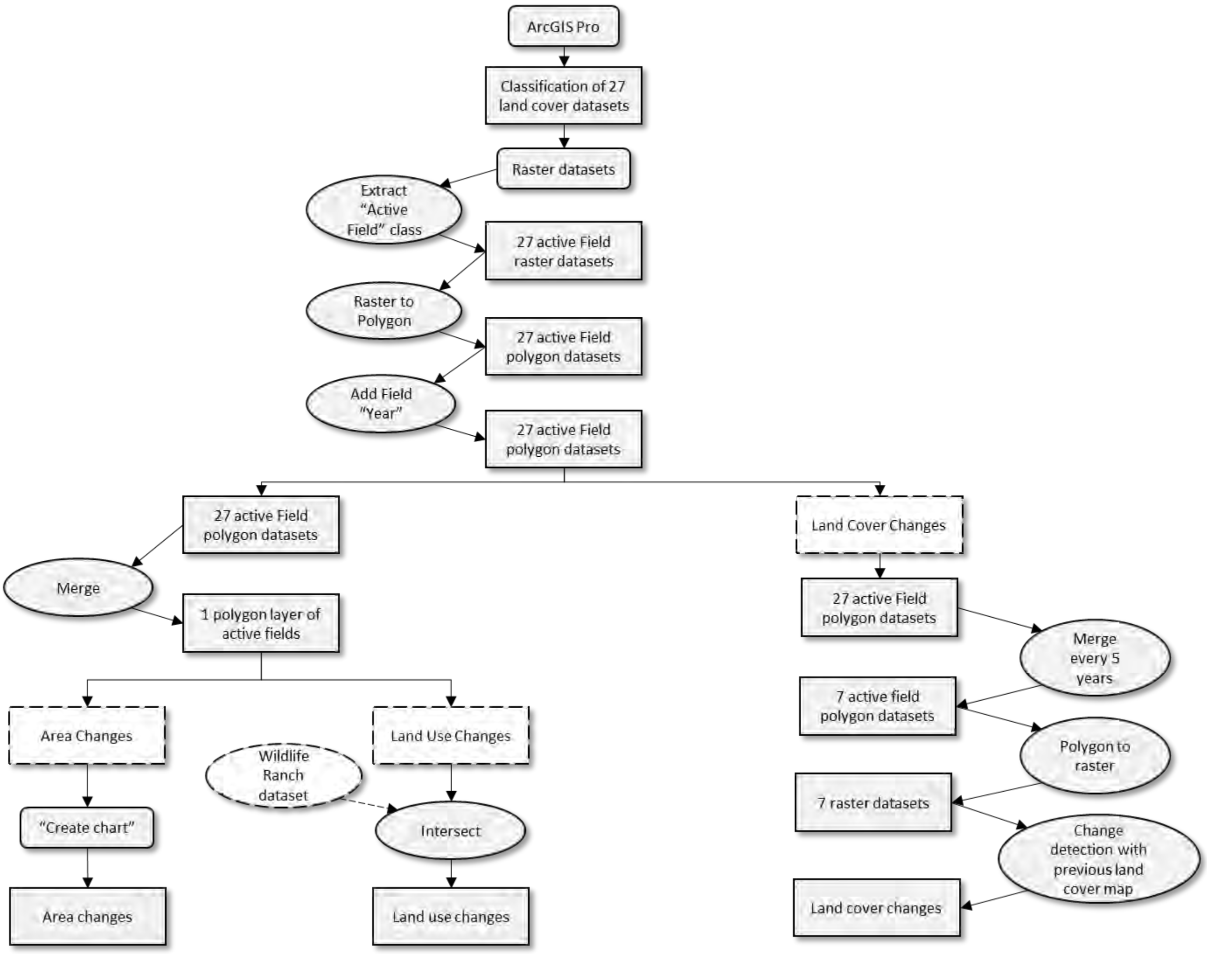


Figure 25: Spatial analysis methodology for area, land use, and land cover changes.

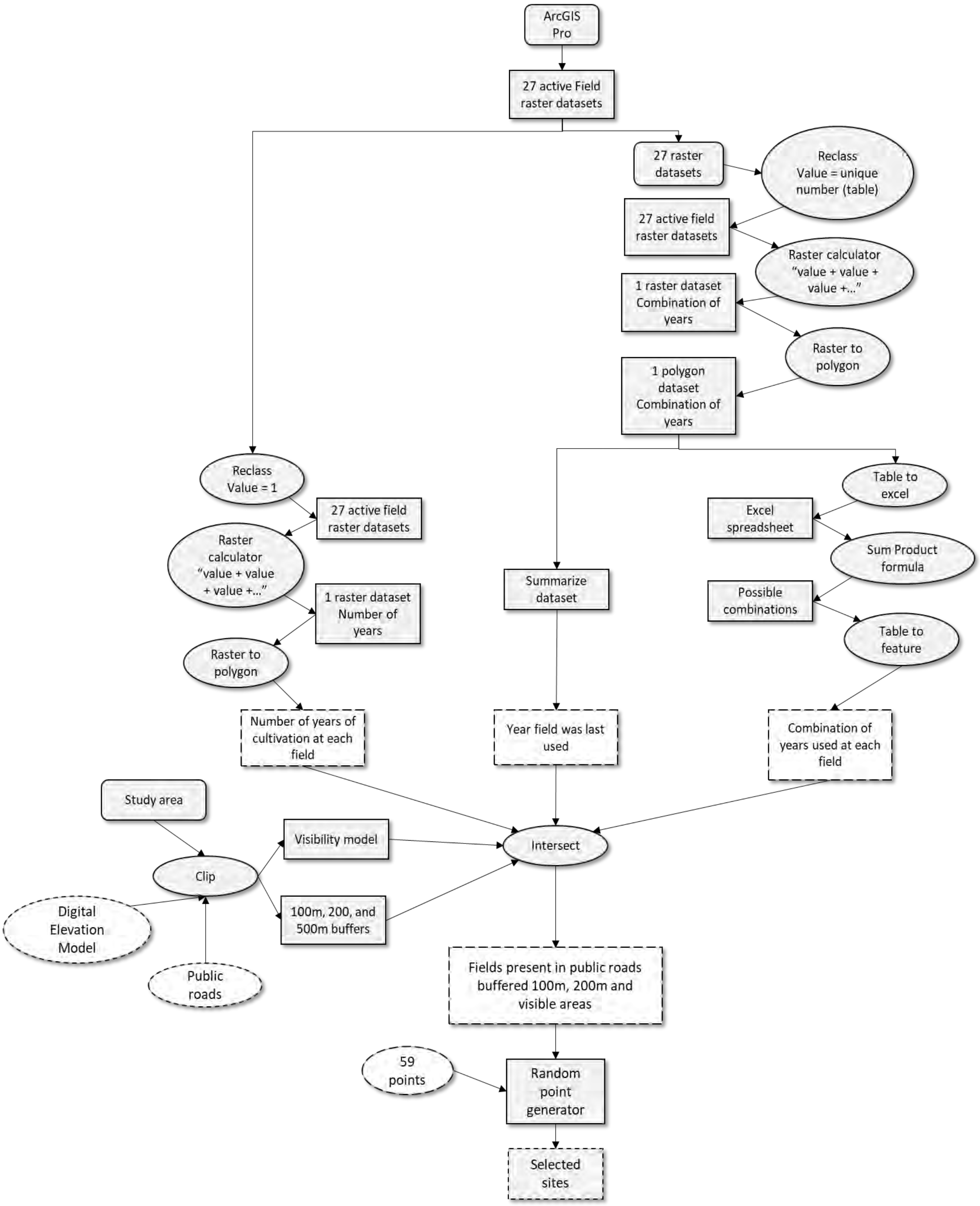


Figure 26: Methodology for site selection.

The following section presents the data preparation of the Landsat satellite imagery, the methodology utilised for the spatial analysis of the area, land use and land cover changes, the selection of randomly generated sites, and the field verification process at each site.

4.4.1. Data preparation

Satellite images with minimal cloud cover, suitable for image classification and interpretation were downloaded from the USGS Earth Explorer website (https://earthexplorer.usgs.gov/) for the analysis of this study (Table 2). Satellite images for each year were only downloaded between January and March to ensure the results could be compared. The reason for this is that, firstly, pineapples are generally harvested in March (Hossain, 2016), and therefore, satellite images between January and March would present mature and spectrally distinct pineapple fields. Secondly, the cloud cover over the study area was observed to be at a minimum between January and March, indicating a higher quality of satellite images for image classification and accurate comparativeness. Satellite images from the latest satellite were downloaded; however, if no images were suitable in a particular year, the previous satellites would be examined to locate the next best image.

Table 2: The downloaded satellite images and their corresponding satellite operators. (Source: USGS Earth Explorer).

Year	Landsat Satellite	Year	Landsat Satellite	Year	Landsat Satellite	Year	Landsat Satellite
1984	5	1994	5	2004	\	2014	8
1985	\	1995	5	2005	5	2015	8
1986	5	1996	5	2006	5	2016	8
1987	\	1997	5	2007	\	2017	8
1988	4	1998	\	2008	\	2018	8
1989	5	1999	7	2009	5	2019	8
1990	5	2000	7	2010	\	2020	8
1991	5	2001	7	2011	\		
1992	\	2002	7	2012	\		
1993	5	2003	7	2013	8		

Landsat satellites were incorporated in this study due to the historic range of imagery compared to Planet and Sentinel-2 satellites. Although Planet and Sentinel-2 satellites provide the highest available pixel resolution, 2 - 5 metres and 10 – 20 metres, respectively, their imagery only dates back to 2019 and 2015, respectively, whereas Landsat satellite imagery is available from 1972 onwards. Utilising Landsat’s greater temporal range of imagery but coarser pixel resolution (Tables 3, 4, and 5) provided a lengthier, and more accurate, analysis of the LULCC resulting from pineapple cultivation.

In total, twenty-seven satellite images were downloaded from various Landsat satellites, as seen in Table 2, including Landsat 4 and 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). The earliest image covering the study area suitable for image interpretation was a 1984 image acquired from the Landsat 5 satellite. Appropriate satellite images that met the requirements of the study were not found for the years 1985, 1987, 1992, 1998, 2004, 1007, 2008, 2010, 2011 and 2012.

Table 5: Landsat 4 and 5 Thematic Mapper (TM) bands, wavelengths, and pixel resolution (Source: USGS, 2023) (https://www.usgs.gov/landsat-missions/landsat-5).

Landsat 4 & 5		
Bands	**Wavelength (µm)**	**Resolution**
Band 1 Visible Blue	0.45 - 0.52	30 m
Band 2 Visible Green	0.52 - 0.60	30 m
Band 3 Visible Red	0.63 - 0.69	30 m
Band 4 Near-Infrared	0.76 - 0.90	30 m
Band 5 Near-Infrared	1.55 - 1.75	30 m
Band 6 Thermal	10.40 - 12.50	120m
Band 7 Mid-Infrared (IR)	2.08 - 2.35	30m

Table 4: Landsat 7 Enhanced Thematic Mapper Plus (ETM+) bands, wavelengths, and pixel resolution (Source: USGS, 2023) (https://www.usgs.gov/landsat-missions/landsat-7).

Landsat 7		
Bands	**Wavelength (µm)**	**Resolution**
Band 1 Visible Blue	0.45 - 0.52	30 m
Band 2 Visible Green	0.52 - 0.60	30 m
Band 3 Visible Red	0.63 - 0.69	30 m
Band 4 Near-Infrared	0.76 - 0.90	30 m
Band 5 Short-wave Infrared	1.55 - 1.75	30 m
Band 6 Thermal	10.40 - 12.50	60m Low Grain / High Grain
Band 7 Mid-Infrared (IR)	2.08 - 2.35	30m
Band 8 Panchromatic (PAN)	0.52 - 0.90	15

Table 3: Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) bands, wavelengths, and pixel resolution (Source: USGS, 2023) (https://www.usgs.gov/landsat-missions/landsat-8).

Landsat 8 (OLI & TIRS)		
Bands	**Wavelength (µm)**	**Resolution**
Band 1 Coastal Aerosol	0.43 - 0.45	30m
Band 2 Visible Blue	0.45 - 0.51	30 m
Band 3 Visible Green	0.53 - 0.59	30 m
Band 4 Visible Red	0.64 - 0.67	30 m
Band 5 Near-Infrared	0.85 - 0.88	30 m
Band 6 Short-wave Infrared 1	1.57 - 1.65	30 m
Band 7 Short-wave Infrared 2	2.11 - 2.29	30m
Band 8 Panchromatic (PAN)	0.50 - 0.68	15m
Band 9 Cirrus	1.36 - 1.38	30m
Band 10 TIRS 1	10.6 - 11.19	100m
Band 11 TIRS 2	11.5 - 12.51	100m

The land cover of the twenty-seven satellite images was classified using the methodology implemented in Objective Two. Training samples were created following the methods discussed in the previous objective. Each layer was projected to the UTM projection with a central meridian of twenty-seven. The following sections describe the methodologies for the spatial analysis and site selection processes illustrated in Figures 25 and 26 and the methodology incorporated for the field verification process.

4.4.2. Spatial analysis

A spatial analysis task was conducted to assess the changes in pineapple cultivation between 1984 and 2020 to identify the specific changes in the area, land use, and land cover resulting from pineapple cultivation within the study area. Three individual outputs were created through this analysis, including a chart displaying changes in land area under pineapple cultivation, land use transitions occurring in the study area, and land cover change detection (Figure 25). To create these, the twenty-seven land cover datasets, created in the previous objective, were added to a new map in ArcGIS Pro. The “Active Field” classes were extracted from each raster dataset, after which the datasets were converted to a polygon feature using the “Raster to Polygon” geoprocessing tool. Each vector layer was dissolved using the “Dissolve” geoprocessing tool to display a single polygon feature for the extent of pineapple fields for the particular year. A new field was added to the attribute table of each layer with the name “Year”, and the field was populated with the year the data was captured, i.e., “2017”. All the fields were merged using the “Merge” geoprocessing tool to create a single dataset containing the extent of the active pineapple fields for each year since 1984. This layer was henceforth called the “Merged polygon layer.” The specific methods for each spatial analysis are discussed in the following sections.

4.4.2.1. Area changes

The change in area analysis aimed to identify the patterns of the changes to land under pineapple cultivation between 1984 and 2020 (Figure 25). A new field was added to the attribute table of the “Merged polygon layer” named “Area.” The field was populated using the “Calculate geometry” option, where the total area in hectares was generated for the extent of pineapple fields each year. Furthermore, a line chart was created using the “Create chart” option in which the x-axis displayed the year of the data, and the y-axis displayed the value of hectares.

4.4.2.2. Land use changes

The analysis of the land use changes aimed to identify the common transitions in land use practices concerning pineapple fields (Figure 25). The study area contains various land use types, including game and nature reserves, urban areas, agricultural zones, and municipal land. Although land use spatial data is widely available in South Africa, it is incomplete and lack sufficient detail for the specific requirements of this study. Therefore, wildlife ranch land parcels were collected from a local conservationist. The dataset contained the shapefiles for numerous protected areas, public and private game reserves, nature reserves, game farms, and eco-estates within the Eastern Cape. The dataset was clipped to the extent of the study area using the “Clip” geoprocessing tool. Furthermore, the clipped dataset and the “Merged polygon layer” were intersected using the “Intersect” geoprocessing tool. The output of the new layer displayed locations where previously active pineapple fields intersected with recently established alternate land use practices. The area, in hectares, of the pineapple fields for each year was calculated for each land use zone and displayed in a map format.

4.4.2.3. Land cover changes

The land cover change methods aimed to identify, through remote sensing technologies, the common land cover transitions from pineapple cultivation (Figure 25). The methods for this task involved a change detection analysis to highlight the land covers that have changed to or from pineapple fields or that have remained the same. Because pineapples are harvested every 5-7 years, the polygon vector layers were merged into 5-year intervals to display the full extent of pineapple fields during a growing period. The twenty-seven active field polygon datasets were merged into 5-year intervals using the “Merge” geoprocessing tool to enable accurate change detection. Each dataset was thereafter converted back into a raster format using the “Polygon to Raster” geoprocessing tool. A change detection analysis was conducted between the 5-year layer and the following land cover dataset. For example, change detection was analysed between the 5-year interval category of 1990-1995 and the 1995 land cover map. This was done to indicate if an alternate land cover or another pineapple field replaced the presence of a previous pineapple field. The results of the analysis were tabulated and presented in a graph format (Figure 50).

4.4.3. Site selection for field verification

The spatial analysis presented in the previous section illustrated the methodology used to detect, through satellite imagery, the area, land use, and land cover changes resulting from pineapple cultivation. A ground-based field verification assessment was conducted to assess the accuracy of the spatial analysis and to provide an in-depth examination of the LULCC resulting from pineapple cultivation. To evaluate this, sites were randomly generated from the dataset illustrating the entire spatial location of pineapple fields since 1984 (Figure 26). These sites needed to meet specific requirements, including visibility and accessibility from a public road. The methods included the creation and intersection of several independent layers, including: 1) a visibility model, 2) a buffer of a) 100 metres, b) 200 metres and c) 500 metres of public roads, 3) the number of years of cultivation at a single field, 4) the specific years during which a field was under production, and 5) the most recent year a field was under cultivation. Fifty-nine random pineapple fields were selected that met the necessary criteria. The methodology of the site selection process is described below:

1) First, a visibility model was created in ArcGIS Pro (Figure 26). A visibility model uses an elevation model to create an output that displays those areas which are visible from a point or line location. For the elevation model, a DEM was created for this analysis using the five-metre elevation lines downloaded from the CD: NGI Geospatial Portal. For the point or line features, the Eastern Cape Road dataset was downloaded from the CD: NGI Geospatial Portal and the public roads were extracted from the dataset. The two layers were clipped to the extent of the study area and added as input features into the “Visibility” geoprocessing tool. An example of a visibility model is illustrated in Figure 27.

2) Second, three buffers of the public roads were created at varying distances (Figure 25). This step indicates the pineapple field’s distance from the public roads for the field verification process. The extracted public road dataset was used as the input feature for the “Buffer” tool in ArcGIS Pro. Individual layers were created at 100, 200 and 500 metre buffers for each public road. The layers were simplified using the “Dissolve” geoprocessing tool to summarise them into one segment. An example of the buffer datasets is presented in Figure 28.

3) Third, a layer displaying the years of cultivation since 1984 for each pineapple field was created (Figure 25). This step aimed to assist the final analysis of this research study by providing information on the number of years a field had undergone cultivation since 1984. Figure 26 above illustrates the methodology followed to create this layer. Each of the twenty-seven active pineapple raster datasets was classified to a value of “1”. Using the Raster Calculator tool, a sum was created to add the values of each reclassified layer. If the fields overlapped, the values were added together (1 + 1 + 1… = n). For example, if a field was only

used in 1984, it would display the value “1”. If a field was identified as having five years of use, the output would display “5”. The output was a single raster layer that displayed the spatial arrangement of pineapple fields with a value of how many times the fields have been used (Figure 29). The raster layer was then converted into a polygon layer. The value field was dissolved, so each value became a single feature in the output.

4) Last, a layer containing information about the year in which each field was under pineapple cultivation was created (Figure 25). This task aimed to assist the final analysis of this research study by providing information as to when the field was last cultivated for pineapples, so as to indicate how long the field had lain dormant. To calculate this, the twenty-seven active field raster datasets were reclassed using the “Reclass” geoprocessing tool to the values illustrated in Table 7, the contents of which are discussed in the following paragraphs. The reclassified datasets were inputted into the “Raster Calculator” geoprocessing tool, and a sum was created that added each layer to create a single raster layer. The raster layer was then converted to a vector using the “Raster to Polygon” geoprocessing tool. This layer is hereafter named the “Unique polygon layer.” The generated values illustrate the specific years of cultivation that occurred in a single field. If the unique number equals a value in Table 7, the field has been cultivated once (32 = 1991). Additionally, if a number is bigger than 32 but smaller than 64, it is the sum of 32, and several smaller numbers (37 = 32 + 4 + 1). Therefore, the year the field was most recently cultivated will always be the largest number in the sum (32 = 1991). A new field was created in the layers attribute table, and the table was populated with the year the field was most recently cultivated. The output of this task is presented in Figure 30.

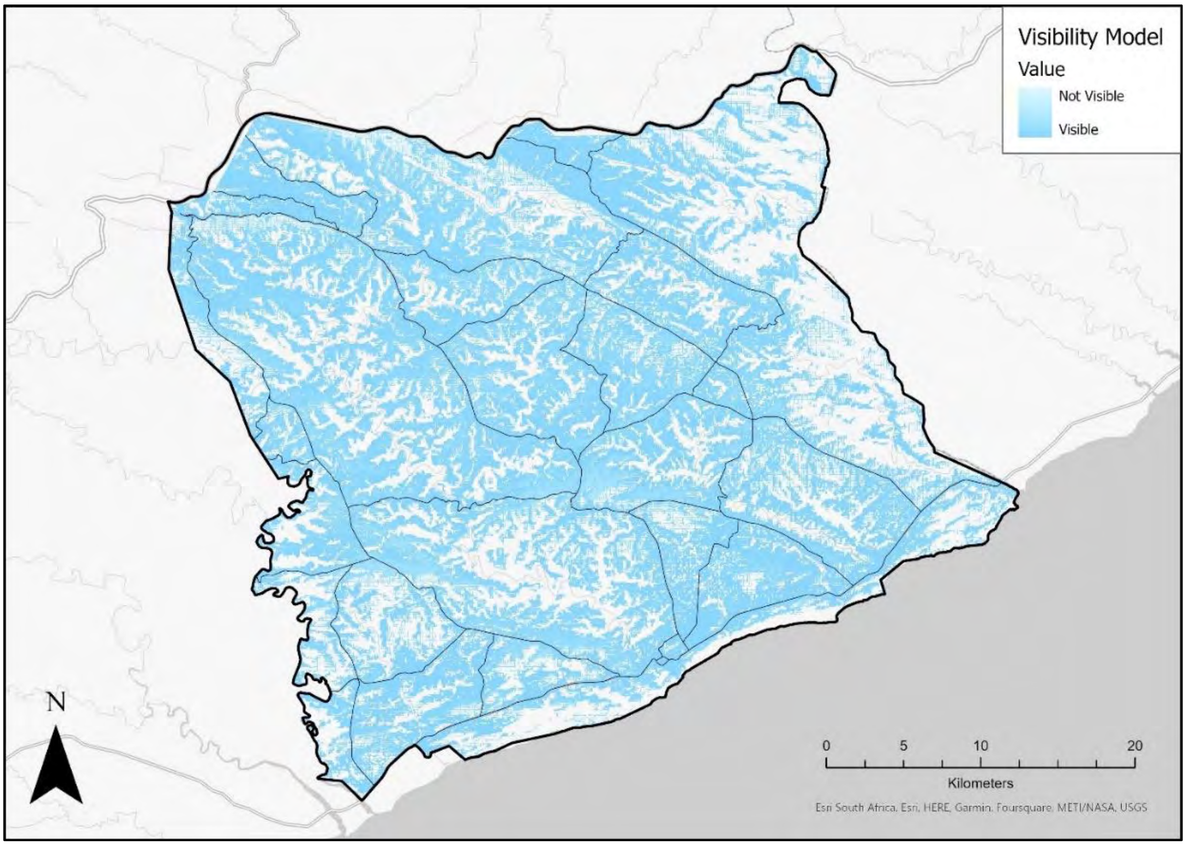


Figure 27: Illustration of the visibility model created for the site selection process. Blue areas are visible from a public road, and transparent areas are not.

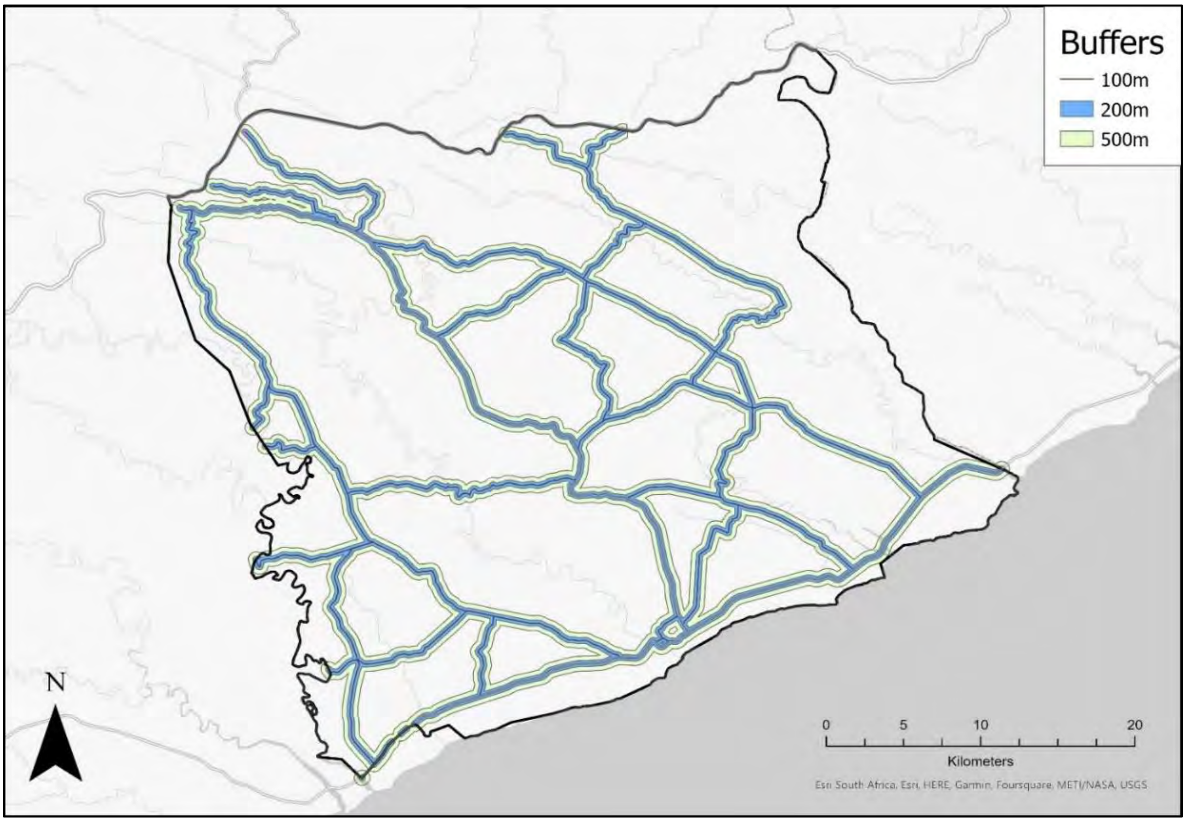


Figure 28: 100, 200, and 500 metre buffers from the public road dataset.

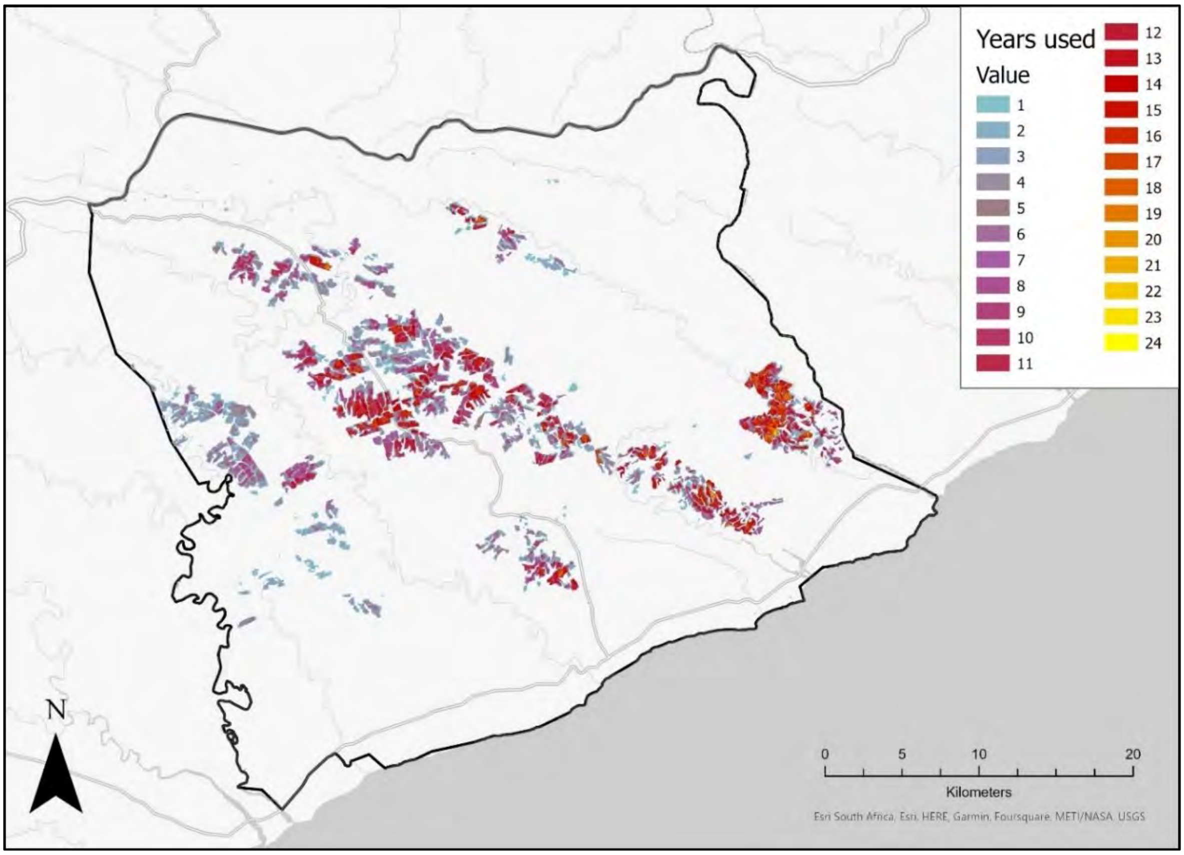


Figure 29: Number of years of pineapple cultivation at each field location since 1984. Blue to purple areas indicate sites with the least number of years of cultivation. Red to yellow indicate the most years of cultivation.

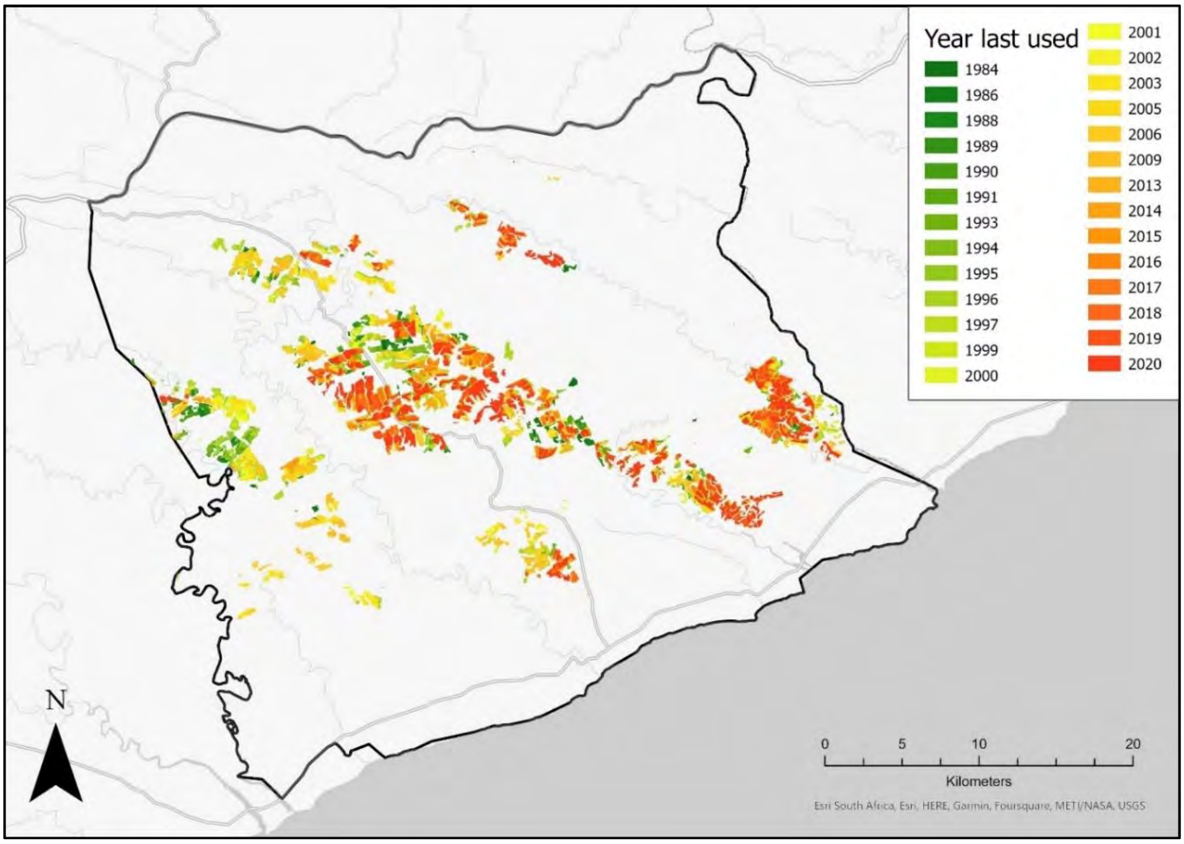


Figure 30: Year of last cultivation at each field location. Green to yellow indicate the longest time since a field was cultivated. Yellow to red indicate the shortest time since a field was cultivated.

The six created layers were intersected to create a single layer representing accessible locations that met the criteria for field verification (Figure 31). The random point generator tool created fifty-nine random sites for field verification. Each point contained information regarding the distance of the site from the road, the number of years under cultivation, the unique number indicating the specific years of cultivation, and the most recent year of cultivation. To identify which specific values (or years) were added to create the generated value, the site layer was exported using the "Table to Excel" geoprocessing tool. Microsoft Excel was used to identify which values in a dataset added to a target value, following the methodology outlined in an article by The Daily CPA (2017).

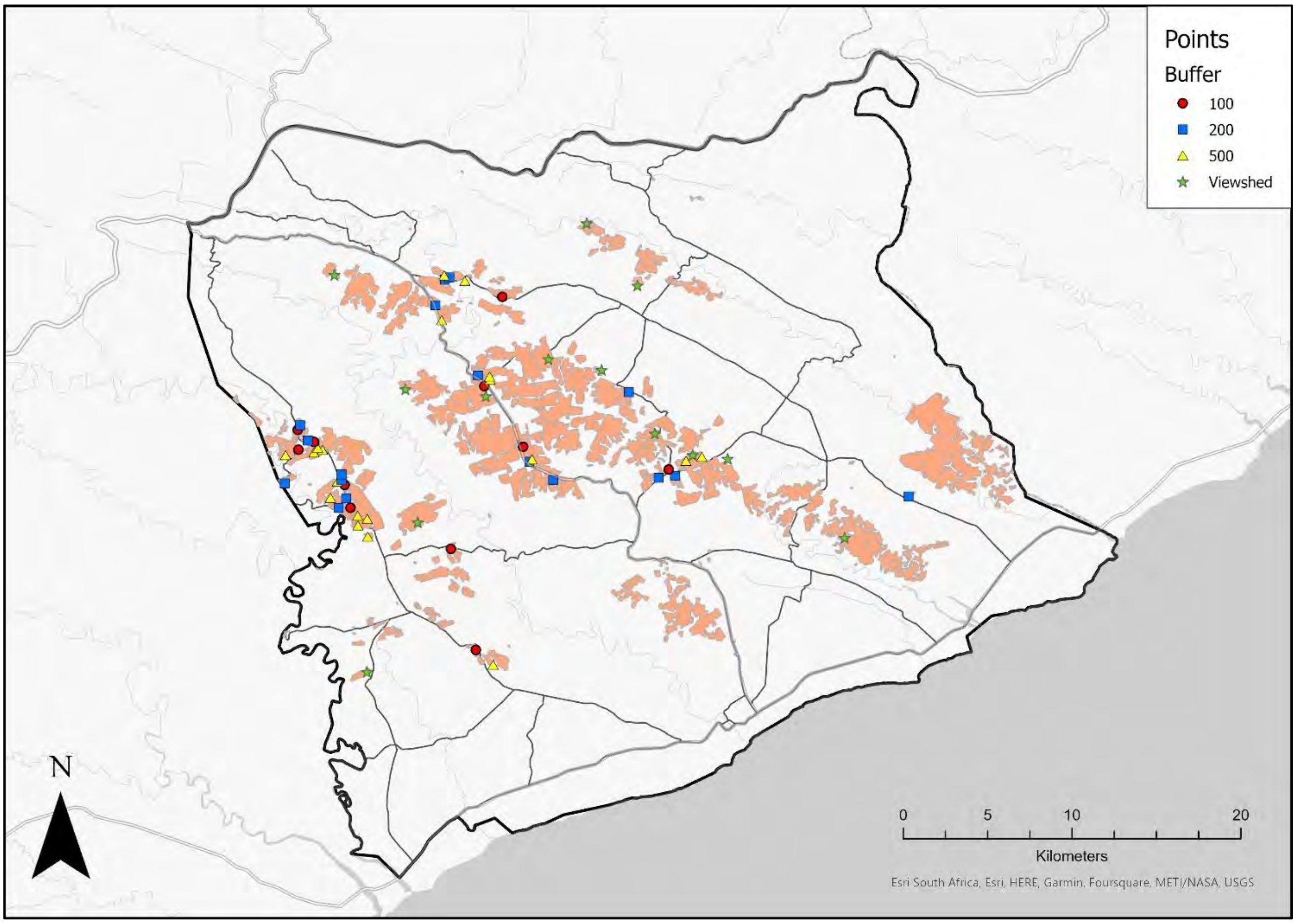


Figure 31: Randomly generated sites. A total of 59 sites for the field verification process.

The "Solver" function in Microsoft Excel was used to identify which unique numbers were added together. In this exercise, the aim was to identify which values ("Unique numbers") were added together to generate a target number (the sum of the "Unique numbers"). In theory, the unique number generated for each year, as illustrated in Table 7, was created to generate a new number of the product of overlapping field locations to identify the specific years of cultivation. For example, if a field in the output displays the value 32, it could only be a field identified as being used in 1991, as displayed in Table 7, where the “Unique Number” was equal to 32 and the “Year” was equal to 1991. Also, if a field displays a value between 16 and 32, 28, for example, it could only be the sum of 16 and several numbers less than 16, 8 and 4 in this case (4 + 8 + 16 = 28) as referred to in Table 7. This was the only combination of numbers that can equal twenty-eight from the unique numbers available in Table 7. Even if all values less than and equal to 16 are added together, the sum will always produce a number less than the following larger number in the series (1 + 2 + 4 + 8 + 16 = 31). The generated values for each of the fifty-nine sites are presented in Table 6, hereafter referred to as the “Target Values”.

The steps of the methodology to identify the specific years of pineapple cultivation are as follows:

1. First, in Microsoft Excel, the unique numbers were organised in a column named “Data” (Table 8). In the adjacent column, the number “1” was added for each cell and named “Multiplier” (Table 8). In the adjacent column, the “Data” and “Multiplier” columns were multiplied (Table 8).
2. Second, a new cell was named “Target” (Table 9). The Target Values in Table 6 would each be added to this cell one at a time. Below this cell, a cell was named “SUM of Product” (Table 9). The total sum of the “Product” column in Table 8 was added to this cell. Below this, a cell was named “Difference” (Table 9). The “Target” cell was subtracted from the “SUM of Product” to display the difference between the values.
3. Last, the Solver Add-In parameters (Figure 32) were configured to identify which values in the “Data” column (Table 8) were added together to create the “Target” value (Table 9). The “Solver” Add-In enables a binary output that changes the values of the “Multiplier” column (Table 8) to either one (if the adjacent value adds to the target value) or zero (if the adjacent value does not add to the target value).

Table 6: Unique numbers generated for each of the fifty-nine sites.

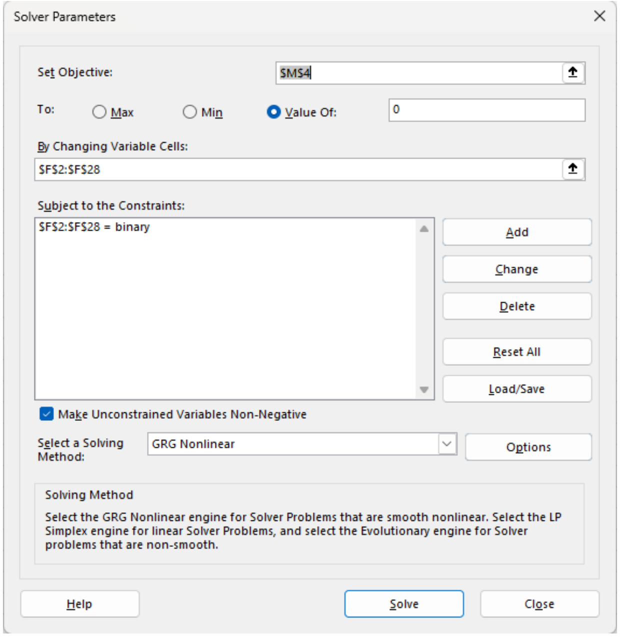
1984	1	**1994**	240	**1999**	3614	**2003**	61540	**2006**	211044	**2016**	8124516
1989	1	**1994**	241	**1999**	2048	**2003**	63012	**2006**	246208	**2016**	8338469
1899	11	**1995**	480	**2000**	7169	**2003**	58980	**2007**	197380	**2017**	16708645
1989	14	**1995**	463	**2000**	6264	**2003**	63591	**2007**	196608	**2018**	31778852
1989	12	**1996**	737	**2000**	5280	**2003**	57458	**2009**	463588	**2018**	25442404
1990	28	**1996**	512	**2001**	14436	**2005**	123947	**2009**	325924	**2019**	63489502
1990	28	**1997**	1152	**2001**	15460	**2005**	115424	**2009**	319588	**2019**	63554526
1991	32	**1997**	1408	**2001**	13924	**2005**	122980	**2013**	720896	**2019**	59456659
1993	112	**1997**	1472	**2002**	30834	**2006**	192612	**2014**	1769472	**2019**	65011712
1993	120	**1997**	1024	**2002**	22752	**2006**	198176	**2014**	68880096		

Table 8: List of the unique number and its corresponding year.

Year	Unique Number
1984	1
1986	2
1988	4
1989	8
1990	16
1991	32
1993	64
1994	128
1995	256
1996	512
1997	1 024
1999	2 048
2000	4 096
2001	8 192
2002	16 384
2003	32 768
2005	65 536
2006	131 072
2009	262 144
2013	524 288
2014	104 857 6
2015	209 715 2
2016	419 430 4
2017	838 860 8
2018	167 772 16
2019	335 544 32
2020	671 088 64

Table 7: Example of the process of identifying the specific years of pineapple cultivation in Microsoft Excel.

Data	Multiplier	Product
1	1	1
2	1	2
4	1	4
8	1	8
16	1	16
32	1	32
64	1	64
128	1	128
256	1	256
512	1	512
1024	1	1024
2048	1	2048
4096	1	4096
8192	1	8192
16384	1	16384
32768	1	32768
65536	1	65536
131072	1	131072
262144	1	262144
524288	1	524288
1048576	1	1048576
2097152	1	2097152
4194304	1	4194304
8388608	1	8388608
16777216	1	16777216
33554432	1	33554432
67108864	1	67108864


Solver Parameters

Set Objective: $M$4

To: ○ Max ○ Min ● Value Of: 0

By Changing Variable Cells: $F$2:$F$28

Subject to the Constraints:
$F$2:$F$28 = binary

☑ Make Unconstrained Variables Non-Negative

Select a Solving Method: GRG Nonlinear

Solving Method

Select the GRG Nonlinear engine for Solver Problems that are smooth nonlinear. Select the LP Simplex engine for linear Solver Problems, and select the Evolutionary engine for Solver problems that are non-smooth.

Figure 32: Microsoft Solver parameters.

Table 9: Example of the process of identifying the specific years of pineapple cultivation in Microsoft Excel

Target	246208
SUM of Product	134217727
Difference	133971519

The binary output (Table 10) for each of the fifty-nine sites was converted into a graph format that visually illustrates the specific years of pineapple cultivation at each site (Figure 33). In Table 10, the Target Value was 57458. According to Table 6, this site was last used in 2003. The process illustrated that this site was cultivated with pineapples in 1986, 1990, 1991, 1993, 2001, 2002, and 2003 (Figure 33).

As a result of the incomplete coverage of the entire range of years during the proposed study period, due to inappropriate or unavailable satellite images, Google Earth Pro was utilised to cross-reference each of the fifty-nine sites. The fifty-nine sites were loaded in Google Earth Pro and labelled accordingly. Where there was a gap in the data, imagery from that year was investigated to identify the presence or absence of an active pineapple field. The original table was updated to account for these errors. The final selected sites and updated table guided the field verification process. Completing this analysis, combined with the ground-based field verification, enabled the analysis of the patterns and trends of pineapple cultivation-induced LULCC.

Table 10: Example of the binary output to identify the specific years of pineapple cultivation.

Data	Multiplier	Product
1	0	0
2	1	2
4	0	0
8	0	0
16	1	16
32	1	32
64	1	64
128	0	0
256	0	0
512	0	0
1024	0	0
2048	0	0
4096	0	0
8192	1	8192
16384	1	16384
32768	1	32768
65536	0	0
131072	0	0
262144	0	0
524288	0	0
1048576	0	0
2097152	0	0
4194304	0	0
8388608	0	0
16777216	0	0
33554432	0	0
67108864	0	0

Target	57458
SUM of Products	57458
Difference	0

4.4.4. Field verification

The field verification process aimed to assess the LULC of fifty-nine random pineapple fields identified by remote sensing spatial analysis. A document was created for each site that presented the location of the site and the information regarding the number of years of cultivation, the specific years of cultivation, and the most recent year of cultivation (Figure 33). Additionally, a field verification notebook was created to record the state of the land cover (Table 11). The tools needed for this method included a vehicle for transport to each site, the file containing the location and information of each site, a GPS device to accurately locate the position of each site, a camera for documentation purposes, and a notebook and pen to record notes of the land use and land cover of the site and its surrounds. The time to complete the methodology for each site was approximately 10 minutes, resulting in a full day of data collection over three days. Images were captured with a camera of the land cover at each site. Notes were recorded in the notebook, illustrated in Table 11. The images were downloaded from the camera and stored in a file on a secure hard drive. The notes were converted into a Microsoft Excel spreadsheet and stored on a secure hard drive.

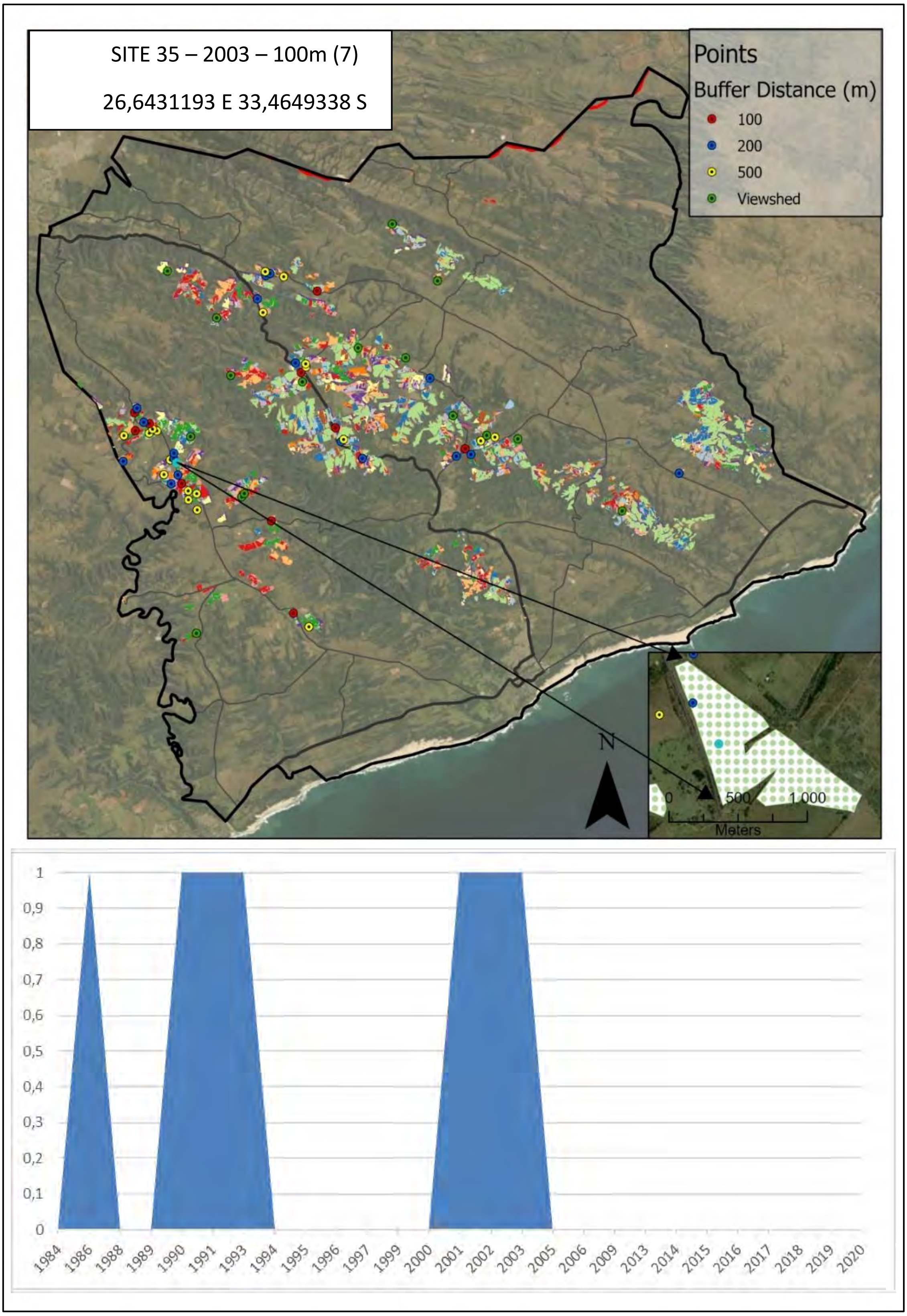


Figure 33: Field verification worksheet.

Table 11: The field notebook used to capture the information surrounding each of the sites visited in the field.

Site number:	Year field was last used productively:	How many years was the field used productively:	Define the land use at the site:	If not a productive field, rank the land cover of the site: 1 = grass, 5 = ecologically productive land cover	Notes of the state of the land cover:

4.5. Summary

The methodology for this research study utilised various methodological frameworks for each of the three objectives. Objective One followed a qualitative approach of secondary data to identify the information pertaining to the pineapple industry from global, national, and local points of view. Firstly, semi-structured interviews were conducted with local pineapple farmers within the study area. These interviews aimed to investigate how the farmers cultivate pineapples, the factors that have affected the industry in the past, the LULC caused by pineapple farming, and the future trajectory of the pineapple industry. Secondly, the interviews guided an in-depth literature review to identify the factors affecting the local pineapple industry from global and national perspectives. The literature review examined information regarding the global pineapple industry, its effect on the national industry, and the political, economic, and spatial factors that have affected the functionality of the local industry. Objective Two followed a quantitative secondary data approach to formulate the most accurate and relevant method for identifying and mapping pineapple fields in a diverse landscape using remote sensing technologies. Similar studies in the literature highlighted supervised image classification of open-sourced medium-resolution satellite imagery as an accurate method for identifying specific crop fields in a diverse landscape (Basheer *et al.,* 2022). Twelve image classifiers across two remote sensing software applications were trialed and evaluated to identify the most accurate methodology for the specific requirements of this research study. The methodology for Objective Three generated yearly landcover maps from 1984 to 2020, using the most accurate image classifier identified by the previous objective. These land cover maps underwent a spatial analysis process to identify the changes in the area, land use, and land cover resulting from pineapple cultivation. Moreover, fifty-nine random pineapple fields were generated for a field verification process to assess the LULCC further. The results of the following methodologies for each objective enabled the creation of a holistic conceptualisation of the LULCC resulting from pineapple cultivation in the study area, and the forces that have influenced the changes identified by the remote sensing spatial analysis.

CHAPTER 5: RESULTS

5.1. Introduction

The results section is divided into three parts: Objective One, Objective Two and Objective Three. The section on Objective One includes an introduction of each participant interviewed in this research study and the results of how each participant responded to the questions in the interview. The section on Objective Two includes the results of the image classification of Landsat satellite imagery using twelve different image classifiers in ArcGIS Pro and GEE, the results of the accuracy assessment of each image classifier, and the final 27 land cover maps from 1984 to 2020 created using the most accurate image classifier. The section on Objective Three includes the results of the spatial analysis of the changes in the area, land use, and land cover resulting from pineapple cultivation between the land cover maps, the site selection results, and the field verification results.

5.2. Objective One: To investigate the information surrounding the changes in the pineapple industry

To holistically examine the factors affecting the pineapple industry, and the subsequent transformation of the industry, information pertaining to these topics was explored through a literature review and interviews with five local stakeholders in the industry. The results of the literature review are presented in Chapter 3. Five pineapple farmers in the study area were interviewed for this research study following the methodology presented in Section 4.2 of Chapter 4. Each participant is a current pineapple farmer in the study area. The interviews provided vital information regarding the pineapple industry in South Africa, specifically the Lower Albany area, including how pineapples are grown, the changes that have occurred in the industry, the challenges that have affected the industry, and the future trajectory of pineapple farming in the country.

5.2.1. Interviews

The interviews with five pineapple farmers provided vital information regarding the changes in the pineapple industry, the common farming practices adopted in the study area, the limitations of farming pineapples, and the future trajectory of the pineapple industry. The key messages obtained from each participant are summarised below. The tabulated results of the interviews are presented in Appendix A.

5.2.1.1. Changes to the pineapple industry

When discussing the changes that have taken place in the industry from the perception of the farmers, the interview participants shared similar views on the direct and indirect changes and challenges they had experienced during their time as pineapple growers. All five interviewees noted that the pricing and economics of producing pineapples is the primary driver of change. "The rising cost of inputs challenges pineapple growers immensely," Pike stated. Harris shared the same view and emphasised that "the rising pressure of the economic sector is the most significant driver of change the industry faces." Arnold shared his experiences while travelling to the major pineapple-producing countries, stating, "South Africa is tiny within the global industry and struggles to compete against the powerful nations, such as Thailand, where they have favourable conditions."

Subsequently, the ever-rising cost of inputs and labour constantly places pressure on the farmers. The participants noted that the significant changes in the industry include the consolidation of pineapple farms and the transition to wildlife ranching in the study area. Harris and Arnold, two long-term pineapple farmers in the region, explained how the number of pineapple farmers in the region had decreased significantly while the footprint of pineapple fields had not done so. Muir presented the opposite of this pattern by introducing pineapples to a farm that had held cattle for four decades.

Furthermore, Harris indicated that social and political interventions had changed the functionality of the agricultural body. Due to strict governmental legislation, farmers cannot clear new lands to expand their agricultural footprint. "It is less expensive to buy a neighbouring farm than it is to try and get the permission to clear new lands," stated Harris. Pike emphasised that the entire industry has reshaped itself as an environmentally friendly operation throughout the last decade. "An environmental/sustainable approach is practised today, ensuring the health of the fields and the systems with which they are intertwined," stated Pike. Muir agreed with this opinion and stated, "The fields will eventually give in if the farmers do not put the necessary nutrients back into the soil."

The last noteworthy change presented by the participants was the dramatic transition in the processing factories and export trade of pineapples. Harris stated that the South African pineapple export industry has reshaped entirely towards a juicing industry, unlike the canned or fresh exports of several years ago. The country had seven export canning factories several years ago, but it only operates one export juicing factory today, at Summerpride Foods in East London. The participants confirmed that a primary reason for the transition was the introduction in 2004 of dangerously high levels of cadmium, via a fertiliser that was granted as acceptable for use by the Department of Agriculture. As a result, all fresh and canned pineapples that had been exposed to the fertiliser had to be destroyed, leaving South African pineapple farmers in an economic crisis. However, and quite fortuitously, the Summerpride Foods factory was already transitioning towards the juicing industry. Harris stated: "Fresh pineapples could only be sold if they were tested within an acceptable range of cadmium." The juices, however, could be developed by combining pineapples with high and low levels of cadmium to create a juice that resulted with an acceptable level, using pineapples that would have gone to waste. The entire industry shifted after this incident and is now an exclusive exporter of pineapple juice. Arnold stated that the cadmium incident was "a blessing in disguise" as the canned market for pineapples was already in decline. The transition to a juice concentrate enabled the revival of the South African pineapple industry.

5.2.1.2. Common farming practices

When discussing the pineapple growing practices adopted by South African growers, the participants highlighted various sustainable strategies used to ensure the industry's sustainability in the future. The participants stated that pineapples are grown over a five-to-seven-year cycle, in which time the fruit is harvested twice or three times. Thereafter, the fields are generally left to recover for 12 months to two years. Handley stated that he sometimes leaves a field for up to seven years to ensure it is optimal for future pineapple growth. During these fallow periods, the leftover plant material is worked back into the soil to release natural and beneficial nutrients. Four of the five participants stated that they had brought cows onto the fields during this time to break down the plant material without using mechanical operators. Handley stated that essential microbes are added to the material when it passes through a cow, eventually ending up in the soil. This process reduces the need for potentially dangerous artificial fertilisers.

However, this move towards sustainability has only sometimes been implemented, stated Pike. Pike illustrated that during the 1900s, the plant material left over after the harvest would be burned, wasting valuable nutrients. As a result, more effort would be placed on working the soils and applying nutrient-rich fertilisers to prepare the soils for replanting. Today, Pike and Harris encourage grass growth on the dormant fields during the fallow periods, and the introduction of cattle to assist in the breakdown of organic matter and the rehabilitation of the soils. "The manure by-product from the presence of cows on the lands is an added benefit as the nutrient-rich matter is worked into the soil," stated Pike. Throughout the fallow period, the soils are constantly tested to assess the nutrient and pH levels. Pineapples require moderately acidic soil to achieve a quality yield. When necessary, natural supplements are added to the soils to achieve the desired planting conditions.

5.2.1.3. *Limiting factors to the pineapple industry*

Harris, Pike and Arnold expressed that pineapples are grown on fields that boast productive qualities for a high yield of the best quality. These fields have been used for generations, and continue to generate the highest-quality pineapples. The participants stated that pineapples are only planted where the conditions are suitable. Participants expressed the view that clearing new land is too expensive and time-consuming. Harris added that it is less expensive and quicker to buy a neighbouring farm than to develop new lands. Therefore, the lands currently under pineapple cultivation will remain productive unless there is a change in the legislation surrounding the expansion of agricultural practices.

Pineapples are also only grown on lands with suitable climatic and topographic conditions. The participants illustrated that pineapples must be grown on slight north-facing slopes perpendicular to the contour lines. The soils need to be acidic, a significant characteristic of pineapple cultivation. Unlike other cash crops, Arnold expressed that pineapples do not need irrigated fields and can be planted away from water sources. Handley stated that pineapples can only survive in frost-free zones. Some past pineapple fields are no longer suitable for cultivation due to the frost-free zone changes. Pike added that pineapples are grown on specific landscapes where the topography is gentle enough for water infiltration and runoff to avoid waterlogging. The soils play a critical role as they provide the foundation for the nutrients served to the fruit. The suitable zones, therefore, have been used for generations, noted Arnold and Harris.

In summary, the information collected through the interview process established a qualitative understanding of the pineapple industry in South Africa, specifically in the Eastern Cape, and of the changes and challenges pineapple growers have encountered. The following section will critically discuss the political, economic, and spatial factors presented in the literature that have affected the functionality of the pineapple industry.

5.2.1.4. *Future of the pineapple industry*

The participants all shared similar views regarding the future trajectory of the pineapple industry in the Lower Albany area. The participants expected a continual consolidation of pineapple farms in the area. "The rising costs of inputs pose a challenging threat for small-scale pineapple growers in the area," stated Harris. Arnold shared that pineapple farming is a generational activity in the area, and that farmers' children generally take over the family business. If the children do not, or cannot, take over the business, the operation is more likely to be consolidated by a neighbouring pineapple farmer, or sold for a different land use practice. The participants also agreed that the transition of pineapple farms into expanding wildlife ranches in the area poses an alternate option for struggling pineapple growers. Harris explained that this transition occurred in the region when a neighbouring game reserve bought out a struggling pineapple farm. "Old pineapple lands are desirable for game farms because of the high nutrient levels and for the open landscape that is added to the game reserve for tourism and game viewing purposes," stated Harris. Therefore, the participants agreed that the current footprint of pineapple fields in the Albany district would remain the same or slightly decrease.

Furthermore, the current pineapple farming practices will continue to transition towards an environmentally friendly and sustainable practice, rather than the chemical and land-intensive practices adopted by the former farmers in the region, stated Pike. Farmers will have to adapt to new farming practices or introduce new fertilisers to ensure the longevity of the lands, stated Muir.

5.3. Objective Two: To identify the most appropriate technique for mapping the spatial-temporal extent of pineapple fields

The section covering Objective Two is divided into three parts: the results of the land cover maps using twelve different image classifiers in ArcGIS Pro and GEE; the results of the accuracy assessment; and the outputs of the final 27 land cover datasets between 1984 and 2020. The results of each section are presented in the sections to follow.

5.3.1. Image classifier assessment

The literature review concluded that image classification of Landsat imagery was the most suitable technique for mapping pineapple fields from 1984 to 2020. Twelve image classifiers, created in ArcGIS Pro and GEE, were used to create land cover maps of the study area. An accuracy assessment was conducted to identify the most appropriate image classifier for the requirements of this research study.

The results of the twelve image classifiers are displayed in Figures 36, 39 and 41. The proportion of each land cover type for each image classifier are displayed in Figures 37, 38, 40 and 42, presented in the following sections. A true (bands 4, 3, and 2) and false (bands 7, 6, 4) colour image of a Landsat 8 satellite image is provided for reference (Figures 34, & 35).

Figure 34: Landsat 8 true colour image (bands 4, 3, 2) of the study area (Source: USGS Earth Explorer https://earthexplorer.usgs.gov/) [Accessed 02-07-2023].

Figure 35: Landsat 8 false colour image (bands 7, 6, 4) of the study area (Source: USGS Earth Explorer https://earthexplorer.usgs.gov/) [Accessed 02-07-2023].

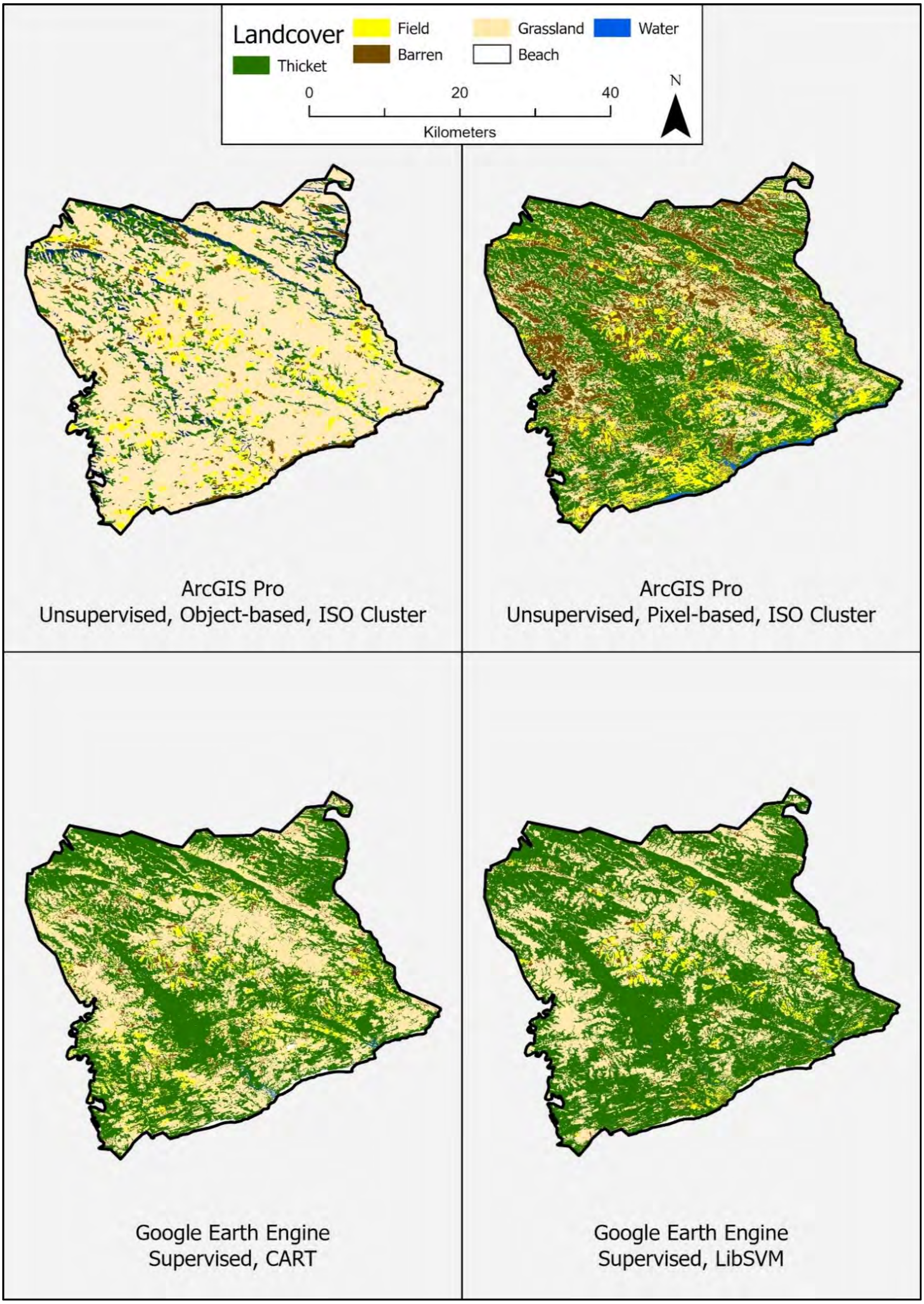


Figure 36: Image classifications of the unsupervised object- and pixel-based ISO Cluster classifiers in ArcGIS Pro, and supervised CART and LibSVM classifiers in GEE.

In ArcGIS Pro, the unsupervised image classification process utilised an ISO Cluster image classifier for object and pixel-based image classification techniques (Figure 36). The object-based ISO Cluster classified 68,549.13 hectares of land as Thicket, 8,181.81 hectares as Active Fields, 2,781.18 hectares as Barren Fields, 1,299.42 hectares as Beach, 75,771.18 hectares as Grassland, and 232.11 hectares as Waterbodies (Figure 37). The pixel-based ISO Cluster image classifier classified 73,099.57 hectares as Thicket, 18,661.49 hectares as Active Fields, 1,434.98 hectares as Barren Fields, 24,032.13 hectares as Grassland, and 39,303.11 hectares as Waterbodies (Figure 37). The unsupervised pixel-based image classifier did not classify the Beach land cover.

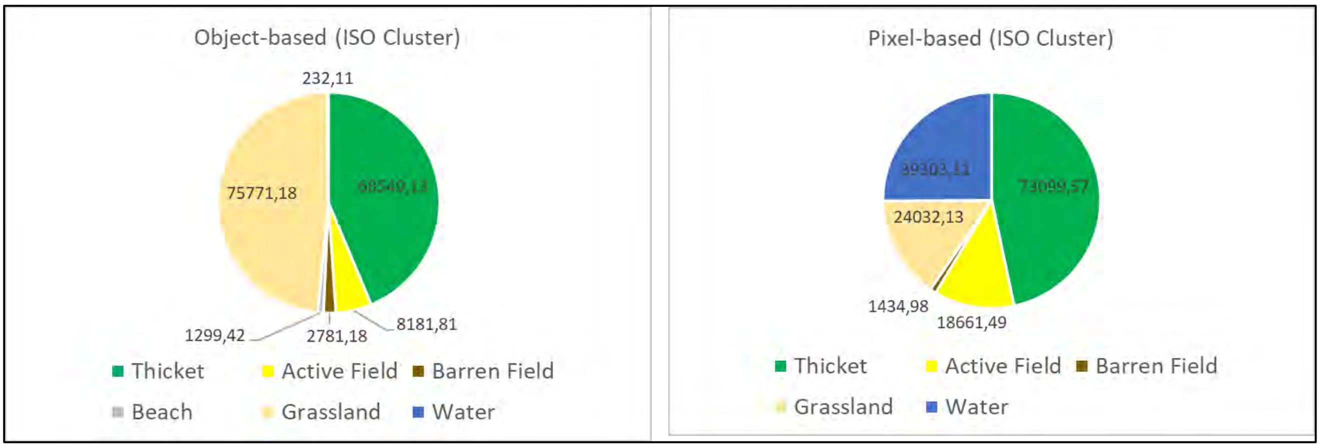


Figure 37: Land cover proportions of the unsupervised object- and pixel-based ISO Cluster image classifiers created in ArcGIS Pro.

In GEE, CART and SVM image classifiers were created (Figure 36). The CART image classifier classified 96,698.79 hectares as Thicket, 12,571.02 hectares as Active Fields, 5,000.4 hectares as Barren Fields, 1,141.92 hectares as Beach, 72,119.25 as Grassland, and 567.45 hectares as Waterbodies (Figure 38). The SVM classified 117,436.7 hectares as Thicket, 5,988.69 hectares as Active Fields, 3,002.94 hectares as Barren Fields, 1,213.56 hectares as Beach, 60,326.28 hectares as Grassland, and 199.71 hectares as Waterbodies (Figure 38).

Figure 38: Land cover proportions of the CART and SVM image classifiers created in GEE.

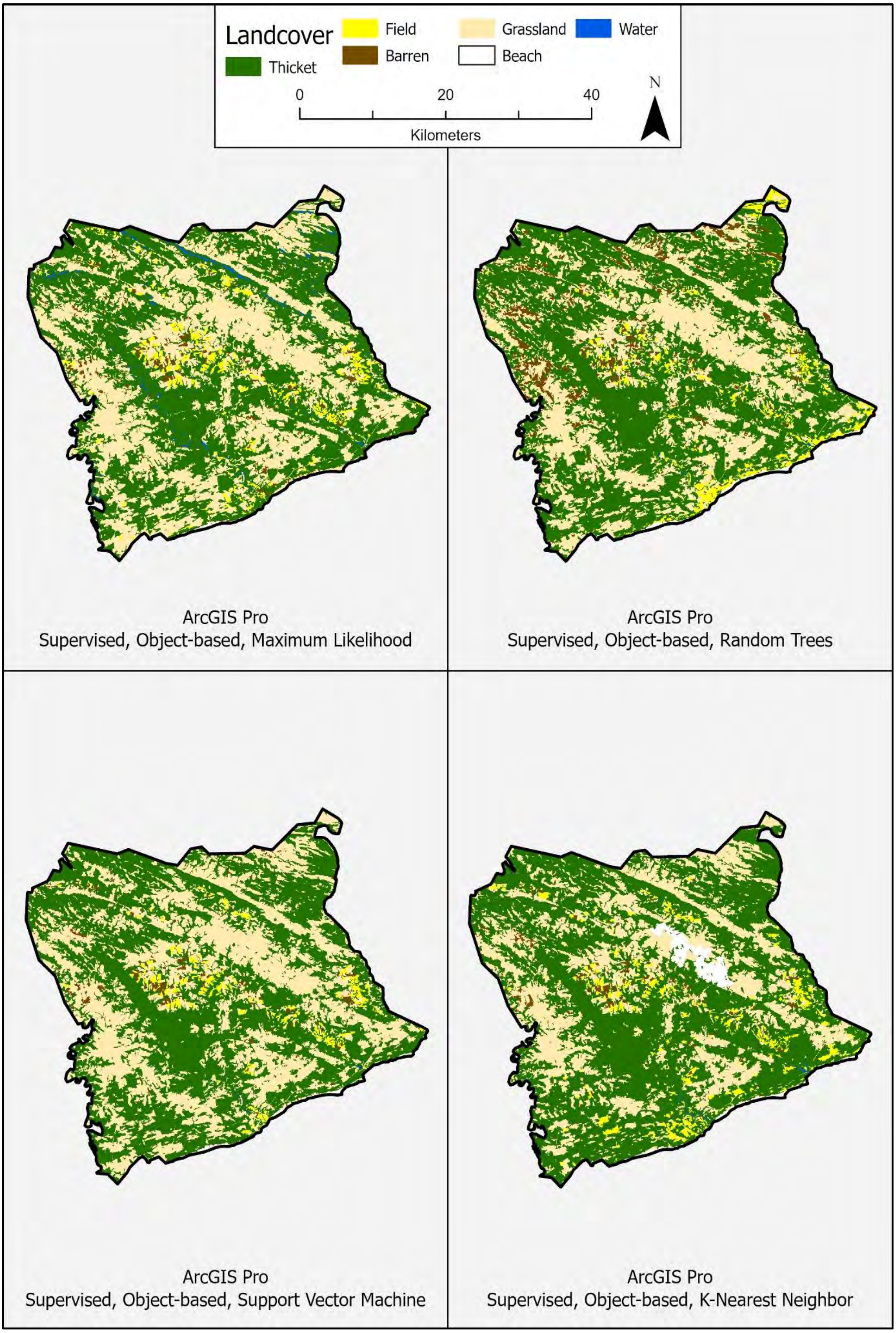


Figure 39: Image classifiers of the supervised object-based ML, RT, SVM, and KNN image classifiers in ArcGIS Pro.

The supervised image classification process utilised Maximum Likelihood, Random Trees, SVM, and K-Nearest Neighbour image classifiers for the object and pixel-based classification techniques (Figures 39 and 41). The proportion of the area of each land cover identified by the supervised object-based image classifiers are presented below (Figure 40).

The ML image classifier classified 79,355.29 hectares as Thicket, 6,220.94 hectares as Active Fields, 2,746.73 hectares as Barren Fields, 263.7 hectares as Beach, 66,481.44 hectares as Grassland, and 1,465.12 hectares as Waterbodies. The RT image classifier classified 87,349.11 hectares of land as Thicket, 7,022.53 hectares as Active Fields, 6,938.96 hectares as Barren Fields, 1,044.9 hectares as Beach, 54,040.26 hectares as Grassland, and 138.13 hectares as Waterbodies. The SVM image classifier classified 84,903.58 hectares as Thicket, 4,121.22 hectares as Active Fields, 2,107.1 hectares as Barren Fields, 976.55 hectares as Beach, 64,251.84 hectares as Grassland, and 173.14 hectares as Waterbodies. The KNN image classifier classified 47,028.16 hectares of land as Thicket, 3,934.16 hectares as Active Fields, 4,946.59 hectares as Barren Fields, 1,270.05 hectares as Beach, 99,187.2 hectares as Grassland, and 152.83 hectares as Waterbodies.

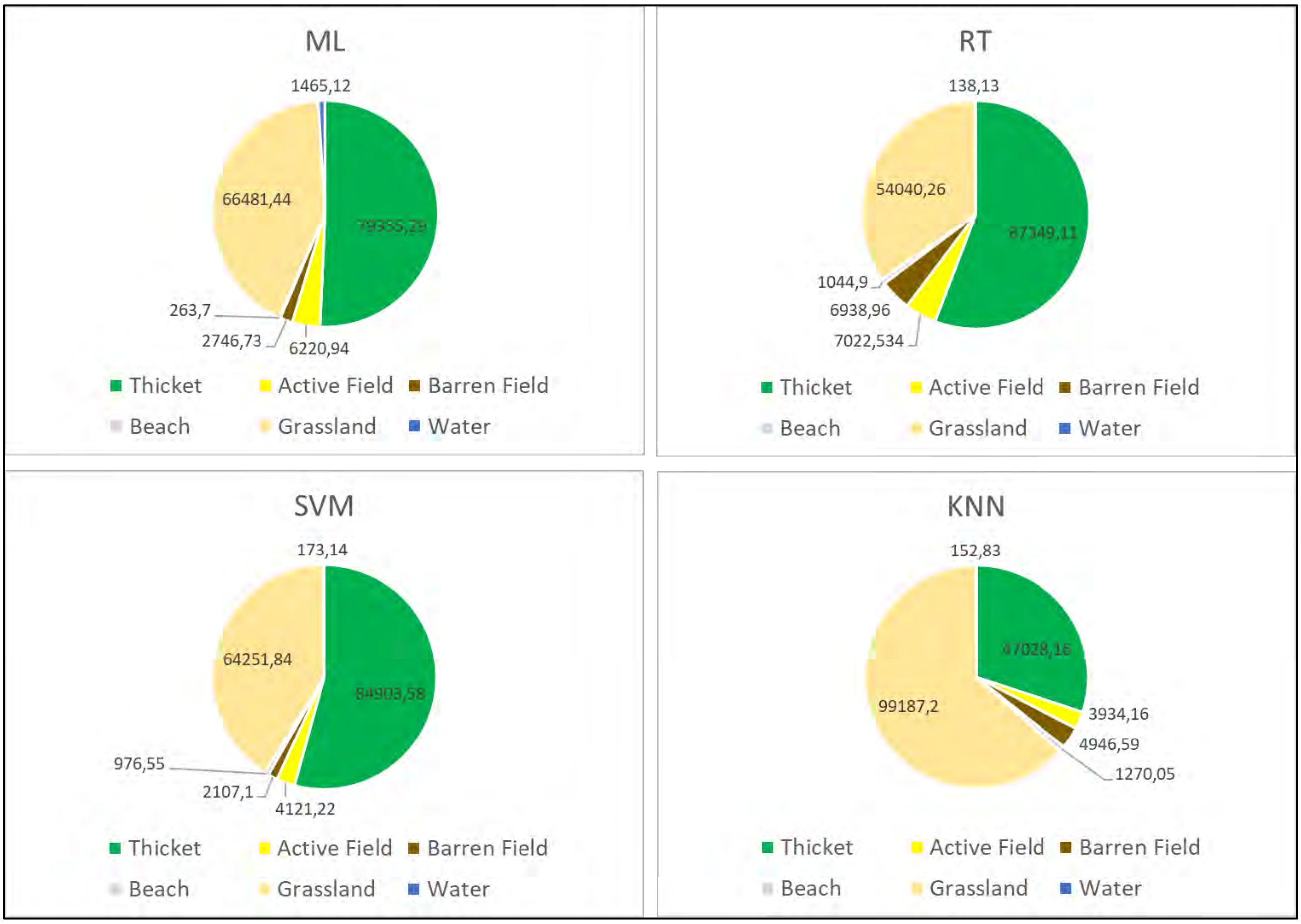


Figure 40: Land cover proportions of the supervised object-based ML, RT, SVM, and KNN image classifiers created in ArcGIS Pro.

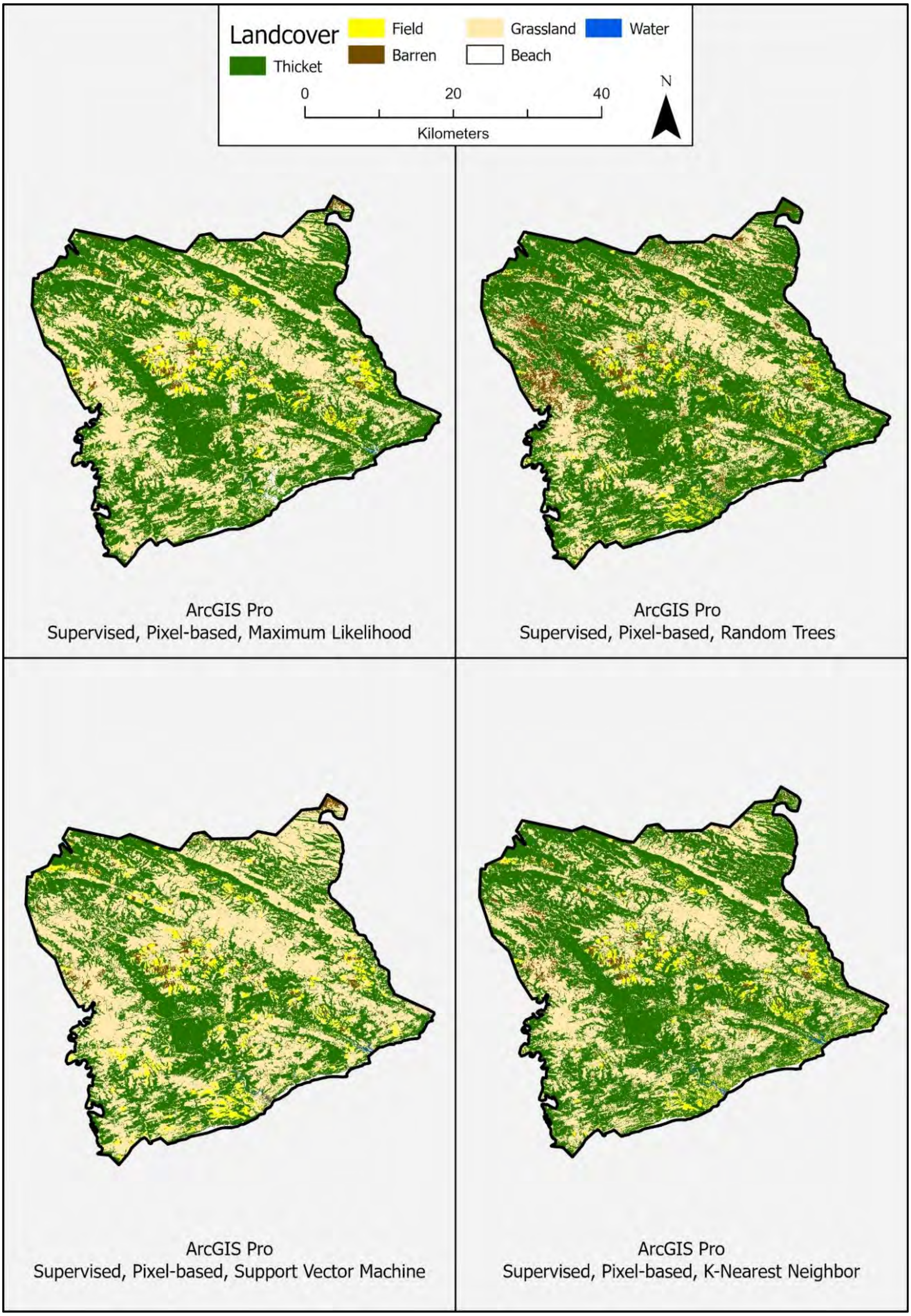


Figure 41: Image classifiers of the supervised pixel-based ML, RT, SVM, and KNN image classifiers in ArcGIS Pro.

The proportions of the area of each land cover identified by the supervised pixel-based image classifiers, displayed in Figure 41, are presented below (Figure 42).

The ML image classifier classified 82,836.95 hectares as Thicket, 7,307.75 hectares as Active Fields, 1,797.34 hectares as Barren Fields, 2,324.47 hectares as Beach, 62,176.06 hectares as Grassland, and 89.72 hectares as Waterbodies. The RT image classifier classified 91,919.08 hectares of land as Thicket, 6,288.28 hectares as Active Fields, 6,579.89 hectares as Barren Fields, 1,079.22 hectares as Beach, 50,844.45 hectares as Grassland, and 122.96 hectares as Waterbodies. The SVM image classifier classified 68,549.13 hectares as Thicket, 8,181.81 hectares as Active Fields, 2,781.18 hectares as Barren Fields, 1,299.42 hectares as Beach, 75,771.18 hectares as Grassland, and 232.11 hectares as Waterbodies. The KNN image classifier classified 83,383.95 hectares of land as Thicket, 7,115.75 hectares as Active Fields, 1,851.34 hectares as Barren Fields, 2,035.47 hectares as Beach, 62,476.06 hectares as Grassland, and 212.72 hectares as Waterbodies.

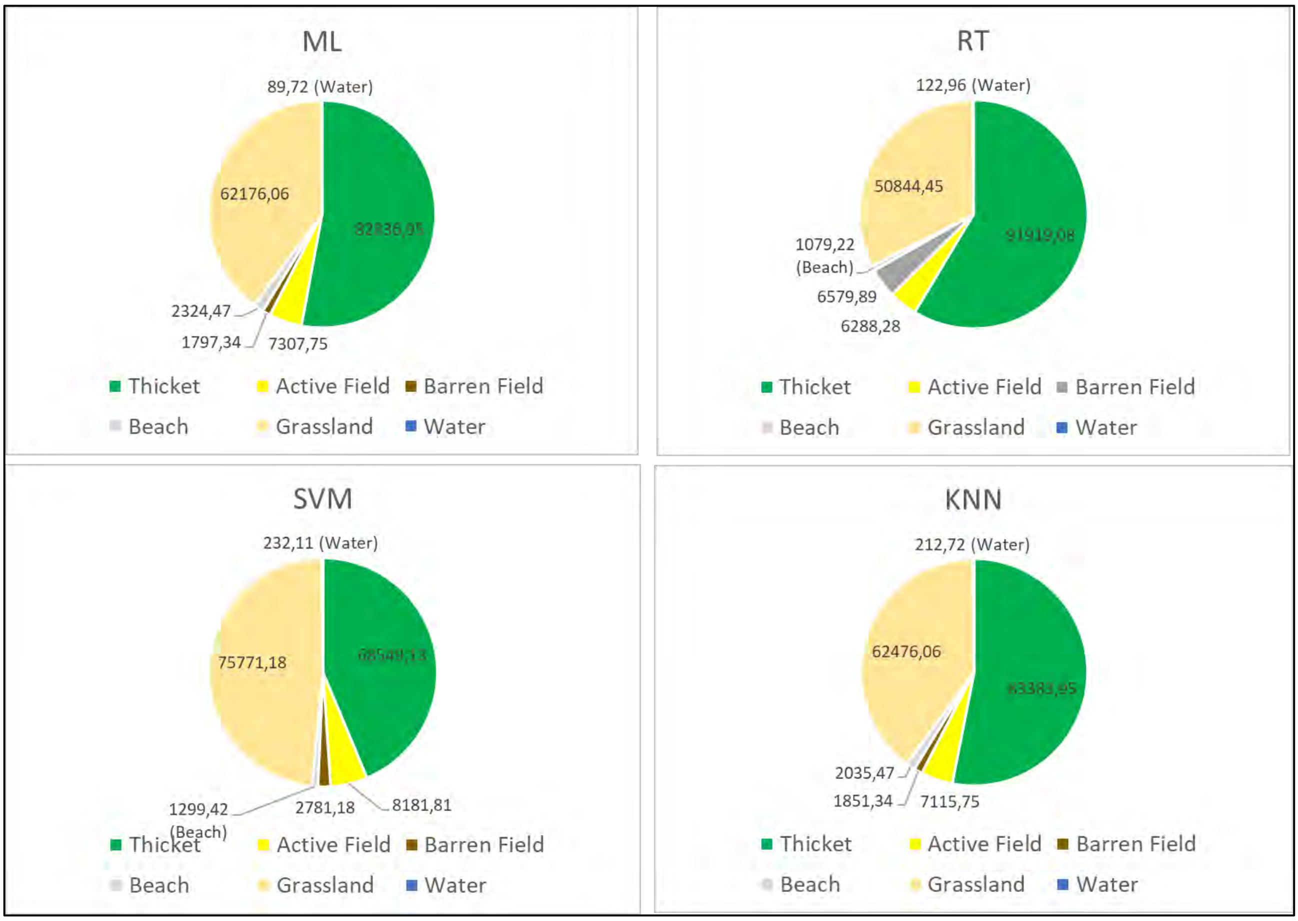


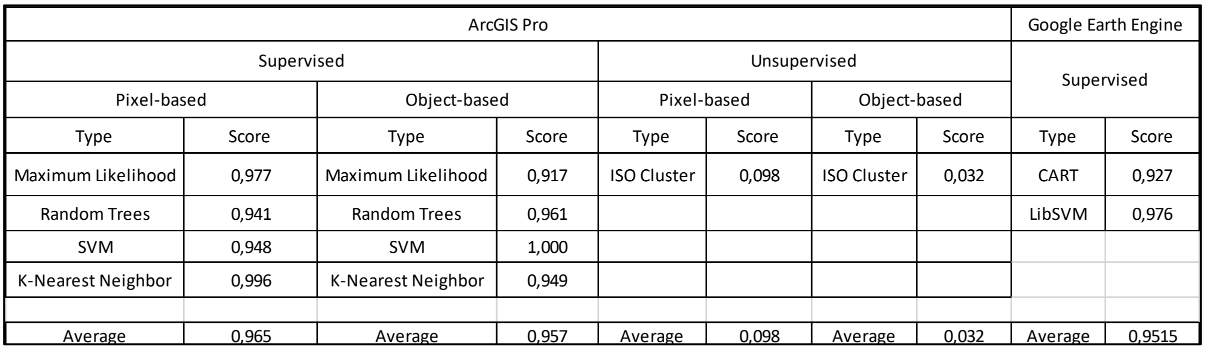
Figure 42: Land cover proportions of the supervised pixel-based ML, RT, SVM, and KNN image classifiers created in ArcGIS Pro.

5.3.2. Accuracy assessment

The accuracy assessment of the 12 different classification techniques indicated a diverse variability of the accuracy of each classification technique in classifying specific land cover types. Overall, the supervised pixel-based classifications in ArcGIS Pro created the land cover classification with the highest accuracy, of a total average of 0,965. The KNN technique held the highest accuracy of 0,996, with ML (0,977), SVM (0,948) and RT (0,941) following. The supervised object-based classification techniques in ArcGIS Pro provided results similar to the pixel-based versions. Most notable was the SVM technique, which created an output that indicated a 100% accuracy compared to the accuracy assessment training samples. RT (0,917), KNN (0,949) and ML (0,917) followed.

The classification techniques in GEE provided significantly accurate results. SVM resulted in an accuracy of 0,976, and CART resulted in 0,927. The results indicated that the most inaccurate land cover classification techniques are the unsupervised pixel and object-based classification techniques. The pixel-based ISO Cluster classification resulted in a 0,098 accuracy, and the object-based ISO Cluster achieved an accuracy of 0,032. Overall, the SVM object-based supervised classification technique generated the highest accuracy when tested against the validation points.

Table 12: The accuracy assessment results of the twelve image classifiers across the two software platforms.



ArcGIS Pro								Google Earth Engine	
Supervised				Unsupervised				Supervised	
Pixel-based		Object-based		Pixel-based		Object-based			
Type	Score	Type	Score	Type	Score	Type	Score	Type	Score
Maximum Likelihood	0,977	Maximum Likelihood	0,917	ISO Cluster	0,098	ISO Cluster	0,032	CART	0,927
Random Trees	0,941	Random Trees	0,961					LibSVM	0,976
SVM	0,948	SVM	1,000						
K-Nearest Neighbor	0,996	K-Nearest Neighbor	0,949						
Average	0,965	Average	0,957	Average	0,098	Average	0,032	Average	0,9515

Although the results indicated that the SVM object-based supervised classification technique was the most accurate for classifying a mixture of land covers (Table 12), the SVM supervised pixel-based classification technique was instead used for the study duration (Basheer, 2022). The object-based version resulted in more inaccuracies than the pixel-based version and misclassified several key landcovers due to the object-based nature of the classifier. The pixel-based version, however, correctly classified the key land covers due to the detection and classification of pixels as opposed to neighbouring objects.

5.4. Objective Three: To conduct a spatial analysis of the LULC changes resulting from pineapple cultivation

The spatial analysis of the changes in pineapple cultivation in the study area highlighted the changes in the area, land use, and land cover of pineapple fields over time. The patterns and trends identified through remote sensing technologies were cross-referenced with a ground-based field verification of sixty randomly generated locations. The results of the analyses are presented in the following section.

5.4.1. Image classification

The results of the 27 SVM supervised pixel-based image classification processes are displayed in Figures 43, 44, 45 and 46. Each classified image contained a varying proportion of pixels for each of the six land covers: Thicket, Grassland, Barren Fields, Active Fields, Waterbodies, and Beach. Sufficient image classification depends on several variables, most notably satellite image quality and resolution.

The image classification results for 1984 to 1991 are displayed in Figure 43, and the proportions of the land cover are illustrated in Table 13. The most common land cover observed for each year is Grassland. Grassland accounted for 45% of the land cover in 1984, 55% in 1986, 53% in 1988, 54% in 1989, 54% in 1990, and 50% in 1991. The second most prominent land cover is Thicket. Thicket accounted for 44% of the land cover in 1984, 26% in 1986, 34% in 1988, 38% in 1989, 36% in 1990, and 38% in 1991. Active Fields and Barren Fields provided a similar proportion of land cover in each of the above-mentioned maps. Active Fields accounted for 4% of the land cover in 1984, 14% in 1986, 5% in 1988, 3% in 1989, 5% in 1990, and 4% in 1991. Barren Fields accounted for 6% of the land cover in 1984, 4% in 1986, 6% in 1988, 4% in 1989, 4% in 1990, and 6% in 1991. Water and Beach land covers contribute a minor proportion of the area in the study area. Water accounted for 0% of land cover in 1984, 1986, 1989, 1990, and 1993, and 1% of the land cover in 1988 and 1991. Beach contributed 1% of the total land cover in the above-mentioned maps.

Table 13: Proportions of the land cover types in each land cover map between 1984 and 1991.

Proportions (%)						
	1984	**1986**	**1988**	**1989**	**1990**	**1991**
Thicket	44	26	34	38	36	38
Active Field	4	14	5	3	5	4
Barren Field	6	4	6	4	4	6
Beach	1	1	1	1	1	1
Grassland	45	55	53	54	54	50
Water	0	0	1	0	0	1

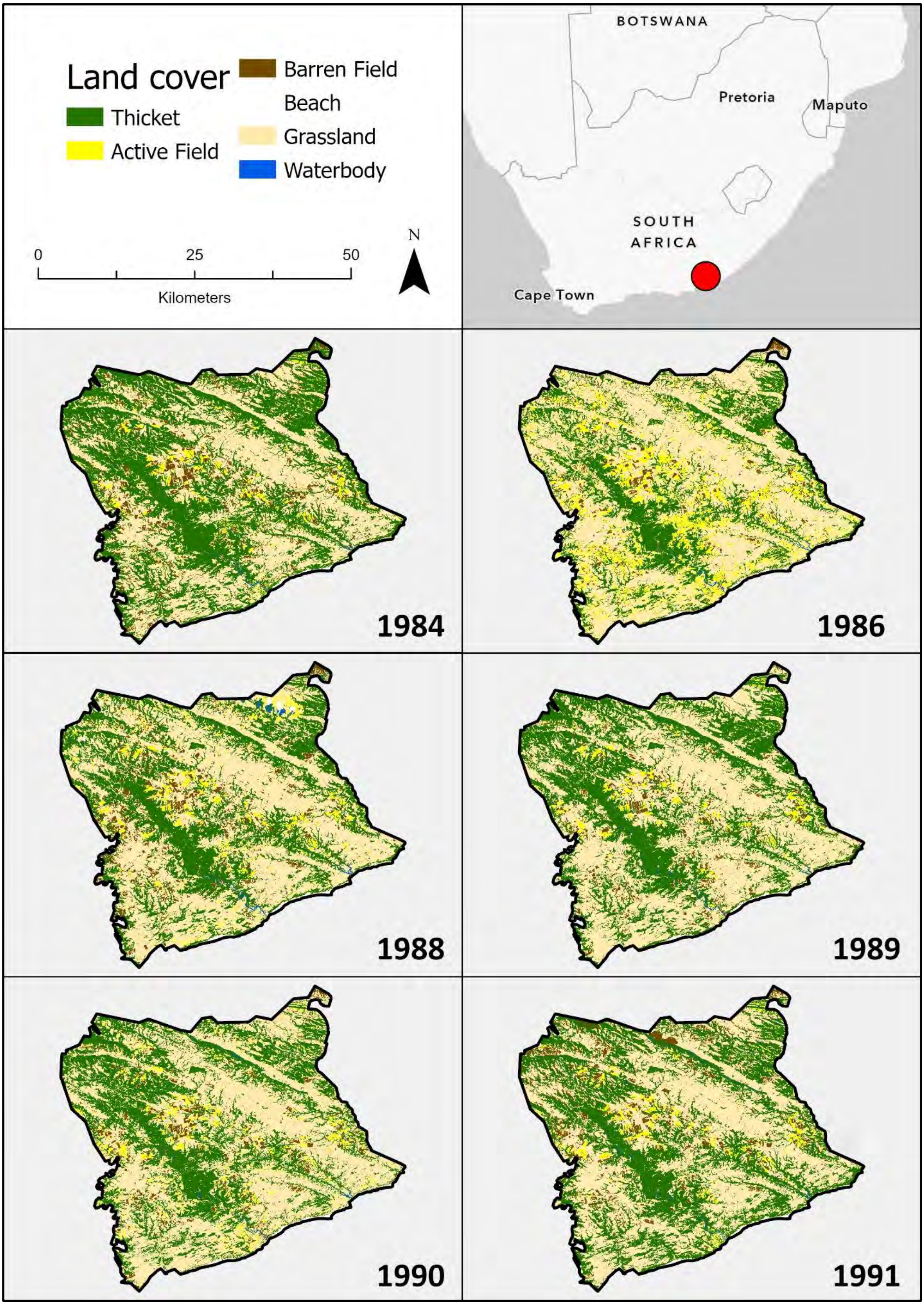


Figure 43: SVM pixel-based supervised classifications for the years 1984-1991. Pie charts displaying the proportions of the various land covers in each classification are displayed.

The image classification results for 1993 to 2000 are displayed in Figure 44, and the proportions of the land cover are illustrated in Table 14. Grassland accounted for the highest proportion of land cover for each year. Grassland accounted for 51% of the land cover in 1993, 51% in 1994, 52% in 1995, 52% in 1996, 44% in 1997, 42% in 1999, and 45% in 2000. Thicket accounted for the second-highest land cover type. Thicket accounted for 40% of the land cover in 1993, 40% in 1994, 36% in 1995, 37% in 1996, 45% in 1997, 44% in 1999, and 44% in 2000. Active field and barren field land covers accounted for similar proportions each year. Active fields accounted for 4% of the land cover in 1993, 4% of the land cover in 1994, 9% in 1995, 6% in 1996, 7% in 1997, 3% in 1999, and 7% in 2000. Barren fields accounted for 4% of the land cover in 1993, 4% in 1994, 2% in 1995, 4% in 1996, 3% in 1997, 10% in 1999, and 3% in 2000. Water and beach land covers held the lowest area in the study area. Water accounted for 0% of the land cover in each land cover map. Beach accounted for 1% of the land cover in each land cover map illustrated.

Table 14: proportions of the land cover type in each land cover map between 1993 and 2000.

	Proportions (%)						
	1993	**1994**	**1995**	**1996**	**1997**	**1999**	**2000**
Thicket	40	40	36	37	45	44	44
Active Field	4	4	9	6	7	3	7
Barren Field	4	4	2	4	3	10	3
Beach	1	1	1	1	1	1	1
Grassland	51	51	52	52	44	42	45
Water	0	0	0	0	0	0	0

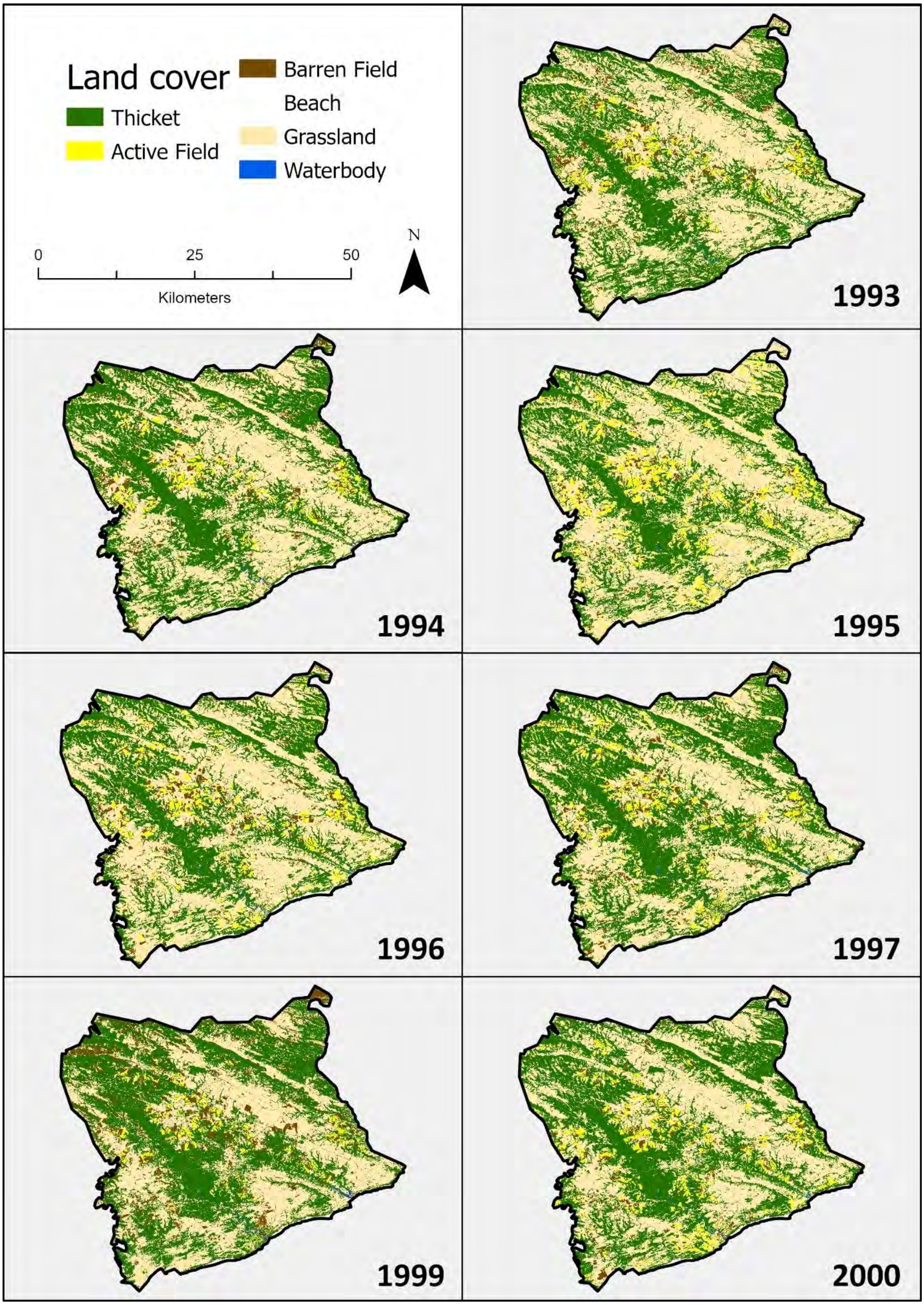


Figure 44: SVM pixel-based supervised classifications for the years 1993-2000. Pie charts displaying the proportions of the various land covers in each classification are displayed.

The image classification results for 2001 to 2013 are illustrated in Figure 45, and the proportions of the land cover are illustrated in Table 15. Grassland accounted for the most significant proportion of land cover for each year. Grassland accounted for 50% of the land cover in 2001, 47% in 2002, 59% in 2003, 47% in 2005, 54% in 2006, 43% in 2009, and 43% in 2013. Thicket accounted for the second highest proportion of land cover for each year. Thicket accounted for 43% of the land cover in 2001, 43% of the land cover in 2002, 33% in 2003, 43% in 2005, 36% in 2006, 46% in 2009, and 48% in 2013. Active and barren fields accounted for a similar proportion of yearly land cover. Active fields accounted for 5% of the land cover in 2001, 4% in 2002, 2003, 2005, and 2009, 7% in 2006, and 6% in 2013. Barren fields accounted for 1% of the land cover in 2001, 5% of the land cover in 2002, 3% in 2003, 4% in 2005, 2% in 2006 and 2013, and 6% in 2009. Water and beach land cover accounted for the smallest proportion for each year. Water accounted for 0% of the land cover in each year. Beach accounted for 1% of the land cover in each year.

Table 15: Proportions of the land cover types in each land cover map between 2001 and 2013.

Proportions (%)							
	2001	**2002**	**2003**	**2005**	**2006**	**2009**	**2013**
Thicket	43	43	33	43	36	46	48
Active Field	5	4	4	4	7	4	6
Barren Field	1	5	3	4	2	6	2
Beach	1	1	1	1	1	1	1
Grassland	50	47	59	47	54	43	43
Water	0	0	0	0	0	0	0

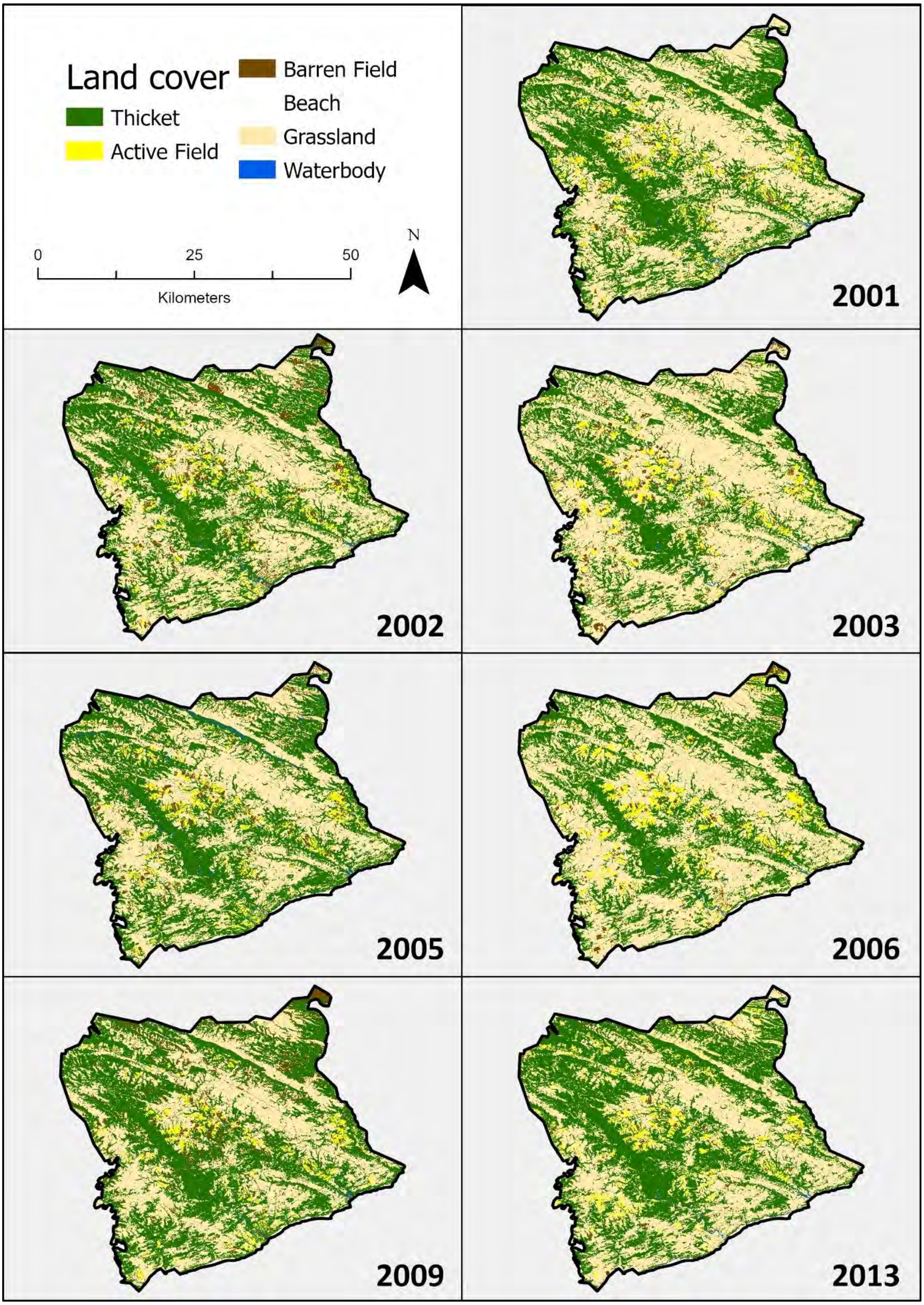


Figure 45: SVM pixel-based supervised classifications for the years 2001-2013. Pie charts displaying the proportions of the various land covers in each classification are displayed.

The image classification results for 2014 to 2020 are illustrated in Figure 46, and the proportions of the land covers are illustrated in Table 16. Grassland accounted for the most significant proportion of land cover in each year. Grassland accounted for 41% of the land cover in 2014, 34% in 2015, 50% in 2016, 47% in 2017, 43% in 2018, 44% in 2019 and 48% in 2020. Thicket accounted for the second highest proportion of land cover for each year. Thicket accounted for 47% of the land cover in 2014, 50% in 2015, 44% in 2016, 43% in 2017, 43% in 2018, 43% in 2019, and 44% in 2020. Active and barren fields accounted for similar proportions in each year. Active fields accounted for 9% of the land cover in 2014, 13% in 2015, 3% in 2016, 5% in 2017, 6% in 2018, 10% in 2019, and 5% in 2020. Barren fields accounted for 2% of the land cover in 2014, 2015, 2016, 2019 and 2020, 4% in 2017, and 3% in 2019. Water and beach land covers presented the smallest proportions each year. Water accounted for 0% of the land cover in each year. Beach accounted for 1% of the land cover for each year.

Table 16: Proportions of the land over types in each land cover map between 2014 and 2020.

	Proportions (%)						
	2014	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
Thicket	47	50	44	43	43	43	44
Active Field	9	13	3	5	6	10	5
Barren Field	2	2	2	4	3	2	2
Beach	1	1	1	1	1	1	1
Grassland	41	34	50	47	43	44	48
Water	0	0	0	0	0	0	0

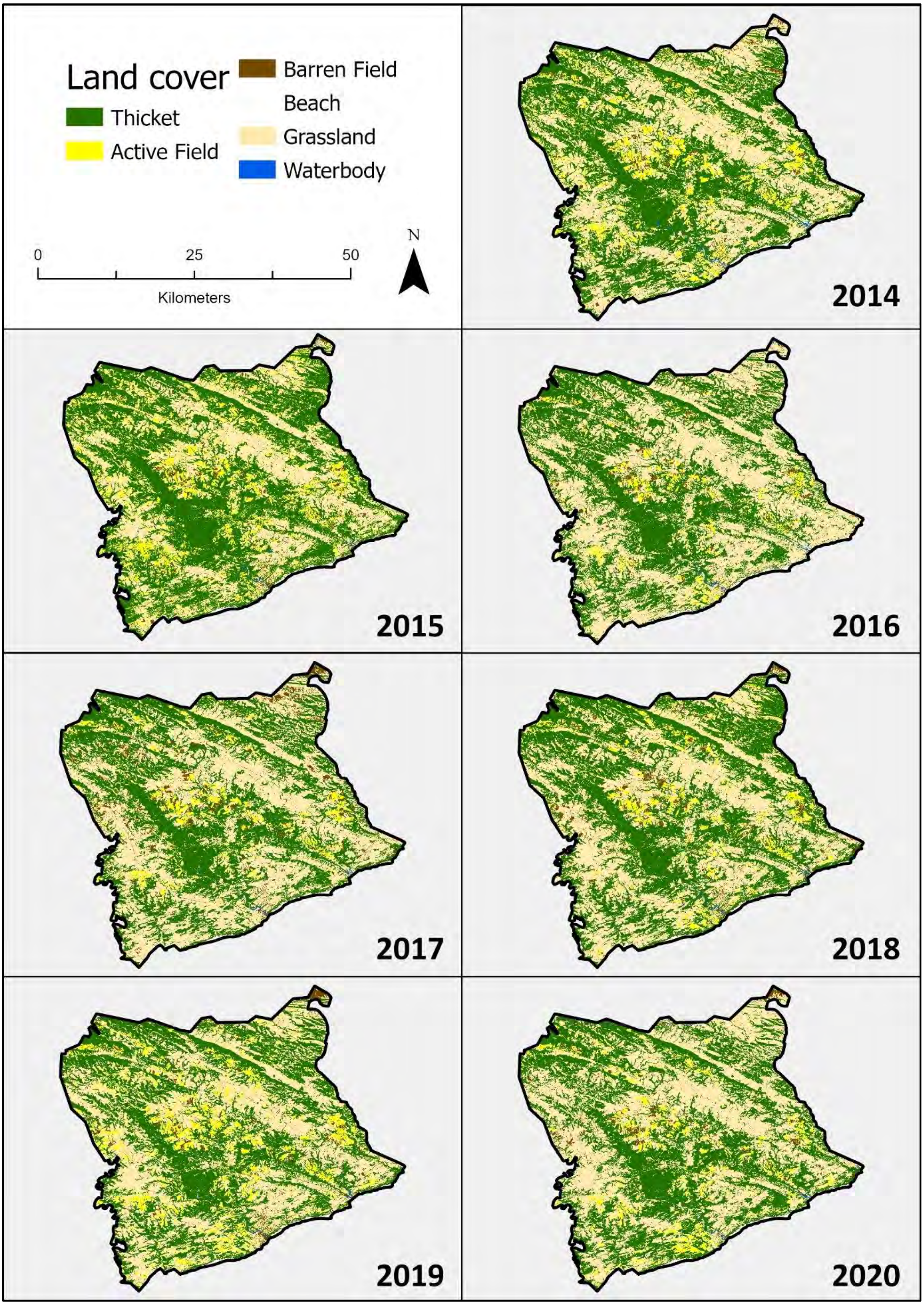


Figure 46: SVM pixel-based supervised classifications for the years 2014-2020. Pie charts displaying the proportions of the various land covers in each classification are displayed.

Figures 43, 44, 45 and 46, and the subsequent Tables 13, 14, 15 and 16, indicate that Grassland is the most significant land cover in the study area, accumulating a mean size of 75 551,60 hectares across 40 years. Thicket is the second largest, accounting for an average of 64 513,53 hectares, followed by Active Fields at an average of 9 110,23 hectares, Barren Fields at an average of 5 803,93 hectares, the Beach at an average of 1 333,00 hectares, and Water at an average of 476,25 hectares. The results of the spatial analysis relating to the changes in these land covers resulting from pineapple cultivation are presented in the following section.

5.4.2. Spatial analysis

The results of the spatial analysis process indicate the changes in the land area, land use, and land cover resulting from pineapple cultivation between 1984 and 2020. The results of the spatial analysis process are presented in the following sections.

5.4.2.1. Area changes

The area of land under active pineapple cultivation for the period of the study is illustrated in Figure 47. It must be stated that Figure 47 represents the area of land that was an active pineapple field in the specific year. The area under active pineapple cultivation has mostly remained constant since 1984. In 1984, pineapple fields accounted for an area of 2700 hectares. Since then, the area under cultivation has experienced one significant trough and one significant spike. The lowest pineapple cultivation area was 2200 hectares in 1990, and the highest was 5329 hectares in 2001. In 2020, the area under pineapple cultivation was 3100 hectares, illustrating a 400 hectare increase since 1984.

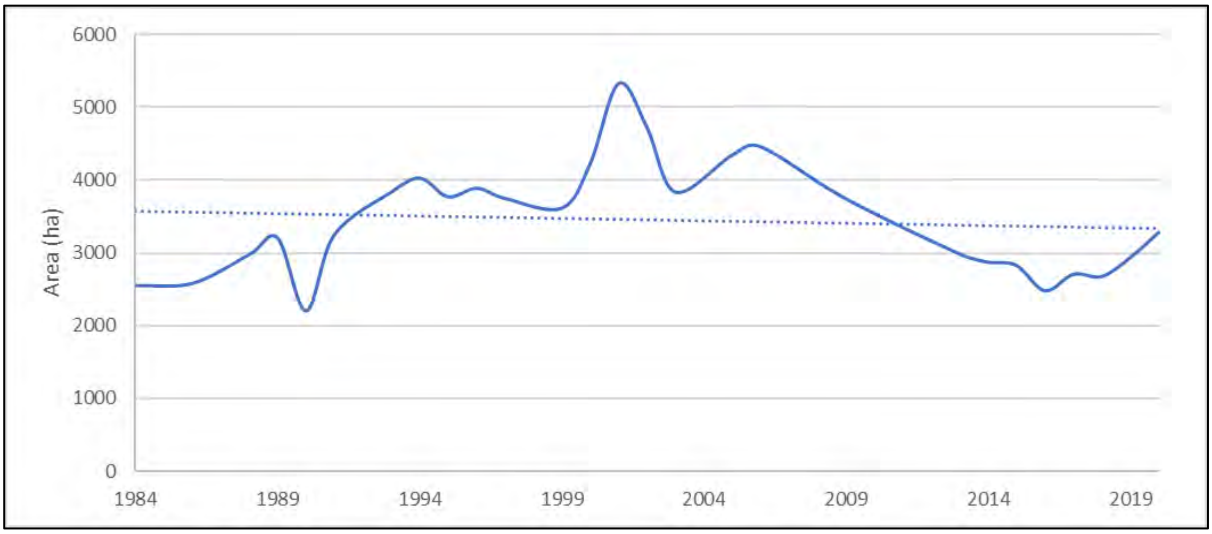


Figure 47: Area of land under active pineapple cultivation identified though the spatial analysis process.

5.4.2.2. Land use changes

The results of the spatial changes in pineapple cultivation in the study area illustrate the spatial distribution of pineapple fields since 1984 (Figure 48). The study area comprises various land uses, including wildlife ranching, urban areas, and agricultural practices. According to the protected areas spatial dataset, wildlife ranches account for 46,454.59 hectares of land within the study area. Figure 49 illustrates the area of pineapple fields that have been converted to wildlife ranches since 1984, and the last use of pineapple cultivation at each of the identified locations. According to the results, eight wildlife ranches have been established on pineapple fields since 1984.

Crossroads Game Farm, a wildlife reserve along the eastern border of the study area, was established in 2009. Before that, the area consistently produced an average of 7,3 hectares of pineapple fields yearly. The greatest extent of pineapple farms was 30 hectares.

Buffalo Kloof, a game reserve in the northern region of the study area, converted many pineapple fields into a high-end game reserve. The conversion occurred in 2009. Before 2009, the area produced an average of 44,04 hectares of pineapple fields yearly. In 2003, the region accounted for 140 hectares of pineapple fields.

Eco-tourism, a wildlife farm in the centre of the study area, converted a significant proportion of pineapple fields into wildlife land use practices. The transition occurred in 2009. Before 2009, the region cultivated an average of 16,23 hectares of pineapple fields yearly. The region produced a high of 57 hectares of pineapple fields in 2009.

Glenhope farm, located in the southern centre of the study area, converted pineapple farms to nature-based tourism activities in 2009. Before 2009, the area produced an average of 19 hectares of pineapple fields annually. A high of 95 hectares of pineapple fields was recorded in 2009. However, in 2020, 7 hectares of pineapple fields were identified.

The Kap River Nature Reserve is located along the eastern border of the study area. Although this region is a nature reserve and boasts wildlife for tourism purposes, the region has contained active pineapple fields since 1984. Kap River Nature Reserve cultivates an average of 6 hectares of pineapple fields yearly. In 2020, 42 hectares of fields were cultivated in this Nature Reserve.

Like the Kap River Nature Reserve, Limestone Game Farm has contained active pineapple cultivation since 1984, even though the region boasts wildlife-based tourism. Limestone Game Farm is in the southern centre of the study area. The region accounts for four hectares of pineapple fields yearly. A high of 29 hectares of pineapple fields was identified in 2020.

Peninsula Game Farm is adjacent to Limestone Game Farm. However, since 2006, this game farm has not produced any pineapples. The region cultivated an average of 7 hectares of pineapple fields before 2006. A high of 37 hectares of fields was identified in 2006.

Lastly, according to the protected areas dataset, an unnamed game farm located along the western border of the study area cultivated a fair amount of pineapples until 2009, when the land use was converted to wildlife-based tourism. The area produced an average of 11 hectares of pineapples before 2009. The area cultivated a high of 59 hectares of pineapple fields in 2003.

Overall, the conversion of pineapple fields to wildlife ranches is a significant trend in the study area. The results illustrate that one wildlife ranch converted 37 hectares of pineapple farms that were last cultivated in 2006, and five wildlife ranches converted 274,16 hectares last cultivated with pineapples in 2009. The notable trend of the conversion of pineapple farms to wildlife ranches provides an opportunity to investigate the land cover changes due to this conversion and other conversions in the study area. The following section discusses the land cover results identified by the remote sensing spatial analysis.

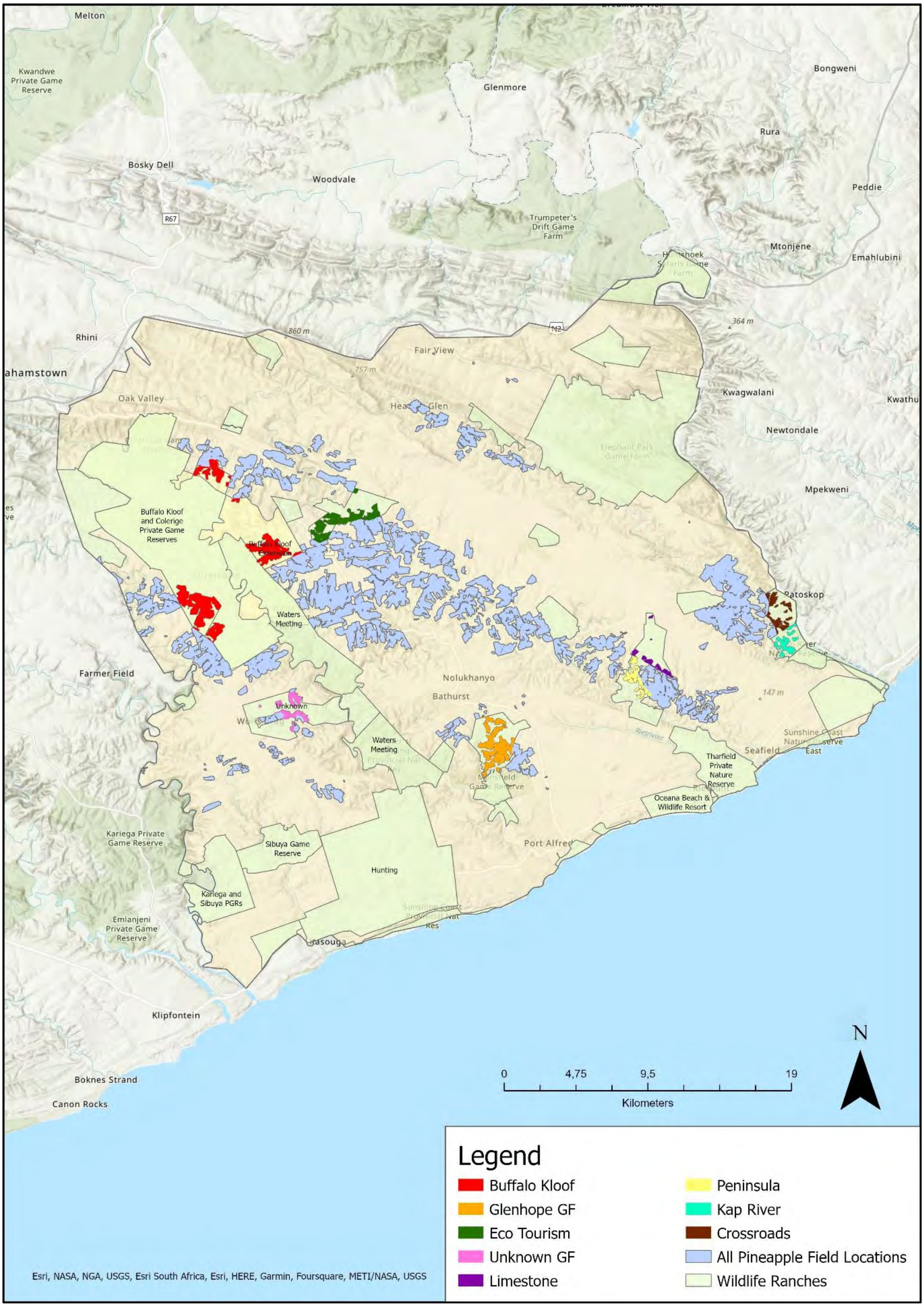


Figure 48: Land use changes identified through the spatial analysis process.

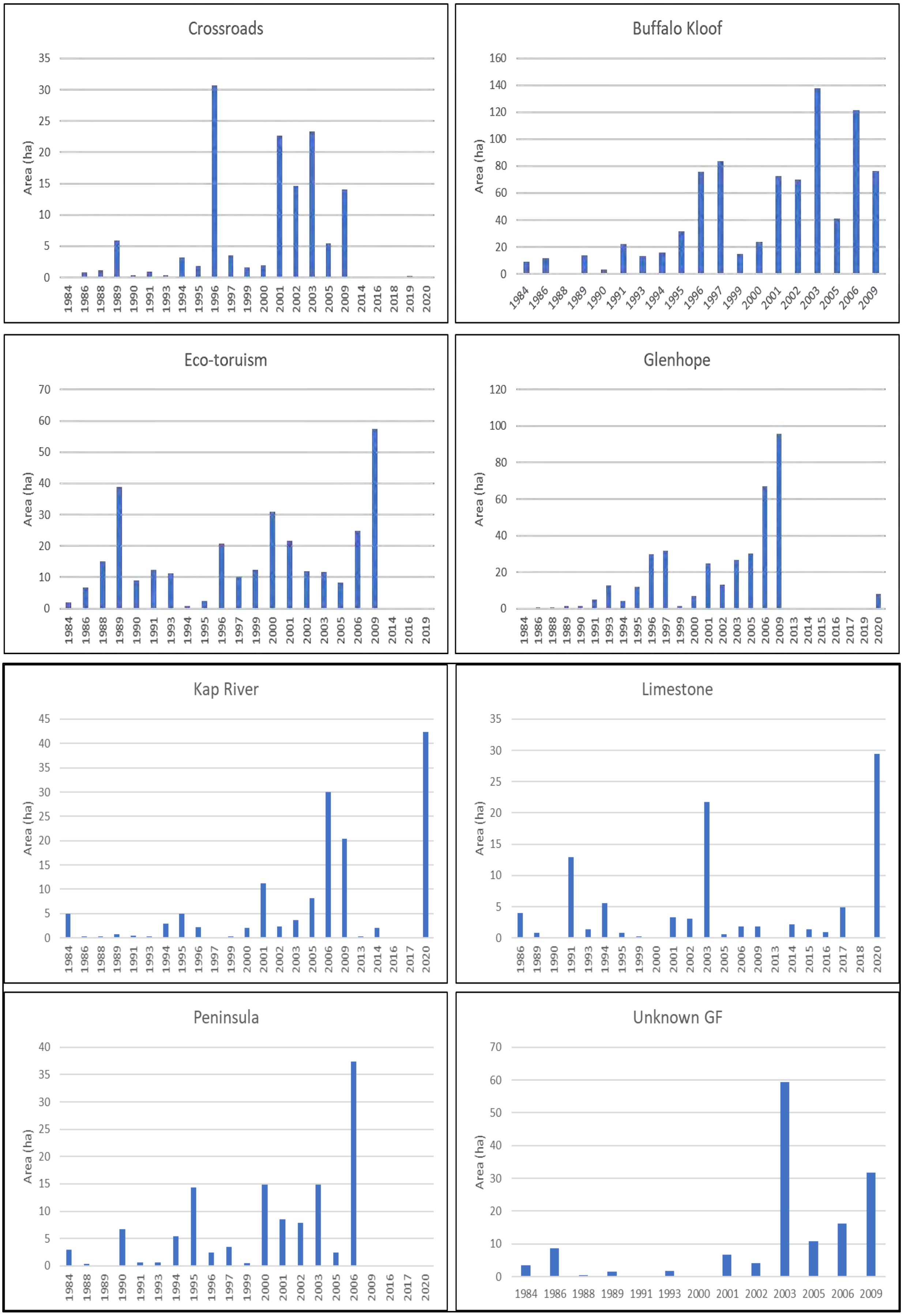


Figure 49: Graphs depicting the area of pineapple fields present at each wildlife ranch before the conversion occurred.

5.4.2.3. *Land cover changes*

The land cover spatial analysis results indicate the trends and patterns of land cover transitions regarding pineapple fields in the study area. Figure 50 represents the 5-year analysis of pineapple land cover changes in the study area since 1984. According to the results:

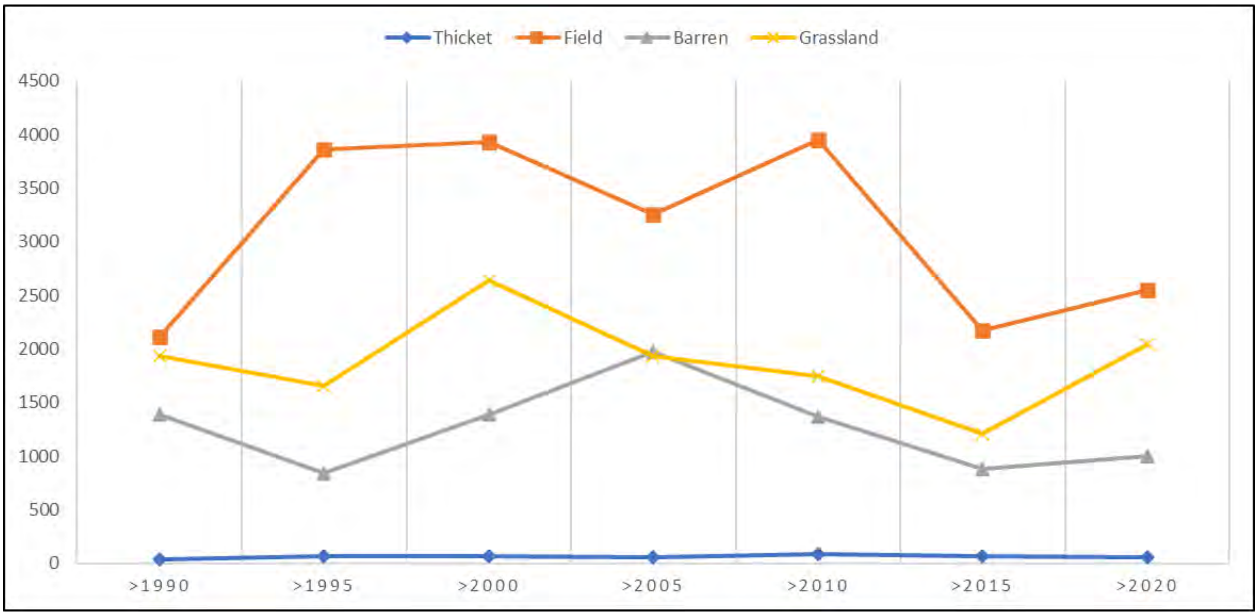


Figure 50: Graph depicting the change detection identified in 5-year intervals in the study area.

- From 1984 to 1990, 2118 hectares of pineapple fields remained active pineapple fields, while 1934 hectares of pineapple fields transitioned to grasslands, 1383 hectares of pineapple fields were barren lands, and 33 hectares of pineapple fields were observed as healthy vegetation, identified through remote sensing technologies.
- From 1990 to 1995, 3863 hectares of pineapple fields remained active pineapple fields, while 1653 hectares of fields transitioned to grasslands, 845 hectares to barren lands, and 62 hectares to healthy vegetation.
- From 1995 to 2000, 3930 hectares of pineapple fields remained active pineapple fields, while 2638 hectares transitioned to grasslands, 1384 hectares transitioned to barren lands, and 71 hectares transitioned to healthy vegetation.
- From 2000 to 2005, 3255 hectares of pineapple fields remained active pineapple fields, 1969 hectares transitioned to barren lands, 1935 hectares transitioned to grasslands, and 53 hectares transitioned to healthy vegetation.
- From 2005 to 2010, 3955 hectares of pineapple fields remained active pineapple fields, 1741 hectares transitioned to grasslands, 1369 hectares transitioned to barren lands, and 88 hectares transitioned to healthy vegetation.

- From 2010 to 2015, 2175 hectares of pineapple fields remained active pineapple fields, 1210 hectares transitioned to grasslands, 880 hectares transitioned to barren lands, and 64 hectares transitioned to healthy vegetation.
- From 2010 to 2020, 2547 hectares of pineapple fields remained active pineapple fields, 2047 hectares transitioned to grasslands, 1004 hectares transitioned to barren lands, and 60 hectares transitioned to healthy vegetation.

5.4.3. Field verification

The results of the field verification process highlighted the current LULC of former pineapple fields since the last year of productive use. The field verification process identified the land use practice and scored the land cover of the fifty-nine sites. The results provide insights into the relationship between the current LULC and the number of years since the last cultivation of pineapples at the site, and the number of years of pineapple cultivation before the transition. The following section presents the findings of the field verification process.

5.4.3.1. Land use changes

The results indicated that former pineapple fields have been converted into four different land use types: fallow/grazing, alternative agriculture use, natural land, or remaining under pineapple cultivation. Fallow/grazing land use was characterised as lands with no obvious cultivation practices, land covered with grassland, shrubs or *Vachellia* plants, or holding cattle for grazing (Figure 51). Pineapple land use was characterised as displaying active cultivation practices or as a harvested (Bare Field) field within a mosaic of neighbouring pineapple fields (Figure 52). Alternative agriculture land use was characterised as displaying any other agricultural practice (Figure 53). Natural land use was characterised as not displaying any agricultural activity, including the cultivation of crops or grazing cattle, and displayed a higher diversity of vegetation than fallow lands (Figure 54). According to the field verification results, as of 2023, 38 (64%) of the randomly selected sites are fallow or grazing pastures, 15 (22%) of the fields are active pineapple fields, 5 (8%) of the sites have transitioned to alternate agricultural practices, and 1 (1%) site displayed a natural state of vegetation.

Figure 51: Grazing lands. Grasses and Vachellia plants. Short fences, often associated with the presence of cattle.

Figure 52: Pineapple farm. Rows of pineapple plants.

Figure 53: Alternative agricultural lands. Agricultural commodities that are not pineapples.

Figure 54: Natural land. Dense and diverse vegetation.

5.4.3.1.1. Land use changes and time since last pineapple cultivation

The relationship between the number of sites currently used as grazing lands and the year pineapples were last cultivated on the same land is displayed in Figure 55. Fallow/grazing lands were identified as the most extensive land use change identified by the field verification results.

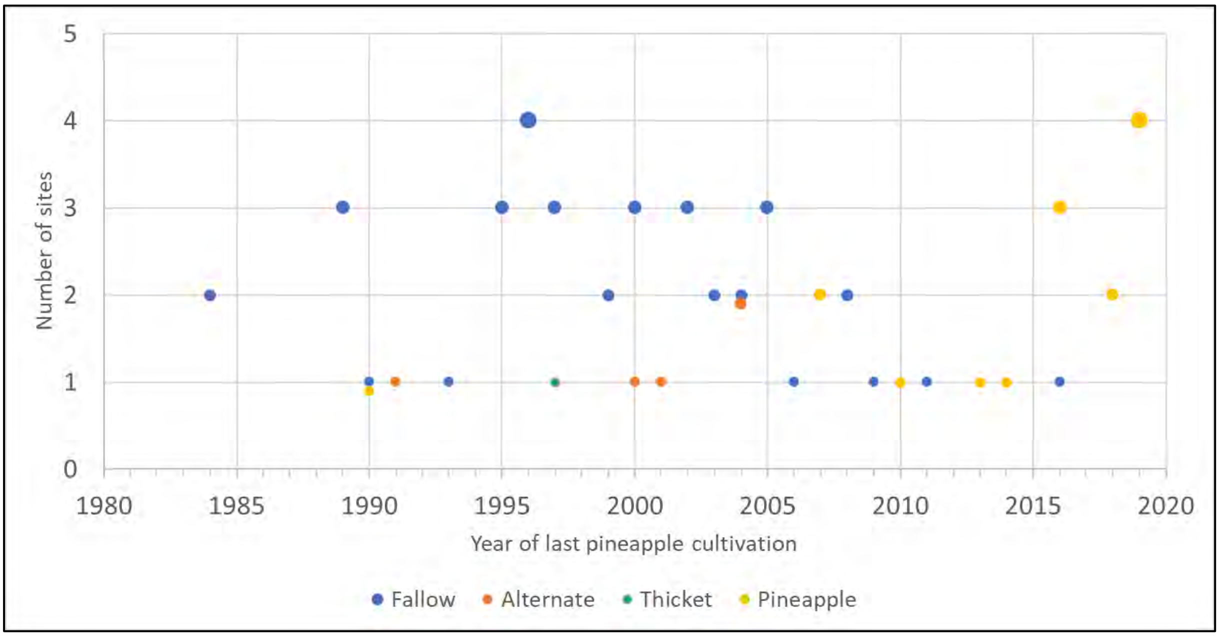


Figure 55: Relationship between the number of years since pineapples were last cultivated at each field and the current land use practice.

According to the results displayed in Figure 55 above, from the fifty-nine sites observed, an average of one field per year has transitioned to fallow/grazing lands for cattle since 1984. The number of sites which have converted to grazing lands in sites that were last cultivated as pineapple fields is as follows:

- Five sites (13.15%) from 1984 to 1990
- Four sites (10,52%) from 1991 to 1995
- Thirteen sites (39,47%) from 1996 to 2000
- Ten sites (26,31%) from 2001 to 2005
- Four sites (13,15%) from 2006 to 2010
- One site (2,63%) from 2011 to 2015
- One site (2,63%) from 2016 to 2019.

The conversion back to pineapple fields was the second largest land use change identified by the field verification process. From the fifty-nine sites, an average of 0,4 fields per year have converted back to pineapple cultivation since their last use:

- Fourteen (93%) sites that converted to pineapple farming were last identified as pineapple fields no earlier than 2007.
- Three sites have converted to pineapple farming between 2007 and 2010.
- Two sites have converted back to pineapple farming between 2011 and 2015.
- Nine sites (60%) have converted back to pineapple farming between 2016 and 2019.

Five sites have converted to alternate agricultural land use practices since pineapple cultivation was last identified:

- One site last used for pineapple farming in 1991 displayed an alternate agricultural land use practice.
- Two sites last used for pineapple farming in 2004 displayed alternate land use practices.
- Four sites (80%) last cultivated for pineapples since 2000 have converted to alternate agricultural practices.

One site that was last cultivated for pineapples in 1997 displayed a semi-natural state of vegetation. This site was mosaiced within dense vegetation, indicating that it had transformed into an ecological land use practice after 1997.

5.4.3.1.2. Land use change and the number of years of pineapple cultivation

The relationship between the current land use practice and the number of years of pineapple cultivation before the conversion is illustrated in Figure 56. It must be stated that the number of years of pineapple cultivation is recorded based on the number of years identified from the availability of satellite imagery during this research study period. Therefore, a site which was last identified as cultivating pineapples in 1984 would indicate one year of cultivation. In contrast, a site last identified as cultivating pineapples in 2019 could indicate a value of thirty-five years of cultivation. Therefore, the results of this analysis do not accurately represent the actual relationship between the number of years of pineapple cultivation and the current land use practice. Nonetheless, the results of this analysis are presented to examine the patterns of land use change regarding the number of years of pineapple cultivation, knowing that the data does not accurately represent the situation.

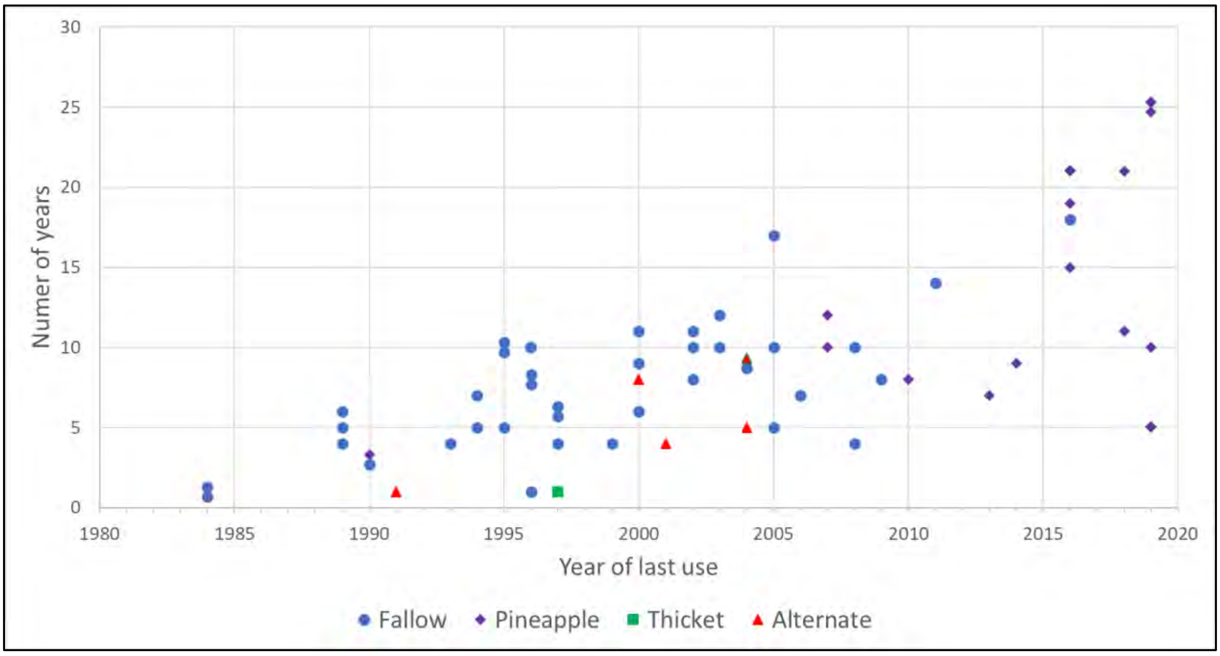


Figure 56: Relationship between the number of years of pineapple cultivation and the current land use practice.

Of the thirty-eight sites that displayed a land use transition from pineapple cultivation to fallow/grazing lands, the results recorded an average of 7.5 years of pineapple cultivation at each site before the transition.

- From 1984 to 1990, six sites transitioned to grazing lands, with an average of 3,3 years of pineapple cultivation per site, with a low of 1 year and a high of 6 years.
- From 1991 to 1995, six sites transitioned to grazing lands, with an average of 6,8 years of pineapple cultivation per site, with a low of 4 and a high of 10.
- From 1996 to 2000, eleven sites transitioned to grazing lands, with an average of 6,6 years of pineapple cultivation per site, with a low of 1 and a high of 11.
- From 2001 to 2005, nine sites transitioned to grazing lands, with an average of 10,2 years of pineapple cultivation per site, with a low of 5 and a high of 12.
- From 2006 to 2010, four sites transitioned to grazing lands, with an average of 7,25 years of pineapple cultivation per site, with a low of 4 and a high of 10.
- From 2011-2016, two sites transitioned to grazing lands, with an average of 16 years of pineapple cultivation per site, with a low of 14 and a high of 18.

Fifteen sites displayed active pineapple cultivation from the field verification conducted in 2023. The spatial analysis process recorded that pineapple cultivation at these sites ended prior to the field verification process. The results indicate the number of years of active pineapple cultivation at these sites until the last year of cultivation:

- From 2007 to 2010, three sites were active pineapple fields with an average of 10 years of pineapple cultivation per site, a low of 8 and a high of 12.
- From 2013 to 2014, two sites were active pineapple fields with an average of 8 years of pineapple cultivation per site, a low of 7 and a high of 9.
- From 2016 to 2019, nine sites were active pineapple fields, with an average of 16 years of pineapple cultivation per site, a low of 5 and a high of 25.

Five sites displayed alternate agricultural land use practices from the field verification conducted in 2023:

- One site that last cultivated pineapples in 1991 contained one year of cultivation.
- One site in 2000 contained eight years of active pineapple cultivation.
- One site in 2001 contained four years of pineapple cultivation.
- In 2004, two sites contained active pineapple cultivation with an average of 7 years, a low of 5 and a high of 9.

One site displayed a semi-natural state of natural vegetation with no other prominent land use practices. This site ended pineapple cultivation in 1997 and was only recorded to contain one year of active pineapple cultivation before the transition.

5.4.3.2. Land cover

The land cover of the fifty-nine sites was scored during the field verification process. A value ranging between 0 and 5 was assigned to each site, indicating the level of restoration, with 0 indicating use for agricultural purposes and 5 indicating pristine natural Thicket. The results of the relationship between the land cover, excluding the sites that displayed current agricultural practices, and the number of years since the last cultivation of pineapples are presented in the following sections.

Figure 57: Example of land cover score 0. Agricultural field, therefore, unnatural and monoculture.

Figure 58: Example of land cover score 1. Short grasses with a low diversity of other plants/trees.

Figure 59: Example of land over score 2. Long grasses with the presence of Vachellia or other pioneer species.

Figure 60: Example of land cover score 3. Taller Vachellia species and a higher diversity of plants/trees.

Figure 61: Example of land cover score 4. Dense bush. High diversity of plants/trees.

Figure 62: Example of land cover score 5. Pristine Thicket. No through visibility. Extremely high diversity of plants/trees.

5.4.3.2.1. Years since the last pineapple cultivation

The relationship between the current land cover of non-agricultural sites, and the year of the last cultivation of pineapples at each site, is illustrated in Figure 63.

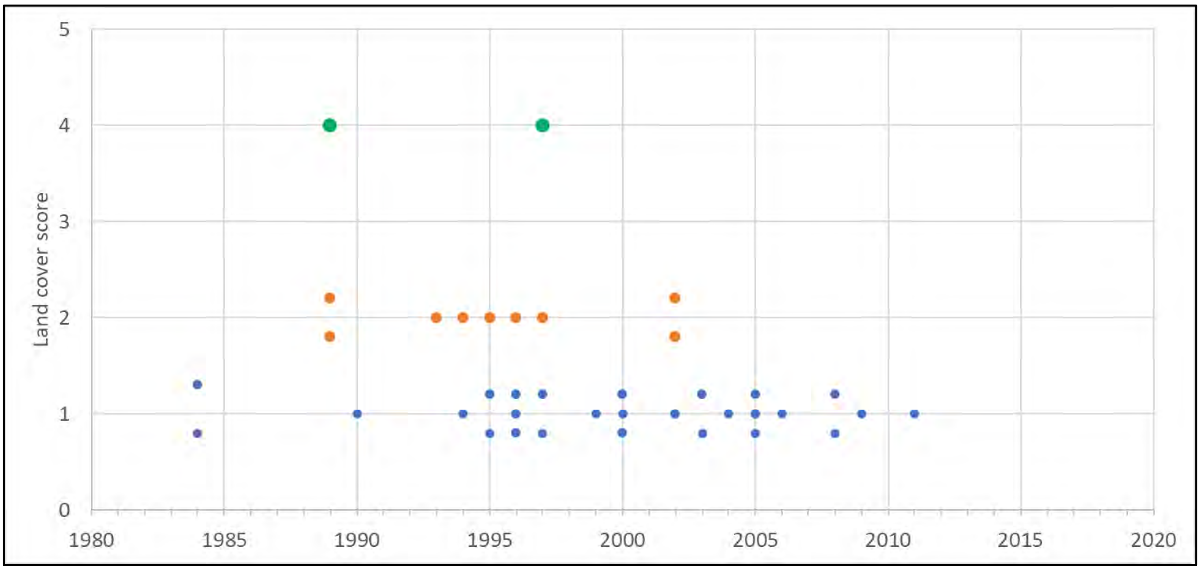


Figure 63: Relationship between the number of years since pineapple cultivation and the current land cover.

Twenty-seven sites displayed a land cover score of 1, ranging from thirty-nine years ago (1984) to twelve years ago (2011):

- Three (11%) of the sites were last cultivated with pineapples between 1984 and 1990, more than thirty-three years ago.
- Three (11%) between 1991 and 1995, more than twenty-eight years ago.
- Nine (33%) between 1996 and 2000, more than twenty-three years ago.
- Seven (25%) between 2001 and 2005, more than eighteen years ago.
- Four (14%) between 2006 and 2010, more than thirteen years ago.
- One site (3%) in 2011, twelve years ago.

Nine sites displayed a land cover score of 2, last cultivated with pineapples ranging from thirty-four years ago (1989) to twenty-two years ago (2001):

- Two (22%) of the sites were last cultivated with pineapples between 1984 and 1990, more than thirty-three years ago.
- Three (33%) between 1991 and 1995, more than twenty-eight years ago.
- Two (22%) between 1996 and 2000, more than twenty-three years ago.
- Two (22%) between 2001 and 2005, more than eighteen years ago.

Two sites displayed a land cover score of 4, a remarkably successful vegetation regrowth, last cultivated with pineapples thirty-four years ago in 1989 and twenty-six years ago in 1997:

- One site was last cultivated with pineapples in 1989, thirty-four years ago,
- and one site in 1997, twenty-six years ago.

No sites displayed a land cover score of 3 or 5.

5.4.3.2.2. Number of years of cultivation

The relationship between the number of years of pineapple cultivation, identified through the remote sensing spatial analysis and the land cover score, is represented in Figure 64. The following results present the findings for the sites that displayed non-agricultural land use practices. The land cover scores for the years a field was under cultivation are presented. It must be stated that the number of years of pineapple cultivation is recorded based on the number of years identified from the availability of satellite imagery during this research study period. Therefore, a site last identified to cultivate pineapples in 1984 would indicate one year of cultivation, whereas a site last identified in 2019 could indicate a value of thirty-five years of cultivation. Therefore, the results of this analysis do not accurately represent the relationship between the number of years of pineapple cultivation and the current land cover. Nonetheless, the results of this analysis are presented to examine any patterns of land use change regarding the number of years of pineapple cultivation, knowing that the data does not accurately represent the situation.

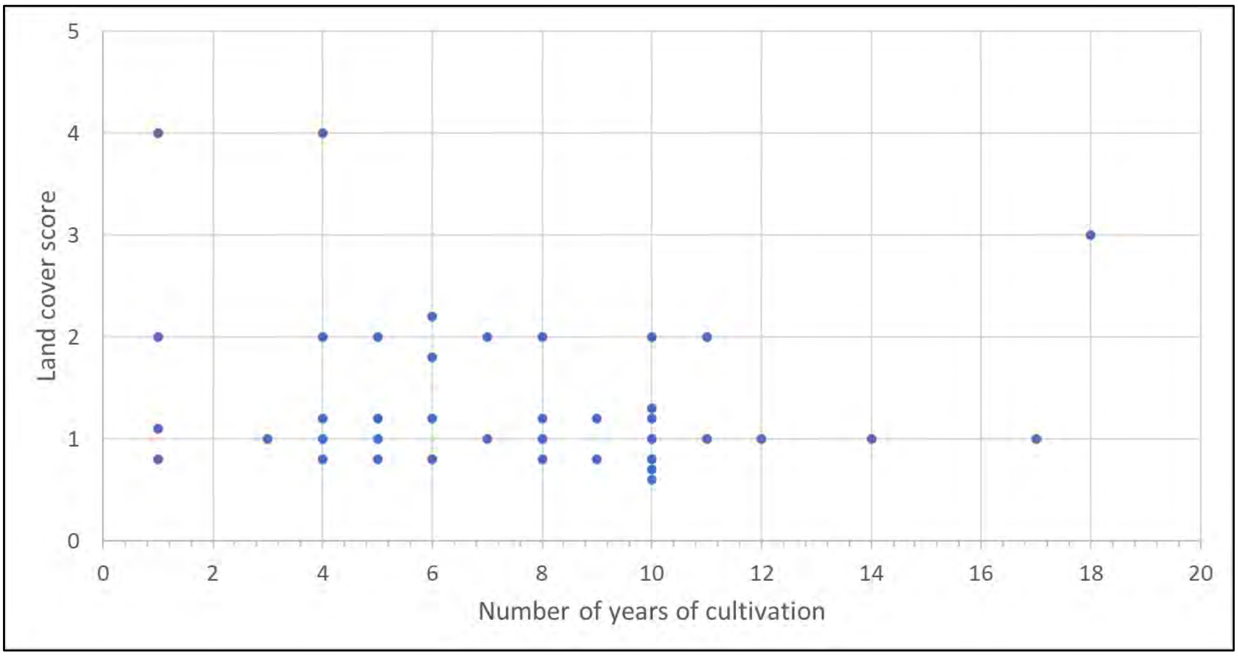


Figure 64: Relationship between number of years of pineapple cultivation and current land cover.

Of the thirty-nine non-agricultural sites, the remote sensing spatial analysis recorded:

- Four sites that contained one year of pineapple cultivation, recording an average land cover score of 2, with a low of 1 and a high of 4.
- One site that contained three years of pineapple cultivation, recording a land cover score of 1.
- Five sites that contained four years of pineapple cultivation, recording an average land cover score of 1,8 per site, with a low of 1 and a high of 4.
- Four sites that contained five years of pineapple cultivation, recording an average land cover score of 1,25, with a low of 1 and a high of 2.
- Four sites that contained six years of pineapple cultivation with an average land cover score of 1,5, a low of 1 and a high of 2.
- Two sites that contained seven years of pineapple cultivation with an average land cover score of 1,5, a low of 1 and a high of 2.
- Four sites that contained eight years of pineapple cultivation with an average land cover score of 1,25, a low of 1 and a high of 2.
- One site that contained nine years of pineapple cultivation with a land score of 1.
- Seven sites that contained ten years of pineapple cultivation with an average land score of 1,1, a low of 1 and a high of 2.
- Two sites that contained 11 years of pineapple cultivation with an average land cover score of 1,5, a low of 1 and a high of 2.
- One site that contained 12 years of pineapple cultivation with a land score of 1.
- One site that contained 14 years of pineapple cultivation with a land score of 1.
- One site that contained 17 years of pineapple cultivation with a land score of 1.
- One site that contained 18 years of pineapple cultivation with a land score of 3.

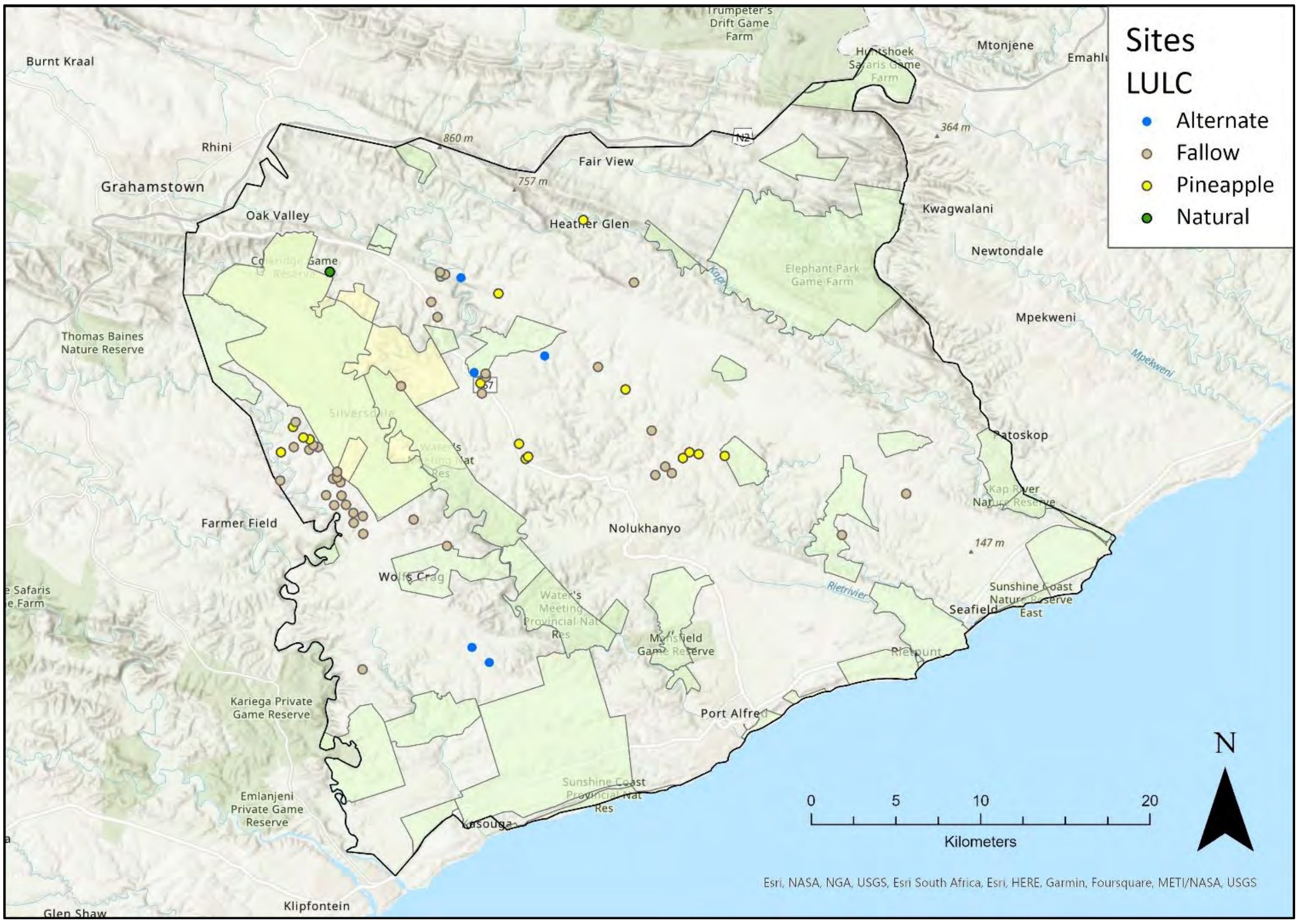


Figure 65: Location of sites in relation to land use land use practices.

5.5. Summary

The results of this research study provided the information for a holistic interpretation of the study area's pineapple industry. Primary and secondary data sources were utilised to generate an in-depth understanding of the changes to the industry in the area. The interviews provided an extensive wealth of knowledge about current farming practices, the changes to the industry, the limitations affecting the industry, and the future trajectory of the industry from the perspectives of local pineapple farmers in the region. Additionally, the literature review provided an in-depth examination of the factors that have affected the industry both nationally and globally, including political, economic and spatial factors. Furthermore, the results of the literature review provided the basis for the generation and interpretation of the LULCC resulting from pineapple cultivation that has occurred in the study area.

The image classification process confirmed that the supervised pixel-based SVM image classifier is the most appropriate method for classifying the study area's diverse land cover, using Landsat satellite imagery. Thereafter, the twenty-seven resultant land cover maps generated a successful interpretation of the study area's land cover since 1984. Gaps in the data, where satellite images could not be located, or were of a poor quality, were mitigated using satellite imagery through Google Earth Pro. The analysis of the LULCC indicated that the area under pineapple cultivation has fluctuated between 1984 and 2020; however, the pineapple industry in the area has not grown extensively. The remote sensing land use analysis indicated that LULC changes have occurred within the industry, most notably the conversion to grasslands and wildlife ranches. Furthermore, the field verification process highlighted that three major land use changes have occurred, including the conversion to grazing uses, or alternative agricultural uses, or a conversion to natural land. The results discovered that, in some cases, lands that were cultivated for pineapples have returned to pineapple cultivation after many years since the last cultivation was observed. The field verification process also noted that the land cover of the former fields has altered to varying states of vegetation recovery.

CHAPTER 6: DISCUSSION

6.1. Introduction

This research study aimed to map the spatial and temporal extent of active pineapple fields in the Lower Albany area from 1984 to 2020, using remote sensing, and to investigate the LULCC patterns and trends resulting from pineapple cultivation. The analysis of this study was restricted to a 156,939-hectare region of a significant pineapple-producing location in the Eastern Cape province of South Africa. The objectives of this study were to gather secondary information regarding the changes in the pineapple industry, evaluate the effectiveness of remote sensing techniques for mapping pineapple fields, use remote sensing to analyse spatial-temporal changes in the land area, land use and land cover resulting from pineapple cultivation over the study period, and create a holistic conceptual model of the patterns and trends of the changes that have occurred in the study area's pineapple industry. The following discussion will critically examine the methodology and results of this research study. Following this examination, an overview of the interconnectivity of the entire suite of results will be presented, discussing the trends and patterns of the observed changes in pineapple cultivation within the study area. The global and national factors influencing the observed changes are integrated into the discussion. Finally, the conceptual model is presented at the end of the discussion (Figures 66, 67 and 68), illustrating the connectivity of the entire suite of analyses covered in the research study to achieve the overarching aim of the research study.

6.2. Image classification

The twelve image classifiers tested over two GIS/RS software applications provided a non-biased approach to identify the most suitable image classifier for the requirements of this research study. The results indicated that the supervised, pixel-based SVM image classifier in ArcGIS Pro was the most suitable for this study. The results of the image classifications were successful and generated accurate yearly land cover maps for a spatial analysis of the LULCC resulting from pineapple cultivation in the study area. However, several research limitations were identified during the image classification process which hampered the accuracy of the spatial analysis process.

Between 1984 and 2020, satellite imagery for ten years was not sufficiently suitable to download, leaving a gap in the data for the study. The requirements for the collection of satellite imagery indicated that the images must be collected during the same months each year to ensure comparable results. The slow return rate of the earlier Landsat satellites, Landsat 4 and 5, limited the availability of clear images suitable for the interpretation of the land cover datasets. Four of the ten missing images resulted from Landsat 4 and 5 satellites. Additionally, the Landsat 7 satellite produced scan-line errors from 2005 onwards, which could not be mitigated with the present tools and technologies. These errors resulted in the images being unusable, therefore Landsat 5 satellite images were collected instead (2005, 2006, 2009). Conversely, the Landsat 5 operation retired in 2009, and the Landsat 8 operation began in 2013, leaving a gap of four years exclusively covered by Landsat 7, the satellite imagery of which could not be downloaded. These errors were mitigated by Google Earth's satellite imagery which was used to fill in the missing gaps.

Nonetheless, the image classification process produced twenty-seven land cover maps that illustrated the changes that have occurred in the study area's pineapple industry between 1984 and 2020. Accurate image classification is dependent on the quality of the satellite imagery, which is largely affected by atmospheric conditions. This can alter the spectral profile of different land covers, which was observed in this research study. Land cover variability was observed within the twenty-seven land cover maps. In some cases, the image classification did not differentiate accurately between healthy natural vegetation and agricultural fields. In addition, because the study area is at a low latitude, prominent shadows resulted from the south-facing slopes. In some cases, the image classifier classified shadows as Waterbodies.

Overall, the image classification process, using a supervised, pixel-based SVM image classifier, proved to be a successful methodology for mapping pineapple fields in a diverse landscape. The results of the image classification process enabled a detailed examination of the changes that have resulted from pineapple cultivation in the study area.

6.3. Area changes

The results of this research study indicate that the land under pineapple cultivation in the study area has fluctuated between 1984 and 2020, and has largely followed the patterns and trends of the South African pineapple industry (Figure 68). The troughs and peaks represent the changes affecting the national industry as highlighted in the literature. However, the analysis of this research study identified additional factors that have both positively and/or negatively influenced the pineapple industry in the study area.

According to the RS analysis results, the area of land under active pineapple cultivation in the study area has fluctuated from 1984 (2549 hectares) to 2020 (3282 hectares) (Figure 68). Over the thirty-six years, an average of 3442 hectares of land under pineapple cultivation per year was recorded.

A high of 5329 hectares was recorded in 2001, and a low of 2200 hectares in 1990. Although the findings of the analysis indicate that the industry has fluctuated over time, the industry in the study area has only grown by 733 hectares in thirty-six years (Figure 68). According to the literature, the South African pineapple industry has grown by 3900 hectares over the same period, from 5500 hectares in 1984 to 9400 hectares in 2020 (FAO, 2022) (Figure 68). The study area contains 48% of cultivated pineapple land in South Africa (DFFE, 2023), indicating that the pineapple industry in the study area has not supported the growth of land area under pineapple cultivation in the South African pineapple industry, specifically the dominant Ndlambe Municipality. The Ndlambe Municipality, where the study area is located, produces more than 60% of the country's pineapples (DARRLD, 2018) and the Eastern Cape province, in which the Ndlambe Municipality is located, contains more than 70% of the country's land under pineapple cultivation (DFFE, 2023). Additionally, the lack of growth within the study area is inconsistent with the global pineapple industry. Globally, the pineapple industry has doubled land under pineapple cultivation, with 579159 hectares in 1984 and 1046712 hectares in 2021 (FAO, 2022). Factors identified by the literature review and the interviews with local pineapple farmers support this claim.

The results of the interviews indicated that the most significant barrier restricting the growth of land area under pineapple cultivation in the study area is the governmental legislation regarding the clearing of virgin lands for agricultural purposes. According to the literature, the legislation regarding the clearing of virgin land for agricultural purposes has undergone numerous reviews, most notably the CARA 43 of 1983 and the more recent NEMA 107 of 1998, and Amendment Act 8 of 2004. The participants indicated that the strenuous legislations required EIAs that are expensive and are often not approved, especially in the study area which supports the unique Albany Thicket Biome. These legislative Acts have restricted the ability of pineapple farmers to expand their agricultural footprint, as a substantial portion of the study area is identified as Thicket according to the land cover maps illustrated in the results. According to Figure 68, a decrease in the land under pineapple cultivation was observed for both the greater South African and the study area's pineapple industries after the introduction of the NEMA act of 2004.

In conclusion, the interview participants noted that, as a result of this legislation, the trends in the pineapple industry in the study area is the consolidation of pineapple farms, and the transition of the farms into wildlife ranches, which the study area extensively supports. The literature review and the interviews indicated that the number of pineapple farmers in the region decreased from eighty in the 1980s to less than 20 in 2020.

6.4. Land use changes

Land use changes were identified through spatial analysis using remote sensing techniques and direct observations obtained from a field verification process. In addition, information regarding the patterns and trends of land use changes in pineapple farms was obtained through interviews with local pineapple farmers, and a comprehensive review of the literature. The research study results reveal significant land use changes that have occurred among former pineapple farmers, particularly in the conversion to wildlife ranches, to grazing lands, and to alternative agricultural practices. Conversely, the findings also indicate cases where land use has reverted to pineapple cultivation.

The spatial analysis results highlight the substantial conversion of pineapple farms to wildlife ranches in the study area. In 2006, a total of 37 hectares of previously active pineapple fields were converted, and an additional 274.16 hectares were converted in 2009. The sudden shift towards wildlife ranches in 2006, and more prominently in 2009, can be attributed to the contamination of fertilisers used by pineapple farmers during that period. The literature review and interviews suggest that many farmers were unable to recover financially from this disaster, forcing them to sell their farms. Consequently, there was a decline in the land area under pineapple cultivation from 2006 onwards. Despite negatively impacting most farmers, the contaminated fertiliser incident had an unintended positive consequence by reshaping the South African pineapple industry. Prior to the incident, South African pineapple farmers primarily exported canned pineapple products and competed with established industry giants. However, the incident prompted the South African pineapple factories to produce and export pineapple juice as an alternative, thereby successfully exploiting a profitable niche in the global market. The stabilisation of the area under pineapple cultivation can be attributed to the recovery of the South African pineapple industry following the contaminated fertiliser incident.

The field verification of 59 randomly selected sites revealed that 64% of the sites had converted to grazing lands, while 22% remained pineapple fields, 8% transitioned to alternate agricultural practices, and 1% returned to a semi-natural state of vegetation (Figure 66). Although visual field verification does not always provide an exact determination of land use, the sites were differentiated based on different land covers, providing an indication of the land use at each site. Furthermore, the presence of cattle, crops, and fences of varying heights enabled more accurate identification of the land use at each site.

The transition from pineapple farms to grazing lands emerged as the most significant land use change. The interview results confirmed that pineapple farmers often utilise cattle to help break down plant material during fallow periods between harvesting and planting. As a result, cattle are commonly associated with pineapple farms and can serve as an easy alternative if the field is not yielding high-quality pineapple crops. Transitions to grazing lands have been observed in pineapple fields that were last cultivated between 1984 and 2016. The results indicate that 65% of the sites identified as grazing lands were last cultivated for pineapples between 1996 and 2005, approximately 27 to 18 years ago respectively. Additionally, 5% of the observed sites were last cultivated with pineapples between 2011 and 2016. These findings suggest that pineapple fields can be converted to grazing lands after a period of seven or more years since the last pineapple cultivation.

Furthermore, the analysis of the relationship between the number of years under pineapple cultivation and the current land use indicates that pineapple farming does not significantly affect cattle grazing land use (Figure 66). Although this analysis did not provide an accurate observation of the actual number of years under pineapple cultivation per field, the results indicated that sites with more than 10 years of pineapple cultivation tended to transition to cattle grazing land use. For instance, one interview participant mentioned that his family farm converted to cattle farming in the 1980s, but the land was reverted to pineapples in 2018, approximately 38 years later. Therefore, the large proportion of sites that converted to grazing lands (64% out of the fifty-nine sites) suggests that pineapple cultivation does not significantly affect the usability of the fields for cattle grazing purposes.

The field verification results indicated that 22% of the sites remained or returned to pineapple farms. The interview participants mentioned that the time between planting varies depending on the quality of the soil. In this case, three sites were converted back to pineapples in 2016, two in 2018, and four in 2019, all falling within the time frames indicated by the various farmers. However, during the field verification process, two sites that were last active pineapple farms in 2007 were observed as pineapple fields. Similarly, sites that were observed as re-emerging pineapple farms had last cultivated pineapples in 2010, 2013, and 2014. These instances fall outside the time frames indicated by the farmers. Additionally, according to the NEMA guidelines, lands left uncultivated for more than ten years are considered virgin soil and require an Environmental Impact Assessment (EIA) for agricultural activities. The farmers indicated that obtaining approval for an EIA is expensive and time-consuming. Therefore, these sites likely transitioned to an additional land use practice between the last and current cultivation of pineapples. An interesting outlier is a site currently observed as a pineapple field, despite the last cultivation of pineapples taking place in 1990. More than two decades have passed since the cultivation of pineapples at this site. However, one of the farmers mentioned that he has returned to his family home to resume pineapple cultivation. The farm had last cultivated pineapples prior to 1984 and transitioned to cattle grazing instead.

The field verification results also indicate that five sites transitioned from pineapple farming to alternative agricultural practices (Figure 66). The verifications observed that 8% of the fifty-nine sites had converted to alternative agricultural practices. One site had last cultivated pineapples 32, 23, and 22 years ago, in 1991, 2000, and 2001 respectively, while two sites had last cultivated pineapples 19 years ago in 2004. The interviews with the participants and the literature review did not reveal a clear correlation explaining why the sites last cultivated with pineapples in 1991, 2000, and 2001 transitioned to alternative agricultural practices. However, the sites last cultivated in 2004 were attributed to the contaminated fertiliser incident first reported in 2004. The interviews suggested that conversions to this land use generally occurred among small-scale pineapple farming operations facing financial struggles. Furthermore, the literature review highlighted that some pineapple farmers were greatly affected by this incident and were forced to exit the industry, due to their inability to recover financially.

Finally, the field verification process also revealed a notable land use change, from pineapple farming practices to natural land. Among the fifty-nine sites, one site (1%) displayed a healthy and diverse vegetation structure, resembling a natural landscape. This particular site had last been cultivated with pineapples 27 years ago in 1996, and had only experienced one year of pineapple cultivation. It was situated on the outskirts of an established wildlife ranch, indicating its proximity to ecological activities. These results suggest that, with proper treatment, former pineapple fields can successfully transition to diverse landscapes that support ecological systems. However, the literature review emphasised that the natural and endemic Albany Thicket Biome is slow-growing and does not recover quickly. Therefore, the vegetation observed at this site consisted primarily of pioneer species, representing a step towards eventual recovery to Albany Thicket.

6.5. Land cover changes

Land cover changes were identified through a spatial analysis of remote sensing techniques and direct observations obtained from the field verification process. The spatial analysis process included a change detection analysis, between a five-year group of pineapple fields and the latest land cover map, to indicate the land cover changes that have occurred. The field verification process scored the land cover of each site between 0 and 5, where 0 was agricultural land, and 5 was pristine Thicket. Furthermore, relationships were highlighted between the land cover score, the number of years since the site was last cultivated with pineapples, and the number of years of pineapple cultivation at the site. In addition, information regarding the patterns and trends of land cover changes resulting from pineapple cultivation was captured through interviews with local pineapple farmers and a comprehensive review of the literature. The research study results reveal significant land cover changes that have occurred among former pineapple farms, particularly to grasslands with little vegetation regrowth.

The results of the land cover change from the spatial analysis indicated that, since 1984, pineapple fields have largely remained pineapple fields. The literature review and interviews present the barriers affecting the growth of the pineapple industry, specifically from 2004 onwards, confirming the reasons for the relative stability of the land cover. Moreover, the change detection analysis observed that pineapple fields commonly transition to Barren land, which occurs after harvesting pineapples or before replanting begins. Therefore, the identification of this land cover can be viewed as the preparation of the same pineapple field.

Additionally, the change detection analysis indicated a noticeable transition of pineapple fields to grasslands. The results of the interviews highlighted that, between harvesting and planting, cattle are introduced to the lands as a natural method to break down the remaining plant material. The interviews also highlighted that these fallow periods could last between two and seven years, depending on the amount of time needed for the soil to recover. It is possible that a significant portion of the grasslands identified by the change detection analysis are pineapple fields in the fallow period. However, the land use section discussed above indicated that the majority of the former pineapple fields observed were converted to grazing lands for cattle, indicating that a significant portion of the observed grasslands are the result of land use changes.

Lastly, an insignificant portion of the land cover changes were attributed to the conversion to natural vegetation. These observations may result in errors from image classification of medium-resolution satellite imagery. Land cover maps through image classification are completed by averaging the pixel spectral reflectance patterns for each training sample type and identifying areas in the sample image. In this case, the pixel resolution of Landsat satellite imagery is 30x30m. Furthermore, the clarity of satellite imagery is not uniform across a broad study period, especially if images are collected across multiple satellite missions. Therefore, it is likely that the image classification process generated errors, and may have misclassified some land covers. However, the field verification process identified one site that displayed a semi-natural state of vegetation, indicating that old pineapple fields can accept vegetation regrowth. Although the literature indicated that the Albany Thicket vegetation is slow growing, it was confirmed that pineapple fields can accept pioneer species, which could lead to comprehensive regrowth of Albany Thicket. Additionally, numerous pineapple fields were transitioned to wildlife ranches, indicating that old pineapple farms can support the needs of animals within a biodiverse region.

The results of the field verification process indicated that 38 of the 59 sites transitioned to non-agricultural land use practices, which enabled an investigation of the land cover changes that have occurred (Figure 67). Twenty-seven sites displayed a land cover score of 1, nine sites displayed a score of 2, and two sites displayed a score of 4. It must be stated that the type of activities at each site affected the land cover.

The relationship between the number of years of pineapple cultivation and the land cover presented a correlation between how the land cover reacts and the number of years of cultivation (Figure 67). The results indicated that low grasses and minimal plant/tree diversity were common on sites which displayed a land cover score of 1. These sites were last cultivated with pineapples between thirty-three and nineteen years ago. Longer grasses, with a higher diversity and height, were evident on the nine sites that displayed a land cover score of 2. These sites were last cultivated with pineapples between thirty-three and eighteen years ago. No sites displayed a land cover of 3, however, two sites displayed a land cover score of 4, and included a high diversity and height of plants/trees. These sites were last cultivated with pineapples between thirty-four and twenty-six years ago. Therefore, these results indicate that vegetation recovery can occur if the former field is left for an extended period, of more than two to three decades in this case. No sites displayed a land cover score of 5, indicating that the land use at former pineapple fields must be managed correctly for more than three decades in order to achieve a comprehensive return of the Albany Thicket vegetation types.

The findings of this analysis provide valuable insights into the effects of pineapple cultivation on the landscape. The literature review provided contrasting evidence regarding the sustainability of pineapple agricultural practices. A study by Boucher (1991) indicated that pineapple cultivation "increases soil erodibility"; however, recent literature, interviews with local farmers, RS analysis, and direct field verifications dismiss this claim. Interviews with experienced pineapple farmers in the study area, and a notable interview with the President of the PGA, emphasised that the techniques in which pineapples are farmed today have transitioned to a more sustainable and eco-friendly practice. The interview participants acknowledged that the former pineapple farming practices were not sustainable. Today, however, pineapple farmers prepare, plant, harvest, and rehabilitate the pineapple fields to achieve maximum productivity and longevity for the security of their livelihoods.

In conclusion, the results of this research study indicated that LULCC has directly resulted from pineapple cultivation in the Lower Albany area. The conceptual model (Figure 68) illustrates that the factors that have influenced the national industry, obtained from the literature review and interviews with farmers, have had a knock-on effect on the local industry. As a result, extensive farm consolidation has occurred, as well as a transition of pineapple farms to different land use practices. Furthermore, the results of the LULC field verification illustrated the relationship between the current LULC and the number of years since pineapple cultivation at a single field as well as the number of years of pineapple cultivation prior to the conversion. The land use transition to grazing fields occurs more regularly on sites that have had a long absence from cultivation rather than sites that were recently cultivated (Figure 66). However, the conversion to agricultural activities occurred more frequently on sites that were recently cultivated. Grazing and agricultural practices occurred more frequently in fields that contained a greater number of years of cultivation, provided that the results are obtained within a narrow temporal scale and do not represent the true situation. The land cover health of former pineapple fields will increase with the number of years since the field was last cultivated (Figure 67). Additionally, the land cover will be healthier on land that were cultivated for fewer years than fields that was cultivated more intensely.

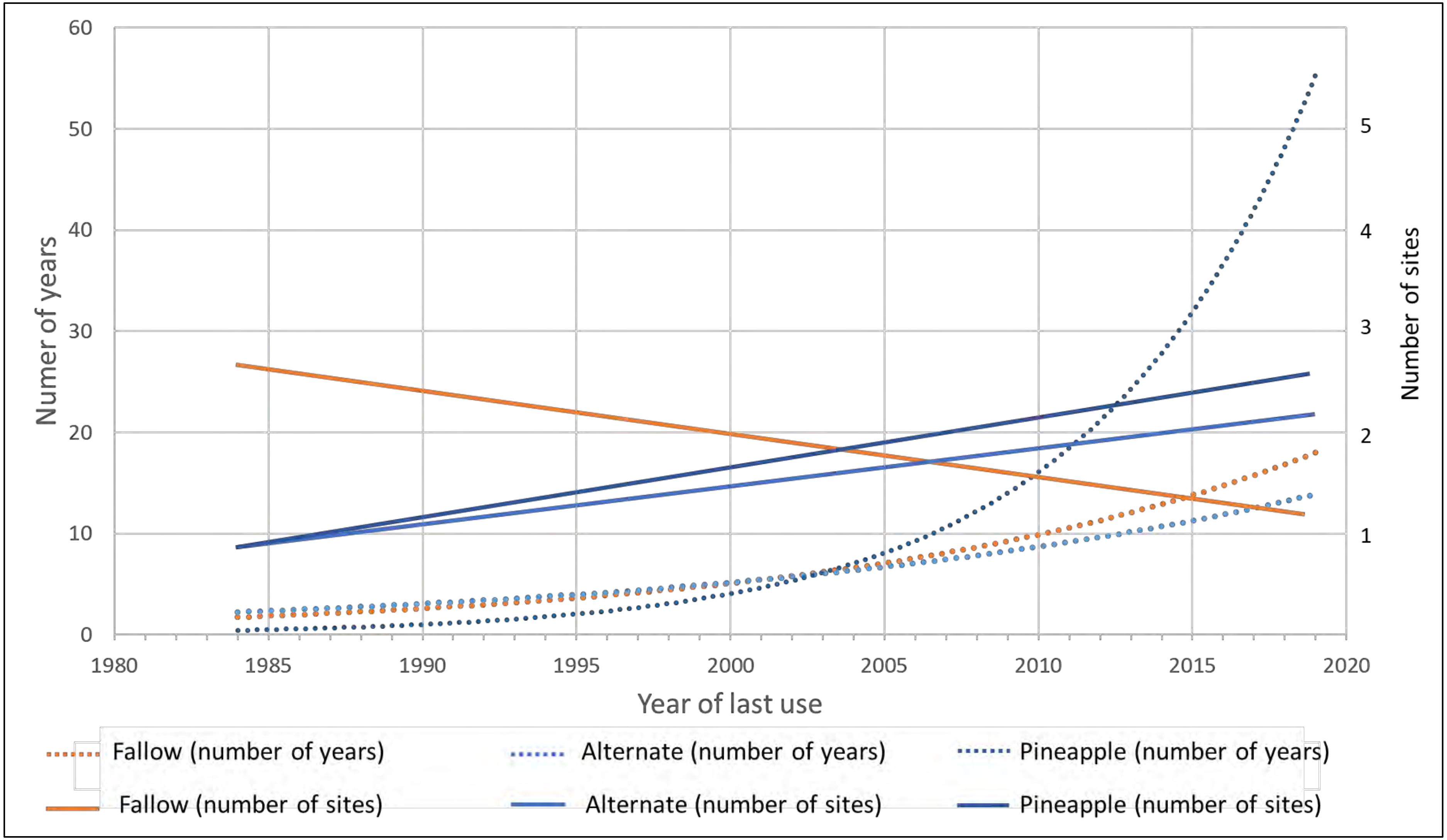


Figure 66: Patterns and trends of land use change.

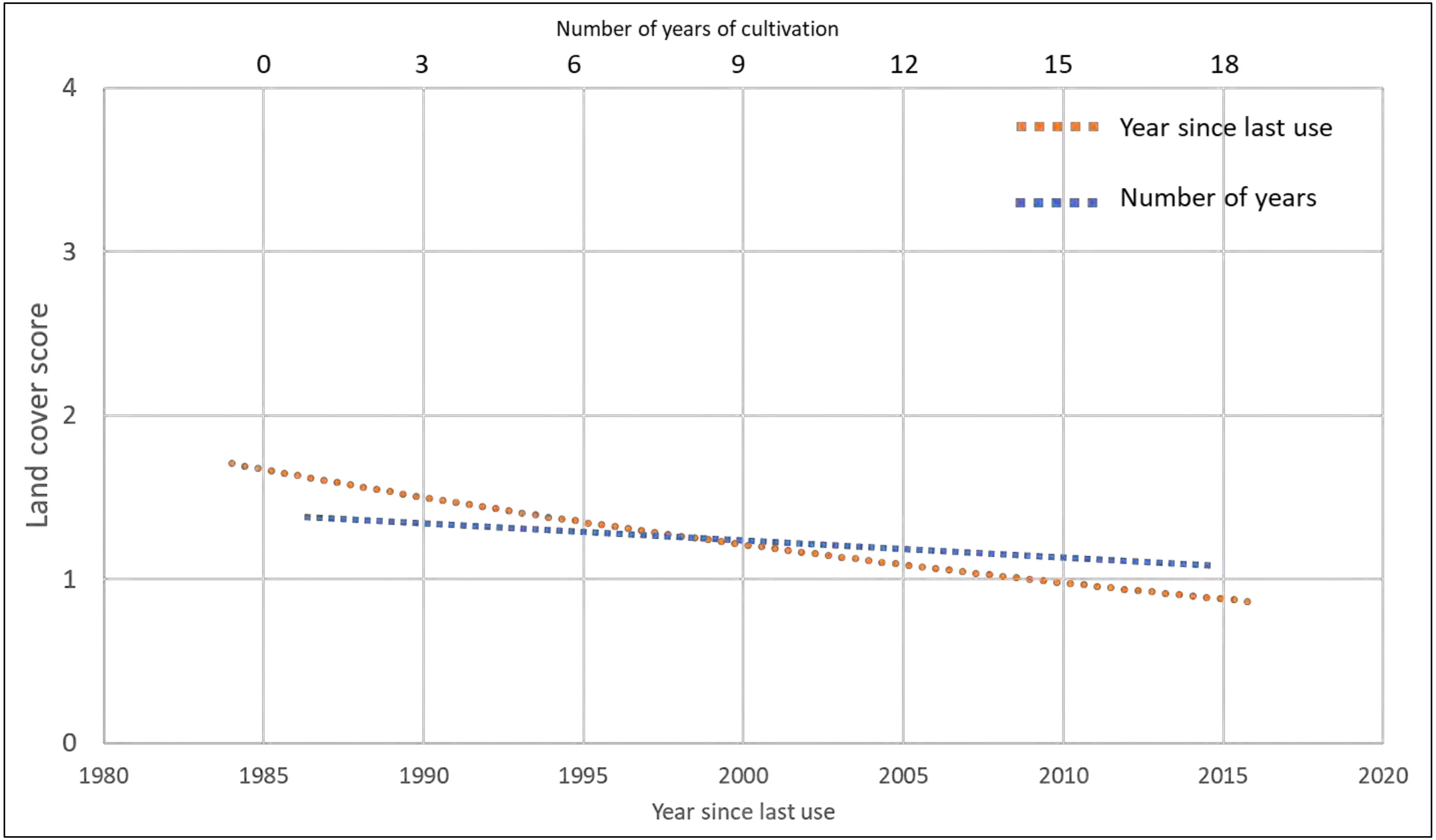


Figure 67: Patterns and trends of land cover changes.

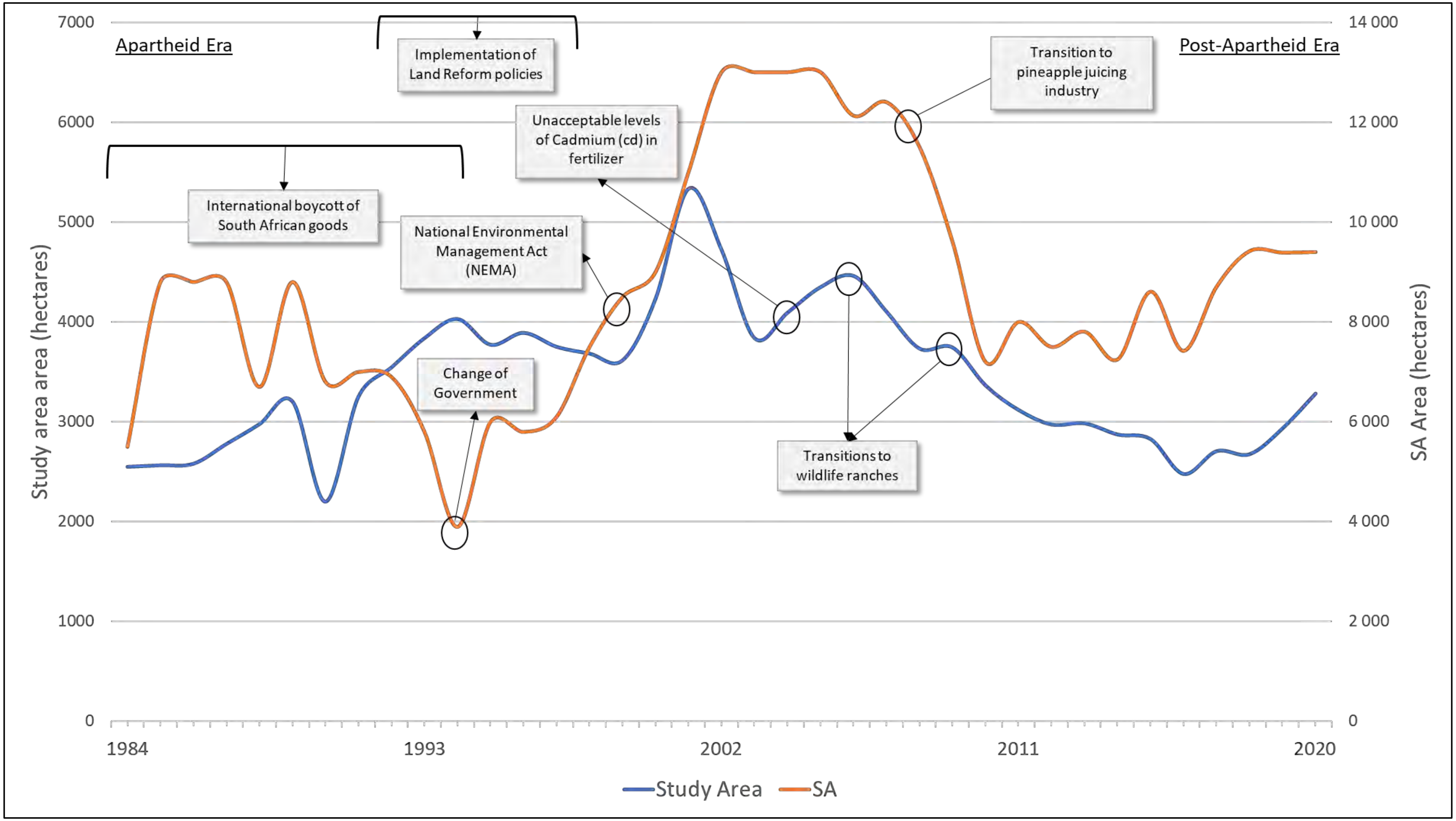


Figure 68: Factors that have caused notable changes within the study area's pineapple industry.

CHAPTER 7: Conclusion

The deeply embedded history of the pineapple industry in the Bathurst district enabled the opportunity to investigate the effectiveness of remote sensing technologies on distinguishing pineapple fields from other land covers, and investigate the LULCC that has resulted from pineapple cultivation within the study area. While the literature highlighted the forces and the extent of transformation on the Albany Thicket Biome, no studies have investigated the LULCC relationship between pineapple cultivation and the Albany Thicket Biome. Given that pineapple cultivation in the study area has thrived since 1865 (Strauss, 1961), and knowing that Albany Thicket Biome is floristically unique and boasts high levels of species endemism (Hoare *et al.*, 2006), remote sensing technologies could provide an assessment on how the industry has changed the landscape, and whether the vegetation can recover on fields that are no longer in use. This research study aimed to investigate the LULCC resulting from pineapple cultivation in the Lower Albany area between 1984 and 2020 using remote sensing technologies. The research objectives were to investigate the changes in the pineapple industry, identify an appropriate technique for mapping pineapple fields, conduct a spatial analysis of LULCC, and create a conceptual model of LULCC resulting from pineapple cultivation. Remote sensing provided the spatial and temporal information of pineapple fields and enabled further examination through direct observations. All the objectives were completed and provide a holistic conceptualisation of LULCC resulting from pineapple cultivation.

The interviews with local farmers were a valuable step in assisting the conceptualisation of the findings of the spatial analysis process. The participants came from diverse backgrounds with varying levels of experience and expertise in farming pineapples, which provided a holistic array of information. Interviewing five participants proved to be suitable for the purposes of this research study, given that the information from the interviews became repetitive. Landsat satellites were demonstrated to be the dominant satellite imagery provider in providing a historic array of satellite imagery, with imagery available since 1972, as opposed to Planet or Sentinel-2 satellites that provide imagery from 2019 and 2016, respectively. However, the coarser resolution of Landsat's 30 metre/pixel limited the accuracy of the image classification in generating land cover maps, resulting in inaccuracies between some land cover types. Nonetheless, Landsat satellite imagery, coupled with the supervised pixel-based SVM image classifier, was successful in differentiating pineapple fields from other land cover types in the study area. Overall, the twenty-seven land cover maps enabled a successful spatial analysis of the changes in the land area of pineapple fields, and the LULCC resulting from pineapple cultivation. The spatial analysis process successfully identified the changes in area under pineapple cultivation between 1984 and 2020; however, limitations were experienced in the years where appropriate and suitable satellite images could not be found. The transition to wildlife ranches was the only land use change that could be identified through the spatial analysis process, as this was the only GIS layer that illustrated a noteworthy land use. This limited a more extensive analysis of land use changes. Additionally, the coarse resolution of the Landsat satellite images restricted the land cover change detection analysis by limiting the search to four land cover types. Nonetheless, the spatial analysis process enabled a field verification task to further investigate the LULC of former pineapple fields. The 59 randomly generated sites that were accessible from public roads presented a suitable portion of the locations of former pineapple fields in the study area. The direct observations proved to be an invaluable task in this research study. Although the observations were performed without prior experience in the study of identifying and scoring LULC, the results provided suitable information to identify the patterns and trends of LULCC resulting from pineapple cultivation.

The findings of this research clearly demonstrate that LULCC has occurred as a direct consequence of pineapple cultivation in the Lower Albany area. Although the availability of satellite imagery could not verify this, the findings from the literature review and interviews with pineapple farmers confirmed that landowners could clear natural vegetation for agricultural purposes before the CARA 43 of 1983 and NEMA 107 of 1998 were authorised. The insignificant increase of pineapple fields in the study area, identified by satellite imagery after 1984, illustrates the effect of the environmental legislation. Additionally, remote sensing enabled a view into how the landscape changes after pineapple cultivation. The identified land use changes resulting from pineapple cultivation primarily involve the conversion of land to game reserves and cattle grazing lands, indicating that pineapple fields can return to local ecosystems and support wildlife habitats. Furthermore, the analysis of land cover changes revealed that vegetation has the ability to recover on former pineapple fields, supporting the regeneration of ecological systems. This finding is encouraging from an environmental perspective, as it indicates the potential for natural restoration processes to occur following the cessation of pineapple cultivation.

In conclusion, this research study has shed light on the LULCC resulting from pineapple cultivation in the Lower Albany area. The research findings contribute to the existing body of knowledge on land use dynamics and provide valuable insights for land managers, policymakers, and stakeholders involved in agricultural and environmental planning. Additionally, this study provided a methodology for identifying and assessing the LULCC of pineapple fields from Landsat satellite imagery. The methodology can be followed for other agricultural activities in a diverse landscape. It is hoped that this study will serve as a foundation for further research and stimulate land management strategies in similar agricultural landscapes.

7.1. Future recommendations

Although Landsat's 30 metre/pixel spectral resolution generated errors in the classification process, it is the only satellite imagery provider that offers annual and freely available satellite imagery from 1972. Therefore, the use of Landsat satellites enabled a wider scope of the spatial and temporal extent of pineapple fields than the other, higher resolution but temporally limited, satellite servers. However, using higher resolution satellite imagery, such as Sentinel-2 (10 – 20 metre resolution) or Planet Labs (3 and 5 metre resolution), would provide a more detailed and precise understanding of the current LULCC resulting from pineapple cultivation. Additionally, further investigating the socio-economic and environmental impacts of pineapple cultivation would provide a comprehensive assessment of the industry's sustainability and help guide land use planning decisions. Long-term monitoring and assessment of land recovery and ecological restoration on former pineapple fields would also contribute valuable insights into the resilience and biodiversity conservation potential of these areas. Lastly, conducting comparative studies across different pineapple cultivation regions, or analysing the influence of other factors, such as climate change or agricultural practices, on LULCC would enhance our understanding of the broader implications and drivers of land use change in pineapple-growing areas. Addressing these future research directions would expand our knowledge and inform sustainable land management strategies and policies for the pineapple industry and similar agricultural landscapes.

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APPENDICES

APPENDIX A: Record of interviews

	Mark Harris	**Greg Pike**	**Nigel Arnold**	**Richard Muir**	**Brandon Handley**
1) How many years have you farmed pineapples at this farm?	1982	Family owned farm since early 1900s	Family owned farm since early 1900s	Family owned since early 1900s until 1980. Richard started farming pineapples there again in 2018	Family owned farm since early 1900s
2) Did you buy the pineapple farm or was it already a pineapple farm?	Already established pineapple farm	Already established pineapple farm	Already established pineapple farm	Established pineapple farm until 1980s. Transitioned into cattle farm. Brought back to pineapples when Richard bought the farm	Already established pineapple farm
2.1) If you started the farm, what occurred at the farm before you bought it?				Cattle	
2.2) If it was already a farm, what products were farmed?	Pineapples	Pineapples	Pineapples	Cattle	Pineapples
3) What changes have taken place in the pineapple industry in the area?	Consolidation of farms. Primary driver is economics. Transition to game farms. Only one factory now, only juicing.	Spike in price of costs. Transition to biological-based fertilizers. Change in field management and rehabilitation. Change driven by environmental/sustainability and economics.	Consolidation of farms. Transition to game reserves. The country only produces juice concentrate now. Has taken 15 years to figure out how to produce juice from pineapples. Cadmium issue was "a blesing in disguise".	Major transition towards sustainable-based agriculture. Instead of using harsh chemicals, farmers are now using natural-based fertilizers.	Emphasis on sustainability procedures of agriculture. Transition towards sustainable methods of harvesting and ploughing fields. Natural fertilizers rather than harsh chemicals.
4) What happens to pineapple fields after harvesting? Are they replanted with pineapples? Or are they abandoned?	5 - 7 years growth period. After harvesting, work the crop material back into the soil. Bring in cows to help break down the material. Grass for 2 years.	5-7 year cycle. 2-3 crop cycle. Ratoon system. 12 month - 2 year fallow period. Work the plant material back into the soil. Use cows to manure and break down the material.	5-year growing period. 2 crop cycle. Leave fallow for 2 years until replaning again. Bring in cows to help work the plant material back into the soil.	Rotational planing and harvesting. 5-7 year cycle. 2-3 crop cycle. 2 years of grass or cover crop. Argued that a 1-year fallow period can be more successful than 2 years.	5-7 year cycle. 2-3 crop cycle. Sometime pineapple fields are left in fallow for 7 years to fully revcover. Majority of the time is a 2 year fallow period.
4.1) If replanted with pineapples, is there a limit to how many cycles a single field can go through until it is no longer functional?	No. Fields need to be managed correctly for their longevity.	No. Moved away from chemical fertilizers and towards biological products. Manuring and liming soil during fallow periods.	No, only if it is managed and utilized responsibly. Some fields at Nigels farm have were used by his parents in the early 1900s and are still producing quality yields.	Argues that there has to be a breaking point somewhere down the line with all the chemicals and work done to the soil. However, as long as it is managed sustainable and given the necessary nutrients, it should last indefinitely.	As long as the fields are given the right amount of time to recover, the fields will continue to produce quality yield. Some fields have been used since the 1800s and are still being utilised today.
4.2) If not replanted, what happens to the lands?	Converted into grass pastures for cattle. Another economic commodity.	Bring cows into the lands. Work the plant material back into the soils. Liming/ manuring. Adding phosphates into the soils.	Left to fallow for 2-5 years. The plant material is worked back into the soil and the tests are conducted on the soil to identify which nutrients need to be put back into the soil.	The lands are left for 1-7 years, depending on the time the land needs to recover. Nutrients are put back into the soil. The plant material is also worked back into the soil.	The lands are left to fallow for 2-7 years. The plant material is broken down. Cows are brought onto the fields to help break the material down and put it back into the system.
5) Where do you see the future of pineapple cultivation in the Bathurst area going?	Large consolidation. Same footprint, less growers. Transition into game farms. Too expensive to clear new lands. Politcal interventions.	Game farming. Pineapples only farmed on high potential lands. Transition away from burning plant material. Becoming more sustainable and responsible.	The actual footprint of pineapple fields are more likely to decrease than increase. It is too expensive and time consuming to clear virgin land, so consolidation of farms will occur. Or the transition to game farms and alternate agricultural practices.	Consolidation of farms. Improvement of sustainable methods of planting, fertilizing and harvesting. Transition to game reserves or alternate agricultural practices.	Getting permission to clear virgin land is a lost cause. Therefore, the pineapple farms present today will remain the same for the next few decades. More likely to decrease than increase in size.
6) Why are pineapples only grown in certain areas within the study area?	Government legislation regarding clearning of new lands restricts the expandion of pineapple fields. Pineapples are grown where pineapples can be farmed.	Only using high potential lands that have been recognised in the past.	The pineapple farms today are the continuation of historic pineapple farms. Today, virgin land cannot be cleared easily. Therefore, pineapple fields are grown where pineapples have been grown in the past.	Very specific to climatic and topographic condisitions. If a field was successful in the past, it will be successful today	Pineapple growers today farm on lands that have been used in the past, by parents or family members.
7) What are the geographic criteria for cultivating pineapples?	Slope, aspect, suitable soil conditions.	Planting across the contour. Slightly sloped land. Acidic soil. North Facing slope.	Doesn't need constant access to water. Can survive through droughts. Sloped lands with acidic soils.	Pineapples are drought resistant and, therefore, can be planted almost everywhere as long as it is a frost free area.	Cant be in a frost area. Over time, pineapple fields have moved further up the slopes because the frost comes higher and hiogher out of the valleys.