TITLE

Spatio-Temporal Analysis of Land Cover Change in the Perspective of Modelling Land Uses: a case study in Kavango East, Namibia.

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Thesis submitted in partial fulfillment of the requirements for the degree of Master of Geo-Information Science and Earth Observation at the Namibia University of Science and Technology

NAMIBIA UNIVERSITY OF SCIENCE AND TECHNOLOGY

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Declaration

I, *Edward Mukoya Muhoko*, hereby declare that the work contained in the thesis entitled: *Spatio-Temporal Analysis of Land Cover Change in the Perspective of Modelling Land Uses* is my own original work and that I have not previously in its entirety or in part submitted it at any university or higher education institution for the award of a degree.

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List of Acronyms

BRT: Boosted Regression Trees

CART: Classification and Regression Trees

DOS: Dark Object Subtraction

DN: Digital Numbers

ENVI: Environment for Visualizing Images

FLAASH: Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes

FORA: Future Okavango Research Area

GIS: Geographic Information Systems

IPCC: International Panel on Climate Change

KAZA-TFCA: Kavango Zambezi Trans Frontier Conservation Area

MAWF: Ministry of Agriculture, Water and Forestry

MMU: Minimum Mapping Unit

NFFP: Namibia-Finland Forestry Programme

NDBI: Normalized Difference Built-up Index

NDVI: Normalized Difference Vegetation Index

ROI: Region Of Interest

TOA: Top of the Atmosphere

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Dedication

This thesis is dedicated to my father, the late Aloys Kangoro Muhoko. Even though you did not get the chance to see me grow up, I am sure you would have been proud of the man I have become. There is no single day that passes by without me thinking of you. Rest in peace.

Abstract

Land cover change is a global problem but effects can be particularly severe in developing countries such as Namibia because it affects the social, cultural, and ecological functions of ecosystems, and can negatively affect sustainable development. Detailed studies on land cover change and the associated spatial drivers which are either directly or indirectly driving this change in the north-eastern parts of Namibia are limited. This is despite the area being part of the Kavango Zambezi Trans Frontier Conservation Area (KAZA-TFCA) which is the largest transboundary conservation area in the world. The purpose of this study was to determine the extent of land cover change during the period 1990 - 2016 in Kavango East Region, Namibia, as well as the spatial variables that may influence land cover change, their interactions and variability over time. Using Remote Sensing, GIS and Boosted Regression Trees, the study analysed the relationship between land cover change and the spatial variables, and evaluated the evolution of the spatial variables based on the statistical models during the 26-year period. The results showed that a large portion of the study has remained unchanged. The influence from the variables varied in each epoch. The predictor variables such as population density, distance to road, distance to river and distance to settlement were found to have the highest influence in the conversion of forest land to cropland. Human related predictor variables contributed more to model performance than natural factors. Further studies should use high resolution satellite imagery like Sentinel data, and other variables such as cattle density, game density, annual mean temperature, precipitation seasonality, NDVI, crown cover and slope to provide a comprehensive land cover change analysis including the variability of these predictor variables over time. The results from the models in this study may be used in a land cover change framework for environmental monitoring, spatial planning and situation analysis at local and national levels of government.

Keywords: segmentation, classification, spatial variables, land cover change, boosted regression trees

Chapter 1: General Introduction

1.1 Background

The environment is dynamic in nature and changes over time. These changes are influenced by abiotic and biotics factors. It has been estimated that about 6 million km² of the world's forests and woodlands were converted into agricultural land from 1850 to 1992 (Pröpper *et al.* 2010, Ramankutty and Foley 1999). Land cover change is a global problem but its effects can be particularly severe in developing countries such as Namibia because it affects the social, cultural, ecological functions of ecosystems and can negatively affect sustainable development (Kamwi *et al.* 2015). It is therefore important to understand the dynamics of land cover change in the Namibian context because natural resources which constitute the land cover are important to the livelihoods of the people. About two-thirds of the Namibian population depend on agricultural activities (FAO 2001, Pröpper *et al.* 2010). A reduction of these resources due to naturogenic and anthropogenic drivers can contribute to the impoverishment of rural households. In particular, forest ecosystems provide a number of important services to Namibia (Kamwi *et al.* 2015). This includes the provision of wood and non-wood products such as wild foods, medication; regulation of floods and the climate system; and supporting services such as nutrient cycling and soil formation (McIntyre *et al.* 2009). McIntyre et al. (2009) reported that most households in sub-Saharan Africa heavily rely on wood or charcoal for their source of energy. In Namibia, it is estimated that more than 54% of Namibians use wood or charcoal as their source of energy (NSA 2012).

The Kavango East is ecologically one of the most important regions in Namibia as it is part of the broad-leafed savanna biome, which has high tree species diversity and a large population of mammals (NBSAP 2014). Mendelsohn and Obeid (2003) reported that between 1943 and 1996, the area size of cleared land increased from 26,140 ha to 94,550 ha in the Kavango Region. The increase and expansion of agricultural activities, extraction of tradeable resources and logging often cause a degradation of habitats and the over-exploitation of species in the region (Ashley 1996, Biggs *et al.* 2008, Fox 2008, Geist and Lambin 2001, Mendelsohn and Obeid 2003, Strohbach and Petersen 2007, Hoffman *et al.* 2010, Yaron *et al.* 1992). It is projected that land cover change due to agricultural expansion will remain the main driver of biodiversity loss in Southern Africa for more than 100 years to come (Pröpper *et al.* 2010, Biggs *et al.* 2008, Sala *et al.* 2000, Millennium Ecosystem Assessment 2005). Drivers of land cover change are complex and originate from the relationships between human and environmental arrangements (Geist and Lambin 2002, Overmars and Verburg 2005). Although political and socioeconomic variables of land cover change have been established in other parts of the world (Roebeling *et al.* 2013, Vihervaara *et al.* 2012, Yousheng *et al.* 2012), and in Namibia (Kamwi 2015), detailed spatial studies on land cover change and the associated spatial variables in the north-eastern parts of Namibia are limited (Kamwi *et al.* 2015, Pröpper *et al.* 2010). This is despite the area being part of the Kavango Zambezi Trans Frontier Conservation Area (KAZA-TFCA) which is the largest transboundary conservation area in the world (GIZ 2015).

Most studies on land cover change in Namibia are limited in scope and do not provide a detailed account on land cover change on a regional level (Kamwi 2015, Erkkilä 2001). Therefore, there is a need to link case studies to large study areas such as political regions or national scales using statistical models (Reid *et al.* 2000, Turner *et al.* 1990). Analysing land cover change across large areas over long periods of time is an important requirement for natural resource management (Lambin *et al.* 2003, Wulder and Franklin 2007, Roy *et al.* 2014, Franklin *et al.* 2015). This can be an important approach in the design of land cover change models with an aim to identify and quantify drivers which influence land cover change over different geographic extents (Sluiter and de Jong 2007). Spatial factors such as elevation, distance to the settlement and soils are recognized as core drivers of land cover change (Geist and Lambin 2002, Kamwi 2015, Sluiter and de Jong 2007).

Classification and Regression Trees (CART) are machine learning methods which are increasingly being used by the Remote Sensing community to monitor land cover change (Rodriguez-Galiano *et al.* 2011). Some of the advantages of using CART include high classification accuracy, their capability to use non-parametric data and their capabilities of ranking variables in terms of their contribution to model performance. In the Kavango East Region, studies on land cover change modelling using classification and regression trees (CART) are rare to non-existent. Of those which have been conducted, the focus has been mostly on species distribution and composition (De Cauwer *et al.* 2016, De Cauwer et al 2017). This study attempts to fill this gap by exploring the capabilities of CART methods to model land cover change for Kavango East Region. Understanding spatial drivers of land cover change, their interactions with one another, and the consequences to ecosystem services including human well-being, is crucial for the design of effective environmental management responses (Geist and Lambin 2002). This study may provide an understanding of the major spatial drivers of land cover change in Kavango East and how they change over time. Furthermore, the results from the models in this study may be used in a land cover change framework for environmental monitoring, spatial planning and situation analysis at local and national levels of government (Kamwi *et al.* 2015).

Land use and land cover have always been used interchangeably. However, Geist and Lambin (2002) describes land use as human activities which are found on the land cover. While land cover refers to features which constitutes the Earth land surface which includes trees, soil, water, among others (Geist and Lambin 2002). Deforestation can be defined as the conversion from forest land to non-forest land (Kamwi 2015). In this study, this definition has been adopted to refer to the conversion from forest land to cropland.

1.2 Overall Research Objective and Research Questions

1.2.1 Overall Research Objective

The overall objective of this study was to determine the extent of land cover change during the period 1990 - 2016 in Kavango East Region, Namibia, as well as the spatial variables influencing land cover change, their interactions and variability over time.

1.2.2 Research Questions

In order to address the overall objective, the following research questions were formulated:

a) What is the extent of land cover change in Kavango East over the 26-year period?

b) What is the relationship between land cover change and spatial variables related to human and natural factors?

c) How have the spatial variables related to human and natural factors that influence land cover change evolved over time during the 26-year period (1990, 2000, 2009 and 2016)?

1.3 Literature Review

Africa has been regarded to have high rates of deforestation compared to other continents (Cabral et al 2010). However, historical earth observation data oppose this generally accepted portrait among the international community. For instance, Cabral et al (2010) used medium to high resolution multi-temporal remote sensing data to obtain objective information and further demonstrate the complex process of deforestation in the central plateau of Angola. Land cover change was assessed from 1990-2009 using Landsat TM and ETM+ imageries. The results indicated an overall negative deforestation rate of -0.16 %, which was far lower than the reported +0.20 % for the entire country. Despite this overall recovery, in the densely woodland types such as the miombo, there was a slight increase in deforestation in the first decade while there was a reduction in the second decade. During the same period, agricultural expansion experienced a constant growth.

Schneibel et al (2018) used Landsat imagery to apply a bi-temporal and multi-seasonal change detection method between 1989 and 2013, to estimate forest loss due to agricultural expansion in south-central Angola. They discovered that large-scale agricultural conversion is common as does the constant extraction of woody resources which leads to forest degradation. The spatial delineation of crop fields was concentrated along roads and settlements. Furthermore, the end of the civil war in 2002 resulted in an increase in the expansion of new crop fields to about 10 000 ha annually. The removal of forests and agricultural expansion are strongly linked to population migration and the need for basic services (Schneibel *et al.* 2018). Drivers of forest disturbance such as infrastructure development, wood extraction and agricultural expansion as highlighted by Geist and Lambin (2002), are also applicable in south central Angola.

Cross border studies can be used to compare land use practices in neighboring countries. For example, Revermann et al (2017) conducted a cross border study to investigate the effects of spatially diffuse land use practices on the diversity of dry tropical woodlands along the Okavango river. Accessibility was regarded as the main determining factor in land use change, distance to road was used to determine the intensity in land use. The findings by Revermann et al (2017) indicate that diverging land use patterns have an effect on the diversity of dry tropical woodlands and distance to road acts as the main drivers of change. Moreover, Chidumayo (2013) analyzed changes in tree biomass after wood clearing in the miombo woodland of central Zambia. The results showed that forest fires were the main cause of root biomass loss post wood clearing. These fires occurred annually or biannually. It was suggested that fire management strategies be enforced to ensure carbon storage and sequestration in the miombo woodlands.

Changes in land cover may affect ecosystem services that sustain livelihoods and services such as food production, climate regulation, biodiversity maintenance and erosion control (Mendoza-González *et al.* 2012, Portela and Rademacher 2001). Biophysical factors of land cover change are intermediate, they are not directly or indirectly the main drivers of land cover change (Lambin and Geist 2006, Turner *et al.* 1990). Different methods have been used to study the drivers of land cover change. For instance, Kamwi (2015) applied post classification change detection and binary logistic regression to study spatial drivers of land use and land cover change in the communal and protected areas of the Zambezi Region, Namibia. The results showed that drivers such as distance to road and distance to settlement were found to significantly influence land cover change. However, it was found that population density does not influence land cover change. The study recommended that other spatial variables which may drive land cover change including forest fires, rainfall, soil data, elevation and distance to river should be further investigated to provide a detailed account on the spatial drivers of land use and land cover change.

The findings by Kamwi (2015) are consistent with the findings of other scholars who conducted a related study in South America. With the study period spanning over 30 years, land cover data was integrated with logistic regression models to study vegetation trajectories, and the associated biophysical driving factors of land cover change in central Mediterranean Chile (Schulz *et al.* 2011). It was found that there is a strong relationship between distance to road and deforestation, while there exists a weak relationship between forest regeneration and distance to road, and between shrub regeneration and distance to road. Land cover maps produced from either aerial photographs or satellite imagery can be integrated into 'ecological time lines' to provide information on landscape dynamics over time (Reid *et al.* 2000). Ecological timelines were used by Reid et al. (2000) and the results showed that the scale of land cover change and the associated consequences vary over time, and factors such as rainfall variation and population migration caused a rapid land cover change in southwestern Ethiopia. Sluiter and de Jong (2007) reported that soil class is the main factor which influences the main types and rate of vegetation change in southern France. Moreover, soil cover differences may lead to land abandonment and development of different land cover types (Sluiter and de Jong 2007).

Combining statistical models can improve the understanding of the dynamic forces of land cover change. Kolb *et al.* (2013) used the Weight of Evidence and Regression Models to complement each other and produce different probability maps of land cover change (Kolb *et al.* 2013). Furthermore, this ensures that the advantages and disadvantages of both methods are compared. This may lead to the accurate production of probability maps to predict future land cover changes. Boosted Regression Trees (BRT) is a powerful statistical method used in all kinds of environmental research modelling on non-parametric data (Aertsen *et al.* 2010, Leathwick *et al.* 2006, Guisan and Thuiller 2005, Elith *et al.* 2008). BRT fits several models together to improve the prediction accuracy (Aertsen *et al.* 2010). Other scholars have used BRT to model spatial variables of land cover change or species distribution. For instance, the BRT in the form of a logistic regression was used to model the probability of covariates such as slope, rain and distance to the coast, to influence the spatial location of the eel *Anguilla australis* (Elith *et al.* 2008). Furthermore, satellite image analysis was combined with BRT to study the drivers of cropland abandonment in Albania and Romania from 1990 to 2005 (Müller *et al.* 2013). Their findings showed that there were similarities in cropland abandonment in both countries and cropland abandonment was highly correlated with elevation and slope. Distance to major roads did not have any influence on cropland abandonment.

BRT models have been applied in North-eastern Namibia to predict the productivity of the *Pterocarpus angolensis* timber tree. De Cauwer *et al.* (2017) used BRT to model site productivity using indicators such as species presence, site form, proportional basal area and basal area. The results showed that species presence can be more successfully modelled compared to the basal area or the proportional basal area. The main spatial variables explaining species presence were temperature annual range, Enhanced Vegetation Index (EVI), distance to fossil rivers and cattle density. They recommended that the findings could be used to establish species growth models and could also be used in forest and fire management to predict the most productive areas of the species

1.4 Thesis outline

This thesis is divided into 5 chapters. Chapter one deals with a brief introduction of this research, the overall research objective and research questions. The literature review then describes previous studies, the methods used and their findings which may be related to this study. Chapter 2 provides a brief description of the study area and outlines the image processing and modelling techniques applied. Chapter 3 shows the image processing and modelling results for each epoch. The 4th chapter deals with discussion, which interprets and explains the results obtained. Finally, chapter 5 deals with the conclusion and recommendations for future research.

Chapter 2: Methods

2.1 Description of the Study Area

The study area is the Kavango East Region and is located in the north-eastern parts of Namibia (figure 2.1). It has an area size of 2,388,200 ha of which most parts have been declared as communal land. The region is bordered by Angola in the north and Botswana in the south east. Within Namibia, the Kavango East Region is bordered by Otjozondjupa, Kavango West and Zambezi Regions. Kalahari sands are predominant in the study area, specifically Ferralic Arenosols dominate the soil composition. The soils are formed by sand deposits and are more than 1 m deep (MET 2000, Mendelsohn *et al.* 2002), thus decreasing the water table as well as the water drainage to depths plant roots cannot reach (Mendelsohn *et al.* 2002). The landscape is uniform with a predominantly plain topography. The mean maximum temperature is higher than 30°C for most of the year while average minimums of less than 10°C are recorded in the winter months of June, July and August (MLR 2015). The annual rainfall ranges from 500 mm - 750 mm, while the mean elevation is 900 m above sea level (Mendelsohn *et al.* 2002).

Kavango East consists of two national parks namely the Kaudum and Bwabwata national parks, and conservancies such as Shamungwa and Joseph Mbambangandu (Figure 2.1). Furthermore, it also consists of gazetted community forests such as Cuma, Gcwatjinga, Hans Kanyinga, Likwaterera, Ncaute and Shamungwa. George Mukoya and Muduva Nyangana are both declared as conservancies and community forests. The dominant tree species in the study area are *Burkea africana*, *Baikiaea plurijuga* and *Pterocarpus angolensis*. *Pterocarpus angolensis* is regarded as the most economical tree species in Namibia, and it is mostly used for timber (De Cauwer 2015). Due to its high economic value, *Pterocarpus angolensis* has become one of the targeted timber species as a source of extra cash for the local land users (Pröpper and Vollan 2013). The most common type of farming is small-scale subsistence crop farming with a few domesticated animals such as cattle and goats (Mendelsohn 2009). Most people live along the Okavango river as the river provides food resources and water. Seasonal fires begin from June up to November, just before the beginning of the rainy season, with high burned area figures usually recorded during the months of August/September (Stellmes *et al.* 2013a). Burned area figures are among the highest in the country due to high biomass content in the study area (Directorate of Forestry 2012).

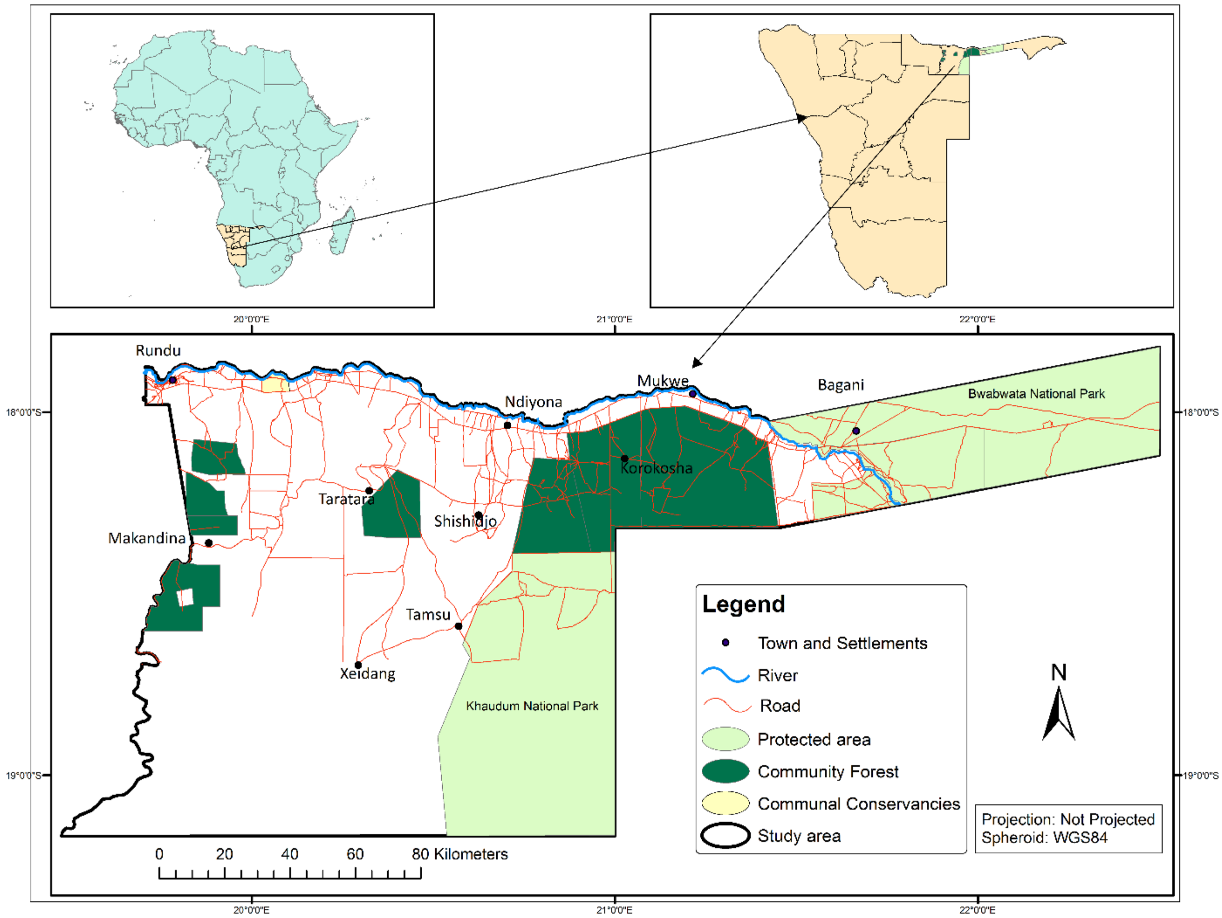


Figure 2. 1: Location of the Kavango East region, the study area in north-eastern Namibia

2.2 Image Analysis and Modelling

This chapter describes in detail the steps performed in this study as shown in figure 2.2. The methodology was divided into 3 main steps namely, Image acquisition and pre-processing, Image processing and Deforestation models. Geographic Information Systems (GIS), Remote Sensing and modelling techniques were applied in order to produce land cover and land cover change maps and to statistically model the spatial relationship between land cover change and spatial variables.

2.2.1 Image acquisition and Pre-processing

The optical and multi-temporal Landsat data series were freely downloaded from the United States Geological Survey's website (table 2.1).[1] The downloaded data were for the May-June period. This period was chosen because it is the beginning of the dry season and vegetation greenness is still in peak condition. The sensor types were Thematic Mapper (TM) for the period 1990, 2000 and 2009, and the Operational Land Imager (OLI) for 2016. The OLI sensor has a better radiometric resolution with 16 bits compared to the TM's 8 bits. Satellite imagery are affected by atmospheric conditions such as haze, sun-illumination angle and atmospheric scattering. Therefore, preprocessing of satellite imagery is a fundamental step in digital image analysis as this improves the quality of the image before further analysis is performed (Campbell and Wynne 2011). All the datasets were level 1 products, therefore geometric correction was not necessary as it was already performed by the data provider. Radiometric calibration was performed to convert Digital Numbers (DN) to radiance values. The radiance values were then converted to Top of the Atmosphere (TOA) reflectance (Flood 2014). To complete the atmospheric correction process, the TOA was converted to surface reflectance using the Dark Object Subtraction (DOS) technique. The DOS modifies the additive effects of scattering due to the atmosphere. The atmosphere can cause dark pixels to appear bright and bright pixels to appear dark (Campbell and Wynne 2011). Therefore, the DOS method adjusts pixels to their 'true surface' reflectance values. Atmospheric correction techniques such as the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) could not be used because it inconsistently removes scattering effects caused by aerosol and water vapour (López-Serrano *et al.* 2016).

[1] https://earthexplorer.usgs.gov

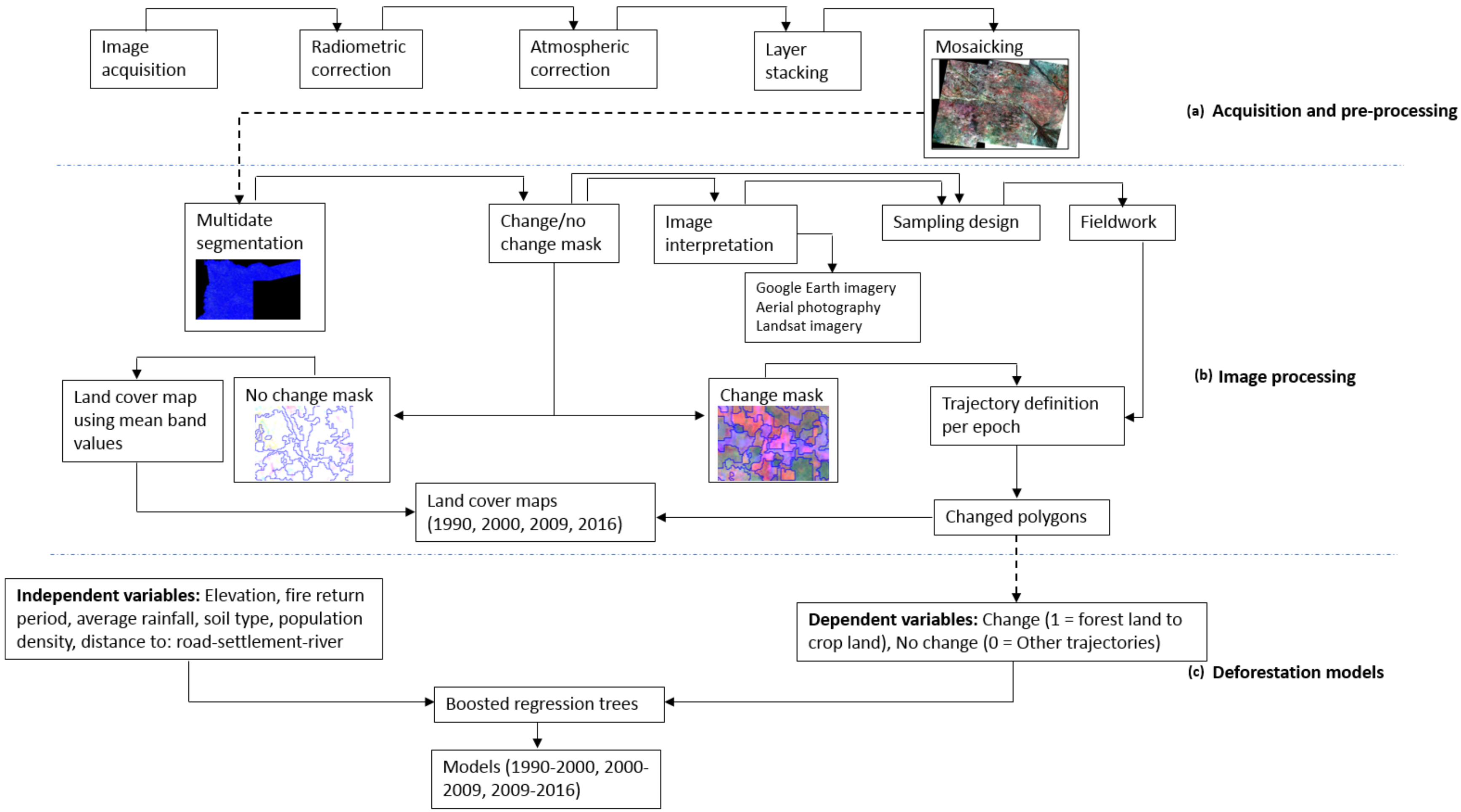


Figure 2. 2: Flow chart of image processing and modelling. The dashed lines indicate the completion of the main steps.

Table 2. 1: Satellite data specifications

Year	Satellite	Sensor	Pixel Size (m)	Path	Row	Acquisition Date
1990	Landsat 5	TM	30	175	72	26-06-1990
				175	73	26-06-1990
				176	72	17-06-1990
				176	73	17-06-1990
				177	72	24-06-1990
				177	73	24-06-1990
2000	Landsat 5	TM	30	175	72	07-06-2000
				175	73	07-06-2000
				176	72	28-06-2000
				176	73	28-06-2000
				177	72	25-05-2000
				177	73	25-05-2000
2009	Landsat 5	TM	30	175	72	16-05-2009
				175	73	16-05-2009
				176	72	04-05-2009
				176	73	04-05-2009
				177	72	27-05-2009
				177	73	27-05-2009
2016	Landsat 8	OLI	30	175	72	01-06-2016
				175	73	01-06-2016
				176	72	08-06-2016
				176	73	08-06-2016
				177	72	15-06-2016
				177	73	15-06-2016

A total of 6 Landsat scenes covered the study area. Each of the scenes were separately layer stacked to produce 6 single image files with merged bands. Landsat 5 bands had a total number of 6 bands which was the Blue, Green, Red, Near Infrared (NIR), Short-wave Infrared 1 (SWIR1) and Short-wave Infrared 2 (SWIR2) bands. Landsat 8 had a total of 7 bands which was the Coastal Aerosol, Blue, Green, Red, Near Infrared (NIR), Short-wave Infrared 1 (SWIR1) and Short-wave Infrared 2 (SWIR2) bands. The panchromatic and the thermal bands were not used in this study because they have different spatial resolutions. A seamless mosaic was then applied on the image files to produce a single image file from the 6 image files for each year of the study. The whole preprocessing steps were performed using the software Environment for Visualizing Images (ENVI) version 5.2.

2.2.2 Image Processing

Image Segmentation involves using algorithms in Trimble's eCognition Developer version 9.0. to divide an image at pixel level into smaller clusters called objects, the objects then become the building blocks for further image analysis (Trimble 2014). The multi-date Image segmentation approach delineates objects from a minimum of two different years into spectrally and spatially homogenous and identical land cover change trajectories (Desclée *et al.* 2006, Baatz and Schäpe 1999, Ernst *et al.* 2010). The multi-temporal segmentation was applied on 4 dates (1990, 2000, 2009 and 2016). The purpose of this approach was to detect and identify changed and unchanged objects from four-time periods. Four bands from OLI and TM were used and had equal layer weights: Red, NIR, SWIR1 and SWIR2. The Coastal Aerosol, Blue and Green bands were not used due to their susceptibility to atmospheric scattering (Krueger and Fischer 1994, Verhegghen *et al.* 2010). The multi-resolution segmentation algorithm was used to partition the objects. To obtain a satisfactory segmentation, parameters were adjusted so both the shape and compactness values were set to 0, and the scale parameter set to 1. These settings produced the best object segmentation results and a scale parameter of 1 ha ensures a pure land cover for all the segmented objects (Bodart et al. 2010). Therefore, the scale parameter of 1 ha was the Minimum Mapping Unit (MMU) for this study.

The change and no change masks were created by performing an initial classification using the 'max diff' and 'mean brightness' tools (Trimble 2014) (figure 2.2). The 'max diff' tool measures the mean intensity of an object from a minimum of two image layers in relation to the brightness of such an object (see appendix 6). The mean brightness tool measures the average intensity of an object based on an image layer (see appendix 7). The creation of the masks ensured that the land cover change trajectories would only be interpreted and mapped within the change masks, while the unchanged land cover would only be mapped within the no change mask (Desclée *et al.* 2006, Verhegghen *et al.* 2010). Changed objects have abnormal spectral signature characteristics and are therefore, brighter compared to unchanged objects (Desclée *et al.* 2006, Ernst *et al.* 2010, Verhegghen *et al.* 2010). The no change mask was classified using 'max diff' and 'mean brightness' values which were less than 1 (<1), the change mask was classified using both 'max diff' and 'mean brightness' values greater than 1 (1>). These threshold values appeared to discriminate the classes from one another. Objects under the change mask were mostly observed along the river, roads and settlements. While objects under the no change mask were observed in areas with little to no land use activities.

The spectral signatures of the land cover features were analysed over the 26-year period on the TM and OLI imagery. Furthermore, aerial photographs and Google Earth imagery were used to supplement the photo interpretation of the Landsat imagery. Aerial photographs for the year 1996, 2007 and 2012 were used. The 1996 photographs were obtained from Raison Namibia while the 2007 and 2012 photographs were obtained from Namibia Statistics Agency (NSA). This was used to observe the temporal characteristics of the land cover features and validate the changed and no change masks.

A total of 210 sample points were created using the stratified random sampling method based on the change and no change mask, this ensured that both strata were sampled. However, only 127 sample points were visited due to inaccessibility to the sites. Field work which was carried out in November 2017, included recording the existing land cover classes and capturing geotagged photographs of the site in the Northern, Eastern, Western and Southern directions on the field data sheet (see appendix 1). Furthermore, observed human and natural events such as logging, soil erosion, among others, were recorded. The goal of the field work was to gain an understanding about the history of the land cover change trajectories. To achieve this, local residents were interviewed about their possible knowledge on the land cover change trajectories in the past, including land use activities (figure 2.3). The local residents interviewed were village headmen (4), a traditional chief (1), commercial and subsistence farmers (18), forest rangers (2), game ranger (1), local authority officials (2) and teachers (6). The information provided by the local residents was only used to interpret imagery in the change and no change mask.

Local knowledge of the events was valuable as it gave an insight on the dynamics of land cover and land use change. It should be noted that local input could not be collected at all sample points as a large portion of the study area is uninhabited. In this scenario, field visual interpretation and image interpretation were used in an attempt to gain understanding on the types of land cover change trajectories. Furthermore, 486-point data collected on forest and non-forest either by forest inventory, field observations by De Cauwer (2014), Kamwi (2002), DoF (2003, 2013), CFNEN (2006) and Google Earth imagery were used in addition to the 127 samples collected from fieldwork.

Figure 2. 3: Subsistence farmers provided valuable information on land cover change

The classification legend used was mostly based on the International Panel on Climate Change (IPCC) classification scheme (IPCC 2003). The bushland and bare land were added by the author. Therefore, a total of 7 classes were used in this study namely; Forest land, Bushland, Grassland, Bare land, Wetland, Cropland and Settlement. Table 2.2 describes these land cover classes.

Table 2. 2: Classification scheme description

Class	Description
Forest land	Areas of more than 0.5 ha consisting of trees with a minimum height of 3m and a canopy cover of more than 10 %
Bushland	Areas of more than 0.5 ha predominantly consisting of bushes, shrubs and trees with a height less than 3m and a canopy cover of less than 10 %
Grassland	Areas dominated by grass including rangelands and pasture with a few shrubs, trees and bushes
Settlement	Areas consisting of built up areas, road infrastructure and human settlements with a population of more than 1000
Cropland	Areas used to produce food for both subsistence and commercial purposes
Wetland	Areas predominantly wet for most of the year consisting of rivers and lakes
Bare land	Area not classified as forest, bushland, grassland, settlement, cropland and wet land and are bare in nature. This includes rocky areas and pans.

Object-based classification uses information on the spectral and spatial characteristics of image pixels to assign homogenous pixels into objects. Pixel-based classification has limitations because it is only based on spectral classes and each pixel is assigned to one class only. Object based image analysis often produce far more accurate results compared to pixel-based analyses (Weih and Riggan 2010, Yadav *et al.* 2015, Juniati and Arrofigoh 2017). The object-based approach uses characteristics such as tone, size, shape, texture, patterns and the association between objects to assign a class. This extends the capabilities within image analysis (Jasani *et al.* 2009).

Object-based classification was analysed using Trimble's eCognition Developer version 9.0. The eCognition software uses rule sets to perform a segmentation, classification and exports the output either as raster or vector data. Rule sets are decision rules which use thresholds determined by the user to perform a function. The Normalized Difference Vegetation Index (NDVI) was used to classify forest and non-forest areas. The NDVI uses a ratio of the reflectance values between the Near infrared band and Red band and is one of the most used indices in remote sensing (Tucker 1979, Cracknell 2001). The NDVI is highly correlated with photosynthetic activities and chlorophyll content in vegetation (Myneni *et al.* 1995, Tucker *et al.* 2005). Forest areas tend to have high NDVI values compared to non-forest areas.

Under the no change mask, mean band values were used to classify the land cover types. For instance, because objects under this mask have remained unchanged over the 26-year period. The NDVI for all the years (1990, 2000, 2009 and 2016) were averaged and used to classify forest land, bushland and grassland. The settlement class was extracted using a combination of the NDVI and the Normalized Difference Built-up Index (NDBI) values. The NDBI is a ratio between the short-wave infrared band and the near infrared band. Built up areas and Bare land have higher reflectance values in the short wave infrared band than in the near infrared band (Zha *et al.* 2003). To separate the built-up areas and bare land from vegetation, the NDBI values were subtracted from the NDVI (NDVI-NDBI). The positive values are built-up areas and bare land while negative values are water and vegetation (Zha *et al.* 2003). Based on this, settlements and bare land were extracted. To separate the settlements from bare land, a polygon of settlements was extracted using the NDVI-NDBI equation to mask and classify settlements. The other class was renamed to bare land.

Data from field observations and image interpretation was used to determine a threshold value to discriminate forestland from bushland and grassland. A NDVI of 0.31 was the minimum value for forest land. Using the NDVI value of 0.31 threshold, all vegetation which had a minimum value of 0.31 was classified as forest land. The NDVI values for bushland ranged from 0.25 to 0.30. All NDVI values of less than 0.25 were classified as grassland.

Based on field observations and image interpretation, cropland areas were extracted using the brightness, rectangular and elliptic feature tools. The 'rectangular fit' tool can be used to label how well objects will fit into a rectangle of the same proportion and size, values range from 0 to 1, with 1 indicating a perfect rectangular object shape (Trimble 2014). Furthermore, the Elliptic fit can be used to label how well objects will fit into an ellipse or circle of the same size and proportion. A value of 1 indicates that the object has a perfect elliptic or circular shape while 0 indicates that the object is not round at all (Trimble 2014). Cropland had brightness values bigger than 0.2. Crop fields were rectangular in shape in the communal areas while there were a few irrigation circles on commercial farms. The brightness threshold value together with the Rectangular fit value of more than 0.5 and the Elliptic fit value of more than 0.5 were used to classify cropland. These values seemed to produce a satisfactory discrimination between cropland and non-cropland features. Wetland was classified using near infrared values. Water completely absorbs the near infrared band and therefore appears dark in colour. All the water bodies were extracted by setting the threshold of all near infrared band values of less than 0.18 and labeled Wetland. The resultant product from this ruleset classification was the unchanged land cover map.

Land cover change trajectories were analysed on the change mask. To track the land cover trajectory per epoch, the copy map and synchronize map tools were used. In the eCognition software, a map refers to scenes and image objects which are loaded (Trimble 2014). Rulesets and data are operated on the map. The software is capable of dealing with multiple maps and the copy map tool is used to copy the map, image layers and its objects from one view to another, while the 'synchronize map' tool is used to only copy image objects from one view to another (Trimble 2014). Change trajectories were identified and defined per epoch (1990-2000, 2000-2009 and 2009-2016). The copy map tool was used to copy the 1990 image layers, 2000 image layers and the objects produced from the multidate segmentation stage into the new 1990-2000 map. Mean band values from the difference of the NIR between the two years (NIR2000-NIR1990) were used to detect land cover trajectories (Desclée *et al.* 2006). Values greater than 0.01 (the difference of the NIR>0.01) seemed to appropriately map the detected changes. Information gathered from the image interpretation stage, field work as well insights from the locals was used to define the detected trajectory. For instance, if from image interpretation it was identified that forest land in 1990 became crop land in 2000, the farmer or residents who have lived at the site since 1990 were briefly inquired to confirm this trajectory. Under the 1990 land cover map, the trajectory 'forest land in 1990 to cropland in 2000' was labeled as forest land, while on the 2000 land cover map it was labeled as cropland. These procedures were repeated for the 2000-2009 and 2009-2016 epochs. The changed polygons from the change masks and the land cover map from the unchanged mask were combined to produce 1990, 2000, 2009 and 2016 land cover maps.

The accuracy of the land cover maps was assessed using validation points produced from Google Earth imagery. For each map, validation points were randomly created in ESRI's ArcGIS 10.1 software and overlaid in Google Earth. The land cover was recorded by zooming on the random point and record the existing land cover on such a point. The time slider tool was used to observe the historical images for

2009, 2000 and 1990. As a result, a total of 591 random points were acquired for 2016, 265 for 2009, 253 for 2000 and 200 for 1990. The 'Confusion Matrix Using Ground Truth ROI' tool in ENVI 5.2 was used to measure the accuracy of the land cover maps. The validation points were converted to Region Of Interest (ROI) points to produce a confusion matrix. The overall accuracy, kappa coefficient, user accuracy and producer accuracy values were obtained from the confusion matrix.

2.2.3 Deforestation Models

Deforestation models were produced using Boosted Regression Trees (BRT) which is an ensemble machine-learning method which builds algorithms from available data. It is part of a CART group which are based on building decision trees repeatedly on all branches in the trees until all trees are pure (Alpaydin 2010). The BRT models were used to determine the most important spatial variables that affected land cover change from 1990-2016. The land cover change of interest in this study was the trajectory from forest land to cropland (figure 2.2). Table 2.3 shows the sources of the independent data (covariates or predictors) used in the study.

Table 2. 3: Spatial data used to derive independent variables

Data	**Type**	**Spatial Resolution (m)**	**Source**
Roads	Vector	N/A	Roads Authority Namibia
Settlement	Vector	N/A	Ministry of Land Reform
Mean Rainfall (1990-2016)	Vector	N/A	Ministry of Agriculture, Water and Forestry
Elevation	Raster	30	NASA; https://earthexplorer.usgs.gov
Burned Area polygons (1990-2016)	Vector	N/A	Ministry of Agriculture, Water and Forestry
Permanent Rivers	Vector	N/A	Ministry of Agriculture, Water and Forestry
Soil	Vector	N/A	Ministry of Agriculture, Water and Forestry
Population Density (1991, 2001 and 2011)	Vector	N/A	Namibia Statistics Agency

Due to the size of the study area, a total of 400 stratified random points were generated for each epoch using ArcGIS 10.1 software. The sample size of 400 was deemed sufficient to be representative of the study area. As crop farming is the main source of the livelihoods for the people of Kavango East (Mendelsohn 2009), the change trajectory modelled was from forest land to cropland or in other words, deforestation due to cropland expansion. If a point was within the boundary of the forest land to cropland class, it was assigned a value of 1 for 'change' otherwise 0 for 'no change'. Hence the probability distribution is binomial.

Fire return period was produced from the burned area polygons by first creating codes 1 and 0 for burned and unburned, respectively. The datasets were then added using ArcGIS 10.1 'raster calculator' tool (table 2.4). The average rainfall data used was the mean rainfall figures from 1990 to 2016. Using the 'proximity tool', the distance from the points to the nearest roads, river and settlements in vector format was calculated. The nearest distance is calculated by evaluating the shortest distance between the points and near features such as roads, settlements and river (table 2.4). The value of all predictor variables such as population density, soil data, fire return period, elevation and average rainfall, was extracted using the 'extract to multi-values' tool for each point.

Table 2. 4: Description of the predictor variables

Spatial variable	Description
Distance to River	The distance in km from the sample point to the river
Distance to Road	The distance in km from the sample point to the nearest road
Distance to Settlement	The distance in km from the sample point to the nearest settlement
Population Density	The number of persons per square km
Elevation	The altitude above sea level in meters
Fire Return Period	The number of years a fire was detected on the same area
Average Rainfall	The mean rainfall in mm
Soil type	The classes on different soil types

The BRT was performed using methods and codes developed by (Elith *et al.* 2008) in the open source software R version 3.4. The open source software R has packages (especially gbm) and functions to fit the BRT model. For each of the study period, change (1) was present in 200 sample points and no change (0) was also present in 200 sample points for each dataset. In total, there were 400 points created for each epoch. The training data were used to calibrate the model. The same points were used to validate the model through cross-validation. The *gbm.step* function was used to initially fit the models with the

Bernoulli family distribution, with a tree complexity of 5, learning rate of 0.005 and bag fraction of 0.5. The percentage explained deviance, which represents the goodness of fit of a model was calculated by obtaining the difference of the mean total deviance and mean residual deviance divided by the total deviance and converted to percentage. The higher the explained deviance, the better the model fits the data (Leathwick *et al.* 2006, Martínez-Rincón *et al.* 2012). The percentage Cross Validation (CV) deviance is calculated in the same manner but instead of using the mean residual deviance, the estimated CV deviance is used. These parameters were obtained from the model output.

The models were then further simplified by removing variables which did not improve model performance according to procedures indicated by Elith et al. (2008). After performing the *gbm.simplify* function, the models had a higher percentage explained deviance than the initial fitted models. These steps were done for each epoch. The predictor variables were then ranked in terms of their importance to relative contribution to model performance.

Chapter 3: Results

The field work was conducted in the month of November 2017 where a total of 127 field observation points were used as training points. Of the 127, 41 points were forest land, 34 points were bushland, 6 were bare land, 23 were cropland, 12 were grassland, 9 for settlement and 4 for wetland. An additional 468 points were used as training points mainly on forest and non-forest classes. These data were collected by De Cauwer (2014), Kamwi (2002) DoF (2003, 2013) and CFNEN (2006).

3.1 Land Cover in Kavango East

Figure 3.1 shows the nature and extent of land cover in the study area from 1990 to 2016. The land cover maps show that the cropland class exhibited a linear pattern along the Okavango river and other dry fossil rivers. Furthermore, there has been an expansion in cropland areas in the northwestern and north eastern parts of the study area. There has been a little change (57.6 % in 1990 to 54.2 % in 2016) in the distribution of the forest class over the 26-year period, most disturbances are along the rivers (dry and permanent) and roads. The central, southwestern, and eastern parts of the study area has largely remained unchanged. These unchanged areas are known to have low population density (NSA 2012). The Bushland class was mainly distributed on the south western and southeastern parts of the study area while a few patches can be observed on the north eastern parts. These parts have high annual fire occurrences (Directorate of Forestry 2012).

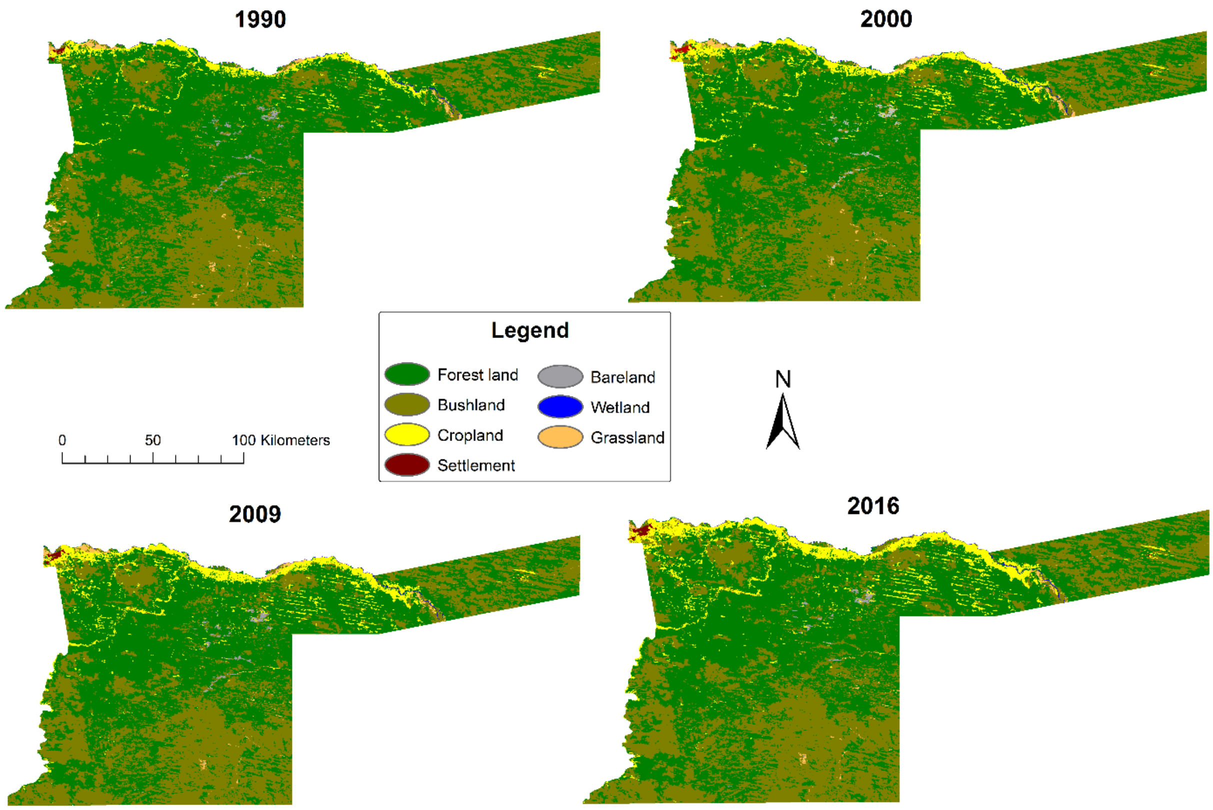


Figure 3. 1: The distribution of land cover types in the study area

The grassland class was found mostly in the northern parts in the flood plains along the river, with a few patches in the south. Bare land was mainly distributed in the northeastern parts were few patches of salt pans are found.

	1990		2000		2009		2016	
Land Cover type	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)	Area (ha)	Area (%)
Forest land	1376140.0	57.6	1326960.0	55.6	1310680.0	54.9	1293680.0	54.2
Bushland	906245.0	37.9	925139.0	38.7	917318.0	38.4	928193.0	38.9
Cropland	69838.1	2.9	102208.0	4.3	129881.0	5.4	145405.0	6.1
Grassland	21223.6	0.9	18337.1	0.8	14522.8	0.6	8582.6	0.4
Settlement	1724.94	0.1	2616.2	0.1	2850.2	0.1	3376.1	0.1
Bare land	9633.1	0.4	9641.0	0.4	9591.9	0.4	5638.3	0.2
Wetland	3474.5	0.1	3338.2	0.1	3409.3	0.1	3409.3	0.1
Total	2388287	100	2388287	100	2388287	100	2388287	100

Table 3. 1: Land cover composition for 1990, 2000, 2009 and 2016

Table 3.1 shows that forest land was the dominant land cover in all the years followed by bushland in second and cropland third. In fact, more than half of the study area was covered by forest land (57.6 % in 1990, 55.6 % in 2000, 54.9 % in 2009 and 54.2 % in 2016). This indicated a gradual decrease in forest land for each year of study. The highest land cover for the bushland class was in 2016 with 38.9 %. Furthermore, there was a consistent increase in the area covered by cropland from 1990 to 2016. For instance, the area covered more than doubled from 2.9 % in 1990 to 6.1 % in 2016. This indicates that agriculture still remained the main source of the livelihood for the people of Kavango East. The settlement class consistently covered 0.1 % of the study area in 2000, 2009 and 2016. However, there was an increase when compared to the previous year. For instance, 2000 compared to 1990, 2009 compared to 2000 and 2016 compared 2009. There was a slight fluctuation in the wetland class over the 4 year, this may be due to the variability in rainfall patterns over the years.

3.2 Accuracy of the Classification

Independent reference points generated from Google Earth using visual interpretation and were used to assess the accuracy of the classification for all the maps. 591 reference points were used for the 2016 map, 265 reference points were used for the 2009 map, 291 reference points were used for the 2000 map and 150 for the 1990 map. Table 3.2 shows the accuracy assessment results for the 2016 classified image. The overall classification accuracy achieved for the 2016 classification was 81.2 % with a Kappa coefficient of 0.76. Most authors have achieved overall accuracy values in the range of 60 % to 90 % when image classification was performed using Landsat imagery (Mango 2010, Kamwi 2015). A Kappa value between 0.70-0.80 is interpreted as substantial agreement (Viera and Garret 2005). Therefore, the values obtained in this study denote an acceptable classification result. Cropland and Forest land had the highest producer accuracy of 94.5 % and 90.4 %, respectively. Wetland and settlement had the highest user accuracy of 100 %. This then corresponded to the lowest commission errors of 0 % for both. Bare land and Grassland had the lowest producer accuracy with 25.4 % and 55.6 % corresponding to high omission errors of 74.6 % and 44.4 %, respectively. The overall accuracy for the 2009 classification was 77.7 %, for the 2000 classification was 81.0 % and 1990 classification was 75.0 % (see appendices).

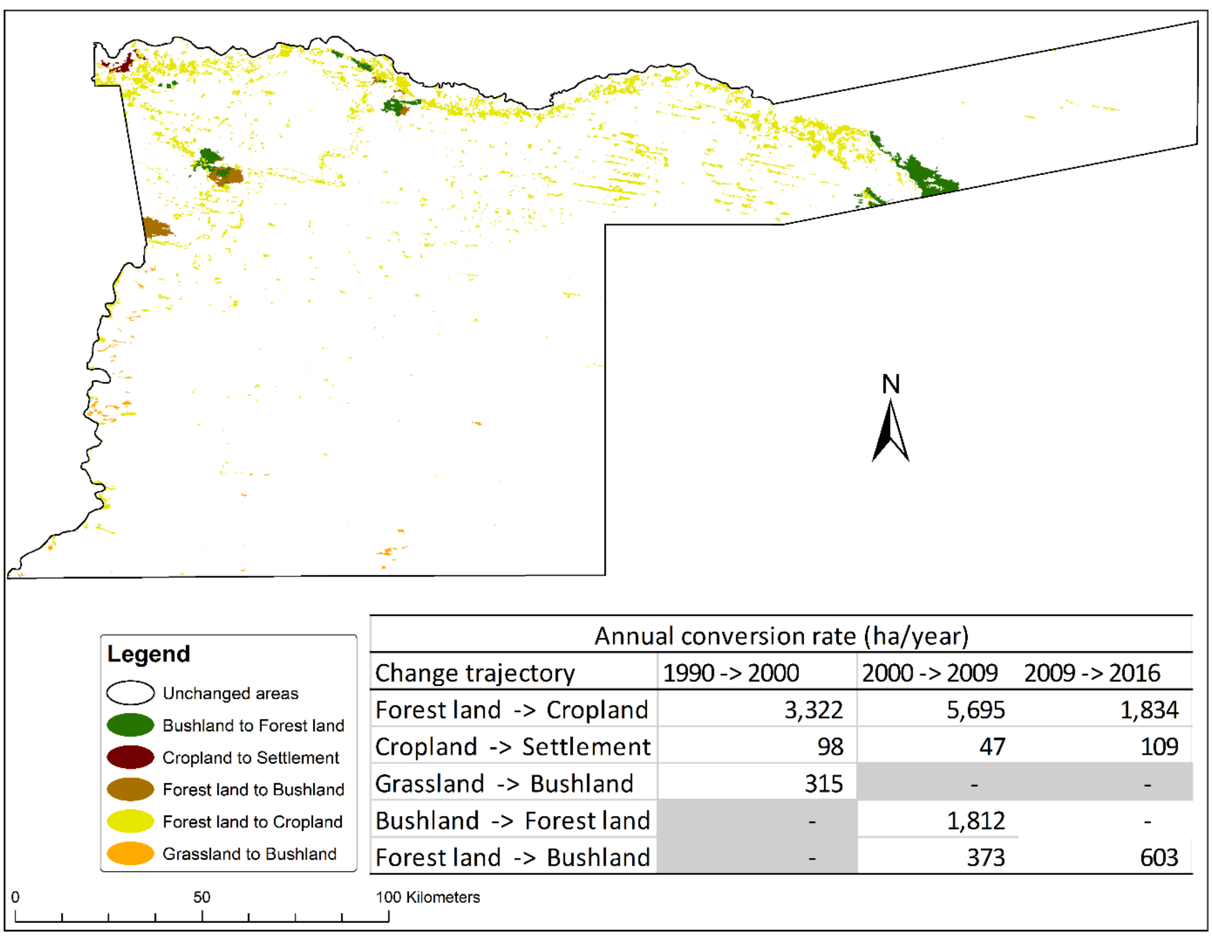
Table 3. 2: Accuracy assessment results for the 2016 classification

Class	Producer accuracy (%)	User accuracy (%)	Commission error (%)	Omission error (%)	Reference points
Bare land	25.4	93.8	6.3	74.6	16
Bushland	84.3	68.4	31.6	15.7	133
Forest land	90.4	87.0	13.0	9.6	162
Cropland	94.5	86.5	13.5	5.5	178
Grassland	55.6	54.0	46.0	44.4	37
Settlement	86.7	100.0	0.0	13.3	26
Wetland	84.6	100.0	0.0	15.4	33
Total					591
Overall Accuracy (%)	81.2				
Kappa Coefficient	0.76				

3.3 Change Trajectories

Figure 3.2 shows the changed areas related to land use such as agricultural expansion from 1990 to 2016 in Kavango East. Other changes such as vegetation loss due to wild fires were also observed but they were regarded to be beyond the scope of this study. For instance, by applying the multidate segmentation technique, it was discovered that a large portion of the study area appeared to have been disturbed especially in the central, southern, western, southwestern, eastern and northeastern parts. This was an unrealistic scenario considering the low population density and accessibility to these areas. To gain an understanding on the detected changes, 1990 to 2016 burned area polygons obtained from the DoF in Namibia and fire return periods products revealed that forest fires are frequent in these areas.

Visual observations on Google Earth further showed that forest fires mainly burn bushes and grasses, but the vegetation quickly regenerates after the next rainy season (Directorate of Forestry 2012, Own observations). It can be observed from figure 3.2 that the trajectory forest land to cropland occurred in all the epochs. From 1990 to 2000 to 33223 hectares of forest land were converted to cropland. This then corresponded to annual conversion of 3322 ha. There was a sharp in increase in forest areas which were cleared for cropland expansion in the 2000 -2009 epoch. A total of 51253 ha of forest land was converted to cropland with an annual conversion of 5695 ha. In the 2009-2016, forest loss due to cropland expansion decreased to 12838 ha and annual conversion of 1834 ha. This was the highest figure of forest land converted to cropland in all the epochs. Furthermore, this corresponded to 3322 ha of forest land were cleared for cropland expansion per annuum between 1990-2000



Annual conversion rate (ha/year)			
Change trajectory	1990 -> 2000	2000 -> 2009	2009 -> 2016
Forest land -> Cropland	3,322	5,695	1,834
Cropland -> Settlement	98	47	109
Grassland -> Bushland	315	-	-
Bushland -> Forest land	-	1,812	-
Forest land -> Bushland	-	373	603

Figure 3. 2: Changed areas for the from 1990 to 2016. Grey areas represent no trajectory was observed within an epoch.

The trajectory from cropland to settlement was observed in all the epochs, especially in the northwestern parts of the study area. About 98 ha of cropland were converted to settlement per year in the 1990-2000 epoch. In 2000-2009, it decreased to 47 ha per year before increasing to 107 ha per year between 2009-2016. Urbanization rates are relatively low in Kavango East as most people still live in rural areas (NSA 2012). Even if people are to migrate in search of better socio-economic opportunities, Windhoek remains their preferred destination (NSA 2012). Forest regrowth was detected in the 2009-2016 epoch. A total of 16309 ha of bushland became forest land in 2016. This may be related to the above normal rainfall Namibia received in 2006 and 2009 (World Bank 2018)

3.4 Land Cover Change Modelling

The Boosted Regression Trees (BRT) models were performed for the period of 2016-2009, 2009-2000 and 2000-1990 to study the relationship between land cover change and the spatial variables, and their evolution over the 26-year period. For each epoch, change (1), which was the conversion from forest land to cropland, was present in 200 sample points and no change (0) was also present in 200 sample points for each dataset which was used for model calibration. In total, there were 400 points created per epoch. Figure 3.3 shows the trajectories of interest per epoch.

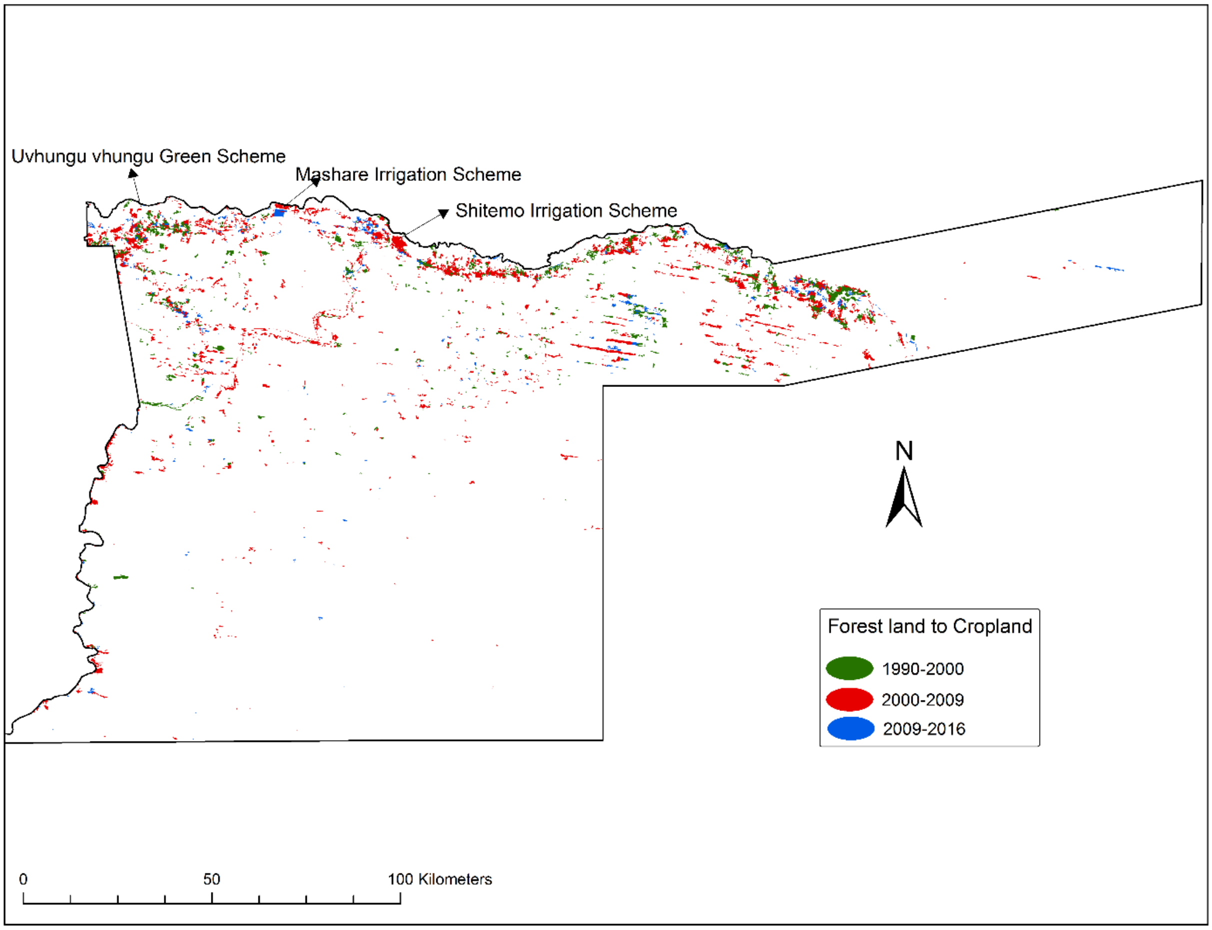


Figure 3. 3: Trajectories of interest modelled

3.4.1 BRT Models for the period of 2009-2016

The model was initially fitted with 1150 trees, the explained deviance was 59 % and the cross validated deviance was 37 %. The model was further simplified and as a result, 1250 trees were fitted. The simplify function indicated that 1 variable should be dropped. Average rainfall did not contribute to model performance so was therefore dropped. The final model had a higher explained deviance of 62 % and cross validated deviance of 38 % (table 3.3).

Table 3. 1: BRT simplified model predictive performance

Dataset	Explained Deviance for the training data (%)	Explained Deviance for the CV (%)
Response	62	38

Table 3.4 shows the influence of each predictor in the conversion of forest land to cropland in the 2009-2016 epoch.

Table 3. 2: Relative contributions of the predictor variables in the deforestation model for the 2016-2009 period

Predictor	Relative contribution (%)
Population Density	41
Distance to Settlement	17
Distance to River	14
Elevation	9
Soil Type	9
Distance to Road	6
Fire Return Period	4

The 7 predictor variables and their influence in the conversion from forest land to cropland were plotted using partial dependence plots (figure 3.4). The influence of population density is highest when the population density is about 60-100 people per km^2. The influence of distance to settlement is highest within 8 km from the settlement. The influence of distance to the river was the highest within 10 km from the river. Therefore, forests which are closer to densely populated areas, settlements and to the river were more likely to be converted to cropland. +

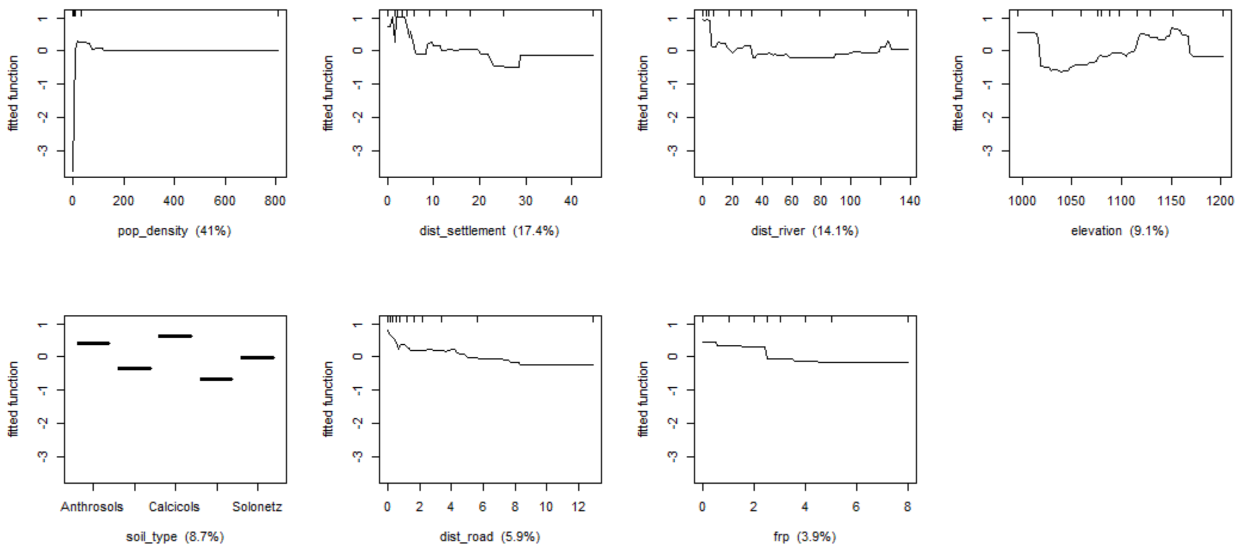


Figure 3.4: The partial dependence plots of relative contributions of the predictor variables for the 2016-2009 period

3.4.2 BRT Models for the period of 2000-2009

The model was fitted with 1050 trees initially, the explained deviance was 63 % and the cross validated deviance was 42 %. The model was then simplified and fitted with 1200 trees, and the predictor average rainfall was dropped. The final explained deviance of 65 % and cross validated deviance of 44 % (table 3.5). This was the best model in comparison to the models of the other epoch. Table 3.6 lists the predictors in terms of their influence to model contribution.

Table 3. 3: The simplified BRT model predictive performance evaluation for the 2009-2000 epoch

Dataset	Explained Deviance for the training data (%)	Explained Deviance for the CV (%)
Response	65	44

Table 3. 4: Relative contributions of the predictor variables

Predictor	Relative contribution (%)
Population Density	51
Distance to Road	12
Distance to River	9
Elevation	8
Distance to Settlement	8
Fire Return Period	8
Soil Type	4

The partial dependence plots in figure 3.5 shows the predictor variables and their influence in the conversion from forest land to cropland. Population density of more than 30 people per km^2 likely influenced the conversion from forest land to cropland than lower population density values such as 5 persons per km^2. The influence from distance to settlement was usually highest within 4 km of a settlement. Moreover, the influence from distance to river is also highest within 30 km from the river. The influence from fire return period decreases as the return period increases. Calcicols and Anthrosols had a higher influence on cropland conversion from forest land.

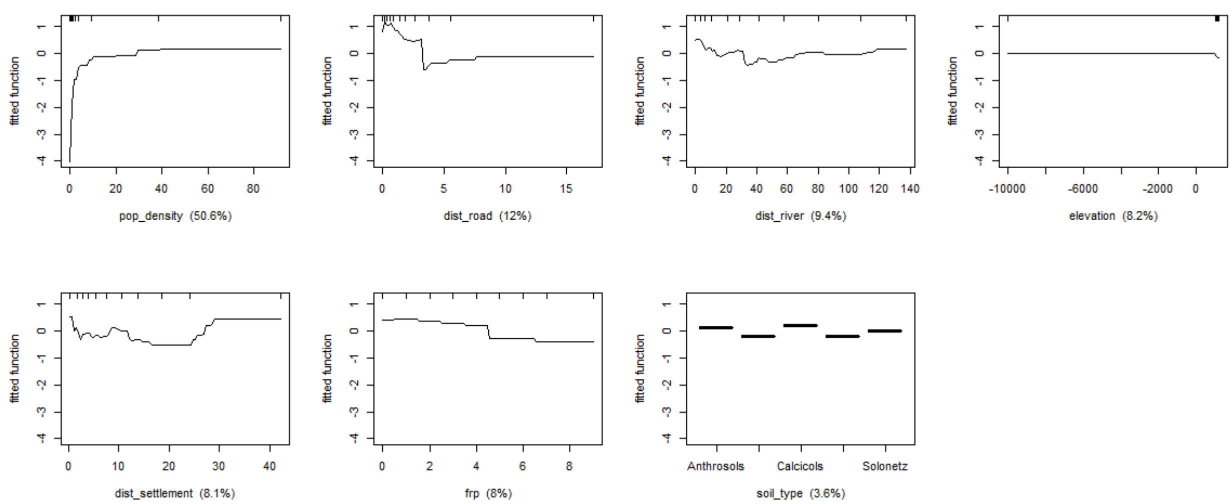


Figure 3. 5: The partial dependence plots for the 2009-2000 period

3.4.3 BRT Models for the period of 1990-2000

The last model fitted was for the 1990-2000 with an initial 850 trees. The explained deviance was 60 % and the cross validated deviance was 39 %. After the model was simplified, 800 trees were fitted and two predictor variables were dropped, which was average rainfall and soil type. The 6 predictors retained are shown in table 3.7 below. The final explained deviance was still 60 % while the cross validated deviance increased to 41 % (table 3.7).

Table 3. 5: BRT model predictive performance evaluation for the 1990-2000 epoch

Dataset	Explained Deviance for the training data (%)	Explained Deviance for the CV (%)
Response	60	41

Table 3. 8: Relative contributions of the predictor variables

Predictor	Relative contribution (%)
Distance to River	35
Distance to Settlement	28
Elevation	11
Fire Return Period	11
Population Density	8
Distance to Road	7

Distance to river had the highest influence in this epoch (table3.8). Population density had a low contribution compared to other epochs. Distance to road had the lowest contribution in this epoch with just 7%. The influence of distance to river was highest within 20 km from the river (figure 3.6). Furthermore, the influence from distance to the settlement to was highest within 10 km from the settlement and decreases with an increase from the settlement. While geographic areas with an elevation of more than 1100 m had a higher relative influence. The influence from fire return period decreases as the return period increases. The influence of population density were highest with average values of less than 10 persons per km^2 while the influence by distance to road was highest within 5 km from the road.

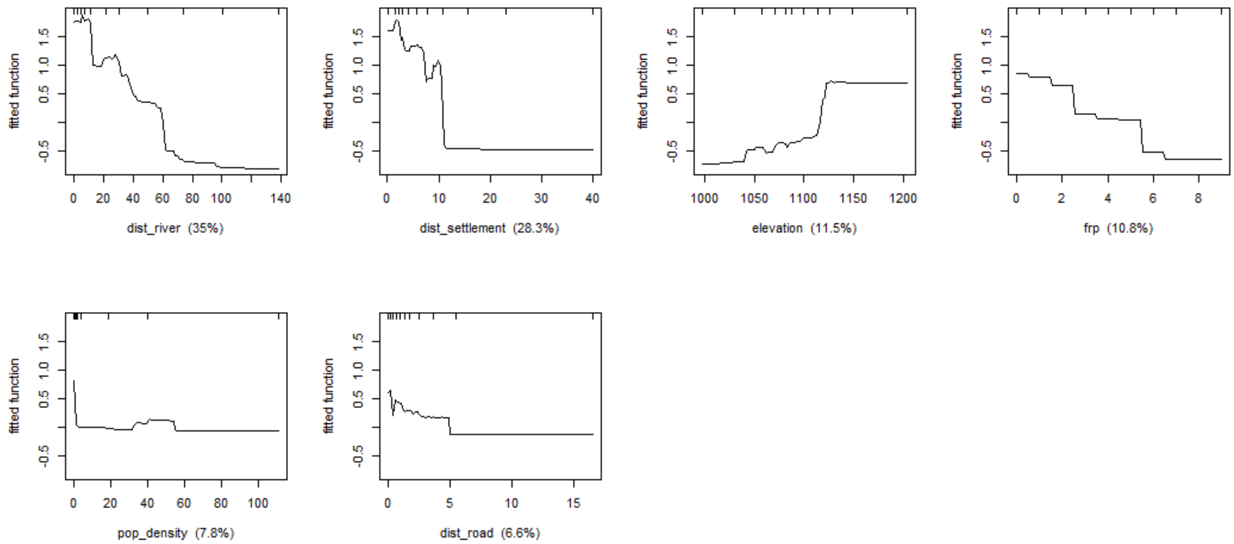


Figure 3. 6: The partial dependence plots for the 2000-1990 period

When the 8 predictor variables are compared over the 3 epochs (table 3.9), their influence on the trajectory forest land to cropland varied in each epoch. However, this excludes average rainfall which consistently contributed 0 % to model performance and was thus dropped in each model. Moreover, spatial variables related to human (distance to settlement, distance to road, population density, fire return period and distance to river) can be compared with natural variables (elevation, soil type, and average rainfall). Fire return period was regarded as a human related variable in this study because over 84 % of wild fires are caused by humans (Balch *et al.* 2017).

Table 3. 9: An overview of the relative contributions of the predictor variables for each epoch

1990-2000 Epoch	**2000-2009 Epoch**	**2009-2016 Epoch**
Distance to River (35 %)	Population Density (51 %)	Population Density (41 %)
Distance to Settlement (28 %)	Distance to Road (12 %)	Distance to Settlement (17 %)
Elevation (11 %)	Distance to River (9 %)	Distance to River (14 %)
Fire Return Period (11 %)	Elevation (8 %)	Elevation (9 %)
Population Density (8 %)	Distance to Settlement (8 %)	Soil Type (9 %)
Distance to Road (7 %)	Fire Return Period (8 %)	Distance to Road (6 %)
Soil Type (0 %)	Soil Type (4 %)	Fire Return Period (4 %)
Average Rainfall (0 %)	Average Rainfall (0 %)	Average Rainfall (0 %)

Chapter 4: Discussion

4.1 Land Cover and Change Mapping

The land cover mapping process assessed the spatial distribution of the land cover types as well as the extent of land cover change as displayed by the thematic maps for 1990, 2000, 2009 and 2016. The land cover change of interest for modelling in this study was the conversion from forest land to cropland (figure 3.3). These change trajectories have a direct effect on the livelihoods of people especially in the communal areas of Namibia (FAO 2001, Pröpper *et al.* 2010, Kamwi 2015).

The multi-date image analysis method has proven to be effective in land cover change mapping approaches (Desclée *et al.* 2006, Baatz and Schäpe 1999, Ernst *et al.* 2010, Verhegghen et al. 2010). The method was tested in Africa's tropical wet forests where the effects of seasonality were minimal (Verhegghen et al. 2010). May-June images were used for the image analysis in this study while the field work was conducted in the late dry season of November 2017. This created a mismatch between what was interpreted on the imagery to what was observed in the field. Furthermore, seasonal forest fires are frequent in the study area (Directorate of Forestry 2012, Stellmes et al 2013). This may have changed the reflectance characteristics of the land cover features on the ground.

The overall accuracy results ranged between 75% and 81.2% for the years under investigation (1990, 2000, 2009 and 2016). This is within accuracy range of 60 % to 90 % which was observed on Landsat-based image classifications by most studies (Mango 2010, Kamwi 2015). The use of mean NDVI values to map forest land and bushland resulted in high producer accuracy values of 90.4 % and 84.3 %, respectively. This corroborates the findings by Verlinden and Laamanen (2010) that Landsat imagery is suitable for estimating tree cover and biomass at regional level in northern Namibia. Furthermore, forest land class appeared to be unaffected by forest fires as field observations and image analysis showed that areas with high NDVI values remained unchanged compared to areas with low NDVI values. This is in line with the findings by le Roux (2011) and Stellmes et al (2013) who concluded that wild fires mostly affect grassland and other vegetation types but not forest crowns.

The object-based method took into consideration not only the spectral signatures of crop fields, but also their shape and size. The use of the 'rectangular fit' and 'elliptic fit' tools enabled to map the rectangular shapes of crop fields on subsistence farms and the circular shapes of irrigated crop fields on commercial farms. This may be attributed to the high producer accuracy of 94.5 % for the cropland class. Furthermore, this eliminated the challenge of discriminating between cropland and grassland due to their identical spectral characteristic in the dry season. This further confirms the findings by Yadav et al. (2015) that object-based image analysis is more accurate than pixel-based approaches. The use of NIR mean band values to classify wetland resulted in a high producer accuracy of 84.6 %.

The largest conversion from forest land to cropland was observed in the 2000-2009 epoch. The period coincided with the launch of the Ndonga Linena green scheme project by the Ministry of Agriculture, Water and Forestry (MAWF) where forest land was cleared to establish a commercial farm (MAWF 2008). The commercial farm is located alongside the Trans-Caprivi highway just a few kilometers from the Okavango river where water for irrigation was sourced. In the 1990-2000 epoch, considerable amount of forest land was converted to cropland. This is attributed to the fact that since Namibia gained independence in 1990, green scheme farms such as Mashare, Uvhungu vhungu, Shitemo have been established in Kavango East with an aim of ensuring food security in the country (MAWF 2008). The present study found that cleared land increased between 1990 and 2009 but reduced in 2016. The increase in cleared land corroborates the findings by Mendelsohn and Obeid (2003) who reported an increase in cleared land between 1943 and 1996 in the former Kavango region. A possible explanation for the decrease in cleared between 2009 and 2016 may be that people began to view economic opportunities such as employment and education being far more attractive compared to subsistence farming (NSA 2012).

Fire scars, seasonality and rainfall variability complicated interpretation on the Landsat imagery. Despite conducting a comprehensive field work, a large portion of the study area was not visited due to inaccessibility to the sampling sites. However, Google Earth imagery was used to collect data on such sample points although some of the Google Earth imagery were outdated. For instance, in the southern parts of the study area, the available images were for the year 2012 when the 2016 reference points were collected. Furthermore, the required months were either May or June but some of the available google earth imagery were taken between September and November resulting in seasonality effects on the data collected. This may have resulted inaccuracies in some of the reference points collected.

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There was a challenge in classifying grassland and bare land as evidenced by their low producer accuracy values of 25.4 % and 55.6 %, respectively. Despite using the NDVI and NDBI ratios to classify grassland and bare land, the two classes appeared identical. Discriminating identical classes on a 30 m Landsat imagery proved difficult. In addition, there was a challenge in discriminating settlements from bare land on the 30 m Landsat 5 imagery as they have a related spectral signature. The land cover mapping approach provided little information on other trajectories apart from the change from forest land to grassland. There was a possibility that large areas of grasslands and bushlands were converted to cropland. Similarly, there was a possibility that tracks of cropland may have been abandoned and may have been converted to grassland or bushland. Furthermore, false forest regrowth and deforestation were detected on some images. This may be linked to rainfall variation between the years of study as well as limited field work undertaken in the study area. Despite incidences of logging observed when field work was conducted, the classified maps and the changed polygons did not reveal this scenario. This corroborates the findings by Asner et al. (2001) that Landsat imagery has challenges in quantifying incidences of forest logging. However, this contrary to what Verlinden and Laamanen (2010) found in Northeastern Namibia.

There is a lack of available land cover datasets in Namibia which can be used to make comparisons with the data in table 3.1. Despite this, Stellmes et al. (2013) reported that forests covered about 62.3% of the total area of the Future Okavango Research Area (FORA), while grassland and shrubland covered about 17.6 %. These figures appear to be lower in comparison with the results presented in table 3.1. The possible reason for this could be that the datasets for the FORA were derived from 250 m Modis imagery and the classification legend used was completely different to what was applied in this study. The FAO (2015) reported that there has been a gradual decrease in areas covered by forests in Namibia, from 8 762 496 ha in 1990 to 6 918 691 ha in 2015. On the other hand, there has been an increase in areas classified as ‘Other land’, this includes cropland and bushland. This scenario is also reflected in table 3.1. It is important to note that the FAO estimates were not based on Remote Sensing data but on field inventories and linear extrapolations.

4.2 Modelling with BRT

The BRT models were performed to determine the relationship between land cover change and the spatial variables, and to study the evolution of the spatial variables over the 26-year period. The results obtained provide an understanding of the nature of the relationship between the response variable and the predictor variables. Population density had the highest contribution to the BRT model performance in the 2016-2009 and the 2000-2009 period (table 3.9). Mendelsohn (2009) reported that population migration due to the civil war in the neighboring Angola from 1961 to 2002 had a key influence on the land cover and land use change in the Kavango region. Furthermore, most people in Kavango East live next to the Okavango river with about 68 % of the rural residents living within a swath distance of 10 km along the river, where the natural resources are intensely used and are under great pressure (Mendelsohn 2009). The 8% relative contribution to model performance by population density in the 1990-2000 epoch is justifiable by the fact that in this epoch, there was less economic activities to drive deforestation due to agricultural expansion, noting that it is the epoch immediately after independence. Furthermore, the vector data obtained from NSA from which the population density dataset was calculated had no metadata. Therefore, the accuracy of the datasets could not be verified.

The dependency plots for distance to river showed that the maximum distance of 10 km in which land cover change was observed remained constant in all the three epochs. This suggests that water remained a key natural resource in the daily lives of the people of Kavango East. Moreover, this then had a direct effect on land cover change because water has many uses from domestic uses to agricultural uses. Population density, elevation, distance to road, distance to settlement and soil type showed a variation in their influence on land cover change (table 3.8). The influence on land cover change by the spatial variables evolved per epoch. For instance, the dependency plots for distance to settlement showed that in the 1990-2000 period, the influence from distance to settlement was highest within 10 km from a settlement. In the 2000-2009, this fluctuated between 4km-30km and in 2009-2016 the distance was 10 km. In fact, both human-related and natural-related spatial drivers exhibited variations per epoch. This confirms the findings by Lambin and Geist (2003) that spatial drivers of land cover change evolve over time. The distribution of settlements along the river and along the roads means that there will always be a demand for agricultural land to produce food. The need for agricultural land led to the removal of forest which are then disposed of by slash and burn resulting in uncontrolled fires. Slash and burn is normally practiced during the hottest months of August to October every year. Therefore, the annual slash and burn coupled with the availability of fuel increases the fire frequencies in the area. Despite the high fire frequencies in the study area, fire return period had a low relative contribution to model performance in all the epochs. This may be explained by the fact that wild fires are less likely to affect tree crowns (le Roux 2011, Stellmes et al 2013).

The influence of soil types on land cover change varied with time during the 26-year period, this variation was based on the different soil types over the epochs. This influence cannot necessarily be regarded as 'high' in terms of the relationship between the soil type and its relationship in the conversion of forest land to cropland. The findings from this study showed that there was not enough evidence to conclude that predictors such as elevation and soil types are the main drivers of land cover change. This is contrary to the findings by Geist and Lambin (2002), Sluiter and de Jong (2007) who reported that elevation and soil types are some of the spatial variables which were recognised as core drivers of land cover change. However, it should be noted that elevation and soil types in Kavango East region are mostly homogenous in nature and the soil type is mostly Arenosol, this may have minimized the influence of these predictors on land cover change. Average rainfall showed no influence on land cover change as it was dropped in all the models for each epoch. This is contrary to what Nainggolan *et al.* (2012), van der Werf et al. (2010) and Eva and Lambin (2000) who reported that average rainfall significantly influenced land cover change. A possible explanation for this may due the high variability of rainfall patterns in Namibia. Furthermore, the accuracy of the rainfall data and soil types data sets could not be verified.

Chapter 5: Conclusion and Recommendations

5.1 Conclusion

A multi-date object-based image analysis was applied to study the dynamics of land cover change in the Kavango East Region. Large areas of the study remained intact especially in the southern, western and eastern parts of the region. This may be due to low population density hence fewer human activities in these areas. However, these parts experiences high seasonal fire frequencies. Most land cover changes were observed along the Okavango river and the Trans-Caprivi highway. Furthermore, the forest land class gradually reduced per epoch. In 1990 forest land covered 58 % of the land cover in the region but by 2016, 55 % was covered with forests. Cropland covered 2.9 % of the study area in 1990 while this figure doubled to 6.1 % by 2016. The most common conversion was from forest land to cropland in all the epochs. This was because subsistence farming was the main source of livelihood for the people. Despite the trajectory of forest land to cropland being the most common, the land cover maps showed that most forests remain intact especially in areas away from the river and roads.

Boosted Regression Trees models were applied to gain an understanding on the influence of spatial drivers in the conversion from forest land to cropland. It was discovered that distance to river had the highest influence to land cover change from 1990-2000 with a relative contribution to model performance of 35 %. The maximum influence from the river was highest within a distance of 10 km. Distance to settlement had the second highest influence with 28 %, the maximum influence was usually highest within a radius of 5 km from a settlement. In the 2000-2009 epoch it was revealed that population density had a relative contribution of 51 %, far higher than the 35 % contribution by distance to river in the 1990-2000 epoch. This may be attributed to population migration which was caused by the civil war in Angola which as a result increased influenced land use and land cover change in the study area (Mendelsohn 2009). Distance to road had the second highest influence with 12 % with a maximum influence of 2 km from the road. Population density still had the highest contribution to model performance in the 2009-2016 epoch with 41 % with a maximum influence of about 100 persons per km^2. Distance to settlement had the second highest contribution to model performance with a maximum contribution of 5 km radius from a settlement. Average rainfall had no contribution to model performance, therefore had no influence in the conversion forest land to cropland. The accuracy of the data sets such as average rainfall could not be established. This may have led to the low contributions to model performances in all the epochs. The influence of the spatial drivers varied to some extent in each epoch. It was found that human related spatial variables had more influence on land cover change than natural variables.

5.2 Recommendations

The findings of this study have potential management implications considering that the area contains community forests, national parks, communal conservancies and a perennial river. It is therefore recommended that:

- In the future, Sentinel imagery should be used for land cover mapping because not only are Sentinel imageries better in spatial resolution and temporal resolution, it requires fewer scenes to mosaic due to its larger swath width. A 10 m spatial resolution would fully exploit the advantages of object-based image analysis.
- Due to the dynamic nature of land cover change, more trajectories should be studied. There are limited studies on forest regrowth and deforestation in Namibia. Classification and Regression Trees can be used not only to model all the possible trajectories, but also predict future land cover changes.
- In addition to the 8 spatial variables data used in this study, other variables such as cattle density, game density, annual mean temperature, precipitation seasonality, NDVI, crown cover and slope could provide a comprehensive land cover change analysis including the variability of these predictor variables over time.
- In cases where intensive field validation is not possible, high resolution Sentinel and Aster data sets be used in addition to Google Earth imagery. This may solve the mismatch in dates in Google Earth imagery.
- The present study employed a novel approach for land cover change mapping in the open woodland savanna of North-eastern Namibia. This approach shows promising results compared to traditional methods which are prone to errors of propagation. In this regard, in order to improve mapping accuracy in areas under similar environmental and biophysical conditions, the method can be used for long term monitoring of land cover or land use change.

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Appendices

Appendix 1 Field Sheet for Data Collection

Kavango East Land Cover Data Sheet

Site No:		**Date:**			**GPS Co-ordinates**	
Region:					S:	
District/Village:					E:	
Name of Observer:					Altitude:	
Landform						
Riverine	Floodplain	Wetland	Hill	Valley	Plain	Other
If Other, please specify:						

Soil type				
Clay	Silt	Loam	Loamy Sand	Sand

Existing Land Cover type (*please cross*):

Forest land	☐	Bushland	☐
Cropland	☐	Wetland	☐
Grassland	☐	Settlement	☐
Bare land	☐	Other	☐

Photo number: _______________

Land cover codes:

OF= Open Forest **C**= Cropland **G**= Grassland **B**= Bare land **Bu**= Bushland **W**= Wetland
S= Settlement **O**= Other **CF**= Closed Forest

Human and Natural event codes:

Fi= Fire **D**= Drought **L**= Logging **Fl**= Flood **E**= Erosion **De**= Degradation
SF= Subsistence Farming **CF**= Commercial Farming **OG**= Overgrazing
OE= Other Event**:** ____

Time scale

1990 ‘95 ‘00 ‘05 ‘10 ‘15 2016

|____________ |____________|____________|____________ |____________|_____|
| | | | | | |

Comments:

The comments should Include the history of events from 1990 to 2016. This includes human and natural activities, as well as unusual features in the landscape

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Appendix 2 2016 Accuracy Assessment Report

Confusion Matrix: D:\My Data\Academic\Research\MSc\Data\Landsat\Land Cover Change Mapping_KE\Preprocessing\Multidate Change Detetction\Accuracy Assessment\2016\Classes\2016.img

Overall Accuracy = (480/591) 81.2183%
Kappa Coefficient = 0.7626

Ground Truth (Pixels)

Class	EVF:grassland	EVF:bushlandp	forest_landpr	wetlandprj16	settlementprj
unclassified	0	0	0	6	0
Grassland2016	20	0	1	0	0
Bushland2016	9	91	8	0	0
Forestland201	0	15	141	0	0
Wetland2016	0	0	0	33	0
Settlement201	0	0	0	0	26
Cropland2016	6	2	6	0	4
Bareland2016	1	0	0	0	0
Total	36	108	156	39	30

Ground Truth (Pixels)

Class	croplandprj16	barelandprj16	Total
unclassified	0	0	6
Grassland2016	0	16	37
Bushland2016	4	21	133
Forestland201	5	1	162
Wetland2016	0	0	33
Settlement201	0	0	26
Cropland2016	154	6	178
Bareland2016	0	15	16
Total	163	59	591

Ground Truth (Percent)

Class EVF:grasslandEVF:bushlandpforest_landpr wetlandprj16settlementprj

unclassified	0.00	0.00	0.00	15.38	0.00
Grassland2016	55.56	0.00	0.64	0.00	0.00
Bushland2016	25.00	84.26	5.13	0.00	0.00
Forestland201	0.00	13.89	90.38	0.00	0.00
Wetland2016	0.00	0.00	0.00	84.62	0.00
Settlement201	0.00	0.00	0.00	0.00	86.67
Cropland2016	16.67	1.85	3.85	0.00	13.33
Bareland2016	2.78	0.00	0.00	0.00	0.00
Total	100.00	100.00	100.00	100.00	100.00

	Ground Truth (Percent)		
Class	croplandprj16	barelandprj16	Total
unclassified	0.00	0.00	1.02
Grassland2016	0.00	27.12	6.26
Bushland2016	2.45	35.59	22.50
Forestland201	3.07	1.69	27.41
Wetland2016	0.00	0.00	5.58
Settlement201	0.00	0.00	4.40
Cropland2016	94.48	10.17	30.12
Bareland2016	0.00	25.42	2.71
Total	100.00	100.00	100.00

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Grassland2016	45.95	44.44	17/37	16/36
Bushland2016	31.58	15.74	42/133	17/108
Forestland201	12.96	9.62	21/162	15/156
Wetland2016	0.00	15.38	0/33	6/39
Settlement201	0.00	13.33	0/26	4/30
Cropland2016	13.48	5.52	24/178	9/163

Bareland2016	6.25	74.58	1/16	44/59

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Grassland2016	55.56	54.05	20/36	20/37
Bushland2016	84.26	68.42	91/108	91/133
Forestland201	90.38	87.04	141/156	141/162
Wetland2016	84.62	100.00	33/39	33/33
Settlement201	86.67	100.00	26/30	26/26
Cropland2016	94.48	86.52	154/163	154/178
Bareland2016	25.42	93.75	15/59	15/16

Appendix 3 2009 Accuracy Assessment Report

Confusion Matrix: D:\My Data\Academic\Research\MSc\Data\Landsat\Land Cover Change Mapping_KE\Preprocessing\Multidate Change Detetction\Classification\Land Cover Datasets\Maps\2009.img

Overall Accuracy = (206/265) 77.7358%
Kappa Coefficient = 0.7268

Ground Truth (Pixels)

Class	settlement_pr	Grassland_prj	Bushland_prj0	Wetland_prj09	forestland_pr
unclassified	0	0	0	2	1
Settlement	7	0	0	0	0
Grassland	0	26	0	0	0
Bushland	0	1	40	1	3
Wetland	0	0	0	32	0
Forest land	0	1	17	0	59
Cropland	3	0	1	0	4
Bareland	0	0	0	0	1
Total	10	28	58	35	68

Ground Truth (Pixels)

Class	Cropland_prj0	Bareland_prj0	Total
unclassified	8	0	11
Settlement	0	0	7
Grassland	0	3	29
Bushland	1	5	51
Wetland	0	0	32
Forest land	4	2	83
Cropland	37	1	46
Bareland	0	5	6
Total	50	16	265

Ground Truth (Percent)

Class	settlement_pr	Grassland_prj	Bushland_prj0	Wetland_prj09	forestland_pr
unclassified	0.00	0.00	0.00	5.71	1.47

Settlement	70.00	0.00	0.00	0.00	0.00
Grassland	0.00	92.86	0.00	0.00	0.00
Bushland	0.00	3.57	68.97	2.86	4.41
Wetland	0.00	0.00	0.00	91.43	0.00
Forest land	0.00	3.57	29.31	0.00	86.76
Cropland	30.00	0.00	1.72	0.00	5.88
Bareland	0.00	0.00	0.00	0.00	1.47
Total	100.00	100.00	100.00	100.00	100.00

	Ground Truth (Percent)		
Class	Cropland_prj0	Bareland_prj0	Total
unclassified	16.00	0.00	4.15
Settlement	0.00	0.00	2.64
Grassland	0.00	18.75	10.94
Bushland	2.00	31.25	19.25
Wetland	0.00	0.00	12.08
Forest land	8.00	12.50	31.32
Cropland	74.00	6.25	17.36
Bareland	0.00	31.25	2.26
Total	100.00	100.00	100.00

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Settlement	0.00	30.00	0/7	3/10
Grassland	10.34	7.14	3/29	2/28
Bushland	21.57	31.03	11/51	18/58
Wetland	0.00	8.57	0/32	3/35
Forest land	28.92	13.24	24/83	9/68
Cropland	19.57	26.00	9/46	13/50
Bareland	16.67	68.75	1/6	11/16

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Settlement	70.00	100.00	7/10	7/7
Grassland	92.86	89.66	26/28	26/29
Bushland	68.97	78.43	40/58	40/51
Wetland	91.43	100.00	32/35	32/32
Forest land	86.76	71.08	59/68	59/83
Cropland	74.00	80.43	37/50	37/46
Bareland	31.25	83.33	5/16	5/6

Appendix 4 2000 Accuracy Assessment Report

Confusion Matrix: D:\My Data\Academic\Research\MSc\Data\Landsat\Land Cover Change Mapping_KE\Preprocessing\Multidate Change Detetction\Accuracy Assessment\2000\Google Earth\For Classification\2000.img

Overall Accuracy = (205/253) 81.0277%
Kappa Coefficient = 0.7595

Ground Truth (Pixels)

Class	EVF:Layer: we	EVF:Layer: se	EVF:Layer: gr	EVF:Layer: fo	EVF:Layer: cr
unclassified	0	0	0	0	1
Wetland_2000	9	0	0	0	0
Settlement_20	0	13	0	0	1
Grassland_200	0	0	13	0	0
Forest land_2	1	1	0	71	3
Cropland_2000	1	1	5	1	44
Bushland_2000	0	0	2	8	1
Bareland_2000	0	0	0	0	0
Total	11	15	20	80	50

Ground Truth (Pixels)

Class	EVF:Layer: bu	EVF:Layer: ba	Total
unclassified	0	0	1
Wetland_2000	0	0	9
Settlement_20	0	0	14
Grassland_200	1	6	20
Forest land_2	4	1	81
Cropland_2000	0	2	54
Bushland_2000	47	8	66
Bareland_2000	0	8	8
Total	52	25	253

Ground Truth (Percent)

Class	EVF:Layer: we	EVF:Layer: se	EVF:Layer: gr	EVF:Layer: fo	EVF:Layer: cr
unclassified	0.00	0.00	0.00	0.00	2.00

Wetland_2000	81.82	0.00	0.00	0.00	0.00
Settlement_20	0.00	86.67	0.00	0.00	2.00
Grassland_200	0.00	0.00	65.00	0.00	0.00
Forest land_2	9.09	6.67	0.00	88.75	6.00
Cropland_2000	9.09	6.67	25.00	1.25	88.00
Bushland_2000	0.00	0.00	10.00	10.00	2.00
Bareland_2000	0.00	0.00	0.00	0.00	0.00
Total	100.00	100.00	100.00	100.00	100.00

	Ground Truth (Percent)		
Class	EVF:Layer: bu	EVF:Layer: ba	Total
unclassified	0.00	0.00	0.40
Wetland_2000	0.00	0.00	3.56
Settlement_20	0.00	0.00	5.53
Grassland_200	1.92	24.00	7.91
Forest land_2	7.69	4.00	32.02
Cropland_2000	0.00	8.00	21.34
Bushland_2000	90.38	32.00	26.09
Bareland_2000	0.00	32.00	3.16
Total	100.00	100.00	100.00

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Wetland_2000	0.00	18.18	0/9	2/11
Settlement_20	7.14	13.33	1/14	2/15
Grassland_200	35.00	35.00	7/20	7/20
Forest land_2	12.35	11.25	10/81	9/80
Cropland_2000	18.52	12.00	10/54	6/50
Bushland_2000	28.79	9.62	19/66	5/52
Bareland_2000	0.00	68.00	0/8	17/25

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Wetland_2000	81.82	100.00	9/11	9/9
Settlement_20	86.67	92.86	13/15	13/14
Grassland_200	65.00	65.00	13/20	13/20
Forest land_2	88.75	87.65	71/80	71/81
Cropland_2000	88.00	81.48	44/50	44/54
Bushland_2000	90.38	71.21	47/52	47/66
Bareland_2000	32.00	100.00	8/25	8/8

Appendix 5 1990 Accuracy Assessment Report

Confusion Matrix: D:\My Data\Academic\Research\MSc\Data\Landsat\Land Cover Change Mapping_KE\Preprocessing\Multidate Change Detetction\Classification\Land Cover Datasets\Maps\1990.img

Overall Accuracy = (150/200) 75.0000%
Kappa Coefficient = 0.6886

Ground Truth (Pixels)

Class	Bareland90_pr	Bushland90_pr	cropland90_pr	forestland90_	Grassland90_p
unclassified	0	0	0	0	0
Bareland	10	0	0	1	1
Bushland	5	25	3	5	4
Cropland	0	0	23	2	1
Forest land	1	13	4	51	0
Grassland	4	0	1	0	9
Settlement	0	0	0	0	0
Wetland	0	0	0	0	0
Total	20	38	31	59	15

Ground Truth (Pixels)

Class	Settlement90_	Wetland90_pro	Total
unclassified	0	1	1
Bareland	0	0	12
Bushland	1	1	44
Cropland	2	0	28
Forest land	0	0	69
Grassland	0	0	14
Settlement	5	0	5
Wetland	0	27	27
Total	8	29	200

Ground Truth (Percent)

Class	Bareland90_pr	Bushland90_pr	cropland90_pr	forestland90_	Grassland90_p
unclassified	0.00	0.00	0.00	0.00	0.00

Bareland	50.00	0.00	0.00	1.69	6.67
Bushland	25.00	65.79	9.68	8.47	26.67
Cropland	0.00	0.00	74.19	3.39	6.67
Forest land	5.00	34.21	12.90	86.44	0.00
Grassland	20.00	0.00	3.23	0.00	60.00
Settlement	0.00	0.00	0.00	0.00	0.00
Wetland	0.00	0.00	0.00	0.00	0.00
Total	100.00	100.00	100.00	100.00	100.00

	Ground Truth (Percent)		
Class	Settlement90_	Wetland90_pro	Total
unclassified	0.00	3.45	0.50
Bareland	0.00	0.00	6.00
Bushland	12.50	3.45	22.00
Cropland	25.00	0.00	14.00
Forest land	0.00	0.00	34.50
Grassland	0.00	0.00	7.00
Settlement	62.50	0.00	2.50
Wetland	0.00	93.10	13.50
Total	100.00	100.00	100.00

Class	Commission (Percent)	Omission (Percent)	Commission (Pixels)	Omission (Pixels)
Bareland	16.67	50.00	2/12	10/20
Bushland	43.18	34.21	19/44	13/38
Cropland	17.86	25.81	5/28	8/31
Forest land	26.09	13.56	18/69	8/59
Grassland	35.71	40.00	5/14	6/15
Settlement	0.00	37.50	0/5	3/8
Wetland	0.00	6.90	0/27	2/29

Class	Prod. Acc. (Percent)	User Acc. (Percent)	Prod. Acc. (Pixels)	User Acc. (Pixels)
Bareland	50.00	83.33	10/20	10/12
Bushland	65.79	56.82	25/38	25/44
Cropland	74.19	82.14	23/31	23/28
Forest land	86.44	73.91	51/59	51/69
Grassland	60.00	64.29	9/15	9/14
Settlement	62.50	100.00	5/8	5/5
Wetland	93.10	100.00	27/29	27/27