FORESTS UNDER THREAT? CHANGES IN LAND USE AND FOREST COVER IN RURAL WESTERN UGANDA

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A thesis submitted to the University of Cambridge for the award of the degree of Doctor of Philosophy

June, 2015
Declaration

I Ronald Twongyirwe solemnly declare that the work presented in this thesis is original emanating from research I undertook, and has never been presented in any university for awarding a degree/diploma. All the material herein is my intellectual property, except where exclusively cited, and listed in the bibliography. This thesis does not exceed 80,000 words as stipulated in the University rules.

Signed

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Dedication

To my dear family: Hope, King, and Krystel Twongyirwe
Acknowledgements

My deepest appreciation goes to my supervisors, Dr. Mike Bithell and Prof. Keith S. Richards, who have tirelessly provided guidance throughout the duration of my PhD. Their dedication and support is invaluable. Am also indebted to Dr. Gareth Rees and Dr. Harriet Allen, my Degree Committee members, for their advice that helped focus this research. Not least in this category, is Dr. Gabriel Amable for the technical guidance with the use of Erdas Imagine and ArcGIS software for the spatial analyses.

I would like to thank my funders for making this accomplishment possible. I received excellent funding support from Cambridge Overseas Trust towards my tuition and upkeep; while research funding was provided by the University fieldwork funds, St. Edmund’s tutorial award, Mary Euphrasia Mosley, Sir Bartle Frere and Worts Travel Funds, and Tim and Wendy Whitmore fund.

Logistical support for my fieldwork was provided by the Institute of Tropical Forest Conservation, Kabale, Uganda. Special thanks to Dr. Robert Bitariho, Medard Twinamatsiko, Desi Tibamanya, Clemencia Akankwasa, Florence Tukamushaba for coordinating this and ensuring success. Am grateful to UK-DMCii for the donated imagery which were used in assessment of classification accuracies of the freely available Landsat images; am particularly thankful to Ms. Katherine Elsom for providing the contact. I worked with an excellent team of research assistants: these include Sam Businge, Kenneth Oburu, Nicholas Muhairwe, Allan Akampulira, and Geoffrey Mwanje (camp keeper). Without their dedication and hard work, it wouldn’t have been possible to cover as much ground as we did. Special thanks to the respondents and various officials for providing their time and knowledge, and camping space. Many people made fieldwork enjoyable and a worthwhile experience.

Along the academic path, there are some truly special and inspirational people that are worth thanking. Dr. Vincent Muwanika and Prof. John Tabuti of Makerere University laid the foundations for my graduate studies culminating in undertaking PhD studies at Cambridge. Muzoora Bishanga (practicing Engineer at Cambridge) and Dr. Yona Baguma (Director, National Agricultural Research Organisation) have provided excellent moral support. I cannot forget to thank Chris and Linsdey Sandbrook for delivering my initial paper application to Cambridge on their way from Uganda, and their continued support at Cambridge.

I shared an office with excellent and supportive colleagues: Andy, Tony, Kinne, Anika, and Nathaniel. I had insightful discussions with James Lester on quantitative data analysis. Many thanks to many other colleagues and academics in the department and college with whom we shared special moments. Space doesn’t permit listing them all.

Lastly but by no means least, I would like to thank my dear wife, Hope, for sacrificing her career time in my PhD study period, to provide moral support to me and the entire family. She provided an excellent learning environment for our 4–year old son (King), and we were blessed with a wonderful addition of Krystel during my doctorate.
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Thesis Summary

Deforestation and land use change are widespread in Western Uganda. However, the spatial patterns and time-series of change and the reasons why it is occurring remain to be fully investigated. In this work a combination of satellite imagery and social surveys is used to quantify forest gains and loss over the last three decades in the region close to Lake Albert, whilst also providing an account of possible drivers of change. This area proves to be interesting as it covers regions with both formally protected areas (gazetted regions) and un-protected forest, the latter being largely under private ownership. Remote sensing data from the Landsat satellites were gathered for forest change detection, and were processed using standard remote sensing techniques, then quantified using GIS and regression methods. Fieldwork allowed these data to be ground truthed while gathering (quantitative) household surveys and (qualitative) key informant interviews. Quantitative surveys were analysed using Principal Components Analysis (PCA) and cluster analysis, and were compared qualitatively with the satellite analysis and stakeholder interviews. The results show that forest cover declined significantly outside gazetted areas at the expense of varying local-scale processes, although the protection of the gazetted forests was remarkably successful. In forest corridors outside gazetted regions, losses exceeded 90% (p<0.05). Survey data suggest that rural poor households were more likely to be situated in forested regions, and were more dependent on forest resources for their livelihoods. However, the drivers of change were spatially variable, with expansion of sugarcane farming being a likely driver in the northern areas, but small-scale agricultural expansion a significant factor in the more southern parts of the study region. While there is wide agreement within the data that the patterns of forest cover and land use changes are anthropogenically driven, more specific drivers are swamped by intricacies of the bio-physical and socio-economic preconditions that are inseparable in both space and time, although agricultural expansion and population growth were evident and pervasive. The analyses provide insights into complex anthropogenic processes at various spatial scales, and policy recommendations provided are widely applicable for developing countries struggling to conserve nature whilst boosting economic growth.
Chapter 1

General Introduction to the Research
1.1 Background and Context

Deforestation has received significant attention in Global Environmental Change discourses in the 21st century, broadly for its threat to: 1) biodiversity (Plumptre 1996; McLennan and Plumptre 2012), 2) climate (Bala et al. 2007), and 3) livelihoods (Angelsen and Kaimowitz 1999; Sheil and Liswanti 2006; van Vliet et al. 2012). Firstly, tropical forests are rich in both floral and faunal species: emphasis has therefore been placed on protection of forests and national parks as a biodiversity conservation strategy (Green et al. 2013), but debates are divided on whether it is more effective to have people-oriented approaches (that favour inclusive human-forest interactions), as opposed to authoritarian ones that maximise exclusion (Jeanrenaud 2002; Durand and Vázquez 2011). Secondly, forests are important carbon sinks especially in their vigorously vegetative stages, sequestering large amounts of carbon from the atmosphere, including approximately $2.4 \pm 0.4$ petagrams per year (Pg C year$^{-1}$) globally between 1990 to 2007 (Pan et al. 2011). Avoiding deforestation has therefore been placed in the climate abatement policy negotiations at the United Nations summits on climate change under the Reducing Emissions from Deforestation and Forest Degradation (REDD+) policy, with a view to incentivising forest protection, particularly in places at high risk of loss (Nielsen 2014). Thirdly, forests support livelihoods through food provisioning, pollution control, and their aesthetic values, among others. These human–forest interactions have been widely recognised, and to control environmental catastrophes resulting from a perceived need to clear forests in these spaces, there is a burgeoning literature and debates on “sustainable development” although often poorly defined, viewed through the lenses of economic growth, and incognisant of social norms and beliefs and influenced by unclear political processes (Haque 2000).

In spite of the human–environmental benefits that accrue from forests, the rate of deforestation in the African tropics remains among the highest in the world (Achard et al. 2002), accounting for over 23% of total forest loss globally per year between 1990–2009 (Houghton 2012). While the effects of deforestation are transboundary in nature (Lewis et al. 2004), they are most devastating in developing countries where a large percentage of the population depends on the natural resource base for their livelihoods (Sunderlin et al. 2005).
The rate of forest loss in Uganda is estimated to between 1–3% per annum (Kayanja and Byarugaba 2001), although these estimates are mostly based on expert opinion (and anecdotal evidence). The amounts, possible causes and impacts are widespread although not well understood (discussed in Chapter 2.2.1). The Northern Albertine Rift region in Western Uganda provides one of the best-case scenarios to understand the complexity of deforestation (and land use change) at regional level. This is an iconic landscape endowed with the largest natural forests in Uganda (Budongo and Bugoma), with rich biodiversity (Plumptre et al. 2007), and yet has suffered extensive deforestation. As a result, the landscape has unsurprisingly attracted a large body of government and Non-Government Organisations (NGOs) working to conserve nature and avert severe effects of deforestation. Work on major drivers of land use change and forest loss in the region has been limited (there is no study that covers the entire region to the best of the author’s knowledge), and what has been done has been limited to particular disciplines (Nangendo 2005) or has been, to a great extent, localised (Mwavu and Witkowski 2008).

Forest loss around Budongo has been reported on private landholdings, and attributed to agricultural expansion, population growth, illegal timber harvesting, unclear land tenure systems and weak forest protection enforcement (Mwavu and Witkowski 2008). There is however a dearth of information on Bugoma (another large forest in the landscape), and forest corridors in the region. Some studies exist by the Wildlife Conservation Society (WCS) and other NGOs working on forest loss in the Albertine Rift region, but only in unpublished reports, and the methods used in the estimation are not rigorous. This study recovers the entire time-series for which good remote sensing imagery are available from Landsat between 1985 and 2014 to study detailed land use and forest cover patterns at regional level (as described in the following chapters), backed by field-based ground truthing (817 ground truth points), extensive household surveys (covering 706 households), and (22) key informant interviews.

Although this study focuses on a small section of the Albertine Rift region in Uganda, highlighting more local-level processes, the project has a wider applicability to developing countries grappling with similar deforestation challenges. The data from this project will guide scientists, policy makers, practitioners and the general public into
new ways of thinking about (and understanding) the complexity of deforestation, as some of the salient human-environmental interactions in this landscape are investigated. Because of its multi-disciplinary nature, this study hopes to bridge the gap between different disciplines, policy makers and practitioners, and to forge concerted efforts amongst the disjointed organisations dealing with a similar problem from a different vantage point within the landscape. This project provides data in what is a chronically data poor area, hence contributing to the realisation of many Non-Governmental Organisations’ and government goals seeking to be relevant through addressing community needs. The research is also valuable to other studies, such as those involved in assessing climate and land use change impacts on ecosystem dynamics (particularly those developing Reducing Emissions from Deforestation and Forest Degradation [REDD+] projects).

In this Chapter, an introduction to the main aspects of the project are made, including the objectives, a description of the study area, a summary of the broad bodies of literature in which this study sits, an overview of the methods, and a brief description of how the chapters fit together in a logical order to understand/address the issues at hand. The remaining chapters (2–5) each provide their own abstract for what is addressed in their main body.

1.2 Objectives

The main aim of this investigation is to improve our understanding of anthropogenically-driven changes in rural land use and forest cover in the African tropics through rigorous quantification and identification of the processes and mechanisms involved, with the Northern Albertine Rift region, western Uganda, as the case study. The notion is that unlike in previous generalisations that have mostly been based on anecdotal evidence (e.g. Struhsaker 1987; Kayanja and Byarugaba 2001; Obua et al. 2010), the data from this project can aid formulation of evidence–based policies, important for the improvement of human–forest interactions and local livelihoods, in a densely populated tropical region. The study therefore aims to improve prevailing deforestation and land use change rates, show regions where the changes are most prevalent, while elucidating leading causes based on empirically–generated survey data
backed by remote sensing analyses and key informant interviews. The main premise is that the day–to–day and seasonal household decision dynamics on land and energy use are to some extent important determinants of deforestation, and that this is affected by interacting proximate and underlying factors which are poorly understood.

1.2.1 General Objectives

Here the general objectives addressed in each chapter of the thesis are highlighted, while the specific detailed research questions addressed in each are provided in the body of the main text within the individual chapters. The general objectives are:

1. To reconstruct detailed land use and forest cover changes in the region over the last 30 years (Chapter 2).

2. To characterise rural livelihoods and household livelihood typologies relative to the different agro-ecological zones in the region (Chapter 3).

3. To assess local and key informant knowledge of land use and forest cover patterns and changes in forested regions (Budongo and Bugoma) in comparison with household types and satellite reconstruction (Chapter 4).

4. To identify and examine theories of leading drivers of land use and forest cover change in the region (Chapter 5).

1.3 Description of the Study Area

The Northern Albertine Rift region in western Uganda lies approximately between 1°18′–2°11′N and 30°40′–31°52′E with an estimated area of 14,100 km². This is the delineated area for this study (in Figure 1.1). The area fits in one row and path of the Landsat imagery (and avoids classification problems related to mosaics of multiple scenes taken at different dates, elaborated in Chapter 2), and covers three contrasting districts in the region: Masindi, Hoima and Buliisa. The full extent of the Albertine Rift however covers many countries (see e.g. Ryan et al. 2014). The Albertine Rift is one of the most important conservation regions in Africa with extensive areas of both
protected and unprotected forest (Owiunji and Plumptre 1998; McLennan and Hill 2012), abundant bird species, high plant and tree species diversity (Eilu et al. 2004), and an unmatched animal species diversity, most of which are endemic to this ecosystem (Plumptre et al. 2007).

The landscape has a characteristically gently sloping terrain, and a tropical climate with two rainfall peaks, March to May and September to November (Eilu et al. 2004; Seimon 2013: Figure 1.2). The region’s ecosystem is threatened by widespread deforestation (Mwavu and Witkowski 2008) perhaps due to a dense population of approximately 123 people km$^{-2}$ (the majority living below the poverty line, on less than a dollar per day) slightly higher than Uganda’s average of 121 people km$^{-2}$ (UBOS, 2002, but this is old, and results from the most recent census [2014] are still in draft form), and a population growth rate of about 3.2% per annum (UBOS, 2002), exacerbated by a large influx of refugees (Mwavu and Witkowski 2008). Small-scale agriculture is the main way of life, although with limited commercial farming to provide raw materials for sugar, tea and tobacco industries in the region (Nangendo et al., 2010).

The landscape has attracted many government and non-government conservation and development organisations such as the World Wide Fund (WWF), Wildlife Conservation Society (WCS), Jane Goodall Institute, Chimpanzee Sanctuary Conservation Trust (CSWCT), among others, with similar aims of nature conservation and sustainable development. Oil was discovered in the Albertine Rift in the mid 2000s and construction of an oil industry is underway. It is not clear how development goals and conservation will work simultaneously in this landscape. While regions around Budongo forest have been studied to some extent in the past (Nangendo et al. 2007; Mwavu and Witkowski 2008), there is a lack of information on areas around Bugoma, the forest corridors and the semi-arid region (in Buliisa).
Figure 1.1 Map of the Northern Albertine Rift region showing parishes where fieldwork was undertaken
Figure 1.2 Rainfall around Budongo forest estimated from gauging stations near Budongo and Sonso (Source: Seimon 2013) (Data for the semi-arid region in a similar format are unavailable, although district reports show general mean annual rainfall amounts reported in Table 3.1).

1.4 Broad Literature Themes

This study lies across five main bodies of literature: 1) deforestation and land use change (patterns, drivers), 2) remote sensing applications, 3) survey techniques in rural sociology, 4) quantitative and qualitative data analyses, 5) and land use and forest cover change modelling. Smaller pockets of literature are included, given the multidisciplinary nature of this project, although they can be seen to fit within the five broad categories. Most of the details and definitions are provided within the main text of each of the chapters. What is presented here are therefore only brief outlines as introductions to more detailed literature reviews are in each chapter. Literature on the first theme – deforestation and land use change – focuses on patterns and drivers of deforestation and land use change at the national level, and within the study area. This literature is reviewed throughout the thesis, in the introduction to this chapter and with further detail in Chapters 2 and 5.

2) Literature on Remote Sensing

In basic terms, Remote Sensing (RS) is the acquisition of data from a place without necessarily having any physical contact (Rees 2013, pg. 1), which information is then
processed in a Geographical Information Systems (GIS) environment. The more detailed review and discussion in Chapter 2 defines related terms, and focuses on Landsat systems, their development, how data are acquired, reasons for the choices of method, and technical details of image processing. There is also emphasis on analysis of the data gathered using sound conventional but improved techniques.

3) Literature on Survey Techniques in Rural Sociology

This body of literature focuses on social surveys, and techniques in gathering sensitive household data. Issues related to framing, positionality, and ethical considerations are also included. The majority of this literature is discussed in Chapter 3.

4) Literature on Quantitative and Qualitative Data Analysis

In this category, literature on handling high-dimensional data is reviewed. The focus is mostly on the application of Principal Components Analysis (PCA) and Cluster Analysis to effect forms of data reduction, and to classify household livelihood types. The majority of this literature review occurs in Chapters 3 and 4.

5) Literature on Land use and Forest Cover Change Modelling

As part of further analysis, modelling paradigms are reviewed, and the Agent-based Modelling (ABM) methodology is suggested for its potential benefits in future work that might build on the results of this thesis. This is mostly highlighted in Chapter 5, with the framework elaborated in Appendices 5.1, 5.2 and 5.3.

1.5 Overview of Materials and Methods

Here an overview of the techniques used in this thesis is provided. Individual chapters provide more specific technical detail as required. In Chapter 2, conventional imagery classification techniques are used, with a novel contribution of estimating uncertainty as a result of spectral confusion. In Chapter 3, household survey techniques are employed, where a novel strategy of identifying participants in a randomised manner is employed, and analysis of high-dimensional data is discussed. In Chapter 4, identifying key informants and working with qualitative data are elaborated.
The research therefore embraces a range of different topics and methods, but there is a logic in the text that shows how the components of the study combine; the linkages between each chapter are elaborated. In summary, in Chapter 2, detailed spatio-temporal land use and vegetation patterns at the regional and local scales in the Northern Albertine Rift region are reconstructed, based on a time-series of Landsat imagery obtained from the USGS archive, and higher resolution UK-DMC imagery. The results from Chapter 2 are then used to identify study areas in forested and non-forested regions that are subsequently elaborated in Chapter 3. Chapter 3 therefore presents and analyses data from an in-depth questionnaire administered to 706 households in 13 parishes situated in forested and non-forested Agro-Ecological Zones in the landscape. Chapter 4 examines perceptions of the locals and key informants on 30-year forest cover change in parishes around Budongo and Bugoma. The results from household typologies generated in Chapter 3 are used to assess the linkage between perceptions of forest change and livelihoods. Chapter 5 includes a summary of possibly leading drivers of forest change in the landscape and some theoretical ideas about the processes, while providing plausible policy recommendation, and suggesting future research. This chapter essentially draws from the work presented in the entire thesis.
Chapter 2

Remote Sensing of Rural Land Use and Vegetation Cover: 30-year Spatio-Temporal Patterns at Regional and Local Scales
Abstract

Detailed spatio–temporal land use and vegetation patterns at the regional and local scales in the Northern Albertine Rift Landscape were reconstructed for the period 1985–2014. A time–series of seven 30 by 30m resolution, ortho–rectified, cloud–free Landsat images obtained from the USGS archive were analysed at the regional– and 3 local–levels; although 17 were analysed for the drier Buliisa region. The images were thoroughly pre-processed for atmospheric effects before a mixture of unsupervised and supervised classification techniques were employed: the classification was strictly spectral signal–driven. Although there was a general linear increase in commercial farming and built–up areas at the regional level ($r^2>0.7$, $p<0.05$), most land use changes were swamped by classification ambiguities (mixing) – this was similar at the local– scales, although with less variability. Dynamics varied by region with possibly more specific local–level processes. The forest signal was the most stable: change detection was therefore undertaken for this class. Forest cover patterns at the regional level were obscured by losses and offsets in dissimilar regions. Local–scale losses were most prominent in unprotected forests around Budongo and Bugoma, with annual losses ~ 3.3% ($p=0.006$) and 3.3% ($p>0.05$) respectively. Forest cover in the protected zones increased linearly but only marginally with annual growth ~ 0.03% ($p=0.04$) and ~ 0.5% ($p>0.05$) in Budongo and Bugoma case studies respectively; these rates do not compare equal extents (areas). The analysis suggests that classification of forest and small-scale farming using Landsat imagery is to a great extent reliable; the results are corroborated by similar amounts obtained from a UK-DMC image (22m resolution) taken a day before the Landsat scene in Dec, 2010. Other land uses are likely to be mixed up in the reflectance signal of the selected bands, making them difficult to separate. Evidence from this is supported by the 817 randomly sampled ground truth data during fieldwork where the overall, producer and user accuracies were low with a wide confidence interval (0–70%), although small–scale farming generally performed well with accuracies often >70%. In this chapter, it is demonstrated that a ‘bird’s eye view’ of the earth’s surface using remote sensing technology could provide insights into the complex anthropogenic processes at various spatial scales, but rigorous analyses are required to provide a ‘good’ measure of confidence in the results. Remote sensing evidence from this chapter sets the scene for the other strands including field–based empirical analyses, discussed in subsequent chapters of this thesis.

Cover page photo: Eastern part of Budongo forest boundary and small holder farming (source: Google Earth, 2011)
2.1 Introduction

Rural landscapes in sub-Saharan Africa have complex land use and vegetation cover mosaics (Lambin et al. 2003; Nangendo et al. 2007; Lambin and Meyfroidt 2011). They include some of the few globally remaining interacting natural forests, savanna grasslands, commercial and subsistence farming systems (Buys 2007). Broadly, such landscapes are important for: 1) food provisioning (Adesina 2010; Lerner and Eakin 2011), 2) biodiversity conservation with endemic fauna and flora (Mclennan and Plumptre 2012), and 3) for their aesthetic values – including health and wellbeing, and attracting revenues for local and national governments from tourism, trade and other activities (Hall 2011; Ezeuduji 2013; Adiyia et al. 2014). A large percentage of the rural population depends on nature for their livelihood (Naughton-treves 1997; Naughton-Treves et al. 2005, 2007; Mclennan and Plumptre 2012), often subjecting the ecosystems to immense pressure, culminating in land use and vegetation cover changes (Lambin et al. 2001; Sunderlin et al. 2005; Wunder et al. 2014; Babigumira et al. 2014).

Uganda’s population is predominantly rural and agrarian (about 85% of the total; UBOS 2007) with over 40% of this living in abject poverty, on less than US$1 per day (ruralpovertyportal.org). The nation’s human population is rapidly expanding at one of the world’s fastest rates, nearly 4% per annum (Bongaarts, 2009). In the face of population pressure, declining soil productivity and underdeveloped technologies (among other factors), many rural communities are abandoning shifting cultivation. Erosion of forests, conversion of savanna grasslands, urbanisation, agricultural intensification and extensification are prevalent in the literature as some of the widespread land use and vegetation cover changes in Uganda’s rural landscapes (Baranga et al. 2009; Ebanyat et al. 2010; Majaliwa et al. 2010; Twongyirwe et al. 2011; Sassen et al. 2013). These changes have been associated with various negative biophysical and socio-economic consequences. They include, but are not limited to, loss of biodiversity, floods, reduced agricultural productivity, and landslides – where both property and lives have been lost (Knapen et al. 2006; Claessens et al. 2007; Mugagga et al. 2012).

Understanding the extent and nature of historical land use and vegetation cover changes could provide the impetus to address local, regional and national needs, and may prove critical for future planning. Remote sensing is one invaluable technique to
monitor rural land use and vegetation cover; and is often preferable to surveys where high costs and difficult access may be prohibitive. Remote sensing is simply defined as the collection of information about an object without making physical contact with it; the context here is earth surface observations from above using electromagnetic radiation and satellite imagery (Rees 2013, pg. 1). Remote sensing data used in this project are obtained from the Landsat archive, with a database from the 1970s, and is now freely accessible to the public from the USGS web portal (Wulder et al. 2012). This digital information requires rigorous processing to make sense of the earth’s surface conditions; a detailed description is provided in this chapter.

Two issues have received limited attention in land use and vegetation cover change literature: 1) the spatial scale of analysis, and 2) handling errors (uncertainty) in spectral–driven classification schemes. 1) A ‘global’ regional–level analysis could provide insights into the connectivity of the land use and vegetation cover mosaics, especially if the focus is on biodiversity conservation, where, for instance, allowing free wildlife movement in a well–connected landscape is important for breeding; but a more localised investigation might unearth intricacies in anthropogenic–related land use selection biases, which could impact on the larger–scale processes. 2) A measure of land use and vegetation classification accuracy, with for instance: producer and user accuracies, quantity and allocation disagreements, and the oft–criticised kappa coefficient, based on a range of classifiers (e.g. Maximum Likelihood Classifier, Support Vector Machines, Spectral Angle Mapper), are often reported in the literature (e.g. Xie et al. 2008; Pontius and Millones 2011; Grinand et al. 2013). They are, however, deficient in reporting the variability in amounts of a derived land use or vegetation cover class. We know though, that each class is obtained by a probabilistic allocation based on a critical threshold of spectral signatures obtained by selecting training sites. The training sites have varying spectral responses and could be selected in different combinations to obtain a mean threshold for a given class; therefore, reporting an absolute value from a probabilistic allocation could be misleading: what is the error associated with each class? Additionally, what are the errors associated with the accuracy measures?

Analyses of land use and vegetation cover patterns were undertaken for the Northern Albertine Rift region between 1985–2014 at varying spatial scales (discussed in the methods section). The rationale for selection and a comprehensive description of the study area is provided in Chapter 1. Accuracy assessment measures are not criticised in
this study *per se*, but variability in classification is reported with a novel emphasis. Ground truthing as a technique of accuracy assessment is tested and discussed.

### 2.1.1 Objectives

The key objective in this chapter is to reconstruct a detailed land use and vegetation cover pattern for the Northern Albertine Rift region between 1985–2014. The following are the related research questions.

i) What were the spatial and temporal distributions of selected land uses and vegetation covers in the Northern Albertine Rift region in between 1985–2014?

ii) Has there been a significant change in land use and forest cover in the 30–year period under investigation?

iii) When and where in the landscape have changes in land use and forest cover been significant (and to what degree)? Does the spatial scale of investigation matter?

iv) What is the efficacy of change detection based on the readily available low resolution Landsat imagery (30m pixel) relative to the ‘costly’ higher resolution (UK-DMC) remotely sensed imagery (22m pixel) and ground truth data?

### 2.1.2 Definitions

In this chapter and throughout the thesis, *land cover* refers to the biophysical attributes of the terrestrial surface (e.g. grassland, forest). *Land use* is defined as the purposes for which humans exploit the land cover (e.g. for agriculture, raising cattle, recreation, settlement) (Lambin et al. 2000). More specific definitions of classes in this study are summarised in Table 2.1.

*Forests* do not have an internationally agreed definition. Each country defines forest cover within some bounds by the percentage of canopy cover: Uganda's National Forest Authority definition is adopted for this study (in Table 2.1). The lack of a universal definition for forests essentially raises ambiguities in what is termed as deforestation. In concert with Decision 11/CP.7 (*UNFCCC, 2001*), *deforestation* in this project is defined as the direct human–induced total conversion of “forested” to “non-forested” land (Schoene et al. 2007), while *forest degradation* is loosely defined as the partial (and sometimes selective) loss of forest cover. Forest degradation if not controlled could lead to deforestation. Fuelwood collection (a form of forest degradation –
discussed in subsequent chapters), may, for instance, gradually result into total forest loss if not controlled.

**Land use change** is the conversion of land use from one type to another (e.g. from small–scale farming to built–up areas). It may also involve changes in cropping history (e.g. from annual to perennial and vice versa) or intensification/extensification. Seasonal rotations that are known to be part of the annual cropping cycles, do not qualify in this change definition.

### Table 2.1 Definition of terms used in the classification scheme

<table>
<thead>
<tr>
<th>Land use/cover</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tropical High Forest</td>
<td>Includes mature and/or regenerating natural forest with a minimum area of land of 1 hectare, with tree crown cover of more than 10–30% with trees having the potential to reach a minimum height of 2–5 metres at maturity in situ (MWE, 2012). In the classification, plantation forests may be included.</td>
</tr>
<tr>
<td>Small–scale farming</td>
<td>Small land holdings less than 1 hectare used for growing food crops for home consumption, and the surplus for sale.</td>
</tr>
<tr>
<td>Commercial farming</td>
<td>Area greater than 1 hectare under ‘uniform cash crop’ cultivation. Crops grown on ‘large scale’ within the landscape mainly include sugarcane and tea.</td>
</tr>
<tr>
<td>Built–up areas/settlements</td>
<td>Refers to small rural towns with business centres, hospitals, schools, settlement, social amenities, and industries. They also include linear/connected rural settlements that can be resolved at a 30 x 30 m² pixel.</td>
</tr>
<tr>
<td>Savanna vegetation</td>
<td>Rangelands, pasture land, with trees and short shrubs of average height ~ 2–3 m – mainly used for grazing livestock, and/or game animals. In this study, this category combines both grassland and woodland.</td>
</tr>
<tr>
<td>Bare ground</td>
<td>Refers to ground surface with no vegetation cover; ground cleared for commercial/small scale farming, or is bare due to over grazing, or due to dry climatic conditions that do not support vegetation. It also comprises of rocky surfaces that are unproductive and remain permanently bare.</td>
</tr>
<tr>
<td>Water body</td>
<td>Permanent open water, lakes, streams and rivers.</td>
</tr>
</tbody>
</table>

### 2.2 Literature and Theoretical Context

In this section, two bodies of literature related to the chapter are reviewed. The first focuses on forest cover change in Uganda. This provides an overview of one of the main losses of natural vegetation cover in the country. Other forms of vegetation loss and land use change have taken place, but are relatively poorly documented and/or of limited importance. Here, the focus is on deforestation. The second area is the background to using Landsat imagery. I provide an overview of the historical context of
the remote sensing technology (system launch successes and failures), policy shifts and implications on data access. Whilst the physics of remote sensing (e.g. electromagnetic radiation interaction with free space, the atmosphere and matter) is important and occasionally considered, it is beyond the scope of this investigation, and therefore not reviewed to a great extent (but for details see Tempfli et al. 2009; Rees 2013). The focus here is more on data availability and access.

2.2.1 Forest Cover Change in Uganda

Scholarly work indicates that deforestation has been on the increase in several parts of Uganda in the last half-century. Some examples include: rapid forest conversion for coffee production around Mt. Elgon in eastern Uganda (Petursson et al. 2013); and making (illegal) livelihoods from harvesting forest timber and non-timber products in the protected forest of Rwenzori National Park in western Uganda (Tumusiime et al. 2011). Deforestation has been reported to be rife in the forests located on protected and private land around Kibale National Park in south-western Uganda. These losses are attributed to charcoal production (with preference for old-growth hardwood tropical species), high fuelwood demand by the tea industry, settlement and agricultural expansion (Naughton-Treves et al. 2007). Forest cover has been lost around Bwindi impenetrable forest in south-western Uganda, attributed mainly to agricultural expansion and ambiguous forest boundaries (Twongyirwe et al. 2011).

There is however evidence of successful forest protection in some National Parks and Forest Reserves by Uganda’s designated forest authorities (e.g. Bwindi impenetrable forest, see Hamilton et al. 2000; Bugoma and Budongo forests–this thesis). We see some regions of forest stability and recovery/gain (but some with losses) in various parts of the country between 2000–2012 from recent global forest cover change mapping (Hansen et al. 2013). Plantation forest is reportedly expanding on some private landholdings with funding support from various initiatives (e.g. FACE Foundation Forest Rehabilitation Project, PlanVivo Project, Nile Basin Reforestation Project, and Namwasa Forestation Project; for detailed reviews see Jindal et al. 2008; Peskett et al. 2011). Although afforestation and reforestation projects are on the rise, it remains
unclear whether they are reducing pressure on natural forests (Ainembabazi and Angelsen 2014) or even whether they are offsetting the current deforestation rates.

While recent discourses in local media highlight the prevalence of deforestation within the Northern Albertine Rift Landscape (e.g. Mugerwa 2011; Mugume 2013; Namutebi 2013; Tenywa 2014), the only published work found is fragmented and limited to Budongo forest (Nangendo 2005; Nangendo et al. 2007; Mwavu and Witkowski 2008). Forest loss around Budongo has been reported on private landholdings, and attributed to agricultural expansion, population growth, illegal timber harvesting, unclear land tenure systems and weak forest protection enforcement (Mwavu and Witkowski 2008). There is however a dearth of information on Bugoma (another large forest in the landscape), and forest corridors in the region. Some studies exist by the Wildlife Conservation Society (WCS) and other NGOs working on forest loss in the Albertine Rift region (including Uganda, Congo, Rwanda, Tanzania and Mozambique), but only in unpublished reports. For instance, the WCS REDD project has estimates of forest loss for the period 1990–2010 although the methods used in the estimation are not rigorous, and the results seem exaggerated.

Deforestation in the region, and more widely in Uganda, received significant attention in academic literature in the 1970s and 1980s (Struhsaker 1987), and relatively recently in the 2000s (Obua et al. 2010). This work could be criticised for having relied heavily on anecdotal evidence, with the techniques of estimation largely based on expert judgement. Such estimates may exaggerate or underrepresent the situation on ground. From this brief review, it is argued that the extent of forest cover change particularly at the regional– and local–scales around Bugoma and Budongo forests in the last 30 years is not thoroughly understood. The review has focused on the coverage of deforestation, and less on its drivers: these will be unpacked in subsequent chapters of this thesis. In this chapter, the aim is to show the extent of forest loss and recovery, if any, at various spatial scales. While literature generally suggests that deforestation is more prevalent in unprotected areas than in protected forests, quantitative empirical work is rare and this study is therefore a valuable contribution.
2.2.2 Landsat Systems

While the first Landsat image was acquired on 23<sup>rd</sup> July, 1972, the conception of the Landsat program was in the 1960s with successful experiments on the Apollo 9 mission where crewmen spent ten days in low Earth Orbit (Bauman 2009; Wulder et al. 2012). Landsat 1 was the first system in operation in a period of transitioning from aircrafts to satellites as primary platforms for carrying remote sensing instruments, and in a period when computer technology was advancing from large mainframe machines to smaller microcomputers with higher processing power (Lauer et al. 1997; Bauman 2009).

The impetus behind the Landsat program was that it would provide reliable, global-level remotely-sensed data for various multi-sectoral and multi-disciplinary applications, including but not limited to: military, business, science, and education (NASA 2010; Wulder et al. 2012). Eight (8) Landsat systems with a swath width of 815 km and slightly varying scene revisit periods have been launched since the inception: all were successful except for Landsat 6 that failed to launch (see Table 2.2). The systems were designed with a 5-year lifespan, but all except for Landsat 6 and Landsat 8 that was recently launched, served beyond this. Remarkably, Landsat 5 was in orbit for 29 years.

The Landsat systems are sophisticated. They are comprised of Remote sensor systems; Data relay systems; Orbit-adjust subsystems; Power supplies; Receivers for ground station commands; Transmitters that send data to ground receiving stations (NASA 2010). A detailed description of each component is beyond the scope of this investigation (but for details, see NASA 2010). Data from the satellite are received at the ground receiving stations, preprocessed before they are made available for public consumption, often supplied in an analysis ready Level 1T (L1T), which incorporates precision georegistration and orthorectification using digital topography (Wulder et al. 2012).

Landsat 1, 2, 3 were mainly considered experimental and operated on similar instruments, although the Return Beam Vidicom (RVB) was found to be inferior and was switched off: consequently, data are only available in 4 bands taken by the Multi-spectral Scanner (MSS) (Bauman 2009). In the 1980s newly-designed satellites
(Landsat 4 and 5) and a sensor system (Thematic Mapper) with more bands were launched. Details are summarised in Table 2.2 and Appendix 2.1.

Landsat 7 was successfully launched in 1999 although on 31st May, 2003, the Scan-line Corrector (SLC) failed. The SLC is an electromechanical device that compensates for the forward motion of the satellite within the ETM+ scanning; its malfunction is in aligning parallel scans; the individual scans alternately overlap and leave large wedge-shaped gaps that range from a single pixel in width near the image nadir to about 14 pixels width towards the edges of the scene, and only in the center of the image do the scans give continuous coverage of the surface scanned below the satellite (Zeng et al. 2013).

The most recent Landsat system, the Landsat Data Continuity Mission (LDCM), also called Landsat 8, was launched in February, 2013. The launch of Landsat 9 is predicted to be around 2017 (Wulder et al. 2012). Overall, each of the Landsat systems had some improvements especially with number of spectral bands available. Band information for each scanner and what they best classify are summarised in Appendix 2.1. The variances in Landsat data gathered and techniques of processing are further explained in the methods section.

**Table 2.2 Landsat mission characteristics** (Adapted from NASA 2010; Wulder et al. 2012)

<table>
<thead>
<tr>
<th>System</th>
<th>Launch date</th>
<th>End of service</th>
<th>Instrument</th>
<th>*Resolution (m)</th>
<th>Altitude (km)</th>
<th>Revisit days</th>
</tr>
</thead>
<tbody>
<tr>
<td>Landsat 1</td>
<td>23/7/1972</td>
<td>6/1/1978</td>
<td>MSS, RVB</td>
<td>80, 80</td>
<td>917</td>
<td>18</td>
</tr>
<tr>
<td>Landsat 2</td>
<td>22/1/1975</td>
<td>22/5/1982</td>
<td>MSS, RVB</td>
<td>80, 80</td>
<td>917</td>
<td>18</td>
</tr>
<tr>
<td>Landsat 4</td>
<td>16/7/1982</td>
<td>Aug/1993</td>
<td>MSS, TM</td>
<td>80, 30</td>
<td>705</td>
<td>16</td>
</tr>
<tr>
<td>Landsat 5</td>
<td>1/3/1984</td>
<td>5/06/2013</td>
<td>MSS, TM</td>
<td>80, 30</td>
<td>705</td>
<td>16</td>
</tr>
<tr>
<td>Landsat 6</td>
<td>5/10/1993</td>
<td>5/10/1993</td>
<td>ETM</td>
<td>15 (pan), 30</td>
<td>705</td>
<td>16</td>
</tr>
<tr>
<td>Landsat 7</td>
<td>15/4/1999</td>
<td>To–date</td>
<td>ETM+</td>
<td>15 (pan), 30</td>
<td>705</td>
<td>16</td>
</tr>
<tr>
<td>Landsat 8</td>
<td>11/2/ 2013</td>
<td>To–date</td>
<td>OLI</td>
<td>15 (pan), 30</td>
<td>705</td>
<td>16</td>
</tr>
</tbody>
</table>

The Landsat program underwent various policy shifts and management regimes, including privatization, public–private partnerships, and back to state agencies (Lauer et al. 1997; Wulder et al. 2012). The management and policy shifts largely inhibited image access until the opening of the Landsat archive to the public free–of–charge in 2008 (Wulder et al. 2012). Following this shift, remote sensing data intensive projects were fuelled (e.g. Potapov et al. 2011). For reasons of free access, longest historical record of earth’s surface data with a wide coverage, a relatively high resolution, Landsat data were selected for the construction of a 30–year land use and vegetation cover pattern for the Northern Albertine Rift Landscape. The archive was thoroughly searched, and a full description of its processing is provided in the methods section.

2.3 Data, Materials and Methods

2.3.1 Remote Sensing Data used in the Analysis

Two remote sensing data sources are used in this study: 1) Landsat (30m resolution) and 2) UK–Disaster Monitoring Constellation International Imaging (UK-DMCii, 22m resolution). Landsat imagery were the main data source; obtained from the USGS archive via the Earth Explorer web–link (http://earthexplorer.usgs.gov/). The archive was thoroughly checked for data from January, 1985 to March, 2014 (when the field–based ground truthing studies ended). Selection was iterative involving initial dismissal of imagery that had more than 50% haze and cloud cover, especially in ‘prime’ case study areas. In total, a time–series of 80 scenes was downloaded.

A further rigorous process of selecting scenes to be included in the classification was undertaken. The criteria were based strictly on being totally cloud-free, and SLC-error free over the region of study, or where the wedge–shaped gaps from the ETM+ sensor failure did not preclude classification. Clouds obscure land uses and vegetation cover as the transparency of the atmosphere is reduced by the condensation of atmospheric water vapour into droplets. The surface of the Earth can still be seen through haze, but the spectral characteristics are often changed, in effect haze can render imagery unusable (Mitchard 2012). All cloudy and hazy scenes were dismissed, although if they were totally clear over the smaller scale ‘case study’ areas, they were included. Accordingly, at the regional–scale (and selected case studies), only 7 scenes were included compared to the drier case study region, where 17 scenes were selected (Table
2.3); essentially, between 8.8–21.3% of the downloaded scenes were useful. Only one of the five scenes obtained from UK-DMCii was included in this study. The other four were largely obscured by haze and clouds, and their areal extent did not cover the region of study satisfactorily.

The study area fits in only one Path/Row (172/059) of the Landsat satellites; therefore a mosaic of multiple scenes was not required. Unsurprisingly, the acquired imagery at the regional scale (and some local scale) used in the analysis were obtained in the dry season, which is more likely to be cloud and haze free. By default, seasonal variability that could have phenological effects on the classification was controlled. Notably, only 2 scenes were acquired in the wet season for the drier Buliisa case study with a view to exploring seasonal variability in farming practices in the dry region of the landscape, although these may be too few for any reliable conclusions. The data on the dry region case study were plotted however, but no seasonality statistics or comparisons were made due to the limited samples.

The period of investigation selected, 1985–2014, was relatively more politically stable than the 1970s to mid-80s. This selection is generally beneficial for the forthcoming agent-based modelling (see Chapter 5.6) for delimiting the parameters that may influence land use and vegetation cover patterns in the landscape. Literature suggests though that there was widespread forest loss in different parts of the country in the lawless, and politically unstable periods (Petursson et al. 2013). However, the first year of study (1985–1986) may have been in the unstable period, as the current regime (headed by President Yoweri K. Museveni) took power on January 26th, 1986.

2.3.2 Image processing

Image processing was undertaken using Erdas Imagine 2013 and ArcGIS 10.0 in three phases: 1) Pre-classification processing, 2) Classification and 3) Post-classification change detection as summarised in Figure 2.1. These are described in turn.
2.3.2.1 Pre-classification processing

**Band selection:** After some preliminary trials with other band combinations, the widely accepted 3–band false colour composite that includes at least red and near infrared bands, known to provide distinct vegetation features were used (He et al. 2011): each band potentially elaborates specific features in a classification scheme (summarised in Appendix 2.1). The number of bands available per downloaded scene varied between 5 (e.g. Jan 14, 1985) and 11 (e.g. Jan 14, 2014), Table 2.4; this is due to the number of bands a sensor could provide at the time, but also possibly due to the pre-processing by USGS. Previous studies based on principal components analysis have shown that additional bands do not improve the classification but have redundant information (Harsanyi and Chang 1994; Chang et al. 1999; Jia and Richards 1999) that unnecessarily slows down the processing. An optimal band set that included at least red and near infrared bands to distinguish the vegetation classes was therefore included. The selection included a band combination of 2, 4 and 5 (green, infra-red, and short-wave infra-red bands respectively) for the classification of Landsat 4 and 5 imagery, while a combination of bands 3, 4 and 5 (green, red and near infra-red) was used to classify the only Landsat 8 image, since Landsat 8 has different optical dimensions for each band compared to the other Landsat systems (Table 2.3). In spite of selection of a different band combination, distinguishing the forest class (and some continuous farmlands) was consistent with the results from the UK-DMC image. The selected band responses from the different instruments produce remarkably consistent results for forest cover: this case is shown by the fact that the protected areas remain stubbornly constant in size while the regions outside change steadily. This suggests that the trend in forest cover described below is a real effect and not an artefact of the bands selected or changing instrumentation between satellites. Processing of the one scene from UK-DMC followed that of Landsat images, using bands (2, 3 and 4).

Table 2.3 Selected bands and their optical dimensions

<table>
<thead>
<tr>
<th>TM5, ETM+ Bands selected</th>
<th>Band width (μm)</th>
<th>OLI Bands selected</th>
<th>Band width (μm)</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>0.52–0.60</td>
<td>4</td>
<td>0.77–0.90</td>
</tr>
<tr>
<td>4</td>
<td>0.53–0.59</td>
<td>4</td>
<td>0.64–0.67</td>
</tr>
<tr>
<td>5</td>
<td>1.55–1.75</td>
<td>5</td>
<td>0.85–0.88</td>
</tr>
</tbody>
</table>

**Atmospheric correction:** Similar to other remote sensing scanners, data from Landsat systems are not without errors, and are often distorted by variations in atmospheric conditions, solar angle, and sensor view angle (Townshend et al. 1991). The rationale for radiometric correction is that it reduces atmospheric variations among multiple
images by adjusting the radiometric properties of target images to appear as if they were acquired from the same sensor (Hall et al. 1991). The Dark Object Subtraction (DOS) method is one such relative technique that is universally accepted. Being simpler than absolute methods, and widely used to correct for radiometric errors (e.g. (Song et al. 2001), it was accordingly used in this project. In an ideal situation, a radiometrically ‘dark’ object (e.g. a clear water body: Lake Albert in this case) produces zero radiance in all wavelengths and hence any radiance received at the sensor for a dark object pixel is due to atmospheric path radiance (Chavez 1988). Thus, for dark objects, the pixels containing the lowest Digital Number (DN) values were selected from the image and their representative value subtracted from the DNs across the whole scene to reduce scattering influences (Song et al. 2001). The sun angle is one issue not to worry about since Landsat satellites follow a sun-synchronous orbit, meaning they image a particular latitude at the same time every day: moreover, imagery captured over a number of years in the same season should have the same sun-angle, creating comparable data (Mitchard 2012). The imagery used in this analysis were obtained in the dry season.

**Image subset:** The delineation of the study area (at the regional scale) largely followed the extents of Hoima, Masindi and Buliisa district boundaries, the international border to the west, and all extents were delimited to the one path/row of the image. The boundaries were then used to extract the study area from a Landsat scene. Case study delineation was based on a visual assessment of processes and patterns that might be obscured at the regional scale. Case studies were delineated around Budongo forest (mostly to the South; as the Northern section has been previously studied), Bugoma forest (which is less studied), dry Buliisa region (which has a different agro-ecological system from the rest of the landscape) and the forest corridors between Budongo, Wambabya and Bugoma (to understand the connectivity changes between the large forests).

**Contrast stretching** was occasionally undertaken when improvement in the visual appearance of the image was required. This does not change the radiometric properties of the image *per se* but changes the range of pixel intensity values to provide a colour scheme that improves visibility of some features (Tempfli et al. 2009, pg. 197). The band stacks were contrast–stretched using histogram equalisation, but this was not always necessary.
### Table 2.4 Attributes of imagery obtained, sources and regions classified

<table>
<thead>
<tr>
<th>Date acquired</th>
<th>Resolution (30 m)</th>
<th>Source (Landsat)</th>
<th>Number of bands available</th>
<th>Climatic season</th>
<th>Entire region</th>
<th>Forest and corridors</th>
<th>Budongo-Masindi</th>
<th>Bugoma case</th>
<th>Buliisa case</th>
<th>Total no. of cloud free scenes/image</th>
</tr>
</thead>
<tbody>
<tr>
<td>1985-Jan-14</td>
<td>TM5</td>
<td>5</td>
<td>Dry</td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>5</td>
</tr>
<tr>
<td>1986-Jan-17</td>
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<td>Dry</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
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</tr>
<tr>
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<td>Dry</td>
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<tr>
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<td>Dry</td>
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<td>✓</td>
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<td>✓</td>
<td>✓</td>
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<tr>
<td>1990-Dec-22</td>
<td>TM4</td>
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<td>Dry</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
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<td>Dry</td>
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<tr>
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<td>Dry</td>
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<td>✓</td>
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<tr>
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<td>Dry</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
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</tr>
<tr>
<td>2000-Feb-17</td>
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<td>Dry</td>
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<td>✓</td>
<td>✓</td>
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<td>✓</td>
<td>✓</td>
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<td>2002-Jan-21</td>
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<td>Dry</td>
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</tr>
<tr>
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<td>Dry</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>5</td>
</tr>
<tr>
<td>2003-Feb-25</td>
<td>ETM</td>
<td>8</td>
<td>Dry</td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>1</td>
</tr>
<tr>
<td>2010-Dec-05</td>
<td>TM5</td>
<td>5</td>
<td>Dry</td>
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<td>✓</td>
<td>✓</td>
<td>5</td>
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<tr>
<td>2011-Jan-06</td>
<td>TM5</td>
<td>5</td>
<td>Dry</td>
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<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>1</td>
</tr>
<tr>
<td>2014-Jan-14</td>
<td>OLI and TIRS</td>
<td>11</td>
<td>Dry</td>
<td></td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>5</td>
</tr>
</tbody>
</table>

**Total no. of images analysed per case**: 7 7 7 7 7 17 Overall total 17

<table>
<thead>
<tr>
<th>Date acquired/Resolution (22 m)</th>
<th>Source (DMCii)</th>
<th>No. of bands</th>
<th>Climatic season</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010-Dec-04</td>
<td>UK-DMC (SLIM-6-22)</td>
<td>3</td>
<td>Dry</td>
</tr>
</tbody>
</table>

MSS-Multi-Spectral Scanner; TM–Thematic Mapper; ETM–Enhanced Thematic Mapper. OLI–Operational Land Imager and Thermal Infrared Sensor (TIRS). Imagery were accessed via the United States Geological Survey (USGS) website, provided as L1T format. Classified regions contain no cloud cover. UK-DMCii– UK Disaster Monitoring Constellations International Imaging.
Figure 2.1 Schematic illustration of Landsat image pre-processing, classification, and post-processing procedures undertaken (Unsupervised classification was not always strictly carried out: it was essential for exploratory assessment of how classes might be distributed in the landscape. 3 replications were undertaken per scene to assess classification variability. Dotted lines show optional procedures included – for instance the case studies were selected and delineated once)
2.3.2.2 Classification

A hybrid of the unsupervised and supervised classification techniques was used (e.g. in (Sassen et al. 2013). An unsupervised classification involves assigning a given number of classes and letting the computer place similar objects in one category using a statistical method of classifying. Unsupervised exploratory classification runs with different numbers of classes forming the basis for the selection of ‘training’ sites whose band characteristics enables extraction of all other pixels, although some previous knowledge of the landscape, and comparison with some existing maps (by WCS, and National Forest Authority) was valuable. A pixel–based classification criterion was adopted in preference to an object–based one, and although results from the two techniques have not been found to differ significantly, the results from the former have been found to be comparatively better (Duro et al. 2012).

At least 12 training sites per class referred to as ‘Areas of interest’ (AOIs), were selected across each image to extract the spectral signatures rigorously. For instance, forest spectral signatures were generated over known forested areas (e.g. Budongo, Bugoma and Wambabya) for the classification of each image, essentially creating a generalised empirical forest classification (e.g. in Hansen et al. 2013), without distinguishing forest classes (e.g. by species and stocking densities). The landscape is flat, with minimal variation in altitude, and therefore variation in slope and aspect do not have a major effect on the spectral signatures. The statistical properties of the selected AOIs were visually assessed in order to dismiss any signatures that deviated significantly. Once the collected signatures had been compared satisfactorily (i.e., close to each other with a ‘similar’ spectral reflectance curve), the group signatures were then merged into one, and were used in the supervised classification for that specific land use/vegetation cover class over which signatures were collected. To test for variability in the classification, the signatures collected for each class were re-sampled in various combinations and merged to provide an average signature, and a classification was rerun. Three replications were considered sufficient.

Various classifiers are available in the literature on land use and vegetation cover mapping (e.g. support vector machines, spectral angle mapper, artificial neural networks) (Srivastava et al. 2012), however the Maximum Likelihood Classifier (MLC) was selected for this project. The MLC is widely used and is able to recognise the spectral characteristics of each class in an unknown dataset by means of the statistical
data (premised on Bayes’ theorem) obtained beforehand from digitised training sites, to assign pixels to the particular classes that have the maximum probability (Coppin et al. 2004; Tempfli et al. 2009, pg. 304). At the regional level, 9 land use and vegetation cover classes were initially selected. As will be shown in the results section, there was a high level of spectral confusion, and it was necessary to merge some classes that had close spectral ranges that made their separation ambiguous. The classification was rerun at case study level (case studies shown in Figure 2.3) with a reduced number of classes, following similar procedures (as the regional level), also with 3 replications. Different case studies have different numbers of classes and different combinations of classes; at the regional level, Budongo, Bugoma, and Buliisa, the number of classes was 8, 5, 4 and 4 respectively.

Figure 2.2 Map of study area showing the landscape, and 4 case study areas: Budongo case (red), Bugoma case (blue), forests including corridors (yellow) and the semi-arid region (purple outline)
2.3.2.3 Post-classification processing

Post-classification visual assessment: In the exploratory phase, eyeballing the classification performance and the distribution of classes in the landscape across the entire stack of imagery was necessary to pick out striking patterns. The emphasis was on identifying regions that have experienced dramatic land use and vegetation cover changes. Case studies were then selected following this close scrutiny. These were then delineated and reclassified with fewer dominant classes in that region.

Detection of forest cover change: As the forest had a stable signal (as explained in sections 2.4.5 and 2.5: crops [e.g. palm oil and bananas] that are known to have a similar signal (Hansen et al. 2013) are generally not grown in this region), change detection was undertaken for this class. The forest class was created as a binary image in ArcGIS 10, with forest allocated values of ‘1” and the other classes assigned “0”. Image differencing was then undertaken, where more recent scenes were subtracted from older ones. It was therefore possible to detect change of land cover from "forested" to "not forested". The layer of the protected forest boundaries obtained from Uganda’s National Forest Authority was overlaid on each binary image, and the forest cover within the boundary delineated and computed in ArcGIS. It was therefore possible to compute areas of forest on private land by subtracting the area under protected forest from the total forest cover within each case. Protected forests are government owned: all forests outside delineated areas are on private land, and categorised as unprotected.

Statistical analyses: regression analyses of area under each land use versus time were undertaken for the entire time-series for all classes at the regional- and selected local-scales, with the level of statistical significance set at p<0.05. The assumptions that go into linear regression do not depend on sample size (provided there are more than 2 points): one assumes that the data are linear, independent with finite variance. Significance measures depend further on the assumption that errors are independent and normally distributed with zero mean. In many cases where regression analysis is applied these assumptions are untestable – assessing whether the errors have constant variance, for example, is often not possible, as one only has one data point for each instance of the independent variable – this is generally the case for time series. However, it is defensible to quote p-values as long as it is borne in mind that these
represent the probability that a pure random process would be likely to generate the observed results by chance, given the above assumptions – small numbers of data points would then be expected to give rise to large p-values, since the effects of random scatter is larger and more likely to swamp systematic changes. The fact that very clear linear trends are obtained with highly significant p-values at such small sample sizes would arguably favour an interpretation in which the trend line really represents a systematic decline, rather than the effects of a random process.

**High resolution imagery classification:** Until now, the processing has described work undertaken on the Landsat images. As only one scene obtained from UK-DMCii was analysed, and given that the data was provided in a ready-to-use format, with 3 bands, (2, 3 and 4), the processing followed that of Landsat image classification from (and including) the atmospheric correction step.

**2.3.3 Accuracy Assessment: Ground Truthing**

817 ground truth points accurate to approximately 2–5m were collated between October 2013 and March 2014 (using a Garmin GPS 62). The points were gathered with the help of four graduate field assistants, and sampling was largely based on uniform land parcels found during household surveys and in transect drives between fieldwork sites. We did not cover the entire region (for time and budget reasons) and points were strictly limited to areas where fieldwork was conducted. Frequent stops were made during transect drives to assess how mixed land uses might affect the classification. While uniform classes such as commercial tea and sugarcane growing could be seen to cover a wide area, driving through them was inhibited by poor access; because these are extensive, error in position may be less significant and identification of field points on the map more likely to be correct, so a poor classification of this on the ground, as a result of few points collected may not necessarily be interpreted as an overall poor classification. Focus was less on ground truthing the forest class (whose classification was relatively stable), but more on classes that might get mixed up in the classification although the problem is that positional accuracy may be poor for small parcels of land. We however took coordinates of small forest patches which were located on private landholdings. The total forest points taken were therefore few (only 20 in total).
The ground coordinates were used to assess classification accuracy of the most recently acquired Landsat image (14th Jan, 2014). The data were also plotted against the earliest image (14th Jan, 1985). The rationale for this was to test whether the current land uses where ground truthing was undertaken could have been different from the earlier period (although results from this ought to be interpreted cautiously). Results were obtained from the 3 classification replications to assess variability in the classification accuracy. Producer, user and overall accuracies were computed. The producer’s accuracy (also referred to as error of omission) refers to the probability that a certain land use/vegetation cover of an area on the ground is classified as such, while the user accuracy (error of commission) refers to the probability that a pixel labelled as a certain land cover class in the map is really that class; and the overall accuracy is the measure of the correctly classified pixels (Binaghi et al. 1999; Foody 2002). The results of accuracy assessment were summarised in confusion matrices.

**Classification Assessment against Ground Truth Data Results**

At the regional scale, 817 ground truth points were collected, and small-scale farming was the largest percentage, followed by built-up area, at 63.7% and 22.9% respectively. The other land uses and vegetation cover have low representation, all fewer than 6% as follows: commercial farming, savanna vegetation, tropical high forest and bare ground having percentages as low as 5.4%, 3.4%, 2.4%, and 2.1% respectively. Against the 2014 image, small-scale farming is well classified, with 409 ± 10.7 (mean ± standard deviation) points on average correctly classified (Table 2.5a), translating to good producer and user accuracies at ~78.4% and 72.1% respectively (Table 2.8). Given the low representation, the other land uses and vegetation cover are poorly represented on the map with producer accuracies less than 30%, although savanna vegetation has a good agreement at ~79.8% (Table 2.8).

At the regional scale, when the ground truth points are compared to the 1985 classification, small-scale farming and savanna vegetation are better represented (Table 2.5b), with good producer but low user accuracies, ~85.0%, 65.7%, and 85.7% and 52.3% respectively (Table 2.7). Notably, the tropical high forest has a higher map total in the 1985 than in the 2014 classification (Tables 2.5a, and b), although the user accuracy is not comparatively better (Table 2.8). Built-up area user accuracy is undefined in the 1985 classification as it was not included in the earlier classification.
Of the total points collected, 382 were in the Budongo region. For this subset, ~37%, 8.6%, 3.4% are small-scale farming, built-up areas and commercial farming respectively while tropical high forest is poorly represented at ~0.5%, and no sampled point represented bare ground, when compared with the 2014 classification (Table 2.6a). Small scale farming has a relatively good user and producer accuracy, 65.1±10.3%, and 64.4±0.9% (mean ± standard deviation) respectively, and the other classes performed poorly although tropical high forest has a relatively good user accuracy (~67%) but the points were very few. Against the 1985 classification, small-scale farming has a high producer accuracy 92.8% although the user accuracy is low (56.9%; Table 2.6b). Notably, tropical high forest map totals in 1985 are higher than in the 2014 classification (Tables 2.6a, and b). The 20 permanent sampling forest plots obtained from the National Forest Authority (Appendix 2.2) are correctly located in the ‘forest class’ in both the 1985 and 2014 classification, representing 100% accuracy.

In the Bugoma case study, small-scale farming dominated the ground truth data gathered, accounting for ~73% of the total (205) against the 2014 classification (Table 2.6a), whose producer and user accuracies are high, at ~81.3% and 90.8% respectively (Table 2.7). When compared against the 1985 classification, only the user accuracy is high at ~94.1% (Tables 2.6b and 2.7). Other land uses have varied classification accuracies when compared against both classified images; for instance tropical high forest compared against the 2014 maps has a low producer accuracy (~6.67%) but a high user accuracy (100%), but it is important to note that it has very few ground truth points (Tables 2.7a, b and 2.8).

Generally, in all the cases, when ground truth points are compared against both the 2014 and 1985 classification, the overall accuracies are relatively low, except in the Bugoma case (2014 overall accuracy ~73.7%). The drier (Buliisa) region and forest corridor ground truth data are too few to be presented for standalone evaluation, although they are included in the regional-scale accuracy assessment.
Table 2.5a Regional–level matrix of mean number of ground coordinates compared to Jan-14-2014 classification map

<table>
<thead>
<tr>
<th>On Ground/ On Map</th>
<th>Tropical High Forest</th>
<th>Small scale farming</th>
<th>Commercial farming</th>
<th>Built–up area</th>
<th>Savanna vegetation</th>
<th>Bare ground</th>
<th>Map total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tropical High Forest</td>
<td>3 (0.58)</td>
<td>2 (0.00)</td>
<td>1 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>6 (0.58)</td>
</tr>
<tr>
<td>Small scale farming</td>
<td>14 (1.53)</td>
<td>409 (10.69)</td>
<td>27 (1.15)</td>
<td>112 (6.03)</td>
<td>2 (0.58)</td>
<td>7 (0.58)</td>
<td>571 (8.89)</td>
</tr>
<tr>
<td>Commercial farming</td>
<td>2 (1.00)</td>
<td>75 (9.17)</td>
<td>13 (0.58)</td>
<td>12 (1.15)</td>
<td>1 (0.00)</td>
<td>0 (0.58)</td>
<td>103 (9.07)</td>
</tr>
<tr>
<td>Built–up area</td>
<td>0 (0.58)</td>
<td>14 (2.31)</td>
<td>4 (0.58)</td>
<td>39 (7.73)</td>
<td>1 (2.31)</td>
<td>2 (0.58)</td>
<td>61 (10.69)</td>
</tr>
<tr>
<td>Savanna vegetation</td>
<td>0 (0.00)</td>
<td>11 (2.31)</td>
<td>0 (0.00)</td>
<td>12 (3.79)</td>
<td>22 (2.08)</td>
<td>7 (0.00)</td>
<td>52 (4.73)</td>
</tr>
<tr>
<td>Bare ground</td>
<td>0 (0.00)</td>
<td>10 (4.73)</td>
<td>0 (0.00)</td>
<td>12 (3.46)</td>
<td>1 (0.00)</td>
<td>0 (0.00)</td>
<td>23 (8.14)</td>
</tr>
<tr>
<td><strong>Ground total</strong></td>
<td>20 (0.00)</td>
<td>521 (0.00)</td>
<td>44 (0.00)</td>
<td>187 (0.00)</td>
<td>28 (0.00)</td>
<td>17 (0.00)</td>
<td>817 (0.00)</td>
</tr>
</tbody>
</table>

Means of counts rounded to the nearest whole number; standard deviations in parenthesis reflecting results from 3 replications

Table 2.5b Regional–level matrix of mean number of ground coordinates compared to Jan-14-1985 classification map

<table>
<thead>
<tr>
<th>On Ground/ On Map</th>
<th>Tropical High Forest</th>
<th>Small scale farming</th>
<th>Commercial farming</th>
<th>Built–up area</th>
<th>Savanna vegetation</th>
<th>Bare ground</th>
<th>Map total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tropical High Forest</td>
<td>6 (0.00)</td>
<td>22 (2.31)</td>
<td>1 (0.00)</td>
<td>1 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>30 (2.31)</td>
</tr>
<tr>
<td>Small scale farming</td>
<td>13 (0.00)</td>
<td>443 (5.71)</td>
<td>39 (2.08)</td>
<td>167 (5.20)</td>
<td>3 (0.00)</td>
<td>9 (0.00)</td>
<td>674 (14.42)</td>
</tr>
<tr>
<td>Commercial farming</td>
<td>1 (0.00)</td>
<td>35 (2.00)</td>
<td>2 (0.00)</td>
<td>3 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>41 (2.00)</td>
</tr>
<tr>
<td>Built–up area</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
</tr>
<tr>
<td>Savanna vegetation</td>
<td>0 (0.00)</td>
<td>6 (9.81)</td>
<td>1 (2.31)</td>
<td>11 (6.08)</td>
<td>24 (0.00)</td>
<td>8 (0.58)</td>
<td>50 (18.50)</td>
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<tr>
<td>Bare ground</td>
<td>0 (0.00)</td>
<td>15 (3.79)</td>
<td>0 (0.58)</td>
<td>5 (1.00)</td>
<td>1 (0.00)</td>
<td>0 (0.58)</td>
<td>22 (5.57)</td>
</tr>
<tr>
<td><strong>Ground total</strong></td>
<td>20 (0.00)</td>
<td>521 (0.00)</td>
<td>44 (0.00)</td>
<td>187 (0.00)</td>
<td>28 (0.00)</td>
<td>17 (0.00)</td>
<td>817 (0.00)</td>
</tr>
</tbody>
</table>

Table 2.6a Budongo case study – matrix of mean number of ground coordinates compared to Jan-14-2014 classification map

<table>
<thead>
<tr>
<th>On Ground/ On Map</th>
<th>Tropical High Forest</th>
<th>Small scale farming</th>
<th>Commercial farming</th>
<th>Built–up area</th>
<th>Bare ground</th>
<th>Map total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tropical High Forest</td>
<td>2 (0.00)</td>
<td>0 (0.00)</td>
<td>1 (0.00)</td>
<td>0 (0.00)</td>
<td>1 (0.00)</td>
<td>3 (0.00)</td>
</tr>
<tr>
<td>Small scale farming</td>
<td>1 (1.00)</td>
<td>143 (22.50)</td>
<td>20 (4.16)</td>
<td>56 (11.02)</td>
<td>3 (0.00)</td>
<td>222 (37.51)</td>
</tr>
<tr>
<td>Commercial farming</td>
<td>1 (0.58)</td>
<td>55 (14.00)</td>
<td>13 (4.04)</td>
<td>15 (8.89)</td>
<td>0 (0.00)</td>
<td>84 (24.43)</td>
</tr>
<tr>
<td>Built–up area</td>
<td>0 (0.00)</td>
<td>20 (9.45)</td>
<td>5 (0.58)</td>
<td>33 (18.52)</td>
<td>0 (0.00)</td>
<td>58 (26.91)</td>
</tr>
<tr>
<td>Bare ground</td>
<td>1 (1.15)</td>
<td>1 (1.00)</td>
<td>0 (0.00)</td>
<td>13 (19.73)</td>
<td>0 (0.00)</td>
<td>15 (19.47)</td>
</tr>
<tr>
<td><strong>Ground total</strong></td>
<td>5 (0.00)</td>
<td>219 (0.00)</td>
<td>38 (0.00)</td>
<td>117 (0.00)</td>
<td>3 (0.00)</td>
<td>382 (0.00)</td>
</tr>
</tbody>
</table>

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### Table 2.6b Budongo case study – matrix of mean number of ground coordinates compared to Jan-14-1985 classification map

<table>
<thead>
<tr>
<th>On Ground / On Map</th>
<th>Tropical High Forest</th>
<th>Small scale farming</th>
<th>Commercial farming</th>
<th>Built-up area</th>
<th>Bare ground</th>
<th>Map total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tropical High Forest</td>
<td>3 (0.00)</td>
<td>10 (0.00)</td>
<td>1 (0.00)</td>
<td>1 (0.00)</td>
<td>0 (0.00)</td>
<td>15 (0.00)</td>
</tr>
<tr>
<td>Small scale farming</td>
<td>2 (0.00)</td>
<td>203 (5.58)</td>
<td>36 (1.53)</td>
<td>114 (0.58)</td>
<td>3 (0.00)</td>
<td>358 (2.31)</td>
</tr>
<tr>
<td>Commercial farming</td>
<td>0 (0.00)</td>
<td>1 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>1 (0.00)</td>
</tr>
<tr>
<td>Built-up area</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
</tr>
<tr>
<td>Bare ground</td>
<td>0 (0.00)</td>
<td>5 (0.58)</td>
<td>1 (1.53)</td>
<td>2 (0.58)</td>
<td>0 (0.00)</td>
<td>8 (2.31)</td>
</tr>
<tr>
<td>Ground total</td>
<td>5 (0.00)</td>
<td>219 (0.00)</td>
<td>38 (0.00)</td>
<td>117 (0.00)</td>
<td>3 (0.00)</td>
<td>382 (0.00)</td>
</tr>
</tbody>
</table>

### Table 2.7a Bugoma case study – matrix of mean number of ground coordinates compared to Jan-14-2014 classification map

<table>
<thead>
<tr>
<th>On Ground / On Map</th>
<th>Tropical High Forest</th>
<th>Small scale farming</th>
<th>Commercial farming</th>
<th>Bare ground</th>
<th>Map total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tropical High Forest</td>
<td>1 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>1 (0.00)</td>
</tr>
<tr>
<td>Small scale farming</td>
<td>11 (2.31)</td>
<td>150 (4.51)</td>
<td>5 (0.58)</td>
<td>0 (0.00)</td>
<td>166 (7.09)</td>
</tr>
<tr>
<td>Commercial farming</td>
<td>3 (2.31)</td>
<td>11 (2.65)</td>
<td>0 (0.58)</td>
<td>0 (0.00)</td>
<td>14 (2.65)</td>
</tr>
<tr>
<td>Bare ground</td>
<td>0 (0.00)</td>
<td>23 (7.09)</td>
<td>0 (0.58)</td>
<td>0 (0.00)</td>
<td>24 (7.64)</td>
</tr>
<tr>
<td>Ground total</td>
<td>15 (0.00)</td>
<td>184 (0.00)</td>
<td>6 (0.00)</td>
<td>0 (0.00)</td>
<td>205 (0.00)</td>
</tr>
</tbody>
</table>

### Table 2.7b Bugoma case study – matrix of mean number of ground coordinates compared to Jan-14-1985 classification map

<table>
<thead>
<tr>
<th>On Ground / On Map</th>
<th>Tropical High Forest</th>
<th>Small scale farming</th>
<th>Commercial farming</th>
<th>Bare ground</th>
<th>Map total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tropical High Forest</td>
<td>2 (1.53)</td>
<td>4 (1.15)</td>
<td>0 (0.00)</td>
<td>0 (0.00)</td>
<td>6 (2.65)</td>
</tr>
<tr>
<td>Small scale farming</td>
<td>3 (0.58)</td>
<td>102 (11.55)</td>
<td>3 (0.00)</td>
<td>0 (0.00)</td>
<td>109 (11.85)</td>
</tr>
<tr>
<td>Commercial farming</td>
<td>2 (1.53)</td>
<td>6 (1.53)</td>
<td>1 (1.73)</td>
<td>0 (0.00)</td>
<td>9 (1.00)</td>
</tr>
<tr>
<td>Bare ground</td>
<td>7 (0.00)</td>
<td>72 (11.85)</td>
<td>2 (1.73)</td>
<td>0 (0.00)</td>
<td>81 (10.12)</td>
</tr>
<tr>
<td>Ground total</td>
<td>15 (0.00)</td>
<td>184 (0.00)</td>
<td>6 (0.00)</td>
<td>0 (0.00)</td>
<td>205 (0.00)</td>
</tr>
</tbody>
</table>
Table 2.8 Mean percentage of Producer, User and Overall 'accuracy' measures of the 2014 and 1985 classification (standard deviations in parenthesis)

<table>
<thead>
<tr>
<th>Scale</th>
<th>Entire region</th>
<th>Budongo</th>
<th>Bugoma</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Producer accuracy (%)</td>
<td>User accuracy (%)</td>
<td>Producer accuracy (%)</td>
</tr>
<tr>
<td>Tropical High Forest</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>16.7 (2.9)</td>
<td>30.0 (0.0)</td>
<td>52.4 (1.4)</td>
</tr>
<tr>
<td>Small scale farming</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>78.4 (2.1)</td>
<td>85.0 (1.4)</td>
<td>72.1 (0.4)</td>
</tr>
<tr>
<td>Commercial farming</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>28.8 (1.3)</td>
<td>4.50 (0.0)</td>
<td>12.3 (0.2)</td>
</tr>
<tr>
<td>Built-up area</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>20.7 (3.9)</td>
<td>0.00 (0.0)</td>
<td>64.5 (0.3)</td>
</tr>
<tr>
<td>Savanna vegetation</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>79.8 (7.4)</td>
<td>85.7 (0.0)</td>
<td>38.4 (2.3)</td>
</tr>
<tr>
<td>Bare ground</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.00 (0.0)</td>
<td>1.9 (3.4)</td>
<td>0.00 (0.0)</td>
</tr>
<tr>
<td>Overall accuracy</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>59.4 (1.8)</td>
<td>58.1 (0.9)</td>
<td>49.8 (2.8)</td>
</tr>
</tbody>
</table>

Only classes included in the classification are indicated in the table (blanks mean such classes were not included in reclassification of those cases) ∞ - undefined: land use not existent on the map or on ground, and classified as zeros on ground or map giving the denominator a value of zero.

**Forest Classification Accuracy Assessment**

Historical maps to test the derived forest extents were lacking, I therefore relied mostly on the consistency of the forest signal to pick out patterns (as is the case in Hansen et al. 2013). For instance the 20 permanent sampling plots demarcated by Uganda’s National Forest Authority within Budongo, were correctly mapped within this classification, and appeared to lie consistently in the forest in the entire time-series. The forestry body has plots in Bugoma too, although these are not geo-referenced. The Landsat image classification obtained on 5th Dec 2010 was compared with a UK-DMC image taken on 4th Dec 2010.

**Forest Classification Accuracy Assessment Results**

The results of the classification of the Landsat scene obtained on 5th December, 2010 were compared to that of the UK-DMC scene obtained on 4th December, 2010 (the data are only a day apart). Remarkably, the forest classification was the most robust in the three cases selected with absolute differences ~ 2.9%, 1.3% and 1.5% in the Budongo, Bugoma and forest corridor cases respectively (Figure 2.22 a, b and c). A comparison at the entire region was not possible as the UK-DMC scene did not cover it (the region) adequately.
Small-scale and commercial farming are less variable than bare ground in the 3 case studies when UK-DMC and Landsat classifications were compared (Figure 2.22). For instance, absolute differences in small-scale farming are ~ 12.0%, 10.9% and 6.9%, and commercial farming differences are ~ 20.0%, 31.5%, and 24.2% for Budongo, Bugoma and forest corridor cases respectively. Bare ground differences are as big as ~ 60.3%, 42.6% and 58.3% for Budongo, Bugoma and forest corridor cases respectively.

The two scale analysis – the landscape and local levels – enabled two, independent classifications, and provided another measure of consistency of allocation of pixels to the forest class. Variability in classification between the two scales of analysis, and within each scene, is minimal, often deviating in the range of 5-10%, suggesting that the forest signal is consistent and therefore the derived quantities are mostly meaningful. While the classification was re-run at the two scales, we see general agreement in the allocation of pixels and forest extents – but the local scale analysis at least highlights the regions where changes have been most prominent (in more detail with easier visualisation).

While the Global Forest Watch dataset by Hansen et al. (2013) is recognised, it is not directly used in the accuracy assessment of forest cover change in this study. The dataset has some similarities, showing the successful protection of Budongo and Bugoma for instance, but the periods under investigation are different. This study considers the period 2002–2010 for which clear remote sensing data are available over the entire region, while the Global Forest Watch data covers the period 2000–2012. As shown in the results, the losses in forest cover around both Budongo and Bugoma are sensitive to time differences, where by losses around Budongo ended possibly by 2010, essentially leaving no clearable forest patches, while those around Bugoma proceed right up to 2014. It is for this reason therefore that a comparison between this study's forest cover change within this period (2002–2010) to that of the Global Forest Watch (2000–2012) would provide misleading assessments, even though there are some regions of agreement.
Figure 2.3 Comparison of area of land use/vegetation cover between UK-DMC and Landsat imagery obtained on Dec-04-2010 and Dec-05-2010 respectively in a) Budongo b) Bugoma and c) Forests and corridors case studies (bars represent standard deviation – a measure of mismatches of pixels. Forest class is robust in the classification across all cases; spectral confusion is more extensive in the other classes)
2.4 Results

2.4.1 Regional-level Spatio-temporal Patterns

Spatial patterns of selected scenes of spectrally-driven classification with 9 classes at the regional level are presented in Figure 2.4. Spatially, high density forest is stable but other classes with closer spectral ranges switched considerably; for instance, low density forest, savanna vegetation and wetland were often spatially mixed. This variability is evident in the large error bars associated with each class seen in the temporal patterns (Figure 2.5). Regression analyses suggest that linear expansion of commercial farming and built-up areas occurred ($r^2>0.7$, $p<0.05$: Table 2.9). Commercial farming expansion accelerated rapidly after 2002, while built-up areas expanded relatively more recently, after 2010 (Figure 2.5).

The region immediately above Budongo forest is a protected area, Murchison Falls National Park: under ideal conditions this region is dominated by savanna vegetation and colonising forest. The time-series analysis (based on rigorous selection of training sites) however gives rather mixed land uses and vegetation cover in this region, a sign of confusion between farming and savanna vegetation classes (Figure 2.4).
Figure 2.4 Spatial patterns of 9 land use and vegetation cover classes at the regional level (selected scenes to show variability in classification. Classes with similar spectral ranges are likely to get mixed up in the classification obscuring rigorous change detection)
Figure 2.5 Regional–level land use and vegetation cover dynamics between 1985 and 2014 with 8 classes (the ‘water body’ class was not included here: bars represent standard deviations)

There are hardly any linear patterns at the regional level (except for commercial farming and built–up areas). This is partly due to classification ambiguities, where classes with tightly close spectral signature ranges may be misclassified. Savanna vegetation, small scale farming and bare ground varied considerably.

Table 2.9 Regional–level linear regression results (Model $y=\alpha x + \beta$)

<table>
<thead>
<tr>
<th>Class</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>S.E</th>
<th>$r^2$</th>
<th>p</th>
<th>95% CI $\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Commercial farming</td>
<td>0.1508</td>
<td>-4395.2</td>
<td>420.2474</td>
<td>0.7342</td>
<td>0.0138</td>
<td>0.046, 0.254</td>
</tr>
<tr>
<td>Built–up area</td>
<td>0.0153</td>
<td>-483.39</td>
<td>42.4776</td>
<td>0.7378</td>
<td>0.0133</td>
<td>0.005, 0.026</td>
</tr>
</tbody>
</table>

CI – Confidence Interval (lower bound and upper bound separated by a comma)
2.4.2 Local-scale Spatio-temporal Patterns: Budongo Region Case Study (1)

Overall, spatially and temporally, variability of the classification is much lower than at the regional level. The forest classes (low and high density) were merged into one (forest) class in the reclassification. Generally, forest cover declined linearly in this region between 1985–2014 ($r^2=0.75$, $p=0.01$). Small forest fragments away from the big block were mainly eroded (Figure 2.6), but the temporal patterns are dominated by the large forest block that remains fairly stable over this period (Figure 2.7). Notably, the general rate of forest loss is low ($\alpha=-0.0074$; Table 2.10).

Commercial farming of sugarcane increased linearly by nearly 7 times in the last 30 years ($r^2=0.82$, $p=0.005$), starting around an initial nucleus near Kibwona and spreading outwards, covering nearly the entire southern section of the Budongo region (Figure 2.5). This increase accelerated mainly after 1995, by nearly 5 times the overall rate ($\alpha=0.05$, $r^2=0.92$, $p<0.05$; Figure 2.6). There is spatial evidence of commercial farming expanding over previously forest fragments, and may have replaced small-scale farmlands, although this relationship is generally weak ($r^2=0.58$, $p=0.04$) as shown in Figure 2.8.

Also, built-up areas have expanded in this part of the landscape in the last 30 years, mainly away from the forest, but close to the sugarcane farming industry and Masindi town (the major rural town in the area). In 1985, built areas were nearly undetected and growth has been mostly recent, 2002–2010 (Figure 2.6).

Surprisingly, the area under small-scale farming decreased ($\alpha=-0.02$, $r^2 = 0.81$, $p=0.004$), but was weakly correlated with bare ground, although not significantly ($r^2=0.62$, $p>0.05$). The data show that, on the whole, non-forested areas increased at the expense of forest in this area, although the gradient of change is nearly undetectable (Table 2.10).
Figure 2.6 Spatial patterns of 5 land use and vegetation cover classes in the Budongo region case study (one of three replications selected per scene for presentation purposes)
Figure 2.7 Land use and vegetation cover dynamics between 1985 and 2014 with 5 classes in and around Budongo forest (bars represent standard deviations)

\[ \log(y) = 6.647 - 0.00146 \times x \quad R^2 = 64.3\% \]

Figure 2.8 Relationship between small-scale farming and commercial farming in the Budongo region in the last 30 years (there is some evidence of commercial farming replacing small-scale farmlands in the remote sensing imagery, corroborated by this figure, although this relationship is generally weak)

\[ n = 7 \quad \text{RMSE} = 0.1082664 \]
Table 2.10 Budongo region linear regression results (Model \(y=\alpha x + \beta\))

<table>
<thead>
<tr>
<th>Class</th>
<th>(\alpha)</th>
<th>(\beta)</th>
<th>S.E</th>
<th>(r^2)</th>
<th>(p)</th>
<th>95% CI (\alpha)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tropical High Forest</td>
<td>-0.0074</td>
<td>610.80</td>
<td>19.5619</td>
<td>0.7509</td>
<td>0.0116</td>
<td>-0.012, -0.003</td>
</tr>
<tr>
<td>Commercial farming</td>
<td>0.0195</td>
<td>-571.89</td>
<td>42.9095</td>
<td>0.8192</td>
<td>0.0054</td>
<td>0.009, 0.023</td>
</tr>
<tr>
<td>Small-scale farming</td>
<td>-0.0228</td>
<td>1461.50</td>
<td>47.2331</td>
<td>0.8160</td>
<td>0.0040</td>
<td>-0.035, -0.011</td>
</tr>
<tr>
<td>Built-up area</td>
<td>0.0030</td>
<td>-95.943</td>
<td>8.1759</td>
<td>0.7504</td>
<td>0.0139</td>
<td>0.001, 0.005</td>
</tr>
<tr>
<td>Non-forest (SSF+BG+CF+BA)</td>
<td>0.0112</td>
<td>953.02</td>
<td>30.6704</td>
<td>0.7418</td>
<td>0.0128</td>
<td>0.004, 0.019</td>
</tr>
</tbody>
</table>

SSF – Small-scale farming, BG – Bare ground, CF – Commercial farming, BA – Built-up area, CI – Confidence Interval (lower bound and upper bound separated by a comma)

2.4.3 Local-scale Spatio-temporal Patterns: Bugoma Region Case Study (2)

In the region surrounding Bugoma forest, the most dramatic linear decline was in the forest class \((r^2=0.83, p=0.004; \text{Table 2.11})\). The large forest block remained relatively stable over the 30-year period (Figure 2.9), and this dominated the overall forest pattern (Figure 2.10). Forest loss appears mostly to have taken place in the south-east and mid south-west; although there were regions of infilling at the western forest boundary (Figure 2.9 e and f).

Small-scale farming increased in the 30-year period at a linear rate \((\alpha=0.02, r^2=0.95, p<0.001)\), and was the dominant farming type. The tea estate adjacent to the forest remained relatively unchanged, and unlike in the Budongo case where sugarcane expanded, here, there was no linear pattern of growth or loss.

What was classified as previously bare ground appears to have been replaced by small-scale farming, which has grown in a linear manner; the two classes are strongly anti-correlated \((r^2=0.8, p=0.004; \text{see also Figure 2.10})\). Overall, the non-forested area (which combines the farming and bare ground classes) increased at a marginally linear rate \((\alpha=0.005)\) at the expense of the forested area \((r^2=0.83, p=0.004)\). Additionally, there is generally less spatial class variability in this small area classified as seen from the small error bars (Figure 2.10).
Figure 2.9 Spatial patterns of 4 land use and vegetation cover classes in the Bugoma region case study (one of three replications selected per year for presentation purposes)
Figure 2.10 Trends in selected land uses and vegetation cover in the Bugoma case study (bars represent standard deviations. There is less classification variability; tropical high forest declined as small-scale farming increased)

Table 2.11 Bugoma case linear regression results (Model $y=\alpha x + \beta$)

<table>
<thead>
<tr>
<th>Class</th>
<th>$\alpha$</th>
<th>$\beta$</th>
<th>S.E</th>
<th>$r^2$</th>
<th>$p$</th>
<th>95% CI $\alpha$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tropical High Forest</td>
<td>-0.0045</td>
<td>517.76</td>
<td>9.6224</td>
<td>0.8282</td>
<td>0.0044</td>
<td>-0.007, -0.002</td>
</tr>
<tr>
<td>Small-scale farming</td>
<td>0.0177</td>
<td>-363.68</td>
<td>18.7081</td>
<td>0.9508</td>
<td>0.0002</td>
<td>0.013, 0.022</td>
</tr>
<tr>
<td>Bare ground</td>
<td>-0.0136</td>
<td>614.83</td>
<td>28.1175</td>
<td>0.8336</td>
<td>0.0040</td>
<td>-0.021, -0.007</td>
</tr>
<tr>
<td>Non-forest (SSF+BG+CF)</td>
<td>0.0046</td>
<td>290.21</td>
<td>9.6224</td>
<td>0.8337</td>
<td>0.0044</td>
<td>0.002, 0.007</td>
</tr>
</tbody>
</table>

CI – Confidence Interval (lower bound and upper bound separated by a comma)
2.4.4 Local-scale Spatio-temporal Patterns: Buliisa Case Study (3)

In the drier region within the landscape (see Plate 2.1), the dominant classes were small-scale farming, savanna grasslands, bare ground and built-up areas. Small-scale farming is dominant in the north-eastern, eastern and some central zones while bare ground is generally widely spread, with savanna grassland sparsely located in nearly all regions, and throughout the 30-year period (Figure 2.11). Built-up areas are concentrated near the western end and in some central zones.

There is temporal variability between small-scale farming and bare ground, and although there is no obvious spatial evidence for the switching between each other, the regression analyses indicate that there is moderately strong and highly significant relationship between the two ($r^2=0.7$, $p<0.0001$; Figure 2.13). There is a weak linear expansion of small scale farming in the study period ($r^2=0.5$, $p=0.002$; Table 2.12), although within scene specific classification, there was high spatial variability evident from some 'large' error bars (Figure 2.12).

During reclassification of this region, built-up areas were not visible in older imagery, and were therefore included in more recent ones. Spatially, there is evidence of recent expansion of built areas around Buliisa town, and although few points are included in the temporal pattern beyond 2010, the data suggests that there is a weak linear increase ($r^2=0.3$, $p=0.2$, Table 2.12; Figure 2.12).

Plate 2.1 Dry region of Buliisa as viewed from above (left) and on ground (right)
(The aerial image was obtained from Google Earth in 2014, taken on 6th Jan, 2011; the ground photo was taken in the dry season during fieldwork in Feb, 2014; these are not necessarily the same scene).
Figure 2.11 Spatial patterns of 4 land use and vegetation cover classes in the Buliisa region case study (built-up areas were more distinct in recent imagery than in the older ones)
Figure 2.12 Trends in selected land uses and vegetation cover in the Buliisa case study (bars represent standard deviations)

Figure 2.13 Relationship between Small-scale farming and bare ground in Buliisa between 1985–2014
(The two land uses are anti-correlated; small-scale farming could be replacing formerly bare ground in seasonal patterns, but the highly unstable signal of each land use makes it difficult to ascertain if this is the case)
Table 2.12 Buliisa case linear regression results (Model y=αx + β)

<table>
<thead>
<tr>
<th>Class</th>
<th>α</th>
<th>β</th>
<th>S.E</th>
<th>r²</th>
<th>p</th>
<th>95% CI α</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small-scale farming</td>
<td>0.0049</td>
<td>-74.851</td>
<td>17.9124</td>
<td>0.4958</td>
<td>0.0018</td>
<td>0.002, 0.007</td>
</tr>
<tr>
<td>Bare ground</td>
<td>-0.0052</td>
<td>378.34</td>
<td>25.3667</td>
<td>0.3443</td>
<td>0.0133</td>
<td>-0.009, -0.001</td>
</tr>
<tr>
<td>Built-up area</td>
<td>0.0011</td>
<td>-35.586</td>
<td>5.6567</td>
<td>0.3073</td>
<td>0.0209</td>
<td>0.0001, 0.002</td>
</tr>
</tbody>
</table>

2.4.5 Spatio-temporal Forest Cover Change Detection

Forest cover change detection was conducted at the regional scale, and for the 3 case studies. The results from each is presented in turn.

2.4.5.1 Forest Cover Change at the Regional Scale

Overall, between 1985 and 2014, there was a 10.7% loss in total forest cover at the regional scale, a rate of 0.4% forest loss per year, although this loss rate was not significant (p=0.16) at the 5% level (Figure 2.15). Forest increased in the earlier period of analysis, 1985–1990 by 7.0%, but this is rapidly followed by a 10.5% loss between 1990–1995, in the same regions where there had been regrowth, and some 4.4% gains in 1995–2002. This rather confused picture begins to become clearer when the spatial patterns are examined. The initial increases appears to be widely distributed across the landscape (Figure 2.14a), whereas later gains (after 2002) seem to be concentrated in the north (Figures 2.14b and c respectively), located especially in Murchison Falls National Park. Many of the more southern regions that had experienced recovery were followed by losses especially in the forest corridors, and 3.3% was lost in total between 2002–2010 in spite of gains in the National Park (Figure 2.14c). Further forest loss of 7.7% occurred in the most recent period 2010–2014 (Figure 2.14e, 2.15).

Spatially, the large protected forest blocks remained relatively stable; deforestation was mostly patchy, situated in the corridor and riverine forests. There were, however, some regions of forest expansion in the period of analysis (Figure 2.14). Forest losses were predominantly in the regions south of Budongo, in the forest corridors ('linking' Budongo and Bugoma), and south (and west) of Bugoma. Forest gain can mostly be seen in the region immediately north of Budongo forest (located in Murchison Falls National Park), and in relatively recent periods, 2002–2010 and 2010–2014 (Figure 2.14d and e respectively). Figure 2.14f shows the total change over the whole period, indicating large overall losses in the riverine and forest corridor areas. Forest gains and offsets in various parts of the landscape obscure local–level dynamics and provide a trend that shows a small overall decrease (Figure 2.15). The noisy signal reflects the spatial pattern of loss and gain, but, the largely unchanged protected forest areas mask the more serious local losses in the rest of the region. For this reason the analysis focussed further on the two major protected forests and the area between them in order to gain a finer-detailed view of the changes.
Figure 2.14 Forest cover change at the regional level between:

Figure 2.15 Trend of total forest cover change at the regional level (bars represent standard deviations)

There is a weak linear relationship between acreage of forest cover and time; which generally shows that forest cover has remained relatively constant over the 30-year period, although this relationship is not significant.
2.4.5.2 Forest Cover Change between the Protected Forests: Forest Corridors

To assess these local changes in more detail, the areas between the large protected forest blocks, of Budongo (to the NE), ‘Wambabaya’ (central) and Bugoma (to the SW of Figure 2.16) are examined. There is a marked forest cover loss of 134 km\(^2\) between 1985–2014 (\(r^2=0.63\), p=0.03). Much of this loss has occurred on private land (Figure 2.16). Losses are most extensive in a relatively recent period, 2002–2010 (Figure 2.16d), although the periods compared are not of equal length. However, there is a rather more convincing and statistically–significant and largely linear trend, notwithstanding a slight increase from 1990 to 2002. Temporally, however, major losses can be traced from 1995 to 2014 (\(r^2=0.93\), p=0.03; Figure 2.17). Thus, although there is an overall decline of 134 km\(^2\) in the total forest cover, the temporal pattern shows that this is mixed with some increases, mostly dominated by the protected forest blocks (Figure 2.17). The protected forest blocks appeared to be stable in the entire period with an overall marginal increase of 1.9% (\(r^2=0.9\), p=0.001); with some regions of recovery and fresh growth, especially in Bugoma forest.
Figure 2.16 Forest cover change in and around Budongo and Bugoma between a) 1985-1990, b) 1990-1995, c) 1995-2002, d) 2002-2010, e) 2010-2014, f) 1985-2014

Figure 2.17 Forest cover trend of protected and unprotected forests in the forest corridors (includes Budongo and Bugoma)
2.4.5.3 Forest Cover Change in the Budongo case study

At this more local spatial scale, the delineation between protected and unprotected forest is clarified in each scene with a clear boundary defining the protected area. The total forest in this case is dominated by the protected forest, which remains relatively stable in the 30-year period of analysis (regression line is nearly flat; Figure 2.19). Generally, approximately 18.8% of the total forest present in the Budongo case study in 1985 was lost by 2014. The piecewise plot suggests that there was some forest gain prior to 1990, but following that period, there is more of a decline ($r^2=0.9$, $p=0.01$; Figure 2.19). Remarkably, though, 99% of the unprotected forest in 1985 was lost by 2014; a high annual loss rate of -3.3% ($p=0.01$). The losses in unprotected forest are mostly visible in the small fragments away from the protected forest block (Figure 2.18). There is a 6.9% increase in unprotected forest between 1990–1995, but most of this was again lost in subsequent periods, until there was nearly no forest left to be cleared (Figure 2.17e – changes between 2010 and 2014 are negligible as a result of the almost total disappearance of the unprotected woodland). On the other hand, there is a slight increase of 0.8% of the protected forest in 2014 compared to what was available in 1985, a nearly undetectable annual rate of increase of 0.03% ($p=0.04$). While the protected forest has an overall increase in area, with a nearly flat temporal pattern, spatially, there is evidence of some encroachment. Losses are mostly visible at the edges, and less in the interior, although some losses in the interior can be seen in the earliest period, 1985–1990, especially in the strict nature reserve.

Commercial farming is moderately anticorrelated with unprotected forest ($r^2=0.7$, $p=0.02$; Figure 2.20), suggesting that its expansion partly eroded the small adjacent forests as shown in Figure 2.18 g. The regression line is dominated, though, by the two points on the left (5th Dec, 2010 and 14th Jan, 2014); without them, the remainder of the points would be consistent with flat.
Figure 2.18 Forest cover change in and around Budongo between a) 1985-1990, b) 1990-1995, c) 1995-2002, d) 2002-2010, e) 2010-2014, f) 1985-2014, g) 1985-2014 with commercial farming of sugarcane (in pink), and built-up areas (in brown) overlaid par 2014 classification.
Figure 2.19 Piece-wise plot of forest cover trend in the protected and unprotected areas in and around Budongo (bars represent standard deviations. Protected forest remained relatively stable, and the most dramatic losses took place in the unprotected forest zones: period before 1990 appears to have taken a trend different to that after 1990, hence the piecewise plot considering the post 1990 period)

Figure 2.20 Relationship between commercial farming and unprotected forest in the Budongo case study (There is a moderate anticorrelation between commercial farming of sugarcane and unprotected forest: possibly, its expansion explaining the majority of the forest loss in the case study)
2.4.5.4 Forest Cover Change in the Bugoma Case Study

In this case study, as in the previous one, the overall signal is dominated by the protected forest; the total forest cover declined significantly (by 55.5 km$^2$, $r^2=0.8$, $p=0.01$) in the last 30 years. There is a marginal linear gain of 3% in the amount of protected forest cover in the 30-year period ($r^2=0.9$, $p=0.001$, Figure 2.22); although major losses to the magnitude of 62.6 km$^2$ occurred in the unprotected zones ($r^2=0.9$, $p=0.002$, Figure 2.21).

Generally, 15.0% of the total forest (when protected forest is included) present in 1985 was lost by 2014 an annual loss of -0.5% ($p=0.01$). Again as in Budongo, 99% of unprotected forest present in 1985 was lost by 2014, which translates to an annual loss rate of -3.3% ($p=0.002$). Forest loss in unprotected forest is most dramatic in the period after 1995 (Figure 2.20). While there are some fluctuations in the earlier period (to 1995), real deforestation seems to take off in the eastern part after 1995 (Figure 2.21c). As the eastern areas decline, forest patches in the west are cleared after 2002 (Figure 2.20d). By 2010 most of the eastern forest patches are gone, leaving a continual decline to the west, taking the removal of forest right up to the protected boundary and continuing into the 2010-2014 period (Figure 2.21e). There was evidence of continued deforestation in unprotected areas in the period during fieldwork in unprotected forests adjacent to Bugoma. The fields were reportedly cleared for small scale farming of food crops (see Plate 2.2). The spatial pattern of the protected forest is mixed; there are regions of infilling, at the western boundary, and small patches attached lost at the boundaries. There are also some patches that were depleted in the protected zones between 2002 and 2010 (Figure 2.21). Figure 2.21f summarizes the situation over the whole period. While the protected forest really has been protected and even shows a slight net gain, the remaining area has been cleared right up to the boundary.

There is a weak anticorrelation between small scale farming and unprotected forests in this case ($r^2=0.4$, $p>0.05$) suggesting that forest on private land is being replaced by small-scale farming.
a) 1985-1990

Legend
- Protected forest boundaries
- Forest Gain
- Forest Loss
- Unchanged Forest

b) 1990-1995

Legend
- Protected forest boundaries
- Forest Gain
- Forest Loss
- Unchanged Forest

c) 1995-2002

Legend
- Protected forest boundaries
- Forest Gain
- Forest Loss
- Unchanged Forest

d) 2002-2010

Legend
- Protected forest boundaries
- Forest Gain
- Forest Loss
- Unchanged Forest
Figure 2.21 Forest cover change in and around Bugoma between a) 1985-1990, b) 1990-1995, c) 1995-2002, d) 2002-2010, e) 2010-2014, f) 1985-2014

Figure 2.22 Forest cover trend in the protected and unprotected areas in and around Bugoma (below: bars are standard deviations)
Plate 2.2 Forest clearance on private land around Bugoma (Taken during fieldwork: Feb, 2014)
2.5 Discussion

This study set out to reconstruct detailed land use and vegetation cover patterns and their changes for the Northern Albertine Rift region between 1985 and 2014. While the investigation began at the regional scale, in the course of the analysis, it was clear that spatial scale had implications for the results obtained, and could offer interesting insights into more local-scale processes in different parts of the landscape. This discussion does not seek to offer an interpretation of the regional- or local-scale processes \textit{per se}, as these are explained from an empirical perspective in following chapters. Here, a brief overview on the quality of data and analysis, and precautions to consider when making interpretations at different scales is provided. Interestingly though, some striking patterns are seen from the results, and these are explained further here. This section is therefore organised according to the various spatial scales of analysis.

2.5.1 Land Use and Vegetation Cover Dynamics at the Regional Scale

\textit{On Classification Mixing at the Regional Scale}

At the regional scale, there was a high tendency for classes to get confused; especially those with similar spectral ranges (e.g. low density forest, savanna vegetation, dry season wetlands, and farming). The confusion is evident from spatial switching from one class to another within the same scene when training sites are selected in varying combinations (as presented in the error bars in Figure 2.4). This essentially makes interpretation of a temporal scale analysis problematic, since this variability may swamp any processes at a large scale. Disentangling which land uses or vegetation covers are likely to be confused, in a strictly detailed statistical (or mathematical) sense, was not the focus of this study (but the problem was essentially catered for by presentation of the errors of mismatch of pixels from the replications). The emphasis was on picking out overall land use and vegetation cover patterns, but taking into consideration that spectral variability in a given class might obscure results. Knowledge of the landscape (and ground truthing) was helpful when looking at the spectral confusion in the classification. For instance, in Murchison Falls National Park, while there may have been some historical farming encroachment, this may not have been as
widespread; this may suggest a classifier mix up between savanna grassland and low density forest with the farming categories throughout the study period.

Studies elsewhere have blamed spectral confusion on phenological effects, suggesting that imagery from different seasons are likely to have varying vegetation growth characteristics and vigour. This essentially demands use of same–season imagery to enable interpretation of changes (Thomas et al. 2011; Prischepov et al. 2012; Grinand et al. 2013). Data used in this study were obtained in the dry season which is characteristically less likely to be cloudy, and phenological variability is more controlled, but could lead to more bare ground, and will depend on recent rain. Here it is argued that selection of scenes from the same season may not be a sufficient control for spectral confusion. Other factors, including selected training sites, are likely to introduce error, as each may have slightly different spectral characteristics. Showing this variability in a meaningful manner (with standard deviations), as is the case in this study, may improve confidence in how the results can be interpreted. Other scholars have suggested that a combination of classifiers or even the use of expert–based classification systems may improve results (Nangendo et al. 2007; Otukei and Blaschke 2010). However, it is not obvious how a combination of classifiers may improve results especially if knowledge of the study area is not robust. The problem may be resolved by conducting more detailed surveys. Entirely relying on survey data would then switch the classification technique significantly from being spectrally–driven to being knowledge–based. Whilst the best results are desirable, in situations where resources are limited, a spectral–driven classification might be necessary. While the Maximum Likelihood Classifier (MLC) has been commonly used in land use and vegetation cover classification literature (for reviews see Coppin et al. 2004; Hussain et al. 2013), the results have often been reported without variability in the allocation of classes, although often measures of classification accuracy (e.g. producer, user and overall accuracy, kappa indices) are reported. We know though that there is a probabilistic allocation of each class based on statistical properties of spectral signatures (in spite of classifier used); this has received limited attention, and is highlighted in this study.
A possible explanation for the spectral mixing could be the pixel resolution of Landsat imagery (30m). Land uses and vegetation covers that are spatially continuous are relatively ‘obvious’ (e.g. water, commercial farming and forest) and are likely to be less confused; small and patchy ones will appear to be noisy. Landsat has some of the oldest remote sensing data available, with short scene revisit days, suitable for longer-term historical analyses, and although there are many emerging higher resolution sensors (e.g. QuickBird, < 5 m resolution), the costs of such data are likely to be prohibitive for small projects with limited budgets. Notably, among the freely available imagery, Landsat has a comparatively better resolution than, for instance, the Moderate Resolution Imaging Spectroradiometer (MODIS, 250 m+), which has a comparable temporal resolution. Higher resolution data from UK-DMCii (22m) was analysed, and as explained later, results from Landsat are closely comparable.

**On Land Use and Forest Cover Patterns at the Regional Scale**

In spite of the spatial variability at the regional scale, classification of the forest was robust. It was also possible to pick out expanding commercial farming and built-up areas in the regression analyses. The growth of these land uses are, however, mostly localised. For instance, commercial farming of sugarcane expansion is mostly south of Budongo forest, as built-up areas, especially commercial centres (e.g. Masindi and Hoima) grew at a distance away from the big forest blocks (Budongo and Bugoma). Previous studies have shown commercial farming and built-up areas to be expanding in rural landscapes, associated with income-generating activities fuelling migrant population growth (Mwavu and Witkowski 2008; Majaliwa et al. 2010), a hypothesis further examined in subsequent chapters.

Forest classification is robust and consistent across the region; errors are from pixel mismatches mostly insignificant, and a spatial assessment indicates that they are located at the forest edges, where there is transition from forest to other land uses (e.g. farming). The regional-scale analysis shows that forest cover patterns may previously have been reported with bias in the media and in unpublished reports that stress losses (see section 2.2.1), and ignoring both localised forest growth supported by various initiatives on private land, and better protection in protected forest estates and national
parks. This analysis indeed shows that at the regional scale, the overall patterns are obscured – where losses in the forest corridors and forests on private land are offset by gains in the Murchison Falls National Park, in the region immediately north of Budongo forest.

The expansion of forest in the National Park is not an artefact of the imagery. A recent global forest mapping project for the period 2000–2012 (Hansen et al. 2013) shows general spatial agreement with this study between 2002–2010 in spite of the different periods. It shows the existence of forest in the region, and largely agrees with other regions having losses and regeneration in other parts of the landscape. Although the Hansen et al (2013) work has been criticised for possible misrepresentation of the forest class (Tropek et al. 2014), they rebut this criticism by arguing that ambiguities mostly arose from their definition of ‘tree cover’ which essentially included all plantations (rubber trees, plantation forests) above 5m (Hansen et al. 2014). Their work shows that a spectral-driven classification offers useful insights at a large spatial scale. Their work is not used for a comparative accuracy assessment of this project’s classification, however, because of the different periods covered. The Hansen et al results only cover two relatively recent dates (2000 and 2012) compared to this study.

Tree regeneration in Murchison Falls National Park may be attributed to improved Park management, which has kept at bay encroachment from illegal slash and burn, hunting and agricultural activities successfully (Nangendo 2005). It is suggested that the section of the National Park immediately north of Budongo forest has similar climatic conditions to Budongo, which favours tropical forest regeneration (Smart et al. 1985); and with better protection in the recent past, tree growth is inevitable. Another hypothesis points to historical reduction in elephant populations (Eltringham and Malpas 1980, Lock 1993). Elephants are known to feed on a large volume of herbage per day, and to disrupt vegetation regeneration although they play a key role in seed dispersal (Ssali et al. 2012); and therefore their reduction would allow forests to emerge. This notion to explain forest regeneration in this part of the landscape is, however, largely based on old studies and some recent anecdotal evidence, and therefore requires further research.
On the contrary, there is evidence of dramatic loss of forest corridors, riverine forests, and forests on private landholdings in the regions south of Budongo forest, but with some cycles of regeneration and loss – similar to other regions of the country (Majaliwa et al., 2010; Twongyirwe et al., 2011; Sassen et al., 2013). The local-level losses are examined more closely in the following sections.

2.5.2 Land Use and Forest Cover Dynamics in the Budongo Case Study

Reduction in the number of classes and the spatial scale of analysis controlled spectral variability in this case study; classification of the forest was more robust. Aggregation of classes increases the spectral range, and improves separability of widely differing spectral signatures (Bruzzone et al. 2009). Expansion of commercial farming of sugarcane and built-up areas are the major land use changes detected in this part of the landscape. These results are corroborated by a previous study around Budongo (Mwavu and Witkowski 2008). Commercial farming expansion accelerated rapidly after 2002, mostly as a result of aggressive expansion of the out-grower scheme which eroded some of the existing forest on private land. “The out-grower scheme started with a radius of 10 km around the sugarcane plantations in 1996 following reopening of the factory (after closure for over 20 years by previous governments). The scheme was later extended to a 25 km radius; a series of management shifts with different boards further relaxed the rules, and now sugarcane growing seems to have expanded more generally. The scheme initially targeted out-growers with 10 ha of land but now allows farmers with up to 2 ha” (Bollampalli, agronomist Kinyara Sugar works, personal communication – quoted with permission).

There is some evidence of small-scale farming reduction at the expense of growing sugarcane. This may have negative implications on food security in the region. While the emphasis may be on improving livelihood, studies are required to understand to what extent conversion of cropping systems is beneficial (or disadvantageous) to the farmers involved. It may be that they are able to earn higher incomes from sugarcane sales, and can then invest in other activities (e.g. sending children to better schools, accessing better medical care). However, they may then have to spend considerably to purchase food, and so the costs cancel out the benefits.
Built-up areas expanded around Budongo forest, but mostly around the sugar industry. A previous study indicated that the growth of settlements in the region is largely due to an influx of migrant workers and refugees settling in the area (Mwavu and Witkowski 2008). This hypothesis is tested empirically in subsequent chapters.

Based on remote sensing evidence, the protected forest remained relatively stable over the 30 years, an indication of successful management although some encroachment is visible in the forest interior and at the boundaries. Spatially, deforestation is mostly patchy, and more prevalent in forests on private land; including corridor forests and those immediately close to the protected ones. There protected forest boundary delineation seems to have been clear throughout the study period – cleared forest patches immediately surrounding the forest follows the boundary extents. The flattening off of forest change in unprotected areas in the recent period (2010-2014) could be an indicator that nearly all the erodible forest is possibly gone, and a potential threat to the remaining protected forest. Annual forest loss rates (3.3%) in this case study are slightly higher than the projected national forest loss rate of 1–3% (Kayanja and Byarugaba 2001).

2.5.2 Land Use and Forest Cover Dynamics in the Bugoma Case Study

Similar to the Budongo case study, variability in classification in this case is better controlled at this scale as the classification was rerun for the dominant land use and vegetation cover classes. Small-scale farming expanded linearly over the period of investigation, largely replacing forest on private land surrounding the protected Bugoma forest. The analysis shows that the protection of Bugoma forest reserve over the 30 years was largely successful although there is some evidence of encroachment in the nature reserve (see the management delineation details in Appendix 2.2). Losses in other areas of the protected forest might be related to management harvesting. This takes place between 30–60 years for trees with a minimum dbh ~ 40 cm (MWE 2013). Guidelines to avoid loss of standing crop not ready for harvesting are known, and often, there is a forest supervisor available to control thinning (MWE 2013). Illegal logging as an additional cause for some losses cannot be dismissed. Later recovery (and an overall
marginal increase) in some areas, and infilling at the boundaries are also evident, possibly due to the clear demarcation and regular surveillance.

Expansion of small-scale farming and a shifting cultivation frontier explains the majority of forest loss in fragmented unprotected landscapes in this region, and poses a potential threat to the remaining protected forest and there was evidence of this during fieldwork. The length of fallow periods is declining in many tropical regions (Houghton 2012), and the lack of agricultural inputs with continuous tillage exhausts soil nutrients (Lambin and Meyfroidt 2011). While this is one potential explanation for agricultural frontier expansion into forested zones, the contribution of expanding populations, and the underlying and proximate drivers remain largely speculative. The role of livelihood conditions (rural incomes, levels of education, land tenure systems, cropping patterns, etc), and bio-physical conditions including but not limited to slope, aspect, and soil quality, may all provide an explanation of the observed trends. These are empirically tested in the following chapters.

In both the Budongo and Bugoma case studies, it is somewhat surprising that no large compartments in the protected blocks were cleared in the last 30 years (based on the image analysis). Management plans for both forests point to the strict surveillance of the boundaries and maintaining of clear borders with private areas. Weaknesses in staffing levels and remuneration (contributing to corruption), and funding constraints are among the main problems highlighted (MWE 2012; MWE 2013). However, this study does not address the issue of forest quality, or the possibility that there may be degradation in the protected areas. More information on this might be obtained from texture-based examination of aerial photographs. Certainly, it is possible to see areas on aerial imagery that suggest removal of natural forest and subsequent replacement with regular plantations. However, availability of historical cloud-free aerial photography is patchy and incomplete, and getting consistent coverage that would give as complete a picture as the satellite archive is likely to be very challenging.
2.5.3 Land Use and Vegetation Cover Dynamics in the Buliisa Case Study

This region is mostly dry and receives a dry monsoon wind from the East African coast which restricts the crops that can be supported. Spectral variability in the land uses in the area was very high, and it was difficult to disentangle cropping from savanna grassland spectral signatures. The results could be imbedded in the grazing grass fluctuations, as well as farming patterns in places where this is suitable. It was however possible to map rather recent expansion of built areas around Buliisa town. This growth could be related to the development of the oil industry. Although oil has been discovered in the Albertine graben in the last decade, its exploration is only recent, and production plans are in their early stages following the passing of the Oil and Petroleum Bill in December, 2012. This has fuelled recent development in the region, and with a recently improved road network, and hydro-electricity power made available, this growth is likely to continue.

2.5.4 Accuracy assessment

The forest class had very few ground truth points, mainly because of the way the study was designed, where the emphasis was on collating coordinates for other classes that were more likely to be mixed in the classification. Its classification was robust though, and this is supported by the low scene-to-scene variability, and comparable aerial estimates from imagery taken by different sensors with a day apart. Also, all the permanent sampling plots located within the Budongo forest were correctly classified in the 1985 and 2014 images. If we believe that the forest classification accuracy is high, when recently gathered points are compared to 1985 image, there is an indication that some areas currently classified as small-scale farming were indeed forested in the past. This is especially around Budongo forest, although this can only be taken as a surrogate of change (since the points were very few). More compelling and consistent evidence of change is derived from image differencing and not necessarily from the ground truth data.

Based on a comparison of UK-DMC and Landsat results, it could be argued that the forest classification works well, but that the errors in other classes are likely to be as large as the differences between the two image classifications, given that these were
subjected to the same classification scheme. The classification of small-scale and commercial farming was relatively good compared to bare ground, and changes to farming are to some extent reallocation of bare ground. Bare soil reflectance is variable; it depends on soil colour, moisture content, presence of carbonates, and iron oxide content (Tempfli et al. 2009, pg. 83), and this variability could have contributed to the mixing of classification. The resolution of the Landsat image makes it appear very noisy outside the forest areas, especially in regions where land use and vegetation cover are not continuous.

While differences may, to some extent, be attributed to Bands 5 and 3 in the Landsat and UK-DMC imagery respectively (as these are the different bands in the band stacks classified), trials with the same band combinations were undertaken, and results were equally variable, except for the forest class that was consistently robust. As discussed earlier, given that different numbers of bands were available per scene, and as the focus was on unambiguous detection of “major” changes, a principal components analysis of the available bands was beyond the scope of this investigation. The selected bands, especially in the infrared spectrum, are suitable for vegetation discrimination and have been widely accepted in the literature as such (Xie et al. 2008; Jia et al. 2014).

The confusion that occurred between built-up areas and small-scale farming in the classification confusion matrices would be considered rather odd, given that these two classes should, under normal circumstances, have clearly separable spectral signatures. The explanation lies in the way built areas were defined in the field, and during the classification. While training sites for built areas during the classification were largely taken from clearly defined rural towns whose rooftops and weather-bound surface roads have relatively consistent reflectance, field-based ground truthing considered some large or linear settlements as “built-up”; the roofing material used is mixed, but mostly dominated by plant material (e.g. grass straws), and therefore their reflectance in a dry season is likely to be close to that of dry vegetation, which would create confusion with small scale farming (see plates 2.2 and 2.3). Separating the built–up area categories at a ‘coarse’ 30m (Landsat) resolution would therefore be problematic in areas of scattered buildings.
Plate 2.3 Built–up areas in rural landscapes in the Northern Albertine Rift: a) Hoima town b) Communities settled near Budongo forest (in the Biiso neck in Buliisa), c) farming settlements in rural Masindi (Reflectance of built–up area of rural towns are likely to be different from those where settlements are dense but scattered within small–scale farmland)

For a long time ground truthing has been considered a gold standard for imagery classification accuracy, without considering that in itself it can be a source of errors causing both an over– or underestimation in the overall accuracy (Foody 2010, 2013). These errors may be a result of transitional classes, intra–pixel boundaries, restricted access to sites, uncertainties in class definition and temporal mismatches between image and field data acquisition, and Global Positioning System (GPS) inaccuracy (Foody 2010). While all these were considered during fieldwork, the mixed ground truth data collection designs may have introduced both random and systematic biases. Considering land use/vegetation cover classes that cover an entire pixel area (~ 900m²) was often difficult during the household surveys, and transect drives caused under–representation of some classes. There were some places where it was not possible to gather data due to time (and other resource) constraints, therefore the regional–scale overall accuracy may not be a true representation of classification accuracy assessment of the entire region. Large expanses of uniform sugarcane and tea estates were seen near Budongo and Bugoma respectively, that appear consistent with the classification maps, but there was not sufficient time to drive around these. Small pockets of mixed commercial and small–scale farming misclassification may obscure an ‘impressive’ correct allocation of pixel values to the right class in the larger areas (an argument also stressed by Foody 2010, 2013).
In spite of the sampling design variation, on the one hand, the classification accuracy of small-scale farming was consistently ‘good’ at the regional and selected local scales. On the other hand, the overall accuracy was generally poor, which could be explained by biases noted above. Accuracy assessment of historical imagery was virtually impossible because of the lack of retrospective ground truth data. Accuracy measures from the recent scene (14th Jan, 2014) could only be used as an indicator of the prior land use and vegetation cover classes, with a potential for mixing in the classification of older imagery.

2.6 Conclusions

In this chapter, the following have been examined: 1) land use and vegetation cover patterns and pattern–changes in the Northern Albertine Rift region between 1985–2014, 2) a background to deforestation in Uganda, 3) methodological approaches employed and associated caveats, and 4) the observed patterns of change at the various spatial scales. Although the initial focus was on a spectral–driven reconstruction of land use and vegetation cover patterns at the regional scale, examination of the various sections of the study area revealed striking patterns, and potentially varying processes which will be disentangled in following chapters.

While the high scene-to-scene spatial variability swamped evidence of overall changes in land use and vegetation cover patterns at the regional scale, regression analyses suggest that commercial farming and built–up areas have expanded in the last 30 years. On the contrary, however, forest classification was the most robust, although changes were obscured by dissimilar processes in the landscape, where gains mostly in Murchison Falls National Park offset widespread losses in the forest corridors and around the protected forest blocks. Deforestation that appears evident at a large scale may misrepresent local level dynamics. Forest losses were more dramatic in regions south of Budongo and around Bugoma, and mostly on privately owned (“unprotected”) land. The protection of the gazetted areas was to a great extent successful, with some regions of infilling in Bugoma forest, although there may have been some (‘minimal’) encroachment in both Bugoma and Budongo in the period of analysis. It was not possible to establish from this analysis whether this was purely management–related or
due to illegal logging or a combination of both. Commercial farming of sugarcane and small-scale farming were the predominant land uses replacing forest around Budongo and Bugoma respectively. The changes (losses in forest and gains in farming) are relatively recent, tending to be between 1995 and 2010, and not much activity is detectable between 2010 and 2014 as possibly all the available clearable forests have already been destroyed. This suggests a potential threat to the remaining protected areas, and indicates that continued efforts to preserve the woodland within the boundaries are likely to be essential. Meanwhile, the small amounts of corridor forest will require extra protection if the last few regions are to be maintained.

A comparative analysis of Landsat data with that of UK-DMC suggests that forest classification from Landsat imagery is robust, while other classes are likely to be mixed. Small-scale farming classification performed relatively well too, and this is corroborated by the ‘high’ accuracy measures in the confusion matrices. The ground truth sampling criteria for the entire region were in some ways biased, especially limited to regions where fieldwork was conducted. The biases are evident in the low overall classification accuracies.

A “bird’s eye view” is necessary to understand activities and patterns in a complex and diverse landscape. The old and rich Landsat archive was thoroughly explored, and the analysis suggests that dominant patterns have been rigorously identified in the Northern Albertine Rift region even though with a limited number of images. This chapter is in many ways more detailed both in the spatial and temporal patterns it reveals than is evident in the published literature, where, for instance, the starting and ending periods are often considered. This conclusion is strengthened by zooming down to smaller scales, where statistically significant trends can be extracted. This work could have made use of some recent cloud free scenes obtained after 2004, but these were made unusable due to the scan-line corrector failure (explained earlier; an example of an affected classified scene is shown in Appendix 2.3); future research is required to fill the gaps. It would take an irregular temporal process (of drastic reforestation and then recovery) to refute the deforestation trends constructed for the last 30 years in this chapter. Algorithms (e.g. Zeng et al. 2013) for infilling the SLC-error gaps could be tested whether they provide forest areas that lie on this study’s temporal regression trends.
Chapter 3

Characterising Rural Livelihoods: Household Demographics, Farming Practices, and Forest Resources
Abstract

Characterising rural livelihoods provides useful insights into the dominant means of household survival mechanisms, and could present the evidence for needs-based and appropriately targeted planning by the local and national governments. These data may also provide new ways of thinking about and testing theories on the drivers of deforestation. An empirical investigation using mixed methods: quantitative techniques and field-based observations was conducted in the Northern Albertine Rift region between October, 2013 and March, 2014. An in-depth questionnaire was administered to 706 households in 13 parishes situated in 4 Agro-Ecological Zones (AEZs): Budongo (4) and Bugoma (3) regions, peri-urban (4) and the semi-arid zones (2). The data gathered included household demographic characteristics, energy use, cropping and livestock husbandry, and seasonal time- and labour- budgets. Exploratory analysis using multivariate statistical techniques including Principal Components Analysis (PCA) and Cluster Analysis (CA) were employed. 22 Principal Components (PCs) and 9 clusters were extracted. These mainly identified dominant groupings in the data to minimise redundancy in the original variables. The strength of the relationship between variables was tested using Spearman's rank correlation. One-way non-parametric analysis of variance (using Kruskal-Wallis test) was used to test the significance of the differences in the means of the household clusters. The PCA results show that significant variation in the households is mainly related to the cultivation time input (“Principal Component” 1, hence forth “PC”1), on-farm income particularly from cropping activities (PC2), livestock husbandry (PC3), demographic characteristics (PC4), agricultural extension activities (PC5), and cultivation labour input (PC6) accounting for 21.6%, 8.6%, 5.7%, 4.9%, 4.4% and 3.7% of the total variation respectively. But livestock income (PC20), usage of forest products (timber and poles) (PC21), and off-farm income (PC22) were the least important variables contributing only 1.5%, 1.4% and 1.3% to the total variation in the data respectively. 17 PCs accounting for 75.4% of the total variation were used in a hierarchical cluster analysis using Ward’s method. Results show that households around forested regions (Budongo and Bugoma AEZs) mostly belonged to cluster 2 (low income mixed farming households), except for households in Kibwona parish dominated by cluster 3 (low income crop specialist households) involved in the out-grower sugarcane production scheme alongside other food crops. As expected, the peri-urban AEZ is dominated by cluster 4 (limited cultivation households with moderate off-farm income). They are also comprised of some cluster 7 households (richest, “elite” mixed farming and trading-based households) albeit few, which are mostly lacking in the Budongo and Bugoma AEZs except for Igwanjura and Bubogo parishes. In the semi-arid AEZ however, there is a mixture of cluster 2 (low income mixed farming households), cluster 4 (limited cultivation households with moderate off-farm income) particularly in Kisansya that is involved in fishing in Lake Albert, and cluster 1 (moderate income, livestock specialist households) in which livelihoods are dependent on free-range grazing of cattle and goats. The other clusters are in mixed proportions in the various AEZs, suggesting marked household heterogeneity at parish level although spatial patterns indicate positive autocorrelation (Moran’s I = 0.099, p=0.001). The analysis suggests that poor households live near the forested regions, and suggests that the rural poor are more reliant on forest products than peri-urban populations. This may at some level contribute to deforestation (constructed in Chapter 2), although expansion of commercial farming of sugarcane also seems to be a significant contributor in some areas: the mechanisms and further analysis will be explored in following chapters.
3.1 Introduction

Uganda’s economy is predominantly agricultural-based (Fan and Zhang 2008). The agriculture sector continues to be viewed as a vehicle through which economic growth and development can be achieved, as stipulated in the National Development Plan in the Vision 2040 (G.o.U 2012). The majority of the agricultural production is however supported by the rural poor who account for over 85% of the total population (UBOS 2007). Rural livelihoods are embedded in complex agro-ecological systems, under which people co-exist with natural resources (e.g. forests, savanna grasslands), and in terms of their general aims seek to maximise agricultural production, maintain a healthy household, cope with seasonal fluctuations, exploit market opportunities, manage risk through diversification to other economic activities, and accumulate wealth for their welfare (Bogdanov et al. 2008; Tesfaye et al. 2011; Chilongo 2014). Due to the numerous production constraints, however, the majority resort to exploitation of the natural resource base to boost their wellbeing, resulting in land cover changes (de Sherbinin et al. 2008).

Although there could be a time-lag between forest loss and household livelihood status, understanding the livelihood characteristics of households where dramatic deforestation has occurred (e.g. Budongo and Bugoma Agro-Ecological Zones [AEZs]: as observed from remote sensing imagery), and contrasting them with the regions that have no forest (e.g. the semi-arid and the peri-urban AEZs in this study) could illuminate key drivers of deforestation. This type of analysis requires large amounts of household socio-economic data often from extensive surveys or censuses to tease out the signal from noise. Whilst Uganda’s national censuses are conducted every decade, its questionnaires cover specific parameters, and therefore cannot answer particular research questions (e.g. on household labour and time budgets), and the raw data are strictly unavailable to the public for ethical reasons. To this end, an empirical investigation of households was undertaken (details are described in the methods section). To capture household heterogeneity, the main data gathering tool contained wide-ranging questions including but not limited to household demographic characteristics, cropping and livestock husbandry, energy use, seasonal time and labour budgets.
The large dimensionality of the data gathered requires robust statistical analytical techniques to unearth and understand systematic structures. Principal Components Analysis (PCA) and Cluster Analysis (CA) commonly used in rural sociology (e.g. Chilongo 2014; Goswami et al. 2014; Mutoko et al. 2014) are employed in this investigation (a detailed description is provided in the methods section). In simplest terms, a PCA is a technique for combining variables into new linear combinations that account systematically for large proportions of the variability in the data. As such it can be used as a dimension reduction technique that condenses the total number of original variables to a smaller set of “new variables” which can be used to describe that data more transparently. The selected principal components can then be used in a cluster analysis in the new dimension space, since the data can now be analysed along directions in which the spread has been made as large as possible. If the variance in the data is a result of groups in the data which have different properties, then the PCA allows the cluster analysis to pick these out effectively.

Cluster analysis is a data mining approach for characterising, in this case, socio-economic groups of households, and is strictly based on the input variables which are in turn dependent on the considered dimensions derived from a PCA (Ottaviani et al. 2003; Mayer et al. 2014). Therefore, as variables are inputted in different combinations, different sets of clusters are possible. However, as more variables are included, distinguishing between, for instance, the poor and very poor becomes possible (Vyas and Kumaranayake 2006). In this project, to ensure a good measure of separability in the classification of households, a wide range of 83 continuous and 9 categorical variables critical to understanding the livelihood characteristics of the households in the landscape is used.

There is a general lack of empirical understanding on how households in the Northern Albertine Rift Landscape and more local regions utilise their resources in the face of changing economic and social conditions. This study provides useful and novel data (e.g. on time- and labour- budgets) for characterising these rural livelihoods, critical in policy formulation, particularly in designing sound agricultural and forestry policies (Pacini et al. 2014). The rest of the chapter is organised as follows. Objectives, methods, results, discussion and conclusions are provided in sections 3.1, 3.2, 3.3, 3.4 and 3.5 respectively.
3.1.1 Objectives

The overarching objective is to examine household-level data empirically to understand major differences in spatial settlement and activity patterns across the landscape, with a view to setting up the analysis that will shed light on factors potentially contributing to dramatic forest loss outside the protected forest estate, on private landscapes. Characterisation of the households is the first step towards achieving this goal. Specific research questions include the following.

1. What are the key discriminators of livelihood characteristics in the region?
2. Are there any clusters in the households relative to their socio-economic characteristics in the four Agro-Ecological Zones (AEZs)?
3. What is the spatial relationship of the household clusters relative to the AEZs?

3.1.2 General Definitions

Definitions of the words appearing on the title page and other parts of this chapter which are subject to different interpretation by other disciplines are provided. Definitions of the variables measured are provided separately in section 3.2.5.1.

3.1.2.1 Household and Livelihood Typology

A household is defined as a unit of primary production, reproduction and decision-making (de Sherbinin et al. 2008). Typically, it is comprised of a group of people related in some way, living together in the same housing unit, and feeding from the same ‘pot’. The surveys were conducted at household level, and only members living in the household at the time of the study were included in the household demographic analyses. Those that have migrated to work or study or because they are married were not included. The household livelihood typology refers to the sum total of socio-economic characteristics that distinguish them from others. In this chapter, they are mostly referred to as clusters.

3.1.2.2 Agro-Ecological Zones (AEZs)

The definition of AEZs is inspired by the results from the remote sensing analysis that indicate dramatic forest loss patterns outside the large protected forests. Climatic conditions in regions around Budongo and Bugoma are dissimilar, and therefore considered as independent AEZs (Table 3.1); they also have different types of cash
crops grown, and different local population compositions. Detailed information on the soil types is however lacking. In order to understand how livelihoods vary between forested and non-forested areas within the landscape, semi-arid (parishes in Buliisa) and peri-urban AEZs (parishes in Hoima and Masindi towns) were included in the study.

Table 3.1 Description and characteristics of the Agro-Ecological Zones

<table>
<thead>
<tr>
<th>Agro-Ecological Zone (AEZ)</th>
<th>Major food crops</th>
<th>Major cash crops</th>
<th>Mean annual rainfall (mm)¹</th>
<th>Mean annual temperature (°C)²</th>
<th>Elevation (m)³</th>
<th>Districts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Budongo</td>
<td>Cassava, maize, sweet potatoes, beans</td>
<td>Sugarcane</td>
<td>1397-1524</td>
<td>23-29 (min), 29-32 (max)</td>
<td>914-1097</td>
<td>Masindi and Buliisa</td>
</tr>
<tr>
<td>Bugoma</td>
<td>Cassava, maize, beans</td>
<td>Rice, tobacco</td>
<td>1100-1350</td>
<td>16-18 (min), 28-29 (max)</td>
<td>1200-1350</td>
<td>Hoima</td>
</tr>
<tr>
<td>Semi-arid</td>
<td>Cassava, beans</td>
<td>Cassava, cotton</td>
<td>800-1000</td>
<td>22-25 (min), 26-32 (max)</td>
<td>600-700</td>
<td>Buliisa</td>
</tr>
<tr>
<td>Peri-urban</td>
<td>Cassava, maize, beans</td>
<td>Tobacco</td>
<td>1000-1250</td>
<td>13-16 (min), 18-30 (max)</td>
<td>1120-1150</td>
<td>Hoima and Masindi</td>
</tr>
</tbody>
</table>

¹, ², and ³ are extracted from unpublished district reports and forest management plans. The rest is extracted from household data.

3.2 Data, Materials and Methods

3.2.1 Selection of Study Parishes

A comprehensive description of the entire study area is provided in Chapter 1. Here I consider the 13 parishes (no. of respondents=706) located in the 4 AEZs (Figure 3.1) where fieldwork was undertaken for a duration of 6 months (1st October, 2013–31st March, 2014). The selection of the parishes was based on 4 main criteria: 1) remote sensing imagery analysis results, 2) accessibility, 3) logistical, and 4) safety. First, prior to fieldwork, analysis of remote sensing imagery was undertaken to identify regions where major anthropogenically-driven forest losses took place (a detailed description is provided in Chapter 2). The results showed that regions immediately adjacent to the protected forest blocks presented an interesting case as they had experienced dramatic deforestation. In accordance to the research design, there was also a need to select parishes from the semi-arid and peri-urban AEZs to compare livelihood characteristics in the forested and non-forested regions. Approximately 20 preliminary parishes were selected using Google Earth and existing maps of the region.

Secondly, lack of information on particular accessibility challenges meant that it was not possible to select which parishes would be best suited prior to visiting them.
Consultations were therefore undertaken with experts in Kampala (capital city) who have worked extensively in the landscape (e.g. from the Wildlife Conservation Society and the Albertine Rift Conservation Society), and at the district headquarters once in the field. Some regions were reported to have bad roads, and were generally not recommended during heavy rains. There was a short rainfall spell at the beginning of October, 2013, but the rest of the period was largely dry.

Thirdly, the project and study areas presented logistical problems. While several parishes were initially selected, including in some regions around Wambabya forest (see Chapter 2 for location), because of time and budget limitations, it was not possible to conduct fieldwork in all of these pre-selected parishes. Also, some parishes lacked essentials like fuel, foodstuffs and first aid items (medicines), or their prices and access were prohibitive. While we mainly transported our own foodstuff and fuel reserves from Kampala, it was necessary that we should have access to these in case of need or emergency. Parishes where these extra difficulties were envisaged were not included.

Lastly but not least, safety in the field was paramount. Fieldwork was conducted in a period of political instability in the eastern part of Democratic Republic of Congo, and an influx of refugees was occurring into the region via Lake Albert. Because we mainly camped in the community areas during fieldwork, it was necessary that the field team was safe over the entire 6 month period. Based on the above criteria, 13 parishes presented in Table 3.2 satisfied the fieldwork conditions.

Table 3.2 Sampled parishes in the four Agro-Ecological Zones

<table>
<thead>
<tr>
<th>Agro-Ecological Zone (AEZ)</th>
<th>Parish</th>
<th>No. of villages in the study parish</th>
<th>No. of respondents</th>
<th>Location (District)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Budongo</td>
<td>Nyabyeya</td>
<td>4</td>
<td>44</td>
<td>Masindi</td>
</tr>
<tr>
<td></td>
<td>Kibwona</td>
<td>3</td>
<td>49</td>
<td>Masindi</td>
</tr>
<tr>
<td></td>
<td>Biiso</td>
<td>4</td>
<td>56</td>
<td>Buliisa</td>
</tr>
<tr>
<td></td>
<td>Busingiro</td>
<td>3</td>
<td>62</td>
<td>Buliisa</td>
</tr>
<tr>
<td>Bugoma</td>
<td>Bubogo</td>
<td>4</td>
<td>49</td>
<td>Hoima</td>
</tr>
<tr>
<td></td>
<td>Igwanjura</td>
<td>2</td>
<td>56</td>
<td>Hoima</td>
</tr>
<tr>
<td></td>
<td>Kyangwali</td>
<td>4</td>
<td>59</td>
<td>Hoima</td>
</tr>
<tr>
<td>Semi-arid</td>
<td>Kisansya</td>
<td>2</td>
<td>58</td>
<td>Buliisa</td>
</tr>
<tr>
<td></td>
<td>Kigwera</td>
<td>2</td>
<td>56</td>
<td>Buliisa</td>
</tr>
<tr>
<td>Peri-urban</td>
<td>Westernward</td>
<td>2</td>
<td>58</td>
<td>Masindi</td>
</tr>
<tr>
<td></td>
<td>Southernward</td>
<td>2</td>
<td>49</td>
<td>Masindi</td>
</tr>
<tr>
<td></td>
<td>Kasingo</td>
<td>3</td>
<td>54</td>
<td>Hoima</td>
</tr>
<tr>
<td></td>
<td>Mparo</td>
<td>3</td>
<td>56</td>
<td>Hoima</td>
</tr>
</tbody>
</table>
3.2.2 Sampling Design: Transects and Randomisation

Within the selected parishes, the aim was to obtain a robust and unbiased sample by randomly selecting households to participate in the survey (although the degree of agreement to participate was beyond the author’s control, and, in some instances, biases in the sample were possible). Ideally, households should have been located based on high resolution remote sensing imagery, and random numbers allocated, to form the
basis for selection using a randomisation algorithm in ArcGIS. Alternatively, a national census register with all households could have been used to assign random numbers to select participating households. These ideal situations were not possible for 3 main reasons. 1) High resolution imagery (with a pixel resolution of 2.5 by 2.5m or 5 by 5m) are able to resolve scattered settlements within rural areas unambiguously (e.g. Kitiş and Şenol, 2013), but the cost of a mosaic of scenes to cover the entire study area was prohibitive for this small project. 2) A register with all the residents in the parish is available at the Uganda Bureau of Statistics (based on the 2002 census), but these data are strictly not available to the public. Changes in settlements may also have taken place since the census was conducted, and therefore the register may not have been up-to-date for this sampling purpose. 3) Additionally, even if the randomly generated participating households had been obtained from the high resolution imagery or registers, access and time constraints would have been problematic. Here, I describe a transect–based randomisation technique that was employed instead during fieldwork to select participating households.

Four graduate Research Assistants (RAs) were recruited based on a competitive open application process. Adverts were posted on Notice Boards in Makerere University and the Institute of Tropical Forest Conservation (ITFC) 6 months before the project commenced. The recruited RAs were thoroughly trained in advance on administering the questionnaire; the ethics and risk assessments were also reviewed. Once in the field, we recruited four field guides (details below) in each parish. The RAs (and four field guides) set off (walking) in four canonical compass directions from the approximate centre of the parish, whenever possible: this was to avoid duplication of surveyed households. The household inclusion technique was different for each assistant to increase randomness. For instance, the first took odd numbered households along a transect (e.g. every 1st, 3rd, 5th, 7th etc), the second included even numbered households (e.g. every 2nd, 4th, 6th, 8th etc), the third took prime numbered households (e.g. every 1st, 3rd, 5th, 7th, 11th etc), while the fourth took every third in a line. These guidelines were intended to avoid consciously selecting certain households, mainly in crowded settlements – but the rules were relaxed if the households were located “long” distances (~1km) apart, at the discretion of the RAs. The distance between each sampled household therefore varied widely (between 50m to 1km), but it was possible to sample across different villages (occurring on the transects) in the parish with this technique. A
further criterion of availability of a household leader (or adult respondent) willing to participate freely in the survey was also considered; this further increased the randomness. The refusal rate was extremely low, with only a handful in each area, usually because a person did not have the time to participate. GPS coordinates of the surveyed households were taken (using Garmin GPS62), accurate to at least 2m.

3.2.3 Household Questionnaire Survey

Based on the above sampling design, with assistance from the 4 trained graduate RAs, questionnaires were administered to a total of 706 households (Table 3.2). The author oversaw the process and gathered specialist information from key informants. Within each parish, the Local Council 1 (“LC1”: lowest administrative unit, at village level) chairman of one of the villages assigned a field guide to each of the RAs, partly to introduce the RAs to the respondents and assure them of the local council’s leadership approval, but also to build rapport between the RA and respondents. They also interpreted some questions where a language barrier was problematic.

The surveys were conducted at the respondents' homes with the household heads, but in a few circumstances with the most senior and knowledgeable of the adults available. The questions included household demographic characteristics (e.g. age, gender, off-farm income), energy use, cropping and livestock husbandry (e.g. farm size, crop histories, yields, number of and income from livestock, land tenure), and seasonal time–and labour– budgets, among others (see Appendix 3.1 for the detailed questionnaire). The purpose of the study was explained to the respondents as being purely scientific and academic, and anonymity of the responses was emphasised. Other ethical considerations of social research such as free, prior and informed consent (FPIC), confidentiality and data protection were explicit. The respondents were informed of a possibility to withdrawal from participation at any stage they wished. Prior to fieldwork, ethical issues arising from this project (see Appendix 3.2) were examined by the Geography Department’s Ethics Review Committee, and an ethical approval was granted (Appendix 3.3). Each household interview lasted, on average, between 45 minutes and 1 hour.
The main languages used in the survey were English and Runyoro, with Kiswahili and some other dialects occasionally being used. The landscape has diverse tribes from within and outside the country. Where more specialised dialects were required, the recruited tour guides worked as interpreters. It was therefore essential that the author (RT) and the Research Assistants spoke the major local dialects (Runyoro in Hoima and Masindi, and Rugungu in Buliisa), but even more importantly that the recruited field guides were fluent in all the local dialects within their parishes. Language abilities were considered during the recruitment.

**Pre-testing:** the questionnaire was piloted with 24 households in Nyabyeya parish in Masindi district. This was to check for clarity of questions, duration of interview, and for the RAs to obtain hands-on-practice, especially in recording the information and keeping within the interview time limit (of 1 hour). We did not find it necessary to adjust the questionnaire following the pilot since all the questions were found relevant for the study. Slight changes were made to the ways in which some questions were asked because of their sensitivity. For instance, on nativity, instead of asking if the respondent was a migrant/native, we asked for their tribe. We know the native tribes in the region are Banyoro (in Hoima and Masindi) and Bagungu in Buliisa, so all other tribes were categorised as migrant irrespective of how long their members have lived in the landscape. Interviews were assigned overall qualitative performance scores by RAs between 1 (for poor), and 5 (for excellent), based on their interaction experience with the respondent, and the author assessed each of the records during evaluation meetings after the interviews and provided an independent score too; and these were compared to those recorded in other parishes when experience had been gained. Based on these scores, the data gathered during the pilot did not appear to have any quality problems, and therefore all the results were included in the final data analyses.

### 3.2.4 Triangulation: Field Observations

A questionnaire approach as a primary data source could be criticised for potential bias, where some responses are exaggerated, incomplete or inaccurate. It was therefore necessary to use various techniques to test for the ‘accuracy’ of the information collated, referred to as “triangulation” in the literature (Erzberger and Prein, 1997). This implies that the views of different respondents, however diverse, have to fit into a logical story
derived from the responses; in a sense a convergence of the data, which could be useful in confirming or dismissing hypotheses.

The questionnaire was designed in such a way that some questions would ‘self-check’ previous responses; or in a way that there should be a logical correlation. An example of a direct check is that in section 1, we inquired about incomes spent on-farm from off-farm sources, and we tracked this in section 3 where we asked for a breakdown of expenses on cropping and livestock activities. An example of a logical check is that the household cannot use household labour greater than the number of members that could reasonably provide labour in the household (e.g. when the elderly and infants are excluded), otherwise, extra labour would have to be out-sourced. Repetitive triangulation questions were, however, controlled to avoid making the questionnaire excessively long. Furthermore, we stayed and camped within the study parishes (see Plate 3.1), and observed firsthand how the rural dwellers went about their day-to-day activities, including collecting firewood for cooking, fetching water, and working in the gardens, among others. This was useful to build rapport, but also the experience enabled us to judge if the responses were exaggerated or not. In any case, all the data were recorded as received, with the hope that “inaccurate data” would emerge as outliers. Interestingly, the results show some remarkably consistent livelihood indicators (as would logically be expected) relative to the different AEZs suggesting a highly successful data gathering campaign.

The study was also backed by an extensive literature review of documents in government libraries (e.g. previous census records), and published literature in academic journals. Key informant interviews were also conducted; these data are however presented in the following chapters.
Plate 3.1 Examples of camping in community areas during data gathering in parishes in the 4 AEZs (the ITFC vehicle was our ‘office’ – it kept datasheets and other valuables; used also for morning and evening meetings before and after fieldwork respectively).

3.2.5 Data Analysis

3.2.5.1 Questionnaire Data: Definition and Computation of Selected Variables

Definitions of variables are in part based on how the data were gathered. The variables are either continuous (Table 3.3a) or categorical (Table 3.3b) based on how the data were measured (the former on at least interval scales, and the latter on a nominal scale). The variables in Table 3.3a are arranged in the order in which they were ranked from the Principal Components Analysis (PCA). Only continuous variables were used to run the PCA although categorical variables were tested for their relationships with the generated clusters as explained in the following sections.
### Table 3.3a Questionnaire continuous variables – category, definition and computation

<table>
<thead>
<tr>
<th>Variable category</th>
<th>Variable</th>
<th>Definition</th>
<th>Computation</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Cultivation time input</strong></td>
<td>Hrs_weeding_wet season</td>
<td>Number of hours spent on weeding in the wet season of 2013</td>
<td>Number of hours spent weeding in a day × number of weeding days in a wet season</td>
</tr>
<tr>
<td></td>
<td>Hrs_weeding_dry season</td>
<td>Number of hours spent on weeding in the dry season of 2013</td>
<td>Number of hours spent weeding in a day × number of weeding days in a dry season</td>
</tr>
<tr>
<td></td>
<td>Hrs_harvesting_wet season</td>
<td>Number of hours spent on harvesting in the wet season of 2013</td>
<td>Number of hours spent harvesting in a day × number of harvesting days in a wet season</td>
</tr>
<tr>
<td></td>
<td>Hrs_harvesting_dry season</td>
<td>Number of hours spent on harvesting in the dry season of 2013</td>
<td>Number of hours spent harvesting in a day × number of harvesting days in a dry season</td>
</tr>
<tr>
<td></td>
<td>Hrs_opening_agric_land_wet season</td>
<td>Number of hours spent on opening agricultural land in the wet season of 2013</td>
<td>Number of hours spent opening agric. land in a day × number of days spent opening agric. land in a wet season</td>
</tr>
<tr>
<td></td>
<td>Hrs_opening_agric_land_dry season</td>
<td>Number of hours spent on opening agricultural land in the dry season of 2013</td>
<td>Number of hours spent opening agric. land in a day × number of days spent opening agric. land in a dry season</td>
</tr>
<tr>
<td></td>
<td>Hrs_postharvest_handling_wet season</td>
<td>Number of hours spent on postharvest handling in the wet season of 2013</td>
<td>Number of hours spent postharvest handling in a day × number of days spent on postharvest handling in a wet season</td>
</tr>
<tr>
<td></td>
<td>Hrs_postharvest_handling_dry season</td>
<td>Number of hours spent on postharvest handling in the dry season of 2013</td>
<td>Number of hours spent postharvest handling in a day × number of days spent on postharvest handling in a dry season</td>
</tr>
<tr>
<td><strong>On-farm income predominantly from cropping activities</strong></td>
<td>Tot_income_crop_current season</td>
<td>Total income obtained from crops in the second half of 2013 (in UGX)</td>
<td>Sum of all crop income from second half of 2013 crop sales</td>
</tr>
<tr>
<td></td>
<td>Tot_income_crop_previous season</td>
<td>Total income obtained from crops in the first half of 2013 (in UGX)</td>
<td>Sum of all crop income from first half of 2013 crop sales</td>
</tr>
<tr>
<td></td>
<td>Tot_on_farm_income_2013</td>
<td>Total on-farm income obtained from both crop and livestock sales in 2013 (in UGX)</td>
<td>Sum of on-farm income obtained from crop and livestock sales in 2013</td>
</tr>
<tr>
<td></td>
<td>Tot_on_farm_income_2012</td>
<td>Total on-farm income obtained from crop and livestock sales in 2012 (in UGX)</td>
<td>Sum of on-farm income obtained from crop and livestock sales in 2012</td>
</tr>
<tr>
<td></td>
<td>Tot_yield_current season</td>
<td>Total yield of all crops grown in the second half of 2013 (in kg)</td>
<td>Sum of yields of all crops grown in the second half of 2013</td>
</tr>
<tr>
<td></td>
<td>Tot_yield_previous season</td>
<td>Total yield of all crops grown in the first half of 2013 (in kg)</td>
<td>Sum of yields of all crops grown in the first half of 2013</td>
</tr>
<tr>
<td><strong>Livestock husbandry</strong></td>
<td>Hrs_grazing_wet season</td>
<td>Number of hours spent on grazing in the wet season of 2013</td>
<td>Number of hours spent grazing in a day × number of days spent on grazing in a wet season</td>
</tr>
<tr>
<td></td>
<td>Hrs_grazing_dry season</td>
<td>Number of hours spent on grazing in the dry season of 2013</td>
<td>Number of hours spent grazing in a day × number of days spent on grazing in a dry season</td>
</tr>
<tr>
<td></td>
<td>HHL_grazing_wet season</td>
<td>Number of household members who provide labour for grazing in the wet season</td>
<td>Tally of HH members providing labour for grazing in the wet season</td>
</tr>
<tr>
<td></td>
<td>HHL_grazing_dry season</td>
<td>Number of household members who provide labour for grazing in the dry season</td>
<td>Tally of HH members providing labour for grazing in the dry season</td>
</tr>
<tr>
<td></td>
<td>Tot_No_livestock_2013</td>
<td>Number of livestock (cattle, goats, sheep, and pigs) owned by the HH in 2013</td>
<td>Tally of livestock numbers in 2013</td>
</tr>
<tr>
<td></td>
<td>Tot_No_livestock_2012</td>
<td>Number of livestock (cattle, goats, sheep, and pigs) owned by the HH in 2012</td>
<td>Tally of livestock numbers in 2012</td>
</tr>
<tr>
<td><strong>Demographic characteristics</strong></td>
<td>No_BC_HH</td>
<td>Number of biological children in the household</td>
<td>Tally of biological children in the household</td>
</tr>
<tr>
<td></td>
<td>No_BC_boys</td>
<td>Number of male biological children in the household</td>
<td>Tally of male biological children in the household</td>
</tr>
<tr>
<td></td>
<td>No_BC_girls</td>
<td>Number of female biological children in the household</td>
<td>Tally of female biological children in the household</td>
</tr>
<tr>
<td></td>
<td>Tot_HH_size</td>
<td>Total number of members in the household including all relatives</td>
<td>Tally of number of individuals in a household</td>
</tr>
<tr>
<td></td>
<td>Mean_age_BC</td>
<td>Mean age of biological children in the household</td>
<td>Average of the ages of the biological children</td>
</tr>
<tr>
<td></td>
<td>Mean_Educ_BC</td>
<td>Mean level of education of biological children (e.g. grade 1=1, grade 6=level 6, etc)</td>
<td>Average level of education of biological children</td>
</tr>
<tr>
<td><strong>Agricultural Extension activities</strong></td>
<td>Hrs_extension_meetings_dry season</td>
<td>Number of hours spent on attending extension meetings in the dry season</td>
<td>Number of hours spent on attending extension meetings in a day × number of extension meeting days in a dry season</td>
</tr>
<tr>
<td></td>
<td>Hrs_extension_meetings_wet season</td>
<td>Number of hours spent on attending extension meetings in the wet season of 2013</td>
<td>Number of hours spent on attending extension meetings in a day × number of extension meeting days in a wet season</td>
</tr>
<tr>
<td></td>
<td>HHL_extension_meetings_wet season</td>
<td>Number of household members who attend extension meetings in the wet season</td>
<td>Tally of HH members attending extension meetings in the wet season</td>
</tr>
<tr>
<td></td>
<td>HHL_extension_meetings_dry season</td>
<td>Number of household members who attend extension meetings in the dry season</td>
<td>Tally of HH members attending extension meetings in the dry season</td>
</tr>
<tr>
<td>Cultivation labour input</td>
<td>HHL_opening_agric.land wet season</td>
<td>Number of household members who provide labour for opening agric. land in the wet season</td>
<td>Tally of HH members providing labour for opening agric. land in the wet season</td>
</tr>
<tr>
<td>--------------------------</td>
<td>----------------------------------</td>
<td>---------------------------------------------------------------------------------</td>
<td>--------------------------------------------------------------------------</td>
</tr>
<tr>
<td>HHL_opening_agric.land dry season</td>
<td>Number of household members who provide labour for opening agric. land in the dry season</td>
<td>Tally of HH members providing labour for opening agric. land in the dry season</td>
<td></td>
</tr>
<tr>
<td>HHL_weeding wet season</td>
<td>Number of household members who provide labour for weeding in the wet season</td>
<td>Tally of HH members providing labour for weeding in the wet season</td>
<td></td>
</tr>
<tr>
<td>HHL_weeding dry season</td>
<td>Number of household members who provide labour for weeding in the dry season</td>
<td>Tally of HH members providing labour for weeding in the dry season</td>
<td></td>
</tr>
<tr>
<td>HHL_postharvest_handling wet season</td>
<td>Number of household members who provide labour for postharvest handling in the wet season</td>
<td>Tally of HH members providing labour for postharvest handling in the wet season</td>
<td></td>
</tr>
<tr>
<td>HHL_postharvest_handling dry season</td>
<td>Number of household members who provide labour for postharvest handling in the dry season</td>
<td>Tally of HH members providing labour for postharvest handling in the dry season</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Household groceries shopping</th>
<th>Hrs_grocery_shopping wet season</th>
<th>Number of hours spent on grocery shopping in the wet season of 2013</th>
<th>Number of hours spent on grocery shopping in a day × number of grocery shopping days in a wet season</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hrs_grocery_shopping dry season</td>
<td>Number of hours spent on grocery shopping in the dry season of 2013</td>
<td>Number of hours spent on grocery shopping in a day × number of grocery shopping days in a dry season</td>
<td></td>
</tr>
<tr>
<td>HHL_grocery_shopping dry season</td>
<td>Number of household members who provide labour for grocery shopping in the dry season</td>
<td>Tally of HH members providing labour for grocery shopping in the dry season</td>
<td></td>
</tr>
<tr>
<td>HHL_grocery_shopping wet season</td>
<td>Number of household members who provide labour for grocery shopping in the wet season</td>
<td>Tally of HH members providing labour for grocery shopping in the wet season</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>On-farm expenditure</th>
<th>Tot_expenditure_crop previous season</th>
<th>Total expenditure on crop production in the first half of 2013 on labour for opening land and weeding, buying seeds, fertiliser, pest control, buying/hiring cropping land</th>
<th>Sum of expenditure on labour for opening land and weeding, buying seeds, fertiliser, pest control, buying/hiring cropping land</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tot_expenditure_crop current season</td>
<td>Total expenditure on crop production in the 2nd half of 2013 on labour for opening land and weeding, buying seeds, fertiliser, pest control, buying/hiring cropping land</td>
<td>Sum of expenditure on labour for opening land and weeding, buying seeds, fertiliser, pest control, buying/hiring cropping land</td>
<td></td>
</tr>
<tr>
<td>Tot_on-farm_expenditure 2012</td>
<td>Total on-farm expenditure in 2012 including all cropping and livestock activities</td>
<td>Sum of expenditure on cropping and livestock activities</td>
<td></td>
</tr>
<tr>
<td>Tot_on-farm_expenditure 2013</td>
<td>Total on-farm expenditure in 2013 including all cropping and livestock activities</td>
<td>Sum of expenditure on cropping and livestock activities</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pest-control activities</th>
<th>HHL_pest_control dry season</th>
<th>Number of household members who provide labour for pest control in the dry season</th>
<th>Tally of HH members providing labour for pest control in the dry season</th>
</tr>
</thead>
<tbody>
<tr>
<td>HHL_pest_control wet season</td>
<td>Number of household members who provide labour for pest control in the wet season</td>
<td>Tally of HH members providing labour for pest control in the wet season</td>
<td></td>
</tr>
<tr>
<td>Hrs_pest_control dry season</td>
<td>Number of hours spent on pest control in the dry season of 2013</td>
<td>Number of hours spent on pest control in a day × number of pest control days in a dry season</td>
<td></td>
</tr>
<tr>
<td>Hrs_pest_control wet season</td>
<td>Number of hours spent on pest control in the wet season of 2013</td>
<td>Number of hours spent on pest control in a day × number of pest control days in a wet season</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Extended family characteristics</th>
<th>No_other_relatives_HH</th>
<th>Number of relatives other than those that comprise a nuclear family in a household: these include grandparents, cousins, nieces, uncles, aunts, etc</th>
<th>Tally of relatives other than those that comprise a nuclear family in a household</th>
</tr>
</thead>
<tbody>
<tr>
<td>No_other_relatives_male</td>
<td>Number of male relatives other than those that comprise a nuclear family in a household</td>
<td>Tally of male relatives other than those that comprise a nuclear family in a household</td>
<td></td>
</tr>
<tr>
<td>No_other_relatives_female</td>
<td>Number of female relatives other than those that comprise a nuclear family in a household</td>
<td>Tally of female relatives other than those that comprise a nuclear family in a household</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Education level</th>
<th>Educ_respondent</th>
<th>Level of education of the respondent (e.g. grade 1=1, grade 6=level 6, etc)</th>
<th>Record of education level response</th>
</tr>
</thead>
<tbody>
<tr>
<td>Educ_father</td>
<td>Level of education of the father in the household</td>
<td>Record of education level response</td>
<td></td>
</tr>
<tr>
<td>Educ_mother</td>
<td>Level of education of the mother in the household</td>
<td>Record of education level response</td>
<td></td>
</tr>
<tr>
<td>Respondent's age</td>
<td>Age of respondent in years</td>
<td>Record of age</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Labour input for food preparation and fetching water</th>
<th>HHL_food_preparation dry season</th>
<th>Number of household members who provide labour for food preparation in the dry season</th>
<th>Tally of HH members providing labour for food preparation in the dry season</th>
</tr>
</thead>
<tbody>
<tr>
<td>HHL_food_preparation wet season</td>
<td>Number of household members who provide labour for food preparation in the wet season</td>
<td>Tally of HH members providing labour for food preparation in the wet season</td>
<td></td>
</tr>
</tbody>
</table>
### Agricultural Implements and Farm Size

<table>
<thead>
<tr>
<th>Measure</th>
<th>Description</th>
<th>Tally/Sum Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>HHL_fetching_water dry season</td>
<td>Number of household members who provide labour for fetching water in the dry season</td>
<td>Tally of HH members providing labour for fetching water in the dry season</td>
</tr>
<tr>
<td>HHL_fetching_water wet season</td>
<td>Number of household members who provide labour for fetching water in the wet season</td>
<td>Tally of HH members providing labour for fetching water in the wet season</td>
</tr>
</tbody>
</table>

### Farming Time Budget

<table>
<thead>
<tr>
<th>Time Budget</th>
<th>Measure</th>
<th>Description</th>
<th>Tally/Sum Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fetching water time budget</td>
<td>Hrs_gathering_firewood dry season</td>
<td>Number of hours spent on firewood gathering in the dry season of 2013</td>
<td>Number of hours spent on firewood gathering in a day × number of firewood gathering days in a season</td>
</tr>
<tr>
<td>Fetching water time budget</td>
<td>Hrs_fetching_water dry season</td>
<td>Number of hours spent on fetching water in the dry season of 2013</td>
<td>Number of hours spent on fetching water in a day × number of fetching water days in a dry season</td>
</tr>
<tr>
<td>Trading own-shop time budget</td>
<td>Hrs_trading_own_shop dry season</td>
<td>Number of hours spent on selling merchandise in a household-owned shop in the dry season of 2013</td>
<td>Number of hours spent on trading own-shop in a day × number of trading own-shop days in a dry season</td>
</tr>
<tr>
<td>Trading own-shop time budget</td>
<td>Hrs_trading_own_shop wet season</td>
<td>Number of hours spent on selling merchandise in a household-owned shop in the wet season of 2013</td>
<td>Number of hours spent on trading own-shop in a day × number of trading own-shop days in a wet season</td>
</tr>
</tbody>
</table>

### Food Preparation Time Budget

<table>
<thead>
<tr>
<th>Time Budget</th>
<th>Measure</th>
<th>Description</th>
<th>Tally/Sum Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Food preparation time budget</td>
<td>Hrs_food_preparation dry season</td>
<td>Number of hours spent on food preparation in the dry season of 2013</td>
<td>Number of hours spent on food preparation in a day × number of food preparation days in a dry season</td>
</tr>
<tr>
<td>Food preparation time budget</td>
<td>Hrs_food_preparation wet season</td>
<td>Number of hours spent on food preparation in the wet season of 2013</td>
<td>Number of hours spent on food preparation in a day × number of food preparation days in a wet season</td>
</tr>
</tbody>
</table>

### Selling Agricultural Produce Time Budget

<table>
<thead>
<tr>
<th>Time Budget</th>
<th>Measure</th>
<th>Description</th>
<th>Tally/Sum Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Selling agricultural produce time budget</td>
<td>Hrs_selling_agric_produce dry season</td>
<td>Number of hours spent on selling agricultural produce in the dry season of 2013</td>
<td>Number of hours spent on selling agric. produce days in a dry season</td>
</tr>
<tr>
<td>Selling agricultural produce time budget</td>
<td>Hrs_selling_agric_produce wet season</td>
<td>Number of hours spent on selling agricultural produce in the wet season of 2013</td>
<td>Number of hours spent on selling agric. produce days in a wet season</td>
</tr>
</tbody>
</table>

### Marriage Age

<table>
<thead>
<tr>
<th>Measure</th>
<th>Description</th>
<th>Record of response</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clan_marriage_age_girls</td>
<td>Age at which girls in the clan get married</td>
<td></td>
</tr>
<tr>
<td>Clan_marriage_age_boys</td>
<td>Age at which boys in the clan get married</td>
<td></td>
</tr>
</tbody>
</table>

### Livestock Income

<table>
<thead>
<tr>
<th>Measure</th>
<th>Description</th>
<th>Lump-sum estimate of livestock income in 2013 (record of response)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tot_income_livestock_2013</td>
<td>Total income from selling livestock and livestock products in 2013</td>
<td></td>
</tr>
<tr>
<td>Tot_income_livestock_2012</td>
<td>Total income from selling livestock and livestock products in 2012</td>
<td></td>
</tr>
</tbody>
</table>

### Forest Products Used

<table>
<thead>
<tr>
<th>Measure</th>
<th>Description</th>
<th>Lump-sum estimate of livestock income in 2012 (record of response)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantity of poles</td>
<td>Volume of poles gathered from a natural forest in 2013</td>
<td></td>
</tr>
<tr>
<td>Quantity of timber</td>
<td>Volume of timber extracted from a natural forest in 2013</td>
<td></td>
</tr>
</tbody>
</table>

### HH Off-Farm Income

<table>
<thead>
<tr>
<th>Measure</th>
<th>Description</th>
<th>Sum of off-farm income of all members of the HH in 2013 (record of response)</th>
</tr>
</thead>
<tbody>
<tr>
<td>HH_tot_off-farm_income</td>
<td>Total amount of off-farm income earned by all members of the HH combined (UGX)</td>
<td></td>
</tr>
</tbody>
</table>

### Cultivation Time Budget

- **Wet season** has a total of 183 days, while **dry season** has 182. This is computed from 2 wet seasons in 2013: March-May (92 days), and Sept-Nov (91 days). Dry season in 2013: Dec-Jan-Feb (90 days), June-Aug (92 days). Responses were often given as number of hours spent on the activity in a day, and how many times they did this in a week if it is a routine activity, or of a one-off activity, how many days are spent on it in a season.
- Most recent period was considered easiest to remember, in this case the dry and wet season activities of 2013. HH – household. *** farm land size was reported in ‘garden’ sizes, and we clarified what the average size of a garden is to enable computation of the total farm size in ha. r – radius, h – height, L – length, w – width. Estimates of dimensions were obtained from samples available in the household.
Table 3.3b Questionnaire categorical variables definition

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Computation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household Nativity</td>
<td>Original inhabitants are the Banyoro (in Hoima and Masindi), and Bagungu (in Buliisa) – all tribes are considered migrants in spite of how long their members have lived in the landscape</td>
<td>Tallies per cluster (and parish)</td>
</tr>
<tr>
<td>Household Land Tenure System</td>
<td>System of ownership of land used for settlement and farming activities – both in the long- and short-term. The categories are defined in the main text</td>
<td>Tallies of land tenure per cluster (and parish)</td>
</tr>
<tr>
<td>Type of house owned by the household</td>
<td>The type of housing unit is permanent, semi-permanent or temporary. A permanent one is built with bricks and has an iron sheet roof. A semi-permanent unit is built with mud and wattle with an iron sheet roof. A temporary one is made of mud and wattle, and is grass thatched</td>
<td>Tallies per cluster and parish</td>
</tr>
<tr>
<td>Forestry Policy Awareness</td>
<td>Awareness of households on policies especially affecting their use and access to forestry resources, both timber and non-timber products</td>
<td>Tallies per cluster (and parish)</td>
</tr>
<tr>
<td>Main Energy type used for Cooking</td>
<td>Main energy source used for cooking including both renewable and non-renewable sources</td>
<td>Tallies per cluster (and parish)</td>
</tr>
<tr>
<td>Who gathers firewood</td>
<td>Member of the households who provides labour for gathering firewood</td>
<td>Tallies per cluster (and parish)</td>
</tr>
<tr>
<td>Where firewood is gathered</td>
<td>Places where firewood is gathered – natural forest, plantation forest, bush-land and shrub, gardens, etc</td>
<td>Tallies per cluster (and parish)</td>
</tr>
<tr>
<td>Distance to firewood collection sites</td>
<td>Average distance to firewood gathering sites</td>
<td>Tallies per cluster (and parish)</td>
</tr>
<tr>
<td>Criteria of selecting firewood collection sites</td>
<td>How households choose where to gather firewood from</td>
<td>Tallies per cluster (and parish)</td>
</tr>
</tbody>
</table>

3.2.5.2 Statistical Modelling and Analysis

Prior to running any more complicated analyses, descriptive statistics of all variables from the questionnaire were computed: continuous variables are mostly non-normally distributed (Kolmogorov-Smirnov test, p<0.05) and are presented in Appendix 3.4; the categorical variables are presented in Appendix 3.5. Exploring the data with descriptive statistics is useful for understanding which statistical tests are appropriate. Because the data-set is comprised of a wide range of variables (as shown in Tables 3.3a and b), it was imperative that a degree of simplification is attempted by screening out redundant variables. This was achieved through a Principal Components Analysis (using SPSS version 22), and is described as follows.

3.2.5.2.1 Dimension Reduction: Principal Components Analysis (PCA)

In a high-dimensional data-set with multiple response (y) and predictor (x) variables (as is the case in this analysis), Principal Components Analysis (PCA) is one approach for mining the ‘important’ response variables. It is a form of multiple linear regressions (see equation below: Vyas and Kumaranayake 2006), where lines (vectors) are drawn through a multi-dimensional data-set such that the sum-of-squares distances from the line to all the points in the data are minimized (Bell et al. 2015). The first vector becomes the first Principal Component (PC), with the projection of the data onto this component explaining a ‘large’ fraction of the overall variation in the data. A second
vector (second PC), perpendicular, and thus completely uncorrelated to the first, is constructed in a similar way: also minimises the sum-of-squares distances and captures a smaller, but different dimension in the data than the first. This process is repeated to generate \( n \) orthogonal vectors, where \( n \) is equivalent to the number of input variables. This set of perpendicular PCs is essentially a rotation of the original multi-dimensional space such that all the original variables have a 'loading' along each PC, with high loadings indicating high correlation between the original variable and the PC, essentially reducing the effective variable set by removing redundancy (Bell et al. 2015). Each household and original variable therefore has a loading on the new variable, which is the PC in this case. To define what each PC means, it is done by finding the original variables correlating most strongly with the new variables. As more components are computed, they explain additional but less variation than the previous component; the \( n^{\text{th}} \) PC explains a greater fraction of the data than that along the \((n + 1)^{\text{th}}\). Essentially the PCs are the eigenvectors of the correlation matrix, ordered by size of the corresponding eigenvalue, where larger eigenvalues correspond to a higher variance (Vyas and Kumaranayake 2006; Bell et al. 2015).

\[
\text{PC}_1 = a_{11}X_1 + a_{12}X_2 + \ldots + a_{1n}X_n \\
\vdots \\
\text{PC}_m = a_{m1}X_1 + a_{m2}X_2 + \ldots + a_{mn}X_n
\]

Where \( a_{mn} \) represents the weight of the \( m \text{th} \) principal component (PC) and the \( n^{\text{th}} \) variable (Vyas and Kumaranayake 2006).

83 continuous variables (~70% of the total data-set) were input to run the PCA algorithm. This number represents variables after screening and excluding ~30% of the total number of variables which had significant amounts (>10%) of missing data (see histograms in Appendix 3.4 for variables that had significantly lower amounts of data). The exclusion rate was set to 10%. It means that all variables which lacked more than 10% of the data were not included in the analysis. This was so that a large number of variables could be kept, while minimising the number of households that would not be classified (if the inclusion rate was relaxed). The missing data are a result of a lack of responses and possible recording omissions during administering the questionnaire. Exclusion of such variables might lower statistical power, but imputing with
means/medians could produce erroneous estimates that could grossly misrepresent the data structure or even treating the missing data as zeros will distort means and medians and lead to bias in analysis, hence providing misleading PCA results. As the categorical data were not used in the classification of households (as explained later), these were not a major concern. In comparison to published literature though (e.g. Bidogeza et al. 2009; Costard et al. 2009; Diwani et al. 2013; Chilongo 2014), the 83 input variables is a ‘larger amount’ of data, and this provided reasonable findings, particularly with regard to household categorisation as presented in the results section.

Prior to running the PCA, the data were standardised using z-scores. The key principle of matrix standardisation is to make every column have a 0 mean, and 1 standard deviation; this ensures that each variable has the same weighting on the analysis particularly as the data are of different types and are recorded using different units (e.g. yields in kg, incomes in UGX, time budgets in hours, etc) (Vickers et al. 2003). Varimax rotation was used to produce components with loadings concentrated onto a smaller number of highly correlated variables than the initial PC set as an aid to interpretation (Bell et al. 2015). All components which account for at least 1.2% of total variation were retained. This decision was based on the following. From the 83 variables, which after standardisation (suppose each variable has a unit variance), each variable contributes, on average, 1.2% (100/83) to the total variation. Each PC that accounts for more than 1.2% of the total variation is therefore more important than the original variable. As will be shown in the results, this effectively reduces the dimension of the data from 83 (original variables) to 22 (new variables, PCs in this case). These new variables are then used in further analysis to classify the households into clusters.

The appropriateness of a PCA on the data (with 706 households, and 83 variables) was confirmed using two tests. The Kaiser-Maier-Olkin test (KMO) gives a solution of 0.78 (essentially a ‘good’ goodness-of-fit of the PCA model: often 0.90+ described as “marvellous”, in the 0.80’s as “meritorious”, in the 0.70’s as “middling”, in the 0.60’s as “mediocre”, in the 0.50’s as “miserable”, and below 0.50 as “unacceptable”: Holland 2013), and Bartlett’s sphericity test is significant ($X^2=98326.6$, df=3403, $p=0.000$). The Bartlett’s test of sphericity evaluates whether each sequential eigenvalue is significantly different from the remaining eigenvalues (Jackson 1993). If the data are overly
correlated or independent, then a PCA may not be successful, hence the need for the KMO and Bartlett’s test (Bidogeza et al. 2009).

Categorical variables are generally not included in the Principal Components Analysis as scaling them produces meaningless results. The categorical variables were however tested for their relationship with the generated clusters using non-parametric chi-squared tests. This further enhanced our understanding of the household characteristics relative to the clusters in the 4 AEZs. The way clusters were generated are discussed in the following section.

3.2.5.2.2 Household Classification: Cluster Analysis

Clustering is an exploratory data mining technique that attempts to group objects (in this case, households) of similar kind into respective classifications: where more similar objects are placed in the same class (Ottaviani et al. 2003; Mayer et al. 2014). A cluster analysis is typically performed on a 2-dimensional data matrix involving cases and variables, where columns are variables and rows are cases/observations (households). A selection from the computed “new variables” from the PCA is used to run the cluster analysis. The choice of how many components to retain to guide the classification could be based on 3 criteria. 1) The scree test. This is based on the break on the scree plot which separates components with large from those with small eigenvalues. 2) Kaiser's rule which states that eigenvalues should be greater than 1. 3) The principle that selected components should explain at least 70–80% of the retained variance (Jackson 1993; Bell et al. 2015). All these rules were considered, and a conservative total variance of 75.4% was therefore considered (~mid-way between 70 and 80%), obtained by considering the first 17 PCs, and each of these PCs has an eigenvalue ≥1.

The next phase is the selection of a classification algorithm. Two classification algorithms generally exist: hierarchical and non-hierarchical techniques. A hierarchical clustering algorithm was preferred to the non-hierarchical techniques for two main reasons (embedded within their definitions). 1) On the one hand, hierarchical cluster methods produce a hierarchy of clusters, ranging from small clusters of very similar items to larger clusters of increasingly dissimilar items. This is useful during data mining when we lack information on the data structure, and therefore difficult to
predetermine the number of clusters to divide the data into. 2) On the other hand, non-hierarchal classification techniques (e.g. K-means clustering that partitions n samples into k clusters) are dependent on assuming the number of clusters \textit{a priori}. This assumes that splitting things by nearest neighbour distance is appropriate, and that clusters should be effectively as near spherical as they can be in the variable space. The solution can possibly also converge to a local optimum which is not actually consistent with some clear cluster structures in the data; this can be heavily influenced by the starting conditions for the algorithm, as with most optimisation problems. Agglomerative hierarchical clustering was therefore used. Starting with individual samples, clusters of the most similar households were formed, progressively joining similar households and clusters until all households have been joined into a single large cluster, and this is presented in a dendrogram. The linking/separation method used was Ward’s technique and the Euclidean distance interval. Ward’s method is widely used in the literature (Bidogeza et al. 2009; Chilongo 2014; Bell et al. 2015), and is based on minimising the within-group sum of squares, and produces compact well-defined clusters (Holland 2013). It is better than the nearest-neighbour or single-linkage method which is based on the elements of two clusters that are most similar, and the farthest-neighbour or complete-linkage method based on the elements that are most dissimilar, and the median, group average, and centroid methods, as all these emphasise the central tendency of clusters and are less sensitive to outliers (\textit{ibid}).

Selecting the number of clusters is more of an art than a science, and a rather exploratory process; different numbers (of clusters) could produce sharply contrasting classification results. From a generated dendrogram, it is common practice to choose a separating distance amongst clusters by drawing a line at a consistent level of similarity; this should be drawn in such a way that the groups are not too few (as households would be highly similar to one another with a wide variance) or too many (as the analysis would become overly complex) (Vickers et al. 2003; Holland 2013). From a critical inspection of the dendrogram constructed using 17 PCs, 9 clusters were successfully delineated. This allowed clear separation of households by their livelihood characteristics (while minimising the confidence intervals), illuminating interesting and contrasting livelihood characteristics relative to the 4 Agro-Ecological Zones (Budongo, Bugoma, semi-arid and peri-urban AEZs).
3.2.5.2.3 Spatial Analysis

Uniquely, we gathered data on location of the households using hand-held GPS units; this makes visualisation of the spatial distribution of household clusters relative to their parishes (and AEZs) possible. This is powerful for assessing the spatial distribution and relationship between households based on proximity to each other. It was however important to protect the respondents in conformity to the ethical procedures: the data were therefore plotted as clusters which represent aggregate statistics rather than individual values. In the plots, household coordinates are not shown to avoid accurately tracing the participating households. Moran’s I statistic was computed for household clusters using GeoDa software to examine the relationship of each household (characterised by cluster) to the most immediate household. This provides a measure of spatial autocorrelation based on Tobler’s ‘first law of Geography’ “*Everything is related to everything else, but near things are more related than distant things*” (Tobler 1970; Miller 2004).

3.2.5.2.4 Non-Parametric Tests

As the data are non-normally distributed, non-parametric tests were used. Kruskal-Wallis test (one-way analysis of variance) was used to test the relationship between the household clusters and the continuous variables, while chi-squared test examined categorical data relationships with the clusters. The strength of the relationship between variables used in the PCA was tested using Spearman’s rank correlation coefficient. All values of p<0.05 were considered significant.
3.3 Results

3.3.1 Dimension Reduction: Principal Components Explaining Important Variation in the Regional-scale Data

Principal Components Analysis (PCA) enabled the reduction of the dimension of the data-set from 83 variables to 22 “new variables” referred to as Principal Components (PCs) based on the rule that each variable that contributes > 1.2% (100/83), and has an eigenvalue ≥ 1 is more important than the original variable. The scree plot (Figure 3.2) shows a sharp kink around PC 3, which is then followed by a gently declining eigenvalue pattern with each additional component until around PC 22, beyond which there is a near levelling off in the eigenvalues with each additional component. The amount of variation explained by each PC is presented in Table 3.4.

Different variable groupings correlate strongly with each component and are interpreted (as variable category) and highlighted in Table 3.5. The components are then labelled after the variables that strongly load on them. Essentially, significant variation in the households is mainly related to the cultivation time input (PC 1), on-farm income particularly from cropping activities (PC 2), livestock husbandry (PC 3), demographic characteristics (PC 4), agricultural extension activities (PC 5), and cultivation labour input (PC 6) accounting for 21.6%, 8.6%, 5.7%, 4.9%, 4.4% and 3.7% of the total variation respectively (Tables 3.4 and 3.5). But livestock income (PC 20), usage of forest products (timber and poles) (PC 21), and off-farm income (PC 22) were the least important variables contributing only 1.5%, 1.4% and 1.3% to the total variation in the data respectively (Tables 3.4 and 3.5). Variable groupings in the mid-table are important too, and are explored in the definition of the clusters.

The aggregate descriptive statistics of all continuous variables gathered during fieldwork are summarised in Appendix 3.6: with this volume of data, given the limited space, it is prudent to explore the variable characteristics alongside the cluster definition (as presented in the next section) to minimise repetition. However the entire population structure (part of the demographic characteristics) of the participating households is plotted on a population pyramid: it includes all members of the household, both the nuclear and extended family. The pyramid is typical of a rapidly
growing population with the majority household population comprised of a large number of children below the age of 20, and very few elderly people, although there are some marked differences in the bins of age groups under 16 (Figure 3.3).

The variable groups that load strongly on each PC are highly correlated to each other. There are several strongly correlating variables (mostly within each PC), again space limits showing all of them here. In this section, an example from the first PC (cultivation time input) where correlation between each variable and the rest of the variables is explored. This is to demonstrate strong correlation of variables within a PC, but weaker correlations with other variables in other PCs: only correlated (Spearman’s rank correlation $\geq 0.4$, $p < 0.0001$) variables are presented.

There is strong positive correlation between hours spent on weeding in the wet season and: weeding (in the dry season), harvesting (both seasons), opening agricultural land (both seasons), and post-harvest handling (both seasons) (Figure 3.4a). There is a moderate positive correlation between hours spent on weeding and household labour for weeding (both seasons) and farm size in 2013 (Figure 3.4a). The clusters in the correlation plots are shown; these will be explained in the next section. Harvesting in the dry season is positively correlated with: postharvest handling (both seasons), opening agricultural land (both seasons), farm size (previous and current season) and household labour for post-harvest handling (Figure 3.4b). Opening agricultural land in the wet season is positively correlated with: opening agricultural land in the dry season, postharvest handling (both seasons), household labour for opening agricultural land (both seasons), household labour for weeding (both seasons) and farm size in 2013 (Figure 3.4c). Finally, postharvest handling in the dry season is positively correlated with: postharvest handling (wet season), household labour weeding (both seasons), household labour for postharvest handling (both seasons), and on-farm income (Figure 3.4d).
Figure 3.2 Scree plot showing the contribution of each PC to the total variation in the data-set

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<td></td>
<td>Total</td>
<td>Total</td>
</tr>
<tr>
<td></td>
<td>% of Variance</td>
<td>% of Variance</td>
</tr>
<tr>
<td></td>
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<td>Cumulative %</td>
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Table 3.4 Total variance explained (rotated solution)
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<th>Component</th>
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<tr>
<td></td>
<td>Hrs_harvesting_dry season</td>
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</tr>
<tr>
<td></td>
<td>Hrs_opening_agric_land wet season</td>
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Table 3.5 Rotated Component matrix – loadings of variables per component
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<th></th>
<th>dry season</th>
<th>Labour input for food preparation and fetching</th>
<th>Household groceries shopping</th>
<th>On-farm expenditure</th>
<th>Pest-control activities</th>
<th>Extended family characteristics</th>
<th>Education level</th>
<th>Cultivation labour input</th>
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<td><strong>-0.01</strong></td>
<td></td>
<td></td>
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<tr>
<td>HHL_food_preparation dry season</td>
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<td>HHL_food_preparation wet season</td>
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<td><strong>0.01</strong></td>
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<tr>
<td>Activity</td>
<td>Hrs_selling_agric.produce dry season</td>
<td>Hrs_selling_agric.produce wet season</td>
<td>Hrs_fetching_water dry season</td>
<td>Hrs_fetching_water wet season</td>
<td>Hrs_gathering_firewood_ wet season</td>
<td>Hrs_gathering_firewood dry season</td>
<td>Tot_income_livestock</td>
<td>Tot_income_Livestock BC</td>
</tr>
<tr>
<td>--------------------------------------</td>
<td>--------------------------------------</td>
<td>-------------------------------------</td>
<td>-------------------------------</td>
<td>-------------------------------</td>
<td>-----------------------------------</td>
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<tr>
<td>Clan_marriage_age_girls</td>
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<td>0.01</td>
<td>0.04</td>
<td>0.04</td>
<td>0.02</td>
<td>0.04</td>
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<tr>
<td>Clan_marriage_age_boys</td>
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<td>0.02</td>
<td>0.04</td>
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</tr>
<tr>
<td>Livestock income 2012</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
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<tr>
<td>Livestock income 2013</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
<td>0.02</td>
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<td>0.02</td>
</tr>
<tr>
<td>Quantity of timber</td>
<td>0.01</td>
<td>0.07</td>
<td>0.07</td>
<td>0.07</td>
<td>0.01</td>
<td>0.07</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>Quantity of poles</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.07</td>
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<tr>
<td>HH_off-farm_income_BC</td>
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<td>HH_off-farm_income</td>
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<td>HH_tot_off-farm_income</td>
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<tr>
<td>Hrs_selling_agric.produce dry season</td>
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<tr>
<td>Hrs_selling_agric.produce wet season</td>
<td>0.19</td>
<td>0.37</td>
<td>0.37</td>
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<td>Hrs_gathering_firewood_ wet season</td>
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<tr>
<td>Hrs_gathering_firewood dry season</td>
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<td>0.02</td>
<td>0.02</td>
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<tr>
<td>Annual volume firewood gathered</td>
<td>0.17</td>
<td>0.10</td>
<td>0.10</td>
<td>0.10</td>
<td>0.10</td>
<td>0.10</td>
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<tr>
<td>Fetching water time budget</td>
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<td>-0.07</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.07</td>
<td>-0.07</td>
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<tr>
<td>Trading owned-shop time budget</td>
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<td>-0.02</td>
<td>-0.02</td>
<td>-0.02</td>
<td>-0.02</td>
<td>-0.02</td>
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</tr>
<tr>
<td>Food preparation time budget</td>
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<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
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<tr>
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<tr>
<td></td>
<td>Tot_No_low_input tools</td>
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<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
<td>0.12</td>
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<td></td>
<td>Tot_No_high_input tools</td>
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<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
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</tr>
<tr>
<td></td>
<td>Tot_farmland_size previous season</td>
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<td>0.32</td>
<td>0.32</td>
<td>0.32</td>
<td>0.32</td>
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<td></td>
<td>Tot_farmland_size current season</td>
<td>0.44</td>
<td>0.35</td>
<td>0.35</td>
<td>0.35</td>
<td>0.35</td>
<td>0.35</td>
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</tr>
</tbody>
</table>
Figure 3.3 Population pyramid of surveyed households (includes all members living in the household at the time of the survey; age in years)
Figure 3.4a Scatter plots of household weeding time budget against significantly correlated cultivation variables

Plots with a correlation coefficient >0.4 are presented
Figure 3.4b Scatter plots of household harvesting time budget against significantly correlated cultivation variables

Plots with a correlation coefficient >0.4 are presented
Figure 3.4c Scatter plots of opening agricultural land time budget against significantly correlated cultivation variables. Plots with a correlation coefficient > 0.4 are presented.
Figure 3.4d Scatter plots of postharvest handling time budget and on-farm income against significantly correlated variables (Plots with a correlation coefficient >0.4 are presented)
3.3.2 Household Classification: Characteristics of the 9 Clusters

9 distinct clusters were extracted based on “long stems” (shown by the point at which the blue lines intersect with the red line) at the rescaled cluster combined distance of approximately 11 (Figure 3.5). The clusters have a heterogeneous number of sub-clusters. Particularly, cluster 2 is the largest accounting for 30.2% of the total number of households (n=706) and has a sequence of four sub-groups that join together at increasing levels of dissimilarity; and cluster 7 accounting for 8.8% of the total number of households, has two groups that join at a relatively low level of similarity (Figure 3.5). The remaining clusters 1, 3, 4, 5, 6, 8 and 9 account for 13.5%, 12.5%, 12.6%, 5.1%, 5.2%, 3.5%, 6.1% of the total number of households (n=706). Only 2.5% of the households were unclassified due to missing data. The characteristics of the household clusters are summarised in Table 3.6, and are elaborated as follows.

3.3.2.1 Cluster 1: Moderate Income, Livestock Specialist Households

These households have their largest source of livelihood from livestock husbandry although they are also involved in small-scale crop production. They kept the largest number of animals (mostly goats, sheep, and few cattle) in 2013, for example, compared to other clusters (Kruskal-Wallis test, $X^2=65.0$, df=8, p=0.000), averaging 4.8±2.0 (hence forth indicating “mean±95% confidence interval”). They spend the longest period grazing animals in both the dry (374.8±119.5 hours: mean±95% confidence interval) and wet (368.0±148.3 hours) seasons compared to other clusters (Figure 3.6d, e; Kruskal-Wallis test, $X^2=65.8$, df=8, p=0.000 for both seasons). These households also earned comparatively high amounts of livestock incomes in 2012 averaging ~UGX 90,000±60,000 (Kruskal-Wallis test, $X^2=22.3$, df=8, p=0.000; Figure 3.5v).

Cluster 1 households are also involved in small-scale crop production, and spend moderate amounts of time and labour investment on cultivation activities (Figure 3.6a), but obtained relatively low crop yields in the both seasons (Figure 3.6c), have a moderate education level albeit low (e.g. fathers’ average 6.1±1.0), low involvement in extension activities, relatively low on-farm expenditure, low involvement in pest control activities, relatively small household size (6.2±0.5 members), small farm sizes (averaging 0.7±0.1ha in both seasons) and few agricultural implements (Figure 3.6p). They also spend moderate amounts of time on food preparation (Figure 3.6t) and firewood gathering and consume moderate amounts of firewood (Figure 3.6q), low forest product use (poles), and a moderate amounts of off-farm income (Figure 3.6x).
Figure 3.5 Dendrogram of household categorisation using Ward’s method

9 clusters extracted from 17 principal components accounting for 75.4% of the total variation in the data. The blue lines indicate the cluster widths, while the dotted red line indicates the rescaled distance at which the clusters were delineated. Each long “cluster stem” cutting the red dotted line indicates that cluster grouping.
<table>
<thead>
<tr>
<th>Cluster</th>
<th>Summary of peculiar characteristics</th>
<th>*Cluster classification</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Moderate time and labour investment in cultivation activities, low crop yields and low involvement in selling agricultural produce, moderate education level (albeit low), low involvement in pest control activities, relatively low on-farm expenditure, low involvement in extension activities, relatively small household size, small farm sizes and few agricultural implements, moderate amount of time on firewood gathering and firewood consumed, low amount of time spent on food preparation, low forest product use (poles), moderate amount of off-farm income, <strong>highest livestock husbandry involvement</strong> (large numbers of small ruminants), <strong>relatively high livestock incomes</strong>, mixed proportions of housing unit types and land ownership regimes</td>
<td><strong>Moderate income, livestock specialist households</strong> with low involvement in small-scale crop production</td>
</tr>
<tr>
<td>2</td>
<td>Relatively high involvement in cultivation activities, <strong>very low on-farm income and crop yields</strong>, lowest off-farm income, least involvement in extension meetings, least on-farm expenditure, not involved in pest control activities, relatively high amount of time spent on gathering firewood but least amount of total firewood used in a year, relatively small farm sizes and number of agricultural implements, moderate number of household members providing labour for agricultural activities, moderate education level (albeit low), moderate number of livestock, moderate amount of time spent on livestock husbandry, moderate household size and level of education, fetching water and cooking, low amount of time spent on selling agricultural produce, moderate use of forest products (poles), mostly use firewood for cooking; majority of which is obtained from natural forests, high proportion of temporary housing structures, land owned mostly under customary tenure</td>
<td><strong>Low income mixed farming households</strong> including crops and livestock, also dependent on forest products</td>
</tr>
<tr>
<td>3</td>
<td>Moderate amount of time spent on crop cultivation activities, moderate amount of off-farm income, <strong>relatively high crop yields</strong>, lowest amount of time spent on livestock grazing, low number of livestock (lowest involvement in livestock husbandry), least involved in grocery shopping, low on-farm expenditure, lowest education level, low amount of time spent on food preparation, low time allocation to selling agricultural produce, low off-farm incomes, relatively high duration of gathering firewood, small farm sizes, moderate number of agricultural implements, moderate household size, low involvement in extension activities, relatively high number of household labour involved in cropping activities, low involvement in pest control activities, relatively high amount of time spent on food preparation and fetching water, moderate use of forest products (particularly timber), mixed proportions of housing unit types and land ownership regimes, mixed proportions of housing unit types and land ownership regimes, mostly use firewood as the main energy source for cooking, gathered from multiple sources</td>
<td><strong>Low income crop specialist households</strong></td>
</tr>
<tr>
<td>4</td>
<td>Lowest cultivation time and labour input, lowest yield and on-farm income, lowest household size, lowest education level for children, lowest number of agricultural implements, least farmland size, consumes the largest amount of firewood but spends relatively low amounts of time of firewood gathering, lowest amount of time spent on selling agricultural produce, lowest incomes from livestock, no evidence of use of forest products (poles and timber), moderate off-farm income, mixed proportions of housing unit types, land ownership regimes are mixed but notably has the <strong>highest proportion of leasehold land tenure type</strong>, mixed use of firewood and charcoal as main energy source for cooking obtained, firewood is mostly obtained from bush-lands</td>
<td><strong>Limited cultivation households with moderate off-farm income</strong></td>
</tr>
<tr>
<td>5</td>
<td>Relatively high amount of cultivation time and labour input, relatively high amount of on-farm income, relatively high crop yields, relatively high involvement in livestock husbandry, highest on-farm expenditure, most involved in pest control, largest number of low input agricultural implements, spends time trading own-</td>
<td><strong>Moderate income, pest controlling diversifying households with mixed crop and</strong></td>
</tr>
<tr>
<td>Cluster Classification</td>
<td>Characteristics</td>
<td></td>
</tr>
<tr>
<td>------------------------</td>
<td>-----------------</td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>shop, highest amount of time spent on selling agricultural produce, relatively large household sizes, relatively high education levels, moderate farmland sizes, involved in agricultural extension activities, relatively high labour and time input to gathering firewood, high use of forest products (poles and timber), <strong>relatively high off-farm income</strong>, mixed proportions of housing unit types and land ownership regimes, mostly use firewood as the main energy source for cooking, gathered from multiple sources</td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>livestock farming</td>
<td></td>
</tr>
<tr>
<td>3</td>
<td>Moderate agricultural time and labour input, <strong>highest amount of time spent on trading own-shop</strong>, relatively low on-farm incomes, relatively low crop yields, moderate amount of time spent on grazing livestock, <strong>moderate number of livestock</strong>, high livestock incomes, no forest product use recorded (poles and timber), moderately large household sizes, moderately involved in extension activities, low involvement in grocery shopping, moderate on-farm expenditure, limited involvement in pest control, moderate education levels, moderate farm size and agricultural implements, moderate amount of time gathering firewood and labour for fetching water and food preparation, moderate off-farm income, <strong>housing units are mostly permanent</strong>, mixed proportions of land ownership regimes, mixed use of firewood and charcoal as the main energy source for cooking; firewood is gathered from multiple sources</td>
<td></td>
</tr>
<tr>
<td>4</td>
<td>Moderate income, mixed farming, shop-trading households</td>
<td></td>
</tr>
<tr>
<td>5</td>
<td>High involvement in agricultural production activities, <strong>highest off-farm income</strong>, moderate on-farm income, low yields, high involvement in livestock husbandry, most involved in agricultural extension activities, high time spent on grocery shopping and food preparation, moderate labour allocation to food preparation and fetching water, relatively high use of forest products (poles and timber), relatively high household sizes, moderate on-farm expenditure, no pest control activities, moderate education levels, <strong>highest total number of agricultural implements</strong>, high amount of time spent on and volume of firewood gathering, moderate amount of time selling agricultural produce and livestock income, moderate forest product use (poles and timber), moderate off-farm income, mixed proportions of housing unit types and land ownership regimes, mostly use firewood as the main energy source for cooking, gathered from multiple sources</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>Richest, &quot;elite&quot; mixed farming and trading-based households</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>Highest cultivation time and labour input, <strong>highest yields and on-farm income</strong>, largest household size (both nuclear and extended), highest education level for children, highest labour input for food preparation and fetching water, highest amount of time spent on gathering firewood, highest amount of time spent of food preparation, <strong>low forest product use</strong>, moderately involved in extension activities, moderate farm sizes, moderate on-farm expenditure, not involved in pest control activities, moderate number of agricultural implements, moderate livestock incomes, moderate off-farm income, mixed proportions of housing unit types, <strong>land ownership mostly under the customary systems</strong>, mostly use firewood as the main energy source for cooking, gathered from multiple sources</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>Moderate income, mixed farming agricultural extension activity oriented households</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>Large size, high labour and time inputting, moderate income, mixed farming households</td>
<td></td>
</tr>
</tbody>
</table>

*Cluster classification names are derived from outstanding characteristics from the continuous variables*
Figure 3.6a Cluster characteristics – cultivation time input (Bars represent 95% confidence interval)

Figure 3.6b Cluster characteristics – on-farm income (from cropping activities) (Bars represent 95% confidence interval)
Figure 3.6c Cluster characteristics – crop yield (Bars represent 95% confidence interval)

Figure 3.6d Cluster characteristics – livestock husbandry (seasonal grazing duration; Bars represent 95% confidence interval)
Figure 3.6e Cluster characteristics – livestock husbandry (number of livestock and household members tending livestock; Bars represent 95% confidence interval)

Figure 3.6f Cluster demographic characteristics (Bars represent 95% confidence interval)
Figure 3.6g Cluster characteristics – agricultural extension activities (Bars represent 95% confidence interval)

Figure 3.6h Cluster characteristics – cultivation household labour input (Bars represent 95% confidence interval)
Figure 3.6i Cluster characteristics – grocery shopping time input (Bars represent 95% confidence interval)

Figure 3.6j Cluster characteristics – grocery shopping household labour input (Bars represent 95% confidence interval)
Figure 3.6k Cluster characteristics – on-farm expenditure (Bars represent 95% confidence interval)

Figure 3.6l Cluster characteristics – pest control activities (Bars represent 95% confidence interval)
Figure 3.6m Cluster extended family characteristics (Bars represent 95% confidence interval)

Figure 3.6n Cluster characteristics – Education Level (Bars represent 95% confidence interval)
Figure 3.6o Cluster characteristics – Household Labour input for food preparation and fetching water (Bars represent 95% confidence interval)

Figure 3.6p Cluster characteristics – agricultural implements and farm land size (Bars represent 95% confidence interval)
Figure 3.6q Cluster characteristics – firewood gathering (Bars represent 95% confidence interval)

Figure 3.6r Cluster characteristics – fetching water (Bars represent 95% confidence interval)
Figure 3.6s: Cluster characteristics – trading own-shop (Bars represent 95% confidence interval)

Figure 3.6t: Cluster characteristics – food preparation time budget (Bars represent 95% confidence interval)
Figure 3.6u Cluster characteristics – selling agricultural produce time budget (Bars represent 95% confidence interval)

Figure 3.6v Cluster characteristics – livestock income (Bars represent 95% confidence interval)
Figure 3.6w Cluster characteristics – quantity of forest products used (Bars represent 95% confidence interval)

Figure 3.6x Cluster characteristics – off-farm income (Bars represent 95% confidence interval)
3.3.2.2 Cluster 2: Low Income, Mixed Farming Households

These households have a relatively high involvement in cultivation activities (Figure 3.6a), but typically obtain very low yields (Figure 3.6c), earn very little amounts of on-income (Figure 3.6b), and spend low amount of time spent on selling agricultural produce (Figure 3.6u). They also earn the lowest amount of off-farm income (Kruskal-Wallis test, $X^2=70.9$, df=8, $p=0.000$), averaging an annual total of UGX 810,000±230,000 (Figure 3.6x: equivalent to an average of US $0.89$ a day [US$1=UGX 2500$, below the internationally recognised poverty line of US $1$ a day). These households are also the least involved in agricultural extension activities in both the dry and wet seasons (Kruskal-Wallis test, $X^2=276.2$[dry], $X^2=277.3$[wet], df=8, $p=0.000$), averaging 0.4±0.2 hours in each season (Figure 3.5g). They also had the lowest on-farm expenditure in 2012 (Kruskal-Wallis test, $X^2=78.1$, df=8, $p=0.000$) and 2013 (Kruskal-Wallis test, $X^2=270.1$, df=8, $p=0.000$) averaging UGX 30,000±20,000 and UGX 20,000±20,000 respectively (Figure 3.6k). They were not involved in pest control activities at all (Figure 3.6l). Whilst the data show that these households spend relatively high amounts of time on firewood gathering, the total amount of firewood gathered in a year is the lowest (Figure 3.6q), although mostly located close to forests.

Cluster 2 households also have small relatively small farm sizes averaging 0.6±0.1 ha and 0.5±0.1 ha in the previous and current seasons (1st half of 2013 and 2nd half of 2013 respectively), and own few agricultural implements, on average, 6.8±0.6 tools in total. The household sizes are moderate (6.5±0.4 members in total), and members have a moderate albeit low level education averaging 5.4±0.6 (Figure 3.6n). They also owned a moderate number of livestock averaging 3.3±1.0 in both 2012 and 2013, and spend moderate amount of time spent on livestock husbandry (Figure 3.6d). A moderate number of household members provides labour for fetching water and cooking (Figure 3.6o). They also moderately use forest products (particularly poles).

3.3.2.3 Cluster 3: Low Income, Crop Specialist Households

Cluster 3 households spend a moderate amount of time on cropping activities (Figure 3.6a), earn a moderate amounts of income particularly from cropping activities (Figure 3.6b), and obtain high crop yields (Figure 3.6c). These households have the lowest
involvement in livestock husbandry with the least amount of time spent on grazing animals (Figures 3.6d, e) with low numbers of livestock 1.3±0.7 and 1.5±0.6 in 2012 and 2013 respectively. They have low on-farm expenditure (Figure 3.6k), low off-farm income (Figure 3.5x), spend limited time selling agricultural produce (Figure 3.6u), and have the least education level (e.g. fathers’ level is on average 3.7±0.9: Kruskal-Wallis test, $X^2=34.1$, df=8, $p=0.000$) (Figure 3.6n). They spend relatively high amounts of time on firewood gathering (Figure 3.6q). In addition, cluster 3 households own small farm sizes (averaging 0.6±0.2ha in the previous and current seasons), own a moderate number of agricultural implements (7.2±1.1 in total), have moderate household sizes (5.9±0.7members: Figure 3.6f), low involvement in extension activities (Figure 3.6g), relatively high number of household labour involved in cropping activities (Figure 3.6h), low involvement in pest control activities (Figure 3.6l), relatively high amount of time spent on food preparation and fetching water (Figure 3.6o), and moderate use of forest products (particularly timber: Figure 3.6w).

### 3.3.2.4 Cluster 4: Limited cultivation Households with Moderate Off-farm Income

Cluster 4 households spend the lowest amount of time (Figure 3.6a) and labour (Figure 3.6h) on cultivation activities. They earn the lowest on-farm income (Kruskal-Wallis test, $X^2=84.3$[previous season], $X^2=78.1$[current season], df=8, $p=0.000$; Figure 3.6b) and produce the least crop yields (Kruskal-Wallis test, $X^2=132.6$ [previous season], $X^2=98.2$ [current season], df=8, $p=0.000$; Figure 3.6c). They however earn a moderate amount of off-farm income (Figure 3.6x).

They also have the lowest household sizes (Kruskal-Wallis test, $X^2=67.2$, df=8, $p=0.000$) averaging 5.3±0.5members (Figure 3.6f), lowest education level for children (3.1±0.7), although education level for children across the 9 clusters is not significantly different (Figure 3.6f). In addition, these households have the smallest farm sizes (Kruskal-Wallis test, $X^2=142.5$, df=8, $p=0.000$), averaging 0.2±0.1ha in both the previous and current seasons (Figure 3.6p), and the lowest number of agricultural implements (Kruskal-Wallis test, $X^2=64.1$, df=8, $p=0.000$) averaging 5.3±1.2 (Figure 3.6p). While they consume the largest amounts of firewood (Kruskal-Wallis test, $X^2=129.5$, df=8, $p=0.000$), they spend the lowest amount of time on gathering it (Figure 3.6q). There is
no evidence of dependence of forest products particularly poles and timber (Figure 3.6w).

3.3.2.5 Cluster 5: Moderate Income, Pest Controlling Diversifying Households

Cluster 5 households spent relatively high amounts of time (Figure 3.6a) and labour (Figure 3.6h) on cultivation activities in 2013. They obtained relatively high crop yields, albeit with large confidence intervals (Figure 3.6c) and earned high amounts of on-farm income (Figure 3.5b). These households are the most involved in pest control activities with the highest time (Kruskal-Wallis test, $X^2=357.9$[dry], $X^2=342.2$[wet], df=8, p=0.000) and labour allocation (Kruskal-Wallis test, $X^2=404.1$[dry], $X^2=367.5$[wet], df=8, p=0.000) compared to other clusters (Figure 3.6l). They own the largest number of agricultural implements (Kruskal-Wallis test, $X^2=64.1$, df=8, p=0.000), averaging 13.1±3.9 and have a moderate farm sizes (averaging 1.1 ± 0.4: Figure 3.6p). They are also moderately involved in livestock husbandry (Figures 3.6d and e). They own shops and spend moderate amounts of time selling merchandise (Figure 3.6s); and spend the highest amount of time on selling agricultural produce in both seasons (Kruskal-Wallis test, $X^2=80.8$[dry], $X^2=81.5$[wet], df=8, p=0.000: Figure 3.6u).

Cluster 5 households have relatively large household sizes (6.6±0.9 members), relatively high education levels for biological children (4.1±1.4: Figure 3.6f), and are involved in agricultural extension activities (Figure 3.6g). They have a relatively high time input to gathering firewood (Figure 3.6q), and use high amounts of forest products including poles and timber (Figure 3.6w).

3.3.2.6 Cluster 6: Moderate Income, Mixed Farming, Shop-Trading Households

Cluster 6 households spend moderate amounts of time (Figure 3.6a) and labour (Figure 3.6h) on agricultural activities, and have moderate farm sizes (0.8±0.3ha in each of the seasons of 2013; Figure 3.6p) and own a moderate number of agricultural implements (6.8±2.1 in total). Compared to the other clusters, they spent the highest amount of time on selling goods and merchandise in their own shops in both seasons in 2013 (Kruskal-Wallis test, $X^2=558.2$[dry], $X^2=557.9$[wet], df=8, p=0.000: Figure 3.6s), which contributes to a moderate amount of off-farm income (Figure 3.6x), and have a
moderate on-farm expenditure (Figure 3.6k). They obtained relatively low crop yields (Figure 3.6c) and earned relatively low on-farm incomes (Figure 3.5b). They own a moderate number of livestock (5.5±5.5[in 2012], 2.2±1.8[in 2013]: Figure 3.6e), spend a moderate amount of time on gazing animals (Figure 3.6d) and earn high amounts of income from livestock albeit with large confidence intervals (Figure 3.6v). There is no use of forest products (poles and timber) recorded (Figure 3.6w).

Cluster 6 households have relatively large sizes (6.5±1.1members: Figure 3.6f), moderately involved in agricultural extension activities (Figure 3.6g), have a low involvement in groceries shopping (Figure 3.6j), limited involvement in pest control activities (Figure 3.6l). They have moderate education levels (e.g. fathers’ education level is on average 5.7±1.6: Figure 3.6n). They spend moderate amounts of time and labour on gathering firewood (Figure 3.6q), and moderate household labour for fetching water (Figure 3.6r), and food preparation (Figure 3.6t).

3.3.2.7 Cluster 7: Richest, “Elite” Mixed Farming and Trading-Based Households

Cluster 7 households have the highest off-farm income (Kruskal-Wallis test, $X^2=70.9$, df=8, p=0.000: Figure 3.6x) averaging UGX 4,900,000±2,160,000 (~US$5.4 per day), and spend relatively high amounts of time on selling goods and merchandise in their owned shops (Figure 3.6s). These households own the largest farm sizes (Kruskal-Wallis test, $X^2=142.5$[both seasons], df=8, p=0.000) averaging 1.5±1.0ha in both seasons (Figure 3.6p), have the highest number of high-input agricultural implements (Kruskal-Wallis test, $X^2=66.8$, df=8, p=0.000) averaging 1.5±1.5 (Figure 3.6p). They are moderately involved in agricultural activities (Figure 3.6a), earn a moderate amount of on-farm income (Figure 3.6b), although they obtained typically low yields (Figure 3.6c) and have relatively high on-farm expenditure (Figure 3.6k). They also have high involvement in livestock husbandry (Figure 3.6d and e), earn moderate amounts of income from livestock (Figure 3.6v), attend agricultural extension meetings (Figure 3.6g), and are highly involved in pest control (Figure 3.6l).

In addition, cluster 7 households have a moderate size averaging 5.3±0.9members, and have the highest levels of education (albeit low) of fathers (on average 9.2±2.5: Kruskal-
Wallis test, $X^2=34.1$, df=8, p=0.000) and mothers (on average $7.0\pm2.5$; Kruskal-Wallis test, $X^2=46.1$, df=8, p=0.000: Figure 3.6n). They have the lowest labour input for fetching water in both seasons (Kruskal-Wallis test, $X^2=182.0$[dry], $X^2=192.8$[wet], df=8, p=0.000: Figure 3.6o) and spend the least amount of time on fetching water (Kruskal-Wallis test, $X^2=131.1$[dry], $X^2=120.0$[wet], df=8, p=0.000: Figure 3.6r). They also spend the least amount of time on firewood gathering in both seasons (Kruskal-Wallis test, $X^2=88.9$[dry], $X^2=78.4$[wet], df=8, p=0.000: Figure 3.6q) and consume the least amount of firewood (Kruskal-Wallis test, $X^2=109.0$, df=8, p=0.000: Figure 3.6q).

### 3.3.2.8 Cluster 8: Moderate Income, Mixed Farming, Agricultural Extension Activities Oriented Households

Cluster 8 households are highly involved in agricultural production activities (Figure 3.6a), but with low crop yields (Figure 3.6c), own the highest number of agricultural implements ($10.4\pm3.3$; Kruskal-Wallis test, $X^2=64.1$, df=8, p=0.000: Figure 3.6p), obtain moderate on-farm income (Figure 3.6b), have moderate on-farm expenditure (Figure 3.5k) and moderate farm sizes ($0.9\pm0.3$ha, Figure 3.6p). They are the most involved group of households in agricultural extension activities (Figure 3.6g); also highly involved in livestock husbandry (Figure 3.6d and e), and earn moderate amounts of income from livestock (Figure 3.6v). They are not involved in pest control activities (Figure 3.6l). They however spend high amounts of time on selling agricultural produce (Figure 3.6u), grocery shopping (Figure 3.6i), food preparation (Figure 3.6t), and allocate moderate amounts of household labour on food preparation and fetching water (Figure 3.6o). In addition, cluster 8 households have relatively high household sizes ($6.6\pm0.7$members), have moderate education levels, albeit low (Figure 3.6n). They also spend high amounts of time on gathering firewood, and consume a moderate volume of firewood (Figure 3.6q).

### 3.3.2.9 Cluster 9: Largest Size, High Labour and Time inputting, Moderate Income Mixed Farming Households

Cluster 9 households spend the highest amount of time and labour on agricultural activities (Figures 3.6a and h respectively). They obtained the highest crop yields albeit with large confidence intervals (Figure 3.6c), highest on-farm income (Figure 3.6b), and
have the largest household size (10.0±1.1 members); that includes the largest number of members in the extended family (Figure 3.6m). They are involved in livestock husbandry (Figure 3.6d and e) and earn moderate incomes from the enterprise (Figure 3.6v). They have the highest level of education of the biological children (4.8±0.9, although not significantly different from other clusters). They have the highest labour input for food preparation and fetching water (Figure 3.6o), spend highest amounts of time on gathering firewood, on average 247.2±68.8 hours (Kruskal-Wallis test, $X^2=118.1$, df=8, p=0.000 in the wet season and 250.6±64.4 hours in the dry season (Kruskal-Wallis test, $X^2=121.4$, df=8, p=0.000: Figure 3.6q). They also spent the highest amount of time on food preparation (Kruskal-Wallis test, $X^2=56.6$[dry], $X^2=60.9$[wet], df=8, p=0.000: Figure 3.6t). They own moderate farm sizes (0.8±0.2 ha, on average), and a high number of agricultural implements (8.8±1.6: Figure 3.6p). These households are not involved in pest control activities (Figure 3.6l).

### 3.3.3 Categorical variable exploration

The relationship between a wide range of categorical variables and the 9 clusters was explored. As there are inconsistent data gaps in the categorical variables and given that some are relatively insensitive, especially where cultural effects dominate (e.g. on decision making in the household, coping strategies under labour and time constraints: for a view of all the categorical data in this investigation, see Appendix 3.5), only those that are interpretable with the available data are presented in this section, summarised in Table 3.7.

**Household nativity**: there are two native populations in the landscape, Banyoro and Bagungu accounting for 50% and 22.8% of the total number of respondents (n=706). The migrants only contribute 27.2% of the total. The ethnicity is mixed within the clusters although there are relatively more natives in 2, 1, 3 and 4 while the majority of the migrants are 2, 3 and 1 (Figure 3.7d).

**The main land tenure system** in the landscape is the customary type accounting for 54.5% of the total (n=706). This is followed by the freehold land tenure system (34.6%), and the least common is the leasehold tenure system (10.9%). Clusters 2, 3 and 4 have a
significantly larger number of households under the customary tenure system than the other clusters while cluster 7 households are predominantly in the freehold system ($X^2=202.2$, df=2, $p=0.000$: Figure 3.7b).

**The type of house owned by the households** varies by cluster ($X^2=38.2$, df=2, $p=0.000$), although there is a tendency for cluster 7 households (richest, “elite” mixed farming and trading-based households) and cluster 6 households (moderate income, mixed farming, shop-trading households) to live in houses made of permanent structures. Lower income households in clusters 1 and 2 have more semi-permanent and temporary structures compared to the other clusters (Figure 3.7a). Generally, *forestry policy awareness* in the landscape is low with 63.2% of the total respondents (n=706) unaware of forest policies. Clusters 2, 1, 4 and 3 have relatively larger numbers of households unaware of forest policies (Figure 3.7c).

The *main sources of energy for cooking* in the landscape are firewood (83.3% of the total, n=706) and charcoal (16.4% of the total). Cluster 2 has a high usage of firewood for fuel (Figure 3.7e); using bush relatively close at hand as the source (although with a significant number obtaining firewood from the forest; Figure 3.6 f and g); and collected by the mother (Figure 3.7i). They mostly revisit the previous collection sites until exhausted before they find new gathering areas (Figure 3.7h). The other clusters have the source of energy, who collects, from where and selection of gathering sites criteria in mixed proportions.

**Table 3.7 Categorical variables exploration by clusters**

<table>
<thead>
<tr>
<th>Categorical variable</th>
<th>$X^2$</th>
<th>Degrees of freedom</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Household nativity</td>
<td>90.3</td>
<td>2</td>
<td>0.000</td>
</tr>
<tr>
<td>Main land tenure system</td>
<td>202.2</td>
<td>2</td>
<td>0.000</td>
</tr>
<tr>
<td>Type of house owned by the household</td>
<td>38.2</td>
<td>2</td>
<td>0.000</td>
</tr>
<tr>
<td>Forest policy awareness</td>
<td>49.6</td>
<td>1</td>
<td>0.000</td>
</tr>
<tr>
<td>Main source of energy for cooking</td>
<td>823.5</td>
<td>2</td>
<td>0.000</td>
</tr>
<tr>
<td>Who gathers firewood</td>
<td>1126.9</td>
<td>5</td>
<td>0.000</td>
</tr>
<tr>
<td>Where firewood is gathered</td>
<td>530.2</td>
<td>5</td>
<td>0.000</td>
</tr>
<tr>
<td>Distance to firewood collection sites</td>
<td>221.0</td>
<td>3</td>
<td>0.000</td>
</tr>
<tr>
<td>Criteria of selecting firewood collection sites</td>
<td>953.2</td>
<td>2</td>
<td>0.000</td>
</tr>
</tbody>
</table>
3.3.4 Agro-Ecological Zone–Level Cluster Composition

Households around forested regions (Budongo and Bugoma AEZs) mostly belonged to cluster 2 (low income mixed farming households) accounting for 60.7%, 45.2%, of the total surveyed households in Biiso and Busingiro parishes respectively located in Budongo AEZ, while 34.7%, 57.1% and 25.4% of households surveyed in Bubogo, Igwanjura and Kyangwali (Bugoma AEZ) respectively belong to cluster 2. In Budongo AEZ however, Kibwona parish is dominated by cluster 3 (low income crop specialist households) involved in the out-grower sugarcane production scheme alongside other food crops, while Nyabyeya has a more mixed composition although dominated by cluster 1 (moderate income, livestock specialist households) (Figure 3.8). Within the sampled households, there is a lack of cluster 7 households (richest, “elite” mixed farming and trading-based households) in all the parishes in Budongo and Bugoma AEZs except for Bubogo and Igwanjura, and even then, these have a low representation, at 2.0% and 1.8% respectively.

As expected, the peri-urban AEZ is dominated by cluster 4 households (limited cultivation households with moderate off-farm income), accounting for 22.4%, 30.6% and 41.1% of the surveyed households in Westernward (Masindi), Southernward...
(Masindi) and Mparo (Hoima) respectively. Kasingo (Hoima) is however dominated by cluster 2 households accounting for 25.9% of the total surveyed households. The peri-urban AEZ also has the highest percentage of cluster 7 households (richest, “elite” mixed farming and trading-based households) compared to the other AEZs accounting for 12.1%, 10.2% and 14.3% in Westernward (Masindi), Southernward (Masindi) and Mparo (Hoima) respectively. Kasingo parish has the smallest percentage (only 3.7%) of cluster 7 households amongst the peri-urban AEZ parishes.

In the semi-arid AEZ, however, cluster 2 (low income mixed farming households) is the most dominant accounting for 32.8% and 50.0% of the total number of surveyed households in Kisansya and Kigwera respectively. There is also a mixture cluster 4 (limited cultivation households with moderate off-farm income) particularly in Kisansya (27.6%) that are involved in fishing in Lake Albert, and cluster 1 (moderate income, livestock specialist households) mostly in Kigwera (23.2%) that are involved in free range grazing of cattle and goats.

The other clusters are in mixed proportions across various parishes in the 4 AEZs indicating marked variation in the household livelihood characteristics at the parish-scale.

### 3.3.5 Cluster Spatial Distribution

Moran’s I test of the relationship between each household with the most immediate shows strong positive spatial autocorrelation (Moran’s I=0.099, z-value=4.60, p=0.001) suggesting clustering in the households by location, confirmed by visual exploration of the distribution of the clusters spatially in Figure 3.9. There is a striking pattern of homogeneity in households along transects taken across the semi-arid AEZ (e.g. cluster 4 and 2 households in Kigwera [in the middle of the plot]). In Budongo AEZ, a similar pattern is seen in Biiso (cluster 2, far left and middle in the plot). In Bugoma AEZ, patterns in transects are visible in Igwanjura (cluster 2, bottom right). As is the case with most of the remaining parishes, settlement patterns along transects of peri-urban AEZ are more heterogeneous.
Figure 3.8 Cluster membership per Agro-Ecological Zone computed from 17 principal components using Ward’s method
Figure 3.9 Clusters of households based on the first 17 principal components: A) Semi-arid zone, B) Budongo region, C) Peri-urban zone, D) Bugoma region (AEZs) (natural forest patches from Jan,2014 image are shown in green where they are available: not drawn to scale to avoid tracing the participating households, but for location of the AEZs see Figure 3.1)
3.4 Discussion

While different aspects of this analysis could be highlighted to emphasise wide-ranging themes (because of the multidisciplinary nature of this investigation), the discussion is tightly structured to address the research questions in two sections. The first section addresses the important variables essentially driving the household classification and the proportions of clusters in each Agro-Ecological Zone (AEZ). In the second, I briefly explore potential hypotheses on spatial distribution of the households relative to the 4 AEZs and allude slightly to the implications of this for deforestation.

3.4.1 Key Discriminators of Livelihood Characteristics in the Landscape

3.4.1.1 Continuous Variables

The application of a Principal Components Analysis (PCA) to reduce redundancy in the large set of field data gathered was successful: 83 original variables were compressed to 22 principal components. The PCA particularly highlights variable grouping that are the most important discriminators of dissimilarity in the entire data, in order starting with the most important. Significant variation was related to agricultural time input (PC1), on-farm income particularly from cropping activities (PC2), livestock husbandry (PC3), demographic characteristics (PC4), agricultural extension activities (PC5), and cultivation labour input (PC6). These are discussed in turn.

The backbone of the rural economy has its basis predominantly in agriculture (Fan and Zhang 2008): this is the main source of food, with the surplus sold for incomes to purchase basic needs (e.g. salt, clothing, pay children's school fees, medical expenses, etc), and therefore, depending on the agro-ecological zoning, households spend considerably different amounts of time and labour on agricultural activities (e.g. opening up agricultural land, weeding, harvesting, postharvest handling, etc). Households in the peri-urban and semi-arid AEZs tend, for instance, to spend less time on agricultural activities, as expected. We observed that the majority of households still use rudimentary low-input technologies, and therefore spend more or less time on agricultural activities based on the amount of labour, time (season), tools available, farm size, among other factors. These activities are routine during both the dry and wet
seasons, and therefore obtain priority, one at a time (or concurrently) depending on the
development stage of the cultivated crops. This is shown by the positive correlation
between the cultivation time variables (Cluster 9 picks this out well on plot 1, Figure
3.4c).

The largest contribution to household on-farm income is from crop sales. Households
particularly in cluster 3 obtain relatively higher crop yields which boosts their income
from sales from the surplus. Households in Kibwona parish however present a peculiar
case, as some of those that participated in the survey are part of the sugarcane out-
grower scheme. Their total yields are therefore considerably boosted by the
involvement in the sugar industry, otherwise, the crop yields from the other crops is
similar to those in the other parishes in Budongo AEZ. Low yields in cluster 7
households who have the largest farms and better access to technology could be related
to low labour input (related to the small household size).

Livestock husbandry is relatively common in the landscape although more pronounced
amongst households in the peri-urban and semi-arid AEZs. They typically keep small
ruminants (goats and sheep) and pigs, and very few cattle. Livestock, particularly cattle,
in the semi-arid AEZ (and other parts of the landscape) are viewed as wealth status
symbol in society. These households (mainly in the semi-arid AEZs) keep moderate
numbers but of low quality (largely malnourished due to limited and seasonal
availability of food and water). The small ruminants are preferred to larger animals due
to housing space limitations, although most of the grazing is the free range type: where
animals are allowed to roam on large communal fields under supervision of a member
of the household (especially in the semi-arid AEZ). In places where there is a mixture of
cropping activities and settlements, households opt for the tethering grazing method,
which controls livestock movements and avoids crop raiding.

Household demographic characteristics are mostly similar, with medium to large
household sizes that include both nuclear and extended families. The population
pyramid shows a very large percentage of the population under 20 years, an indicator of
a rapidly growing population. The population growth rate in the landscape is one of the
highest in the world estimated at nearly 4% per annum (Bongaarts 2009). There are
however marked differences in the bins of males and females under the age of 16, the causes of this are not obvious. It could be due to sampling biases where households with more males under the age of 10 are included, or related to mortality rate differences in children by gender; or perhaps some issues regarding age reporting. The level of education is generally low, the majority having only attained primary education (between primary 4 and 7), and this does not vary much across the AEZs, except for a few elite members (with up to university education) living mostly in the peri-urban areas. This could be related to the distribution of schools in the rural areas, where there are few per parish compared to the peri-urban areas, as well as the challenges of labour for agricultural production being provided by school-going children. Further research is required to understand the causes of early drop-out of school.

Participation in agricultural extension activities stands out as a key variable. Some households have limited access to agricultural extension services and have admitted the lack of visits from the government extension, and agricultural advising officers. Local governments hire extension officers at sub-county level but these are too large to be managed by one staff who is often poorly facilitated due to budget constraints. Households that attend extension services to the greatest degree are those in cluster 8, although some activity is recorded in clusters 5, 6, 7, and 9. These are mostly in rural areas which take part in agricultural production.

Due to limiting factors of production in the rural areas, households diversify with various enterprises for their survival. A variety of the activities are found in the mid-table of the PCA matrix including trading goods and merchandise in their shops, selling agricultural produce from home (where buyers obtain produce on source) or in the markets during market days; however, factors such as livestock income, quantity of forest products used (particularly poles and timber) and off-farm income contribute the least variation in the data. Households typically do not depend on livestock products; besides livestock numbers are generally low to enable them dispose them off for income. The recorded sales during the data gathering were a handful. Few households are however involved in off-farm employment both in the public and private sectors. In the private sector, households predominantly from the semi-arid AEZ, close to Lake Albert engage in fishing to supplement their incomes. Other jobs include providing
informal labour to the sugarcane industry especially by households in Nyabyeya and Kibwona parishes around Budongo AEZ. While it would be expected that the use of forest products (poles and timber) would be a good discriminator of households due to their proximity to the natural forest, it is surprisingly ranking low in the PCA model. It may be that poles and timber are poor indicators of dependence on forest products – but these are products that were relatively easy to quantify (as they have fairly easy dimensions to measure, making volumes consumed easy to compute), unlike those such as medicinal plants, wild fruits, papyrus reeds among others. The data show that households that live near the forests access these products (poles and timber) although in relatively small quantities. It is difficult to judge if the correct quantities were reported, in case these products were a source of income, but if they were only used in construction of their housing structures, then it is logical that not a lot of poles and timber are required.

3.4.1.2 Categorical Variables

The categorical variables were treated in a different manner from the continuous ones: they were not included in the PCA but their relationship with the clusters was explored to unearth further cluster characteristics. Given the data gaps, only the interpretable variables were retained. These include: household nativity, land tenure system, type of household, forest policy awareness, and main energy source for cooking.

**Household nativity (by birthplace):** Previous narratives have suggested that deforestation in the Albertine region is largely driven by migrants (e.g. Mwavu and Witkowski, 2008), but the household survey data suggests that the geography of migrants and natives is more local. More migrants are located around Budongo forest, and natives are dominant around Bugoma. The peri-urban AEZs are dominated by native populations, with Banyoro in the peri-urban AEZ (mostly in Hoima and Masindi) while the Bagungu are located in the semi-arid AEZ. The movement of the people is driven by economic activity around Budongo boosted by the sugar industry, while around Bugoma it was largely due to availability of “free forested land” (clarified in later chapters). The migration was also triggered by various processes including political
instability, particularly around Budongo, dominant tribes are from northern Uganda and DRC; while around Bugoma, dominant tribes are from south-western Uganda.

**Land Tenure System**: Three of the four main land tenure systems in Uganda noted in the survey data at the regional level include (in order of dominance): customary, freehold, and leasehold (Okuku 2006). The definitions of land tenure systems at the local level are similar to those in the 1998 Land Act (although with slight variations). As is the case elsewhere in the country, land is predominantly owned under customary tenure (Batungi and Ruther, 2008; Twongyirwe et al., in press). Under this system, land is inherited from parents/previous generations and is often managed communally (by the family) but is often not formally registered. The 1998 Uganda Land Act aimed to strengthen the rights of customary tenants by offering official certificates of customary tenure (permitting transfer rights of sale, lease or mortgage), and certificates of customary ownership which could be converted to freehold tenure following a survey of the land (although none has been issued to-date to the best of the author’s knowledge). This ownership type provides less incentive to develop the land, and is often fragmented as it is passed on from one generation to another which generally explains the small land sizes owned by households.

The second common land ownership type is the freehold system. Freehold is a legally documented form of private ownership where one party owns registered land in perpetuity with full use rights including its development and use as collateral. Under this system, land can be sold or passed on at free will according to the Uganda Land Act, 1998 (G.o.U 1998). While the majority that mentioned that they bought the land on which they live, they confessed that they only had buyer/seller agreements and not legal titles. This is also likely to be problematic following growing economic interests in the landscape. It may be a disincentive for farmers to keep forests on their private land because of the insecurities involved in the lack of legal titles. Buyers of large amounts of land who are often also able to afford titles have been branded “land grabbers” in prevailing discourses (Muriisa et al., 2013); the deals involved in the purchase often do not reflect the prevailing market prices and are unfair to the rural communities.
The third and the least common land ownership system as suggested by the data is the leasehold tenure type. This system, in accordance with the Uganda Land Act, 1998, involves a contractual agreement between a landlord granting exclusive use, and a tenancy for a defined period often for 49 or 99 years (Okuku 2006). For the period that the land is leased, the tenant can use or develop it and obtain all profits that accrue from its use. Within the parishes however (especially the semi-arid AEZs), the rental periods were far from the legally designated period in the Land Act. The respondents had short-term contracts, agreed by word-of-mouth, lasting between a season and two (up to 1 year), and renewable depending on need.

The fourth type of tenure that is missing in the data is the mailo system. This system was introduced in the 1900 agreement with colonialists where the British allocated to themselves “crown land” while kings and chiefs were offered mailo land. The King would then allocate large pieces of land to his subjects as he pleased. While the Bunyoro Kingdom that was present in 1900 still exists, and this tenure system catered for in the land act, it appears to be uncommon in the region.

The main housing structure is an indicator of the wealth status of the households. The dominant type of housing structures differed by AEZ, with households in peri-urban areas owning housing units mostly made of permanent material (bricks, cement, iron roofs, etc), while poorer households owned mainly semi-permanent (walls made of mud and wattle but with an iron roof) or temporary (walls made of mud and wattle, with a grass thatched roof) housing units, located predominantly in the semi-arid, Budongo and Bugoma AEZs. Households in peri-urban areas have more disposable incomes and are therefore able to afford materials to construct the permanent housing units compared to their rural counterparts.

**Forestry policy awareness:** Fewer than half of the respondents (36.8%) in the landscape reported that they are aware of the forestry policies. This could be attributed to the role played by government and non-government institutions in sensitising communities on collaborative management of these forests. These campaigns are documented in the literature with examples in similar settings elsewhere (Norgrove and Hulme, 2006; Banana, Mohamed et al., 2012; Twongyirwe et al., in press). The data
also show, on the other hand, that the number of respondents who are oblivious to forest policies are the majority. It is not clear whether this is related to the generally low levels of education or a number of other interacting factors. Further research is required to understand why this is the case.

*Main energy type used for cooking:* the main energy source for cooking is from biomass (firewood and charcoal), as is the case in most parts of Uganda (Okello et al. 2013). Firewood is mostly used as it easier to obtain, with minimal costs involved compared to charcoal. There is a gender bias towards women gathering firewood, and often move to the same sites until source is exhausted. This could also be related to the fact that they are the ones who are mostly involved in food preparation.

### 3.4.2 Agro-Ecological Zone Cluster Composition: Examining Spatial Patterns and Livelihood Adaptation

While the result section has a detailed description of the 9 clusters by their socio-economic characteristics, the aggregate properties are not discussed here. They were critically analysed to identify “latent/outstanding” variables that uniquely define the clusters: these were used in the naming of the clusters.

The data show that households that live around forested regions in Budongo and Bugoma AEZs are mostly low income earners (belong to cluster 2: low income mixed farming households) and are more dependent on forest products for their livelihoods than their peri-urban and semi-arid AEZ situated counterparts. They are caught up in what is arguably a vicious cycle of poverty that contributes to environmental degradation (de Sherbinin et al. 2008). They have relatively large household sizes, and as they struggle to sustain them by providing the basic needs (food, shelter, clothing, education, medication, etc), with the limited on-farm and off-farm income, they seek extra livelihood from their environment. Poverty leads to high fertility due to demand for farm labour, ‘insurance births’ owing to high infant mortality: high fertility then contributes to large households which further increases demands for food and resources from an essentially static resource base (de Sherbinin et al. 2008). The deforestation patterns identified in Chapter 2 may to some extent be explained by this
theory except perhaps in regions where commercial cultivation of sugarcane, and illegal large-scale logging are key forest loss drivers. Studies have shown that forest dependent people are poorer, live close to the forest, have lower livestock and crop income (de Sherbinin et al. 2008; Tesfaye et al. 2011).

Unlike the other parishes in the Budongo and Bugoma AEZs, Kibwona and Nyabyeya (both in Budongo AEZ) show striking differences. Kibwona is dominated by cluster 3 households (low income crop specialist households), which are mostly dependent on sugarcane production as part of the out-grower scheme alongside other food crops. The out-grower scheme is a franchise-based program where farmers are given start-up capital in kind (e.g. the company clears land, does the planting, weeding, pest control, application of fertiliser, and harvesting) provided they offer their land for sugarcane production in a contract of often more than 5 years (at least 3 ratoon-harvests: estimates from a key informant). The investment costs by Kinyara Sugar Works are then deducted from the final annual payments made to the farmer after buying the sugarcane from them. While further research is required to understand if the sugarcane industry is improving the socio-economic status of participating households, the data show that they on average remain low income earners. This is possibly due to the fact that the payments are one-offs, made on an annual basis. Because the farmers offer up their land for commercial sugarcane production, they are then left with rather small pieces on which they grow their food. Households in Nyabyeya parish thrive mostly on livestock husbandry. This may be associated with the Budongo community-based conservation project that provided goats to households surrounding Budongo forest as a way to boost their household incomes as an incentive to co-manage and protect the forest (information from a key informant based at the National Forest Authority). In general, households around the protected forest blocks diversify into several activities to boost their livelihoods as indicated by the mixed cluster composition, although the tendency for them to be poorer than those in the peri-urban areas is higher, with for instance, a lack of cluster 7 households (richest, “elite” mixed farming and trading-based households) in both Budongo and Bugoma AEZs except for Bubogo and Igwanjura although with small numbers.
Unsurprisingly, the peri-urban AEZ is dominated by cluster 4 households (limited cultivation households with moderate off-farm income). Typically, urban dwellers are less involved in crop cultivation but more in off-farm formal and odd jobs to earn a living. They own the smallest farm sizes, and invest least time and labour in agricultural production. They purchase most of their food from local markets which source it from more rural areas. Additionally, they have a larger number of cluster 7 households (richest, “elite” mixed farming and trading-based households) compared to other AEZs. This could be related to the availability of social services (e.g. schools, markets) closer to them than the rural counterparts. Only Kasingo however, has dissimilar characteristics from the peri-urban AEZs, is a lot similar to the more rural AEZs, with the highest number of households belonging to cluster 2 (low income mixed farming households). While Kasingo is within Hoima town council, the surveyed households live in the suburbs, and have more rural livelihood tendencies with space to engage in small-scale agriculture (mixed crop and animal husbandry). This also suggests that Hoima town is concentrated in the central trading area, and beyond which, even though areas are classified as being part of the town council, they are less urbanised.

The semi-arid AEZ livelihood dynamics are mixed; similar to Budongo and Bugoma AEZs, cluster 2 households (low income mixed farming households) is the most dominant. The majority of the households are typically poor, and although they lack access to the natural forests, their livelihoods are diversified. This region is mostly dry and receives dry monsoon winds from the East African coast which essentially restricts cropping to those crops that can bear long stress periods (e.g. cassava and maize). The striking pattern of homogeneity in households along transects taken during data gathering (e.g. cluster 4 and 2 households in Kigwera [in the middle of the plot]) is corroborated by a study that found that although settlements are scattered, where there is clustering, such groups belong to the same ancestry (SNV 2012). These families also own or rent land in Ngwedo village (see Figure 3.1 for location) where they have gardens mainly for subsistence farming (ibid). Cluster 4 households (limited cultivation households with moderate off-farm income) particularly in Kisansya are involved in fishing in Lake Albert to supplement their incomes while cluster 1 (moderate income, livestock specialist households) mostly in Kigwera are involved in free range grazing of cattle and goats. The customary land tenure system is one that favours free-range
grazing, but is a disincentive to cultivation even though the soils and climate might be able to support dry-land crops (SNV 2012). Over-grazing is common, and often leaves the land bare, and the stocking densities are reportedly high among a few migrant cattle farming settlers referred to as “Balaalo” (ibid).

3.5 Conclusions

This study sought to characterise households in the Northern Albertine Rift region empirically into livelihood typologies to better understand livelihood adaptation strategies to survival in their respective Agro-Ecological Zones (AEZs), and to set up the next level of analysis that will examine the clusters more critically in light of the dramatic forest loss outside the protected forest estate, on private landscapes. This was successfully achieved through an extensive household survey mixed with field observations and key informant interviews over 6-months (October, 2013–March, 2014), and rigorous statistical analyses.

From the Principal Components Analysis (PCA), the data show that cultivation time budgets, on-farm income especially from cropping activities, livestock husbandry, and household demographic characteristics are among the major sources of variation in the livelihood socio-economic status; while the use of forest products (poles and timber), and off-farm income are the least variable factors. The landscape is predominantly agrarian, with different crops suitable for different areas, and therefore time requirements for crop production turned out to be the main difference in the livelihood typologies. Varying crop yields, farm sizes, among others contributed to the disparity in the on-farm incomes earned across the landscape. As a livelihood adaptation strategy, households kept varying numbers of livestock based on affordability, availability of grazing land, prestige, and time to look after the animals, among other factors. The landscape generally has large household sizes averaging between 6-10 members, and the population pyramid is typical of a rapidly growing population (which is likely to exert more pressure on the already constrained and fragmented resources, with implications on further future forest loss). The data show on the other hand that poles and timber are not widely used forest products amongst the surveyed households, and
therefore, perhaps, a poor surrogate of forest product dependence. Households adjacent to the forests however rely on other forest products such as firewood (this was quantified), and other non-quantified products (e.g. medicinal plants, bush meat, etc) reported in key informant interviews (to be presented in the following chapters). As few members in the households are involved in off-farm activities, off-farm income is also a poor discriminator of the livelihood status.

Categorical variables further distinguished important household characteristics. These include: housing types, forestry policy awareness, land tenure regimes, and dominant energy types used for cooking. There is a mixture in housing units, although more temporary structures are located in the rural areas, particularly, Bugoma, Budongo and semi-arid AEZs. Permanent structures are more common in the peri-urban areas, an indicator of a better wealth status. Forestry policy awareness is generally lacking amongst the majority of the surveyed households, possibly related to their low levels of education, and therefore considerable efforts would be required to improve policy awareness: and natural resources exploitation and protection policies could perhaps be inculcated in the primary school education curriculum. The dominant land tenure type is the customary system that encourages land fragmentation as land is passed on from one generation to another, which could be a disincentive for large-scale agricultural production, and would therefore keep the already poor households in further poverty. While this (land tenure systems) will be examined in the subsequent chapters on its role in deforestation, it is apparent that the incentive for keeping natural forest on private land would be limited without considerable conservation effort with external funding. Biomass is the main source of energy for cooking across the landscape. This is related to its availability and the high costs involved with seeking alternative energy types (e.g. hydro-electricity, solar energy and biofuels).

The cluster analysis from this chapter shows that cluster 2 (low income mixed farming households) is dominant in the landscape, a category common amongst rural households located in parishes around Budongo and Bugoma AEZs, as well as the semi-arid AEZ. Peri-urban households mostly belong to cluster 4 (limited cultivation households with moderate off-farm income). While there is a mixture of clusters within each AEZ, the spatial patterns indicate positive autocorrelation. Households adapt to
livelihood constraints in the various AEZs by diversifying to different agricultural enterprises. For instance, many types of crops are grown on small plots within each season, often with intercropping or further splitting the already small pieces of land to accommodate each crop. On average 3 to 4 different kinds of food crops are grown per household per season. Households adopt marketable agricultural produce, for instance sugarcane around Budongo due to the sugar industry, and rice and tobacco around Budongo due to the available markets from British American Tobacco (BAT), and external/internal demand. The majority of the poor households live near the forests, and are dependent on forest products (other than poles and timber, as these are not clearly picked out in the data) to boost their livelihoods. In the dry region, households travel 10-15km away to cultivable areas each season in a migratory manner; where part of the family members involved in crop production camp in Ngwedo until the crops are grown and return to Kisansya and Kigwera (surveyed parishes) to be part of the social life of the larger family. In all AEZs, households keep livestock (although few) to boost their incomes (especially in a crisis), and for provision of milk. In the peri-urban AEZ, there is a mixture of off-farm employment, and some small-scale farming to support the livelihoods in those areas.

Further analyses and the implications of these results in the wider context of land use and deforestation are explored in the following chapters. However, in spite of the criticism regarding the subjective nature of a PCA and cluster analysis suitable for exploratory analyses (Vyas and Kumararanayake 2006), I argue that the results produced are meaningful and convincing. The PCA was able to compress a rather large data set (83 variables) into a few interpretable dimensions (22 components). The clusters constructed are appropriate as they have been able to meaningfully delineate the different livelihood characteristics in the four AEZs. Overall, this is premised on the quality of the data provided by the respondents during the questionnaire survey: and based on the results, arguably, the data quality is high.
Chapter 4

Local and Key Informant Perceptions of Forest Cover Change around Budongo and Bugoma
Abstract

Validation of scientific findings from satellite remote sensing against local and key informant knowledge could make the interpretation of forest cover patterns more robust. In this chapter, I examine local and key informant knowledge and perceptions on forest cover change in parishes around Budongo and Bugoma in the last 30 years (1985–2014), as well as the drivers of deforestation. The evidence from local and key informant knowledge is compared with that from remote sensing (reported in chapter 2). Furthermore, I investigate whether household livelihood typologies (constructed in Chapter 3) could have influenced perceptions on forest cover change. 375 households in 7 parishes around Budongo and Bugoma forests (part of the total surveyed households: n=706) responded to additional questions in the questionnaire that sought their perceptions on the forest cover trend, and drivers of deforestation (if a decline was perceived). Triangulation of the questionnaire data on perceptions of forest cover trend was undertaken with 22 key informant interviews. Statistical analyses draw from Chapter 3’s Principal Components Analysis (PCA) and cluster analysis, where important variables and household groupings were identified. Here, these clusters are examined in the light of the respondents’ perceptions on forest cover change. Respondents’ ages were considered particularly important as they could have witnessed some or all of the study period. Results show that the majority (70.1%; n=375) of the respondents in the parishes think that there has been a decline in forest cover, and this percentage is larger than the percentage of non-respondents (18.9%), those that thought it had increased (5.6%), not changed (3.7%), and those that did not know (1.6%). The responses were however more mixed amongst parishes especially around Budongo. Although the younger respondents outnumber the older ones, they were more likely to believe that forest cover had declined ($X^2=237.6$, df=66, $p=0.000$). Perceptions on forest change were significantly related to the household livelihood typologies ($X^2=623.4$, df=4, $p=0.000$): respondents who perceived forest cover as having declined and those that provided no response belonged to cluster 2 (low income mixed farming households), which is also the dominant livelihood typology around these forests. Agricultural expansion and poverty were conceived as the leading drivers of deforestation, but the mechanisms of forest change were reported to vary by location between Budongo and Bugoma, with commercial and small-scale farming playing significant roles respectively. The data suggest that there is remarkable agreement between remote sensing results and local and key informant knowledge on forest change: local people and key informants may therefore play a big role in filling data gaps where a dearth of information is prevalent (e.g. around Bugoma forest).

Title page photos: Author conducting surveys/interviews during fieldwork, October 2013–March 2014 ©
4.1 Introduction

Local and key informant knowledge on the historical and current status of forest cover can shed light on deforestation, forest gain and forest stability (Sheil and Wunder, 2002; Sunderlin et al., 2005; Agrawal, 2007). While local knowledge is often context-specific in nature, enhanced by individual and group interaction with their socio-ecological settings, and often a basis for rural survival (Dei 1993), this knowledge base accrues credibility from feedback-based learning (Thompson and Scoones, 1994; Chalmers and Fabricius, 2007). Key informant knowledge (in some cases from experts on the subject), on the other hand, is often grounded in theory, attained as a result of deep understanding, practice and interaction with the subject matter (Chalmers and Fabricius 2007; Martin et al. 2012). These knowledge constructs are especially beneficial in under-researched areas (e.g. in the region around Bugoma forest) and where evidence from scientific techniques such as remote sensing produces fuzzy results. Whilst remote sensing can provide quantities of forest cover change (useful in informing management strategies), we cannot obtain causal information from these data which could be revealed from interviews with local people and key informants. Local people may have a simplistic understanding of land use and forest cover trends and causal mechanisms which could then be elaborated by the key informants: a combination of both knowledge bases could prove complementary and useful.

The merits of local and key informant knowledge are not without criticism in the literature. On the one hand, some scholars argue that local knowledge is fragmentary, partial, and provisional in nature, often emerging from localised experience shaped by cultural, economic, environmental, and socio-political factors (Thompson and Scoones, 1994). Furthermore, it is loaded with ethical and methodological challenges which may obscure its interpretation, and its complementarity to other kinds of science is not always obvious (Chalmers and Fabricius, 2007). Methodological complications may include assessing whose knowledge should be considered credible; the males’ or females’, rich or poor, old or young, native or migrant (Thompson and Scoones, 1994). Also, how questions are framed during data gathering could the affect answers, and requires careful ethical consideration. Furthermore, literature on positionality highlights
that the interviewees can be affected by their perception of the interviewer, while the interviewer could introduce his/her own bias (Kahan et al. 2008; Rice et al. 2015).

Key informant knowledge on the other hand may be biased by the definition and selection of key informants, their experiences in the study area, and their disciplines (and academic qualifications). For instance, an agriculturalist may highlight agricultural causes as the leading drivers of deforestation or downplay the role of agriculture in this negative context while a political scientist may highlight the historical political unrest in the region as the key driver of forest loss in the landscape. An elderly local leader who has witnessed the processes in his/her local village over the study period may be the ‘key informant’, best placed to provide a detailed account of what happened and why.

To forestall the problem of biased views from local and key informant knowledge the following was considered. To obtain (and assess) local knowledge, all respondents around Budongo and Bugoma that participated in the survey were asked to volunteer to respond to questions on deforestation in spite of their age and experiences. In this study, key informants were defined (and selected) as people who either have long working experience in the landscape, or are elderly in the society where they live (and have witnessed and are able to recollect events in the 30-year study period and beyond), or have longstanding professional experience and have undertaken studies related to forest cover change in the landscape. Furthermore, related ethical and methodological challenges were considered and are elaborated in Chapter 3.

Local people’s knowledge on forest cover change could be influenced by livelihood conditions particularly if forests contribute to their survival (Dei 1993). For instance, while on- and off-farm incomes and related on- and off-farm activities may be indicators of rural people’s dependence on forests to meet their day-to-day needs, the age of a respondent will affect trends that have been witnessed/recollected/perceived over the 30 years of the analysis. Perceptions on forest cover change are therefore examined in the light of the constructed clusters in Chapter 3.

Although knowledge and perception have epistemological differences, in this chapter, the terms are loosely defined to refer “an opinion (or response) on forest cover change
(and possible causes)". The Oxford English Dictionary defines knowledge as “facts, information, and skills acquired through experience or education; the theoretical or practical understanding of a subject” while perception is defined as “the way in which something is regarded, understood, or interpreted; intuitive understanding and insight”. In this context, knowledge of forest cover change may be built on individual ‘perceptions’ of the environment, while perceptions underpinned by actions, attitudes, livelihood and beliefs could shape their understanding of existing information, in a knowledge base. Therefore, the term ‘local and key informant knowledge’ are used to encompass the knowledge and perceptions held by local inhabitants (and key informants) in an area regardless of how it has arisen, whether from the collective experiences of people in the area or knowledge brought in from outside (Wilk, 2000).

The focus of the research is at the parish scale (each of which includes two to four villages, see Chapter 3, Table 3.2) for two main reasons. 1) Local people’s day-to-day activities are often place–specific (Ostrom and Nagendra, 2006); they may therefore be knowledgeable of events that occurred within their parish, but not at a larger ‘regional scale’ (which is > 5 times the size of their parishes). Migration and activities at a larger scale are however not dismissed; these are in fact highlighted by the key informants. 2) Parish–scale analysis is considered as the finest resolution to represent local heterogeneity and has been used as a unit of sampling by similar forest cover change studies in Uganda (e.g. Sassen et al., 2013). Villages tend to have few clustered households, and may therefore not provide representative data to understand the heterogeneity of local-scale processes. Details of sampling are provided in the previous chapter (Chapter 3).

This chapter on local and key informant knowledge complements the previous chapter, on remote sensing (Chapter 2), and seeks to evaluate local and key informant knowledge and perceptions on forest cover change in the last 30 years (1985–2014). Respondents who thought forests cover had declined in the last 30 years were further asked to provide what they thought the major drivers are. This chapter introduces the perceived drivers of deforestation explicitly.
4.1.1 Objectives

The main aim of this chapter is to examine local and key informant knowledge and perceptions of forest cover patterns and changes within parishes around Budongo and Bugoma over the last 30 years (1985–2014). The research questions include the following.

i) What are local people’s perceptions on forest cover patterns in their parishes?

ii) Are local people’s perceptions on forest change influenced by their age and livelihood typology?

iii) What are local people’s opinions on the leading drivers of deforestation?

iv) What are key informant opinions on forest cover change and leading drivers of deforestation in the landscape?

v) How do local and key informant perceptions on forest change compare with scientifically reconstructed changes using satellite remote sensing for the 30-year period? (Embedded within the discussion of the above questions; no statistical comparisons are undertaken in this chapter)

4.2 Methods

4.2.1 Study Parishes

A comprehensive description of the entire study area is provided in Chapter 1, and the criteria for the selection of study parishes, sampling design and ethical considerations are elaborated in Chapter 3. For the purposes of this investigation, I highlight the 7 parishes (no. of respondents=375) within a radius of 0 to 15km from Budongo (Figure 4.1a) and Bugoma (Figure 4.1b) forests where additional questions pertaining forest cover change in their respective parishes were administered. These are part of the 706 households described in Chapter 3. The additional questions pertaining forest cover change were administered. The extra consideration made when asking questions regarding deforestation, because of the related ethical implications, it was further stressed that the respondents had an option not to provide a response about forest cover change if they did not wish to.
Figure 4.1 Surveyed parishes around a) Budongo, b) Bugoma Agro-Ecological Zones superimposed on the 1985-2014 forest change map (heavy lines indicate parish boundaries: surveyed households at the boundary of Biiiso and Busingiro are separated based on field data. Surveyed households are shown in yellow; green represents unchanged forest, while red shows lost forest and blue represents forest gain over the 30-year period)
4.2.2 Key Informant Interviews

22 key informant interviews were conducted by the author parallel to the household surveys in the study parishes and in Kampala between October, 2013 and March 2014 (see Appendix 4.1). This category comprised government officials working at the: national level (3), district level (8), local level (4); non-government organisations’ officials working at the national level (2), regional level (entire landscape: 1); an official working in a public–private partnership commercial sugar firm (1); private oil company official (1); and local residents advanced in age (2). Because the interviews were concurrently conducted with the household surveys, it was difficult to schedule them ahead of time. New participants (key informants) were mostly identified using a snowballing sampling technique (Goodman 1961). This is principally a non-probabilistic sampling method where existing study participants identify new participants from among their acquaintances/peers, and is widely accepted and used in social science research (Farquharson 2005; Conrad et al. 2011; Cuppen 2012), although known to struggle to secure representativeness of the sample (Farquharson 2005). In some other instances however, identification of respondents (key informants) was strategic and predetermined to clarify particular aspects of the study (e.g. on sugarcane expansion around Budongo) where information would not otherwise be accessible.

The identified (and selected) respondents however had to fulfil the following criteria. They should have had long working experience in the landscape; or be elderly (in the society where they live), have witnessed and be able to recollect events in the 30-year study period and beyond; or have longstanding professional experience, and have undertaken studies related to forest cover change in the landscape or more broadly, key themes of this project. The questions asked were, therefore, specific, and based on their location or speciality: however, the discussions touched broadly on forest cover patterns, plausible explanations for the observed trends, and an overview of the themes appearing in the household survey questionnaire including: household livelihood quality (based on indicators in the questionnaire), land use patterns, energy use, deforestation, policy awareness of locals and policy implementation. The interviews lasted between 30 minutes and 1 hour and were mostly conducted in English although
the local dialect “Runyoro” was used to communicate to the locals who did not speak English.

No tape recordings were made for ethical reasons (mostly to boost the confidence of the respondent regarding their safety), and the responses are largely presented by “category of respondent” in the results and discussion sections to avoid tracing the respondent, although their names and e-mail addresses are provided with their consent (Appendix 4.1). The responses were recorded in a note book during the interviews and later transcribed and coded in a word processor (Microsoft Word 2007), and then categorised by matching responses to derive emerging themes. The volume of data gathered was manageable with this simple but sound processing, although larger amounts of data would be better handled in a more sophisticated software package (e.g. Atlas ti). Because of the rather small numbers of interviewees (key informants), and given the broad nature of the responses, it was not possible to subject these to any meaningful statistical analyses; however, the tallies for the number of respondents who mentioned a given theme are presented.

4.2.3 Statistical Analysis

The analysis of household data draws on Principal Components Analysis (PCA) and cluster analysis presented in Chapter 3. The responses on perception of forest cover change are tested for their significance given the household clusters using a chi-squared test. Age was categorised with those below 30 years grouped in one category, while those above 30 years are in age groups in 10-year increments. This is to elaborate perceptions of those that have lived longer than the study period (30 years), and compare them with the younger respondents. A chi-squared test of the relationship between age and perception of forest cover change was computed. All p<0.05 was considered significant.
4.3 Results

In this section, local people’s perceptions of forest cover patterns are presented first followed by an exploration of the influence of respondents’ age and livelihood typologies on perceptions of forest change. Local opinions on leading drivers of forest cover change in the landscape are presented next and finally key informant views on forest cover change and leading drivers of deforestation.

4.3.1 Local People’s Perceptions of Forest Cover Patterns – A Comparison with Remote Sensing Analyses

While some respondents declined to answer the question about trends in forest cover (between 15% and 31% in the seven parishes), and even fewer were “don’t knows” (0% to 6%), the majority considered forest cover to have declined (between 56% and 77%). However, a sizeable minority (between 1% and 21%) considered forest cover to have increased. The sample around Bugoma was more consistent in the perceptions of a forest decline, although more mixed responses are recorded in parishes around Budongo (Figure 4.2). Reasons for the variation in the perception of forest change are considered in the following sections.

A comparison of the respondents’ responses to the remote sensing analyses of forest cover change shows remarkable agreement, generally indicating forest loss in regions around Budongo and Bugoma (Figure 4.3). For instance, in Nyabyeya there is a mixture of responses on forest cover patterns, and this corresponds to mixed patterns of forest loss/gain/stability (computed from Landsat imagery) within the landscape (Figure 4.3a). This is similar to other parishes around Budongo, although forest cover patterns in Biiso and Busingiro appear to be less well conceived compared to the remote sensing analyses. This is related to the relatively smaller forest cover in Biiso, while a large percentage of the forest area in Busingiro that has persisted lies under the protected region (see also Figure 4.1). Otherwise, all forest cover outside the protected region was lost.

Around Bugoma forest, on the other hand, the responses are highly consistent with the remote sensing results. The largest part of each of the parishes lies outside the
protected area. The largest percentage of respondents in Bubogo, Igwanjura and Kyangwali highlighted that forest cover had mostly declined, which is consistent with the remote sensing results (Figure 4.3 e, f, g).

4.3.2 Perceptions of Forest Cover Patterns by Respondent’s Age

While there is a general agreement that forest cover has declined in the last 30 years, younger people (aged 15-29) who comprise the majority of the respondents are more likely to think of the forest as declining compared to the older categories except in Biiso where people aged 60+ are more inclined to believe it ($X^2=237.6$, df=66, p=0.000). The other response categories are mixed amongst all the age groups where varying perceptions were recorded, especially in parishes around Budongo (Figure 4.4).

Overall, the average age of the respondents is greater than the length of the period under investigation (30-years) in all surveyed parishes, at 39 years (95% Confidence Interval, henceforth “CI”: 37.3, 40.6), and this varied by parish although not significantly. At parish level, on average, the oldest respondents in decreasing order around Budongo are: in Biiso at 44.5 years (95% CI: 39.8, 49.2), Busingiro at 38.8 years (95% CI: 35.1, 42.4), Nyabyeya at 38.2 years (95% CI: 34.2, 42.1), and Kibwona at 37.1 years (95% CI: 32.6, 41.5). Around Bugoma forest, the oldest respondents were in Bubogo at 39.0 years (95% CI: 33.1, 44.9), followed by Kyangwali at 38.5 years (95% CI: 34.5, 42.5), and Igwanjura at 38.2 years (95% CI: 33.6, 42.9).
Figure 4.2 Summary of perceptions of households on forest cover change in the last 30 years in the parishes around Budongo and Bugoma forests

Generally, it was widely reported (by 70.1% of the total number of respondents: n=375) that forest cover had declined in the last 30 years. The responses varied in parishes around Budongo more than those around Bugoma.
a) Nyabyeya Parish

Percentage of respondents (n=44)

- Declining: 70%
- Increasing: 20%
- No change: 7%
- Don't know: 3%
- No response: 0%

Landsat:
- Loss: 70%
- Gain: 10%
- No change: 20%

b) Kibwona Parish

Percentage of respondents (n=49)

- Declining: 60%
- Increasing: 20%
- No change: 7%
- Don't know: 3%
- No response: 0%

Landsat:
- Loss: 80%
- Gain: 10%
- No change: 10%
Figure 4.3 Comparison of responses on perceived forest cover changes with results from remote sensing analysis at parish level (Forest area is based on total forest area in 1985)
Figure 4.4 Perceptions of forest cover change in the last 30 years in parishes around Budongo and Bugoma by age group

While there is a general agreement that forest cover has declined in the last 30 years, younger people (ages 15-29) who comprise the majority of the respondents believed more that forest cover had declined compared to the older categories except in Biiso where more 60+ perceived forest cover as having declined.
4.3.3 Perceptions of Forest Cover Patterns by Livelihood Typology

While ascertaining the influence of livelihood typologies on forest cover trends is ambiguous, the data suggest that perceptions on forest change are significantly related to the household livelihood typologies ($X^2=623.4$, df=4, p=0.000): respondents who perceived forest cover as having declined and those that provided no response mostly belonged to cluster 2 (low income mixed farming households), although this could be because this is the dominant livelihood typology around Budongo and Bugoma forests. Cluster 7 households (richest “elite” mixed farming and trading-based households) are generally lacking in this part of the landscape, but a handful of respondents who belonged to this group perceived forest cover as either having declined or provided no response (Figure 4.5). The other typologies are in rather small proportions.

4.3.4 Local People’s Perceived Drivers of Deforestation

Respondents who perceived forest to have declined (n=263) widely reported agricultural expansion and poverty as leading drivers of deforestation, topping the list in all parishes around Budongo and Bugoma. Of the total responses, agricultural expansion accounted for 28% and 30% in Nyabyeya (n=25) and Kibwona (n=30) respectively; and 44%, 58.5%, 50%, in Bubogo (n=34), Igwanjura (n=41) and Kyangwali (n=44) respectively. Poverty accounted for 32%, 76% and 75% in Nyabyeya, Biiso (n=41) and Busingiro (n=48) respectively; and 50% and 26% in Bubogo and Igwanjura respectively (Figure 4.5). 36.7% of the respondents who reported forests to have declined in Kibwona mentioned that it was due to population growth. Other factors such as declining soil fertility and charcoal burning were uniquely highlighted by 20.5% and 3% of respondents in Kyangwali and Bubogo respectively. A very small percentage declined to provide reasons for the declining trend, ranging between 2.3% to 7.3% in Kyangwali and Biiso, and none in Bubogo.

There is a significant relationship between the household clusters to which respondents belong and drivers of deforestation ($X^2=239.9$, df=8, p=0.000). The majority (65.3%, n=98) who reported poverty as a driver of deforestation belonging to cluster 2, while the only cluster 7 respondent perceived population growth, and a high percentage of cluster 4 households identifying agricultural expansion as a major deforestation drivers (Figure 4.7).
Figure 4.5 Relationship between perceptions on forest cover change and the household clusters

Households mostly belong to cluster 2 (low income mixed farming households); although statistical analysis using a chi-squared test indicates that perceptions on forest change are significantly related to the household livelihood typology (cluster). The 10 unclassified households around Budongo and Bugoma are excluded from this analysis.
Figure 4.6 Perceived drivers of deforestation by respondents who reported forest cover to have taken a declining trend in the last 30 years

Agricultural expansion and poverty were widely reported as the leading drivers of deforestation.
There is a significant relationship between household clusters to which the respondents belong and their perceptions on drivers of deforestation. Indeed, the poor who belong to cluster 2 mostly perceived poverty as a leading driver of deforestation, for instance, while the only rich elite respondent from cluster 7 perceived population growth as a driver of deforestation, and a high percentage of household type 4 identifying agricultural expansion as a major driver.

Figure 4.7 Perceived drivers of deforestation plotted against household clusters to which the respondents belong
4.3.5 Key Informant Opinion on Forest Cover Change and Drivers of Deforestation

Although the discussions with the key informants were wide-ranging, and aggregate statistics for responses therefore not meaningful (as most of the responses/respondents are either localised or context specific), 8 themes emerged from the interviews (Table 4.1). These could be interpreted in regard to their importance as drivers or mechanisms of deforestation around the large protected forest blocks, Budongo and Bugoma. The main themes identified around Budongo (with more respondents highlighting them) include: nature of forest cover trend within and outside protected areas, agricultural expansion, migrants, settlement and population growth; while around Bugoma, the theme of migrants, settlement and population growth was dominant. Other less important themes around both forests (judged by number of people who mentioned them) include: state of protected forest boundaries, poverty and dependence on forests for livelihood, management constraints, firewood extraction and urbanisation. These themes are presented separately in turn starting with Budongo and then Bugoma (to make highlights around each forest easy to follow). The quotes are presented in the most original format possible (given the need to translate from Runyoro to English in some cases), and for clarification purposes, the author’s notes are presented in ‘square-shaped’ parentheses, “[ ]”.

Table 4.1 Number of key informants who mentioned the “main themes” on knowledge of forest cover trends and drivers of deforestation around Budongo and Bugoma forests

<table>
<thead>
<tr>
<th>Theme</th>
<th>No. of key informants who mentioned the theme in relation to Budongo forest</th>
<th>No. of key informants who mentioned the theme in relation to Bugoma forest</th>
</tr>
</thead>
<tbody>
<tr>
<td>Nature of forest cover trend within and outside protected areas</td>
<td>7</td>
<td>3</td>
</tr>
<tr>
<td>Agricultural expansion</td>
<td>7</td>
<td>2</td>
</tr>
<tr>
<td>Migrants, settlement and population growth</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>State of protected forest boundaries</td>
<td>4</td>
<td>1</td>
</tr>
<tr>
<td>Poverty and dependence on forests for livelihood</td>
<td>4</td>
<td>0</td>
</tr>
<tr>
<td>Management constraints</td>
<td>3</td>
<td>0</td>
</tr>
<tr>
<td>Firewood extraction</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Urbanisation</td>
<td>1</td>
<td>0</td>
</tr>
</tbody>
</table>
4.3.5.1 Key Informant Opinions on Forest Cover Change in and around Budongo

Theme 1: Nature of Forest Cover Trend within and outside Protected Areas

There was general consensus amongst the respondents that the protection of Budongo forest is successful, and that private forests around Budongo were being rapidly cleared. A non-government official highlighted that in fact forest cover in the protected areas is increasing while there is a declining trend outside [the protected areas]. The mechanism of forest loss outside protected areas was reported to involve both large- and small-scale clearing. A district official highlighted that “land is cleared in one go for commercial farming of sugarcane [using bulldozers], otherwise most deforestation is subtle, illegal, and difficult to detect.” An informant involved in sugarcane production reported how he had witnessed a [privately owned] forest in his neighbourhood being cleared “in no time” with heavy machinery to prepare for the new sugarcane growing season.

The forest protection policy was reported to having contributed to successful safeguarding of the forest, although efforts were being frustrated by a parallel legal district income-generating scheme that issues licences for tree cutting. A government official working at the local level said, “there are mixed trends [within and outside protected areas]: the increase in [forest cover in protected areas after] 2004 could be attributed to the 2002 policy which produced the National Tree planting Act of 2003 [that improved demarcation of protected forest boundaries]. The new policy was to address new challenges. [Outside the protected areas, in addition], pine was planted around Budongo in [between] 2002 and 2004, with aid of development partners to reduce pressure on natural forests. [Between] 2006 and 2008, [however], forest encroachment was due to political influence [aspirants condoned some illegal activities to gain the good will of voters: presidential and local government elections were held in 2006]. Districts require revenues: licenses for timber cutting were issued at a high rate, and revenues [were] not invested back in tree planting.” Although the protection of Budongo has been largely successful, a district official noted that illegal selective harvesting of large hard wood species was ongoing in the forest interior, and that a few private forests were being successfully managed. He noted the tree planting scheme by Kinyara Sugar Works to boost tree coverage for instance.
**Theme 2: Agricultural Expansion**

Agricultural expansion of both subsistence and commercial (sugarcane) farming was highlighted as a major driver of deforestation around Budongo. A local forestry official said, “Subsistence agriculture is [the] predominant means of legal livelihood around the forest” while a district official noted that sugarcane expansion was a result of the aggressive expansion of the out-grower scheme. He said, “Sugarcane plantations around Budongo have drastically increased in the last 10 years. The out-grower scheme started with a radius of 10km around the sugarcane plantations, and later extended to 25km, but now seems to have expanded literally everywhere. The scheme initially targeted out-growers with 10ha of land but has relaxed the rules to include up to 2ha.” The growth of the sugarcane industry is said to have attracted many migrant workers who have settled around Budongo. “The Expansion of Kinyara sugar industry has attracted migrant workers: private farmers look for casual jobs in the factory too. Richer farmers hire labourers in the out-grower scheme,” a district official elaborated.

The rapid expansion of sugarcane production after 1995 is attributed to the reopening of Kinyara Sugar Works after closure by the previous turbulent national governments. The company has been under different management regimes with varying emphasis on the expansion of the out-grower scheme. This is elaborated by a key informant as follows: “Kinyara Sugar Works started in 1972, and due to regime changes it collapsed in the late 1970s. It was rehabilitated in 1996 and re-opened. After opening, it was managed by ‘Bukotite’, and a UK board, who were the leading company at the time. They concentrated on the sugar estate. 1500 tonnes of sugar was produced per day by 1996, and out-growers were few at the time, contributing between 3000 to 4000 ha, although sugar production went up to 50,000 tonnes/annum until 2006. In 2006, the government privatised the company, and remained with 51% shares while the 49% was taken by the ‘RAI’ group. Between 2006 and 2008 a new management team, SMC senior management consultants, was hired from Mauritius; they maintained the management plan, and remained at the same production levels, but the expansion plan fell through. In 2008, a new team (Agro-management Resources, UK) came in and exploited the potential in the area. They surveyed and looked for untapped potential: coffee was on the decline, having suffered from pest and disease infestation, they provided sugarcane as an
alternative, and the out-grower scheme grew from 15,000 ha to 20,000 ha: increasing at a rate of an additional 3,500 ha of new land from 2010-2013, in a radius of 35-40 km. Land belonging to the company alone is 8,600 ha. The annual production of sugar currently stands at 100,000 tonnes per annum [at the time of the interview]. In the out-grower scheme, the owner registers his/her land, and Kinyara covers all costs of opening it up, weeding, seedlings, and costs are recovered at harvest time when cane is supplied to the factory. The contracts go up to 5-6 years with 3 ratoon\(^1\) crop harvests.”

He added that the out-grower scheme is considerate to household food security, and has a wide range of socio-economic benefits: “The out-grower scheme radius increased to >35 km to allow farmers some space for cultivation of food crops. The company has > 2000 employees: [of which] cane harvesting [employs] 450, clearing 400, drivers 300, loaders 400-500, guards 1000. These are from different parts of Uganda: the agriculture wing alone has 6 sectors: estates, out-grower, engineering, harvesting, agronomy and haulage. In collaboration with NFA [National Forest Authority], Kinyara plants trees. Other social corporate responsibilities involved in by the industry include road construction and maintenance; sponsors schools (2 primary and 1 secondary in the estate); health centre for employees and community; training centre for 60-70 students for 2 yrs; sports (Kinyara football club); radio sensitisation campaigns on wide-ranging topics; contribution to local district activities and taxes. The company is only closed for 2 months between October and November for maintenance every year.”

The contribution of the sugarcane industry to livelihood quality around Budongo was however criticised by a cultural institution official for not doing enough to provide for the households to reduce the rate of deforestation. She said, “Sugarcane growing has benefitted communities financially, although has contributed to neglect of their cultural roles (e.g. raising children). Money from sugarcane is not sufficient to meet family needs, and communities living near forest boundaries take advantage [of the forests to supplement their livelihood]”.

\(^1\) Sugarcane is a ratooning crop, where new shoots spring from the stem and mature in a period of about 1 year. Once the mature sugarcane is harvested, new shoots sprout from the underground stem without having to go through the entire clearing, and planting process. Fertiliser application and weeding are the main agronomic practices undertaken during the growing season. When 3 ratoons are harvested, land is sometimes re-cleared, to prepare for a new planting campaign.
This theme stood out with some key informants strongly believing settlement patterns have had a key role in deforestation patterns around Budongo: particularly noting that migrants inhabit forested regions and exploit the natural resource for their livelihood while natives settle further away from forested regions, and are therefore less likely to be involved in deforestation. A respondent from a civil society organisation said, “Culturally, it was a taboo for the natives [Banyoro] to cut down trees, and they naturally settled far away from the forests: most deforestation around Budongo is carried out by immigrants.” She elaborated this with an example of their settlement patterns: “Banyoro are the dominant tribe in Masindi. They do not want to stay far away from each other; they lived far away from the park, hence their distribution in Masindi is far from forest boundaries.” The reason for the large influx of migrants is related to a view that natives are tolerant and welcoming. “The natives [Banyoro] are some of the most accommodative tribes in Uganda: they allowed immigrants to come and settle into their region with no conflicts, such that when people come, they do not want to go,” she added.

Most of the migrant tribes around Budongo are reported to have come from conflict-laden Democratic Republic of Congo and northern Uganda. A district official elaborated, “The movement patterns of Congolese into the region around Budongo dates back to the 1960s when insurgency started: [this movement has remained to-date]. Other internally displaced people are from conflict-stricken northern Uganda. Those who settled around the forest cleared it for small-scale farming. The refugees depend on the forests for their fuelwood, and charcoal making, where they obtain hardwood species by selective illegal logging.” Another district official further explained the nature of movement and its relation to forest loss: “Uganda has porous borders via Lake Albert, and Congolese move in and out, and cause deforestation. They deplete but are not the buyers: these [buyers] come from far, in Masindi, Kampala and other areas. The problem is cyclic: they are paid little which keeps them in poverty, while the middle men earn more.”

There was also consensus that the population around Budongo forest has grown over the last 30 years, as a result of the high fertility rates and a reiterated role of the influx
of migrants. A district official noted, “The human population has drastically increased in the landscape and nationwide due to the high fertility rates: particularly, around Budongo, migration patterns have had a role to play in population growth, with many migrants coming from eastern Congo.” A local forestry official estimated this growth to be high. He said, “Population in Uganda is increasing at a rate of 3.2% per annum, and yet the per capita land availability is not increasing. People are looking for more land for farming, and as a result, forests are encroached on.”

**Theme 4: State of the Protected Forest**

It was reported that forest boundaries are clearly demarcated, and that this has had a role in the successful protection of Budongo. A local forest official elaborated as follows: “Budongo forest has clear boundaries; [these are marked by] a river, main road, sign plates, corner posts, [and] direction trenches: these separate forest from community land.” A district official further stressed that emphasising the forest boundaries followed a reform in the forest sector although this resulted in making previously sections of protected forest to lie on “private land” which accelerated forest loss right up to the protected forest boundary. “National Forest Authority delineated boundaries following the forestry sector reform in 2003, and some parts of the forest that were initially protected were opened to private owners who were largely disorganised which increased deforestation,” he said. Although the boundaries of the protected forest are clear, the respondents further stressed on-going illegal logging of hardwood trees. A local forest official noted, “Budongo has diverse tree species of communities’ interest; for instance, mahogany is used for boat making. Depletion is mostly inside the protected forest for particular species, and not at the boundary.”

**Theme 5: Poverty and Dependence on Forests for Livelihood**

While poverty was not defined by the respondents, this was a recurring theme amongst 4 key informants (Table 4.1). They argued that people that live near Budongo are impoverished and heavily reliant on forest products for their livelihood. A local forestry official said, “People around the forest are heavily impoverished. [The carry out] selective logging of trees for charcoal, timber and poles for building, [and] curing tobacco using pitsaws [although data from household surveys does not capture this: it
could be one illegal activity that is not easily reported]. Tree species like Mahogany are now scarce in the forest.” Another forestry official further stressed, “People living around the forest are poor and vulnerable with many malnourished children. They own small plots of land and occasionally seek for odd jobs from Kinyara sugar industry, and are paid little. Some still live on less than a dollar a day. Seasons are changing and crop yields drastically declining. They cut down trees with a view to be alleviated from poverty.”

Theme 6: Management Constraints

This was one of the least mentioned themes related to deforestation in and around Budongo forest, with only 3 respondents highlighting it. Management of Budongo is highly militarised to keep illegal loggers at bay, but understaffing and limited funding undermine conservation efforts. A local forest official noted, “NFA [National Forest Authority] is understaffed and cannot keep all illegal loggers at bay. There is for instance only one vehicle used for the management of the entire Budongo forest. Environmental protection police and the army [Uganda People’s Defence Forces] are supposed to provide enforcement but their activity on ground is thin.” It has a limited number of staff; the locals are aware about this and exploit the gaps. Another forestry official noted, “Deforestation is seasonal. For instance [during] public holidays over Christmas, charcoal and timber loggers take advantage of reduced forest surveillance.” The new forestry policy and Act is blamed for creating further management problems. A district official elaborated as follows, “Forestry policy shift created a management vacuum in 2003 and pieces of forested land were grabbed for sugarcane plantations. There has been some minor recovery through planting trees but natural forests have not recovered.”

Theme 7: Firewood Extraction

Only 2 respondents talked about firewood extraction from Budongo as a threat to the natural forest and as a key driver of deforestation. A forestry officer said, “Locals around the forest use firewood mostly for cooking, obtained directly from the forest – this is acceptable – although as they search for the fuelwood, they then spot hardwood species which are later illegally felled. Fuelwood gathering, if is not well regulated, contributes a
lot to deforestation.” This is reiterated by another forestry official, “Firewood collection is a threat to forest cover. Riverine forests (e.g. Nyamusabo, Nyamageta) used to be fully stocked, and were used for firewood [gathering]; these have now been cleared. Communities now move [from] as far as 10km away to gather firewood from Budongo. In some cases they throw down fresh trees to allow them dry and become firewood.”

**Theme 8: Urbanisation**

This was the least mentioned cause of deforestation. Growth of peri-urban centres around the forest is attributed to the growth in the sugar industry. A district official said, “The booming sugar business has increased built areas around the sugar industry, for instance, Kibwona. The expansion of Masindi town too is attributed to the sugar boom.”

**4.3.5.2 Key Informant Opinions on Forest Cover Change in and around Bugoma**

As for Budongo, the outstanding themes around Bugoma forest are related to migrants, population growth and settlement, and the nature of forest cover within and outside the protected area (Table 4.1). While there is agreement that forest protection was successful in gazetted areas, and that losses are mainly outside the protected forest boundary, major differences are noted in the type of migrants and how they are settled, and the nature of agricultural activities replacing forest cover. Respondents recognise that most of the region had been forested in the last 30 years but increasing population pressure from migrant communities from southern Uganda has increased land grabbing and forest clearance. Interestingly, refugees and migrants are thought of in a different manner from those around Budongo; those from outside the country are kept in planned communities in Kyangwali refugee camp. The main cash crops grown around Bugoma mentioned include rice and tobacco. The above points are elaborated as follows.

**Theme 1: Migrants, Settlement and Population Growth**

Migration and settlement patterns around Bugoma are particularly complex, with a mixture of immigrants from within and outside Uganda. Immigrants from southern and
south-western Uganda (e.g. Bagika) are more common around Bugoma, while immigrants from other countries (e.g. DRC, Rwanda, Sudan, Somalia, etc) are located in well settled refugee camps and communities.

A local resident confirmed that indeed, areas around Bugoma were mostly forested 30 years ago. He said, “In 1980, there lived only 3 families in Kabwoya. All this land was forested. This area was part of the area where President Museveni [the incumbent president who took power in 1986] fought previous regimes.” But immigration contributed to rapid forest clearance. A district official who grew up around Bugoma forest added, “Forest depletion is due to population pressure. I grew up and went to school in Kabwoya in the early 1990s. The population was sparse and a lot of the land was covered by thick bushes and short trees. The land was idle until as recent as the 2000s. People started to come in and captured 10 to 20 ha of land per household. Wild animals that destroyed crops were many at the time. The Bakiga came in with their relatives and split the land amongst themselves.”

An elderly informant (about 70 years old) who is also an immigrant confirms the previous assertion, and attributed the majority of the forest loss around Bugoma to settlement patterns where land was allocated “free-of-charge” in the past. He said, “I moved into Kabwoya from Mbarara [in SW Uganda] about 20 years ago. I cannot recollect the exact date but what am aware of is that the current president had already taken power. I did not have to pay a single coin for this piece of land. At the time, the local council chairpersons demarcated plots for whoever wanted. It was all forested, and the bushes were thick. I acquired over 3 ha, and the challenge then was to clear the forest for settlement and agriculture. I cleared this slowly over time. The hardwood trees I sold provided money for my basic survival. The crops were frequently raided by baboons from the natural forest. This large expanse of my neighbourhood was all natural forest 20 years ago: it is now all settled on and farmed, and the natural forests are no more.” His assertions are also corroborated by a district official who highlighted migration patterns and the influence of migrants on deforestation: he said, “Settlement patterns are influenced by migrants: in the early 1990s, areas around Kyangwali and Kabwoya were forested and vacant – it was initially thought that it was a forest reserve and communities discovered that it wasn’t – people have since encroached on it and
converted it to agriculture – migrants are mostly from Kigezi and Kisoro [in SW Uganda].”

Conflict in the neighbouring countries is the cause of an influx of refugees in Kyangwali Refugee Camp (near Bugoma), but these are organised in settled (and gated) communities, and are less involved in affairs outside. A respondent argued that it was therefore difficult to attribute the ongoing forest loss to them although some cases were found, and culprits were prosecuted in court and returned to the camps. A government official working at the national level said, “Refugees are relocated in camps in Kyangwali [in Hoima district] and not in communities. It currently accommodates approximately 38,000 refugees [at the time of the interview]. 98% are Congolese, followed by south Sudanese, Rwandese, Kenyans, Burundians and Somalis. Each refugee is allocated a 50m by 50m plot where they settle and cultivate. Once in the camp, they can live there for as long as they are in Uganda. Spontaneous returns to their countries are illegal. Within the camp, refugees [can] clear the vegetation to settle. They are not involved in many activities outside their camp: [however], they can do odd jobs, but are not allowed to settle outside the camp. Non-Ugandans living outside the camp are not necessarily refugees.”

Similar to some key informant responses on the role of the natives around Budongo, there were suggestions that natives around Bugoma are mostly cultivators and are less likely to be involved in deforestation. A district official said, “The indigenous Banyoro are mainly cultivators and settled along the road network. Land in Bunyoro has been idle for a long time, and Bakiga [from SW Uganda] came in to cultivate it since Banyoro were not taking advantage of it. One could for instance sell 5 acres of land in Kabale [SW Uganda] and buy 100 acres in Bunyoro as it was also cheap at the time.”

**Theme 2: Nature of Forest Cover Trend within and outside Protected Areas**

Deforestation outside the protected areas was reported to be patchy, and mostly attributed to small-scale farming of food and cash crops, including maize, rice and tobacco, among others. A district official noted, “Small areas of private forest are cleared at a time for rice and tobacco cultivation.” During fieldwork, the author found freshly
cleared forest patches, and informants living adjacent to them mentioned that they were to be used for cultivation of maize and other food crops although they expressed concerns over the vermin menace from the neighbouring natural forest.

Forest clearing within the protected forest was reported to be increasing insecurity in the region. Another district official added: “Deforestation is widespread in the Albertine region, and has been heightened by insecurity [it has also heightened insecurity]. Those involved in illegal logging are now using sophisticated equipment, and are sometimes armed.”

**Themes 3, 4 and 5: Agricultural Expansion, State of the Protected Forest, and Firewood Extraction**

Expansion of farmland is reiterated as a key driver of forest loss. A district official noted: “Farmers clear the forest mostly for subsistence farming. A range of crops is grown for food and the surplus is sold for cash; cassava has remained a staple food in some areas. Most labour is provided by family members [who have a large] household composition [of] 7 to 9 members on average.” Another district official added that the crop types in the rural areas near Bugoma and peri-urban areas in Hoima are largely similar, except for the farm size variations: “Crops grown around Bugoma are similar to those grown near Hoima town. Plot sizes are not very different, although around Bugoma, the population density is lower, and so people can practice shifting cultivation. Around Bugoma households own larger spaces, even up to 7 acres [2.8ha], compared to around town where averages could be less than 1 acre [0.4ha] for cultivation.” The increase in rice growing around Bugoma is only recent though, with its promotion through government programs to alleviate household poverty. A district official noted: “The real boom for rice cultivation started around 2003. The NAADS [National Agricultural Advisory Services] program promoted its adoption, and now there is a rise in the number of privately owned [rice] processing mills from 3 to 70 in the last 10 years.” Tobacco farming around Bugoma has been boosted by the readily available market from British American Tobacco, noted a district official.
Successful protection of Bugoma is attributed to clear boundary delineation and community sensitisation. This was reported to allow fresh forest growth and regeneration in places. “Sensitisation [of the communities on the protected forest boundaries] improved boundary maintenance, and [allowed] regeneration of forest in the western boundary of Bugoma,” a district official stressed.

Similar to Budongo forest, firewood gathering is not considered to be a significant cause of deforestation around Bugoma. A district official noted that it is in fact illegal to gather firewood from Bugoma although adjacent communities continue to do so.

4.4 Discussion

In this section, the data are examined against the literature. Perceptions on forest cover change and perceived drivers of deforestation by the local people and key informants are discussed. This is concurrently presented showing a comparison of two pieces of evidence: forest change as perceived by the locals and key informants, against remote sensing data. Livelihood typologies from the household survey are discussed against perceptions of forest cover change.

4.4.1 Local People’s Perceptions on Forest Cover Change: Role of Age and Livelihood Typology

There is wide agreement between remote sensing data analysis and local people’s knowledge about forest cover change around Budongo and Bugoma; particularly, as is the case from remote sensing analysis, the majority of the respondents noted that forest cover has declined in regions outside the gazetted areas, but protection of Budongo and Bugoma is remarkably successful (a view reinforced by key informants). The mixed responses in some parishes around Budongo may be related to the spatial pattern of forest cover where persistence, losses, and gains all occurred during different periods of the 30 years (see Chapter 2), although the temporal trend is one that shows a decline overall. For instance, in Nyabyeya, the spatial difference map of 1985 and 2014 shows a mixture of large regions of forest gain and losses (see Figure 4.1a, 4.3a), and it is possible that the respondents could have perceived the spatial coverage near where
they live to represent what was happening in the entire parish. It is unclear whether this could also be related to the 2003 forestry policy change.

Because of the illegal nature of some deforestation practices, the survey allowed an optional response to the question about the perceived trend in forest cover within the respondent’s parish. The data show that overall, a relatively large number, 71 out of 375 (18.9%) declined to provide a response, ranking second to those who perceived forest cover as having declined (70.1%) in the last 30 years. The reasons for this remain rather speculative. It could be that they are involved in illegal harvesting of trees from the forest. A study elsewhere within the Albertine Rift region shows that people illegally dependent on natural resources are afraid of being reported to local authorities and can only provide responses under strong assurance of protection (Tumusiime et al., 2011). Although the data gathering team was highly trained on administering the questionnaire and in ethical issues related to the study, scepticism from the respondents could not be ruled out in spite of our assurance to protect them.

The data also show that age of the respondents is significantly related to their perception of forest cover patterns, where, although there was wide agreement on forest decline amongst all age groups, younger people were more likely to think of forest as having declined compared to the older ones. The survey included household heads who were below the age of 30 (but mostly above 20 years) as part of the design to minimise sampling bias provided they were on the transects taken during fieldwork. The data show that the parishes around Budongo and Bugoma have a similar age structure, and as shown by the population pyramid in Chapter 3 (Figure 3.2), the majority of the population in the landscape is young. This age structure is corroborated by the previous census (e.g. in the 2002 census, children below 18 years constituted 56% of the population while those below 15 constituted 49%, in a total of 24.4 million, UBOS, 2002, although recent [2014] unpublished estimates show that the current total population is around 34.9 million). Aggregate statistics, however, show that the average age of the respondents is between 37.3 and 40.6 years, suggesting that a good number of the respondents are old enough to have experienced the period (30 years) under investigation. There is a high probability that they may have witnessed most or part of the forest cover change processes within their parishes. Perceptions on forest cover
change are therefore likely to be shaped by what they have witnessed and by possible involvement in illegal activities for their livelihood. The disparity in the responses on perceptions of forest cover change by age group, particularly why younger people were more likely to think of forest cover as having declined requires further investigation.

Additionally, statistical evidence shows that livelihood typologies are significantly related to the perceptions of forest cover change. Poorer cluster 2 (low income mixed farming) households are generally located near the protected forests, Budongo and Bugoma. As pointed out by the household survey data and by key informant opinion, it is suggested that they supplement their livelihood from use of forest products. It is therefore not counterintuitive for most of them to think of forest cover as having declined in relation to their poverty status if they depend on forests for their livelihood. In fact, Figure 4.6 shows that there may be some real effect on the livelihood status and perceptions on forest change, particularly as most of the rural poor (cluster 2) highlighted poverty as the key deriver of deforestation.

### 4.4.2 Local People’s Perceived Key Drivers of Deforestation

Respondents who perceived forest cover as having declined over the last 30 years highlighted agricultural expansion, poverty and population growth as leading drivers of deforestation around Budongo and Bugoma forests. This is in agreement with what most of the literature suggests (Majaliwa et al., 2010; Twongyirwe et al., 2011). As highlighted by the key informants, the nature of agriculture varies around both forests (although the agriculture differs, it was highlighted in both regions as a major deforestation driver). For instance, while sugarcane is the dominant cash crop around Budongo, rice and tobacco are predominant around Bugoma. Poverty was rather ill-defined, but it may be related to dependence on forests for livelihood. Households (e.g. in Busingiro) that perceived forest to have declined and mentioned that deforestation was due to poverty also generally earned less on-farm and off-farm incomes compared to other parishes. It could, therefore, be inferred that their livelihood is mostly derived from dependence on forests. All other widely hypothesised drivers of deforestation in the literature that were not mentioned by the respondents are examined in Chapter 5.
4.4.3 Key Informant Opinion on Drivers of Deforestation around Budongo and Bugoma

Key informant opinions on drivers of deforestation did not differ much from those of the local respondents, and mapped well to the constructed forest cover patterns in the remote sensing chapter. The key informants however highlighted more intricate causes that were not easily comprehended by the locals. They mostly pointed out remarkable protection of both Budongo and Bugoma (enhanced by clear boundary demarcation) while stressing widespread losses outside the protected areas.

Mechanisms for forest clearance around both forests differ. While large-scale clearing for commercial farming of sugarcane has been reported around Budongo, small-scale clearing of forest patches for subsistence farming is more prominent around Bugoma. This could be related to obvious wealth status differences; where around Budongo mechanisation (e.g. bulldozers) is provided by the sugar industry while more rudimentary tools (e.g. axes, pit saws) are used around Bugoma. Small-scale logging of private forests around Budongo is also common too. Illegal harvesting of hardwood tree species is common in both forests.

While agricultural expansion has been mentioned for its role in deforestation around both Budongo and Bugoma, as a result of commercial farming of sugarcane in the former and subsistence farming in the latter, its role in improving rural people’s welfare remains unknown. The expansion into new subsistence farming areas is often as a result of slash-and-burn/swidden agriculture (as a consequence of declining soil fertility, among other factors), in which case the area under production has not increased, and hence the productivity remains low keeping the farmers in poverty. Shifting cultivation would not necessarily increase per capita land use, but in concert with increasing population it would tend to exacerbate the effects of agriculture on deforestation, as people are using more land than they actually need to.

Migration and settlement patterns around both Budongo and Bugoma are complex, and the household survey data indicate that there is indeed a mixture of tribes especially around Budongo, although natives were more common around Bugoma. And although
the key informants highlighted the role of migrants in deforestation, this is based on their perceptions of dependence on forest products. Data from another study show that deforestation around Budongo for instance, is intricate, driven by key players who are richer, large-scale traders living in urban areas (e.g. Kampala and Masindi: see Muhumuza et al. 2007) who ferry large trucks of timber, charcoal and firewood into the cities. Only one respondent highlighted urbanisation as a cause of deforestation though. The actual contribution of migrants and locals is thought to be relatively smaller although this requires further investigation.

Management problems have been increased by splitting forest categories into different management regimes. The separation of forest management regimes followed the National Tree planting Act of 2003 that allowed protected forests to be managed under either National Forest Authority or Uganda Wildlife Authority (or both), while private forests are managed under District Forest Services (Muhumuza et al. 2007). The districts have jurisdiction over forests on private land, and any forest clearance has to be licensed. Provisioning of licenses is driven by the need to generate local revenue. Broadly, forestry management bodies are largely uncoordinated, sometimes with conflicting agendas and mandates (elaborated in Twongyirwe et al. n.d.). This weakness is often exploited by illegal loggers.

Amongst the key informants (dissimilar to households surveyed, e.g. Figure 4.5), poverty and firewood gathering were some of the least mentioned drivers of deforestation. While there is a direct link between forest dependence and poverty, and rural people’s dependence on biomass for cooking, given that these were less considered (and mentioned) by the key informants, it could be that they are obvious and contribute nothing new to the deforestation conundrum. Firewood quantities gathered are likely to be too small to cause major forest degradation (except in extreme cases) as shown in the household survey data (perhaps firewood for cooking is mostly based on collecting dead wood), although key informants noted that this enables locals identify tree species of interest which are later illegally felled. More data are required to understand the relationship between forest resource use and poverty.
4.5 Conclusions

The 4 main conclusions that can be drawn from this chapter are the following.

1. There is strong agreement between data from remote sensing and local and key informant knowledge on the trend of forest cover change in parishes around Budongo and Bugoma forest in the last 30 years. This agreement generally stresses that forest loss outside the protected forest is widespread but protection of the gazetted Budongo and Bugoma is successful with clear boundaries (defined using a combination of physical features; e.g. rivers, roads, and boundary markers) albeit with some illegal encroachment. Data from local informants is largely credible, although it needs to be interpreted against its specific context (as seen from mixed responses around Nyabyeya for instance) and corroborated with key informant sources (and available literature).

2. There is statistical evidence that age and livelihood typologies are related to perceptions of forest cover change, although reasons for younger people thinking of forest cover as mostly having declined compared to the older ones remains a question for further research. Additionally, judging the influence of livelihood quality on perceptions of forest cover change is inherently complex. Although perceptions of local people on forest change and livelihood typologies have been shown to be statistically related, it could be that such parameters play a role in shaping views on environmental processes, but do not in themselves provide a complete understanding of human psychology. For instance, perceptions about forest decline might be age dependent (especially for the 30 year trend analysis), but other factors (e.g. education, wealth status, etc) may interact in a complex manner to shape perceptions and knowledge on forest cover change. Even though statistical analyses provide some hints, they may only explain a small portion of what we can see and comprehend. For these reasons, the analyses can only enable us to speculate on potential reasons for the interactions, and further studies are often required to test the results.

3. Key informant opinions provide useful explanations that would otherwise have been missing in questionnaire (household survey) and remote sensing data. For instance, the nature of deforestation is explained more explicitly. Around Budongo, while remote
sensing evidence shows that patches are lost within an interval for which we have data, the key informants clarify that the clearing is often on small patches of intact forest at once using ‘modern technology’ (e.g. bull dozers). The clearance of the forest patches is mostly for sugarcane growing. Around Budongo on the other hand, tree loss is more subtle and more spread over time as more rudimentary techniques are used for land clearing. Often, small patches are cleared for settlement and small–scale agriculture.

4. The main drivers of deforestation highlighted by the local people include agricultural expansion and poverty. Key informants also highlight agricultural expansion as the main driver of deforestation, but are mostly silent on the contribution of poverty. The role of population growth involving both migrants and settlements is explicit. Firewood extraction and urbanisation are other drivers of forest loss around both Budongo and Bugoma although ranked low in the response list. These drivers are further explored in Chapter 5 in the light of the available evidence.
Chapter 5

Synthesis and Conclusions: A Review of the Evidence and Drivers of Deforestation in the Region
Abstract

In this chapter, I present broad theories on deforestation (and land use change) in the African tropics suggested by Geist and Lambin (2002) hence forth “Geist and Lambin framework”, and examine these through the lenses of the available evidence from this project, and related literature. The aims are: 1) to provide evidence of secular deforestation in the Northern Albertine Rift region while highlighting the leading drivers presented from analysis of remote sensing, household survey and key informant data, and 2) to present outstanding research questions and gaps that could benefit from further investigation while suggesting plausible policy recommendations. This synthesis suggests that there is sufficient evidence that the majority of the forest cover changes in the landscape are at least anthropogenically driven (with barely any evidence on the role of climate change), and although it is argued that outlining single leading causes of deforestation (and land use change) is inherently problematic (due to intricate interactions of the bio-physical and socio-economic preconditions that are inseparable in both space and time), the role of agricultural expansion and population growth as proximate and underlying drivers (respectively) are considerably outstanding. This project especially makes use of socio-economic data: bio-physical data are lacking. Gathering these empirically would be beneficial for future investigations, where a holistic study of the synergies of a wider set of variables on forest cover change could be considered in one computer-based modelling framework (e.g. agent–based modelling).
5.1 Introduction

Similar to many developing countries, deforestation (and land use change) in Uganda is driven by a number of factors. Often, these factors are generalised and the underpinning causes are not sufficiently identified, hence control measures are not focused (Angelsen and Kaimowitz 1999). Although work by Lambin et al. in the 1990s (and early 2000s) characterised the drivers of deforestation and land use change in the tropics into the proximate and underlying causes (see Figure 5.1; Mertens and Lambin 1999; Geist and Lambin 2002), we lack studies that examine these drivers at the regional scale in the Northern Albertine Rift Landscape. They defined proximate drivers as “human activities or immediate actions at the local level, such as agricultural expansion, that originate from intended land use and directly impact forest cover” and underlying drivers as “fundamental social policies that underpin the proximate causes and either operate at the local level or have an indirect impact from the national or global level” (Geist and Lambin 2002, p.143).

This project employed wide-ranging techniques to ascertain that deforestation and land use change have indeed occurred in the Northern Albertine Rift region; these data were also used to identify the leading drivers of deforestation. In Chapter 2, a description of the remote sensing analyses is provided, while in Chapters 3 and 4, household surveys and key informant data were collated and analysed respectively. In the following sections, the evidence of deforestation (and land use change) and the proximate and underlying drivers suggested by Lambin et al. are critically evaluated in the light of the data gathered and supporting literature; the study is also placed in a broader context highlighting complex interactions of the drivers. Questions for further research are raised within various sections. The implications of these analyses on developing countries grappling with similar challenges, and policy recommendations are presented.

5.2 Research Questions

This chapter attempts to address the following questions.

1. Is it there evidence of anthropogenically-driven changes in rural land use and forest cover in the Northern Albertine Rift region? How strong is it?
2. What are the drivers of land use change and deforestation in the region? How much evidence does this study and supporting literature provide to accept/dismiss theories of tropical deforestation and land use change suggested by Lambin et al.?

5.3 Is Forest Cover Change in the Region driven by Anthropogenic Activities? How Strong is the Evidence?

The remote sensing, household survey, and interview data substantiate each other, and suggest that most of the forest changes reconstructed for the region (in this thesis), are, to a great extent, valid, and a result of anthropogenic activities: both in terms of the gains and losses. As emphasised in Chapter 2, the forest signal is robust, showing that, in the last three decades, larger-scale aggregate measures of total change (where only 10.7% is lost overall) can obscure more local patterns, in which protected areas and the national park maintain or grow forest cover, whilst the forest corridor areas that are not protected suffer drastic losses (of up to 99%). The other land uses were more likely to suffer from spectral confusion, although it was possible to identify continuous (uniform) farmland, such as the expansion of sugarcane south of Budongo forest, and small-scale farming around Bugoma (to a great extent). The thickening of forest cover in Budongo, Bugoma and Murchison Falls National Park is attributed to the protection policy that has been largely successful in the last three decades (albeit with some illegal logging): a sign of positive anthropogenic influence that favoured tree regeneration and new growth. There is however literature that points to declining elephant populations in Murchison Falls National Park (Eltringham and Malpas 1980), but this is old, and new studies are required.

Throughout the data gathered, there was no evidence of natural disasters (e.g. wildfires and landslides) as a cause of forest loss. However, some studies point to the illegally started fires in the northern parts of Budongo, where they were necessary for clearing thick bushes in the forest and Murchison Falls National Park for illegal hunting (Grace Nangendo 2005; Nangendo et al. 2007). The rather flat terrain of the Northern Albertine Rift Landscape ensures the region is at low risk of landslides, although these are common in degraded (and deforested) mountainous parts of Eastern Uganda (Knapen et al. 2006; Claessens et al. 2007; Mugagga et al. 2012).
Up to this point, the role of anthropogenically-driven changes in forest cover is undeniable, although the intrinsic role of climate change is difficult to disentangle, undermined by the paucity of data. Climate change is known to trigger extreme events such as droughts, and floods, which in turn shape agronomic practices, or support weed and pest infestation, for instance, although pinning related land use and deforestation events to climate change alone is complex. Previous archaeological studies have reconstructed the evidence and importance of climate change in western Uganda for the pre-colonial and colonial period (Robertshaw and Taylor 2000; Taylor et al. 2000), for instance, but records showing more recent (post-colonial) periods relevant to this investigation are lacking. These studies are also silent about climate change effects on forest cover though (but focus on changes in swamps, lakes, and socio-economic activities). From the available evidence for the last 30 years, in this investigation, the discussion will only look at anthropogenic impact particularly regarding forest loss around the large protected forest, on private land, as a result of agricultural expansion (e.g. sugarcane growing around Budongo and small-scale farming around Bugoma), and other drivers which are examined in the following sections.

5.4 Proximate Causes

At the proximate level, disentangling single factors is complex; Geist and Lambin (2002) suggested explanation of deforestation based on multiple factors. This section examines three hypothesised drivers of deforestation based on their framework (summarised in Table 5.1): agricultural expansion, wood extraction, and infrastructure extension. Each is explored in turn using the data from this project and available supporting literature.
Figure 5.1 Drivers of land use and land cover change (re-drawn from Geist and Lambin 2002)
5.4.1 Agricultural Expansion

While there is evidence of agricultural expansion (from remote sensing data analyses) in various parts of the region, the processes are dissimilar, and not necessarily a result of household per capita increase in sizes of agricultural land per se. Primary data from household surveys clarifies this. Farmers are likely to cultivate similar sizes of land season-by-season (although this is based on two seasons’ data): land under cultivation did not differ significantly in the first half than the second half of 2013 for annual crops, or between 2012 and 2013 for perennial crops. The majority (>90%) of the households surveyed did not acquire new land on a permanent or temporary basis for cultivation. Rent periods of new land, amongst households that hired them, lasted a season or two at most, and were renewed on the owners’ discretion. Land fragmentation is common as land is passed on from one generation to another in a predominantly customary land tenure system.

For the parishes around Budongo, agricultural expansion has been largely due to the aggressive out-grower scheme, driven by Kinyara Sugar Works, where farmers agree to allocate considerable amounts of their land (including what was previously under small-scale farming and forest) towards sugarcane production. Other than the sugarcane scheme, the small-scale farming (in terms of land sizes and crops grown) is similar to other parishes around Budongo, and the region more generally. Around Bugoma, expansion of agricultural areas supports the hypothesis by Geist and Lambin (2002) that in–migration and, to a much lesser degree, natural population growth drive the expansion of cropped land. They found that this hypothesis accounted for 47% of the total deforestation in the African tropics. The key informant interviews clarified that land was for a long time forested until new settlers came into the region and cleared it using rudimentary slash-and-burn techniques for agricultural purposes. This slash-and-burn agriculture is not thoroughly documented, though, and would benefit from further investigation. It involves clearing the land using fire, and allowing sufficient fallow periods over plots to recuperate as other areas are farmed, and then revisited after a number of seasons. While it is thought that the length of fallow periods are declining due to population growth and rising household-level food insecurity, this is poorly quantified. The data from the household survey suggests that multiple crops are grown per season to increase chances of success, and particular crops (e.g. cassava) are grown
all-year-round as they provide staple food, and are resistant to climatic and soil condition fluctuations.

There is not sufficient evidence for expansion of grazing areas and ranches in the region from these data. Most of the livestock kept were the small type (goats, sheep, pigs), that are economical on space and have less grazing time demand, often managed by tethering and rotating them in vegetated areas where they can browse/feed. Large numbers of cattle are less common except in the semi-arid regions of Buliisa, but were associated with immigrants who moved into the area to take advantage of grazing spaces as the cattle-corridor regions that run from south-western to north-eastern were under severe stress of food and water for the animals. Households that own big herds are generally considered wealthy, and cattle are viewed as a status symbol (mostly in the semi-arid region).

5.4.2 Wood Extraction

Surprisingly, although literature suggests that wood extraction in the protected and unprotected forests in the region is driving forest loss, highlighted in the value-chain analysis by Muhumuza et al. (2007), the survey shows that timber and poles are the least used resources amongst household in both the forested and non-forested regions. This suggests that poor people in communities near the forests are to a large extent excluded from access to the value chains of timber products, which indicates that there may have been a sampling bias in either of the surveys, in that those included in this project may therefore not identify much engagement with the forest as a resource (for poles and timber), while those in Muhumuza et al. (2007) sought out specifically for those involved. It is not clear from their description whether this is the case (as the details of their survey techniques are not provided). It is therefore difficult to ascertain the biases.

In addition, while remote sensing data did not identify large sections of logged areas in the protected Budongo and Bugoma forests, possibly due to the difficult-to-detect scale at which logging occurred, key informant interviews highlighted illegal logging in the protected areas particularly for hardwood tree species. This suggests, in agreement with previous studies (e.g. Muhumuza et al. 2007; Nangendo et al. 2007), that there is a
timber extraction process in Budongo (and Bugoma) which is at variance with the evidence that the forest area has been relatively stable: therefore the extraction is presumably selective and potentially sustainable (or perhaps the forest is being degraded by removal of large old trees), but is taking place. It is possible that some of the respondents from the surveys were involved in the wood extraction but did not disclose this information for fear of reprimand with the authorities. This revelation suggests that, an indirect questioning method (e.g. the un-matched count technique) could be used in future to detect illegal timber extraction (used in similar studies to detect illicit activities, e.g. Nuno et al. 2013). The un-matched count technique involves randomly allocating survey respondents into a control group and a treatment group. The control group members receive a list of non-sensitive items (behaviours e.g. agricultural activities and trading), whereas the treatment group receives the same list but with the addition of the sensitive item (illegal wood extraction). All respondents are asked to indicate how many (but not which) items apply to them, and the differences in means between subsamples are used to estimate the prevalence of the sensitive behaviours (Nuno et al. 2013). While this is a relatively novel technique, the results are promising albeit with large confidence intervals.

5.4.3 Infrastructure Extension

Development of transport networks (e.g. roads, railways), markets, settlements, public service extension (e.g. waterlines, electricity supply) and private company activities (e.g. mining, hydropower, oil exploration) were identified as key drivers of tropical deforestation in the Geist and Lambin (2002) framework. Ascertaining forest loss to infrastructure development in the Northern Albertine Rift region is difficult, but notably, oil was discovered in the Albertine graben in the last decade, and the oil and petroleum bill was passed in December, 2012. Oil companies have since completed exploration and plans of production and processing are underway. A few oil wells are located in sections of the protected reserves, and many are not distant from the protected forests of aesthetic and biodiversity importance. This raises questions about their protection status over the coming decades. Urbanisation, as a result of the oil industry will present extra demand for forest products (e.g. timber and poles), and may drive future deforestation patterns in the landscape. There is some remote sensing
evidence of recent growth (after 2010) in built-up areas in previously bare regions in Buliisa.

During fieldwork, there were extensive road works visible in places especially where the oil refinery will be located, and main roads leading to extraction areas. It remains to be seen if these infrastructure developments will have an effect on the forest cover. Data from elsewhere (in Latin America) however shows accelerated deforestation as a result of improved road access (Geist and Lambin 2002), however, there is little evidence at present from this project that forest loss is as a result of this process.

5.5 Underlying Drivers of Deforestation and Land Use Change

Geist and Lambin’s (2002) framework suggests that the underlying drivers of deforestation and land use change include: demographic, economic, technological, policy and institutional, as well as cultural factors. The underlying causes present the context in which the proximate drivers of deforestation operate. Sassen et al. (2013) argue that the context in which the underlying drivers of deforestation are examined could be more important than the drivers of forest loss per se. They found that the political climate was responsible for lawlessness in forest clearance in and around Mt. Elgon forest reserve/National Park in the turbulent regimes prior to 1986, but that collaborative forest management between communities and forestry officials in a stable regime (after 1986) favoured forest recovery in previously eroded areas. Arguably, while the contexts may be similar, outcomes could vary from place to place (Geist and Lambin 2002). The data from this study for instance show that the majority of forest loss happened in a stable political period, but mostly on private landscapes, and illegal logging of protected forests was to some extent favoured by political activists (who halted relocation of people that had encroached on forests in gazetted areas from being evicted: information from a key informant). In addition, the observed causal factor synergies could be more important than single-factor explanations that blame deforestation on shifting cultivators and population growth (as a result of natural increment) (ibid). Each underlying factor is assessed independently in the following sections though. As the underlying drivers are interrelated, to minimise repetition of similar points, brief outlines are provided.
5.5.1 Demographic Factors

While population growth was not widely viewed as a major driver of deforestation by the local and expert respondents, literature suggests that it has played a leading role in increasing pressure on forests in the Albertine Rift Landscape in the recent decades (Ryan et al. 2014). Indeed, a rather simple exploration of the population trend in two districts, Masindi and Hoima shows a total linear increase of approximately 45% and 75% respectively between 1980 and 2014 (Figure 5.2). The population growth rate in Uganda is one of the highest in the world, estimated at nearly 4% per annum (Bongaarts 2009). The striking population growth rate is associated with high fertility rates, low use of contraceptives, low investment in reproductive health education, reduced mortality rates with improved health systems albeit still poor, among others (Ainsworth et al. 1995; Bhutta et al. 2010). The population pyramid of the surveyed households further corroborates the notion that population growth is likely to continue even further in the coming years given the majority are young, below the age of 20.

Figure 5.2 Population trend in Masindi and Hoima districts in the last 4 censuses

[Most recent census was conducted between August and Oct, 2014, long after my fieldwork, and the results are provisional. Buliisa was carved out of Masindi after the 2002 census, and therefore the 2014 results are a sum of Masindi and Buliisa to obtain a consistent comparison over the entire period. As the 2014 results are provisional, the apparent drop in the Masindi total population between 2002 and 2014 in Masindi is difficult to explain: source (UBOS 2006; UBOS 2015)].
The outstanding demographic aspects pointed out by key informant respondents in relation to deforestation are the migration and settlement patterns in the region and not natural population growth, although a small percentage of the locals considered this important. The nature of the settlements differs around Budongo and Bugoma; where migrants around Budongo generally settle near the forest while those around Bugoma are in settled camps. This is corroborated by the results of the household survey. While it is difficult to delineate the contribution of natives and migrants towards deforestation, there is some evidence to suggest that migrants could be playing a critical role, based on their proximity to the protected forest: although regarding the forest on private land, they could all have had a role to play. There is evidence elsewhere though that suggests that population growth can lead to landscape protection through intensification (Boserup 1965; Tiffen and Mortimore 1994).

5.5.2 Economic Factors

According to Geist and Lambin’s (2002) framework, economic factors include: market growth and commercialisation, urbanisation and industrialisation, and other economic factors (e.g. price increase). Household survey results indicate that although the main economic activity in the landscape is agriculture, a number of other income-generating activities are common, based on the agro-ecological zoning. Clusters in the peri-urban areas are more involved in trading activities compared to other regions (e.g. poorer people [cluster 2 households] located near the protected forests), while cluster 3 households especially in Kibwona parish (around Budongo) are predominantly involved in crop cultivation, and a sizeable number involved in the out-grower scheme as well. Data on profits/losses made by the farmers involved in the scheme, and whether there have been annual increments based on changing market prices of sugar are lacking, and could be sought in future investigations. Trade in firewood and charcoal that could be viewed to have a direct deforestation impact was minimal (from the survey data). Except in the regions where the economic expansion of sugarcane had a direct impact on forest loss, many of the economic activities have had indirect impact and may be difficult to relate to the deforestation patterns in the region. As earlier noted, illicit wood extraction is on-going though, and involves a racket of corrupt forestry and police officials, middle men and wealthy business owners located in distant places (e.g. Masindi, Hoima and Kampala: Muhumuza et al. 2007). Markets and urban centres have
grown around the sugar producing areas, as pointed out in the previous chapters. Sugarcane expansion could also have been driven by multi-faceted factors that require further investigation; some of which may include international trade and rising sugar prices on global market.

5.5.3 Technological Factors

Geist and Lambin's (2002) framework further identifies agro-technical change including intensification and extensification, agricultural production inputs, and applications in wood technology as drivers of tropical deforestation. A wide range of technological changes (e.g. new crops, higher-yielding varieties, mechanization, irrigation, fertilisers, and pest control) are documented in different agricultural systems (including shifting cultivation, permanent upland cultivation, irrigated farming and cattle ranching) although most of the impacts of the technologies are assessed based on modelling rather than empirical studies (e.g. Angelsen and Kaimowitz 2001). Technological change in agriculture are therefore thought to have either positive or negative effects on forest stocks, but more often ambiguous (Soest et al. 2002; Grainger et al. 2003). Technological adoption has been shown (through modelling) to, in fact, accelerate deforestation as the risks of cropping are reduced, making it more attractive to clear new areas for cultivation (Angelsen and Kaimowitz 1999; Angelsen and Kaimowitz 2001; Soest et al. 2002; Grainger et al. 2003). Furthermore, technologies thrive under diverse settings of production and utilities, and their adoption rates are varying, so effects could be more local (Soest et al. 2002).

In the Northern Albertine Rift region however, the data from the household surveys and interviews show limited evidence of technological innovation and use. Most of the agricultural production and wood extraction still use the low input equipment (e.g. hand hoes) and rudimentary methods (e.g. slash-and-burn, pit-saws). The lack of technological advancement could, in itself, be a leading contributor to deforestation, although as previous studies have shown, better technologies could accelerate forest loss. However, in some cases, respondents referred to bulldozing of forest for sugarcane farm expansion that led to very fast loss of some areas of forest.
5.5.4 Policy and Institutional Factors

Policy and institutional arrangements particularly related to property rights, policy climate in which the policies operate, and institutional cohesion are thought to have played a role in deforestation in the region in the last three decades. Policy and institutional factors appear to have been relatively stable in the earlier period of this investigation, until after the enactment of the National Tree planting Act of 2003. From the period the Act was commissioned, forest cover loss around Budongo for instance, was, under bizarre circumstances, accelerated. This was partly as a result of the re-demarcation of boundaries that left some of the previously protected forested land to lie on unclaimed private landscapes. This, according to key informants, encouraged migrants to settle and clear previously forested areas. Furthermore, the Act designated new groupings of forest management regimes into community, local government, private, central government and national park forests which left community and local government forests more exposed to exploitation as a result of insufficient policing, causing striking forest loss outside the protected forest estates (Muhumuza et al. 2007).

Forest loss on private land was exacerbated by a parallel licensing scheme by the District Forest Services that has limited personnel at the district and within the communities to enforce extraction procedures (ibid).

The roles of the various forestry bodies appear to be poorly understood, with some overlaps in the management strategies between forests and wildlife, for instance. While National Forest Authority is incharge of the trees in gazetted forests, Uganda Wildlife Authority is responsible for the game animals within the same forests, but also of trees and wildlife in National Parks. There are some co-managed areas in Budongo for instance. Such ambiguities may cause laxity in management, or budget overlaps leaving fewer resources available to related critical areas.

Institutions are well developed and their mandate is well documented, although under equipped, and poorly funded. There are several higher education and research institutions (e.g Nyabyeya Forestry College, Makerere University), and non-governmental organisations working towards sustainable use of resources to alleviate poverty and improve livelihoods, and train conservation professionals in the region. Their efforts may, to some extent, be frustrated by the lack of political will to implement
recommendations, evident in the dismal annual budget allocation (Nordheim-larsen 2008).

Policy arrangements have produced some positive results however: some Collaborative Forest Management (CFM) schemes have been successfully established around Budongo, although less around Bugoma. An example is the Kapeka Integrated Community Development Association (KICODA) which is a CFM group with an area of about 8 hectares, where the land is held by government while the community owns the trees (Muhumuza et al. 2007). In this arrangement, the communities cannot harvest the trees without government intervention, aimed at preventing resource depletion: membership is based on different interests (e.g. bee keeping, firewood gathering, charcoal burning, herbal medicines and farming), agreed upon during the group formation process in order to avoid conflict. Members interested in farming are given land along the boundaries where they practice agro-forestry (Muhumuza et al. 2007).

Land and tree ownership rights are complex and largely insecure. The predominant land ownership system in the region is the customary type; where, often, legal titling is lacking, and land is passed on from one generation to another. This insecurity makes conservation of tree cover on private landscapes less appealing. Under this regime, livestock are allowed to graze in a free-range manner; soil conservation practices are not readily enforced, resulting in land degradation. Tree planting is discouraged by the low survival rates, partly due to vermin, and domestic animal raiding (source of information from key informants).

5.5.5 Cultural Factors

Cultural factors including public attitudes, values and beliefs are rather complex underpinning drivers of deforestation. Beliefs can shape attitudes towards nature, and play an important role in how rural households relate to and use forests: in terms of what they can obtain from them (e.g. food, bush meat, wild fruits, medicinal plants), or could be viewed as dangerous for spiritual reasons (if there is a strong link between nature and the supernatural) or perhaps as important sacred places of worship with particular tree species left for hundreds of years (if considered to have godly powers) (Scales 2012). While Chapter 4 shows that there may be some relationships between
culture and deforestation, particularly regarding the importance they attach to forests, either as sacred places, or generally a resource that should be conserved, these aspects still remain poorly understood. Studies elsewhere have shown that cultural factors have in fact contributed to conservation of forests in culturally–benign people–forest relationships, where changes in rainfall and river flow regimes were associated with breaking the cultural norms (Scales 2012), but negative cultural norms could have harmful effects on forest cover.

Other factors highlighted in the Geist and Lambin (2002) framework including pre-disposing environmental factors (e.g. soil quality), bio-physical drivers (fires, droughts, floods, pests) and social triggers (war, social disorders, abrupt displacements, economic shifts, and abrupt policy shifts): these have either been discussed previously, or are not included in this review for their potentially minimal contribution, but more so due to lack of data.

5.6 Broader Context and Future Work: Could the Complexity Conundrum be managed?

Drivers of deforestation and land use change in the tropics are complex, embedded in erratic human behaviour, geographical and historical contexts, and mystifying feedback loops. Disentangling the proximate from the underlying drivers (or even within each category) in both space and time is, practically speaking, challenging. A rather simple example is the widely suggested link between poverty and its association with deforestation. While rural poor are deemed to survive mostly on forest resources, models show that even if they got wealthier, they would have more incentives to clear forest, perhaps at an even faster rate as they have access to better and more sophisticated equipment, and can access additional paid labour (Scales 2012). Feedback loops have for instance been shown to amplify the deforestation conundrum: where for instance, road construction and creation of new settlements in a frontier region increase demand for wood and food, in turn, shifting cultivators turn into sedentary cash croppers while permanently settled subsistence farmers respond to market signals to increase production (Geist and Lambin 2002).
Evidence from deforestation studies further suggests that the links between cause and effects are far from universal, and are ever-changing (Geist and Lambin 2002). It may however be beneficial to start asking some more focused questions to bring these intricacies to light. For instance, understanding why people are in forested areas, as opposed to why they moved there in the first place (not what facilitated their movements) and why they carried out forest clearance as opposed to other livelihood strategies (Scales, 2012), may be crucial if we are to get a better understanding of the drivers of tropical deforestation. Such questions may however turn out to be very sensitive and would require careful ethical consideration and framing, and rigorous study designs.

More recently, advancements have been made towards understanding human–environmental interactions through various modelling frameworks, including but not limited to 1) Cellular Automata (CA)–Markov chain based models, 2) Generalised Linear/Additive Models, 3) CA–based Artificial Neural Networks, and 4) Agent–based models. A summary (as well as pros and cons) of the first three models is provided in Table 5.1. Space does not permit discussing them further as they are less favourable than Agent–based models for advancing this research, but for detailed reviews on mechanisms and applications, readers are referred to Heppenstall et al. (2011) and Railsback and Grimm (2011).

Agent–based modelling is the most appropriate technique for further understanding of the intricate land use and forest cover patterns in the region (as explained in the following paragraphs). During the inception of this project, it was envisaged that Agent–based modelling would form the third strand of the analysis. The first strand is the remote sensing data analysis. This established the magnitude and extent of deforestation and land use change, and the sites where it has been extensive. The second strand comprised of the extensive household surveys and interviews. It was hoped that these two strands would provide sufficient information to parameterise the ABM (the third strand). The trends observed (from satellite data) would provide a basis for the calibration and evaluation of the performance of the ABM, and essentially underpin the prediction of a 30 year trend. The baseline year, 1985, would be used to initialise the ABM in order to test the performance of the model, by reconstructing the observed historical trend (1985–2014). The land use and vegetation cover map of 2014
would then be used to initialise the ABM for prediction of a future 30 year trend (2014–2044). The household survey data provide an idea of how land use decisions are possibly made, among other day-to-day decisions for rural survival. Therefore a mixture of the remote sensing and household survey evidence, it was envisaged that a sound model would be developed to test some baseline and future scenarios. However preliminary developments have been made (explained in detail in Appendix 5), but due to time constraints on this project, this is suggested as future work. Below, a comprehensive review (and description) is provided to contextualise the rationale for the selection of the Agent-based modelling paradigm.

Agent Based Modelling is defined as a simulation method where heterogeneous and autonomous individuals (agents) share a common environment and act upon it, while simultaneously interacting amongst each other in quest for realisation of some self- or common-interests (Ligmann-Zielinska and Jankowski 2007). Subsequently, ‘Agents’ are defined as autonomous software entities constructed by human programmers, in a context that they can pursue their goals in an open-ended manner, in mimicry of a defined social system (O’Sullivan and Haklay 2000). Essentially, computer simulations with human–like agents, when constrained with a problem are capable of autonomous reactive or proactive social behaviours which enable us to better understand how an aggregation of individuals leads to complex macro behaviour in ‘reality’: and the model results can be compared with observations (Berger 2001). Agent autonomy allows for endogenous, not necessarily optimised decision-making, where issues of uncertainty, perception, adaptation, and learning may all be present (Ligmann-Zielinska and Jankowski 2007). Notably, however, agents are simplified formal representations of persons (or can be larger-scale entities such as households, governments, countries) which execute their decisions within given rules, and are far from the complexity of real human actors (Moss and Edmonds 2005). The agents interact within a given environment. The ‘Environment’ is a time dependent and possibly dynamical system separate from the agents that may condition agent behaviour but can also be affected by agent actions, often presented within a modelling framework as a cellular–automaton-like entity that is non-deterministic, dynamic and continuous, in which agents interact and make decisions on resource use in an optimal or non-optimal manner (Schindler 2009).
Why Agent-Based Models (ABMs)

Social and natural processes are driven by subsystem interactions and feedback mechanisms, and thus, system-wide behaviour cannot be understood by analysing system components in isolation; rather, the interactions among these components give rise to feedback mechanisms, a characteristic of complexity (Bennett and McGinnis 2008; Le et al. 2008, 2012). ABMs are therefore very useful when connection between the micro and macro behaviour is not well understood (Smith and Conrey 2007). To this end, ABMs have been widely used (see reviews by Parker et al. 2003; Matthews et al. 2007; An 2012). Conventional aggregate process–based modelling (e.g. using system dynamic models) cannot encompass social interaction in full, simply because it represents an averaged, isolated single decision–making entity, scaled–up to represent the whole community (Ligmann-Zielinska and Jankowski 2007). Agent based modelling provides an environment that advances complexity science by allowing one to examine the way in which assumptions about individual behaviours and interactions might lead to emergent system–level phenomena (Heppenstall et al. 2011). Researchers and policy makers are turning to these models for reasons of ethics (e.g. where health risks are involved), cost, timeliness (e.g. where real time evaluation of a system may be prohibitively long) and appropriateness (Louie and Carley 2008). ABMs are particularly useful in data limited areas, where partial knowledge of the system could be used to inform us about how a system might operate under different conditions or what the data might look like (Louie and Carley 2008).

Additionally, ABMs are able to pick-out clustered volatilities within a socio–ecological system. Rapid changes (as a result of strong social interactions) may occur in a microeconomic or land use system, which may lead to macro–level statistical distributions that no statistical or regression analysis based on normal/Poisson distribution are able to represent (Moss and Edmonds 2005). Heterogeneities in ABMs allow thresholds in stimuli to cause changes that enable capturing of ‘fat–tailed’ distributions in non-normally distributed social systems.

Furthermore, the possibility of capturing processes in ABMs may allow us to model and account for sources of variability that would statistically be classified and dismissed as
‘noise’. Conventionally, whatever a statistical model is not able to represent meaningfully is classified as noise. Some authors have argued that just because we cannot understand some aspects of the data does not provide a valid basis for their dismissal simply as (random) noise, suggesting that this could provide the less obvious explanations of the intricacies within a system (Firestein 2012). There is often an implicit assumption that the noise will obey the ‘law of large numbers’, which, broadly stated, is the property that random noise will cancel out faster than any ‘signal’ as sample size increases, or that the expected value gets closer to the mean as many more trials are made (Moss and Edmonds 2005). Social phenomena are inherently complex, and any assumptions about them cannot be reduced to, for instance, physically–based systems (Le 2005). The ABM paradigm may provide analytical solutions to ‘statistical noise’.

Although representing human–environmental interactions is, by its nature, complex, and any kind of modelling would be a simplification of systems we intend to represent (Box 1979), the impetus for attempts to represent complex systems (using ABMs) then lies in the fact that models help us to: understand system functionality through process–based representation of reality, illuminate core uncertainties and dynamics, discover new questions, and offer crisis options in real time (Epstein 2008). The ‘Agent Based Modelling’ (ABM) methodology could therefore be adopted in future investigations (see preliminary modelling framework developed in Appendix 5.1, and described in detail in Appendix 5.2, and the selected modelling platform in Appendix 5.3), with an aim to present a holistic and novel perspective to understanding the intricacies of deforestation and land use change drivers through a detailed analysis of day–to–day and seasonal decisions made by the rural communities on settlements, utilisation of land and energy resources under different socio–economic, bio–physical and policy constraints. This could provide a platform to explore patterns of deforestation and land use in the baseline scenario, and under selected policy scenarios relevant to the on–going activities in the landscape. The model could for instance investigate forest protection success in a Reducing Emissions from Deforestation and forest Degradation (REDD) scenario, potential impacts of the oil industry, and modern agricultural applications in the landscape.
In summary, there is compelling evidence of forest loss in the Northern Albertine Rift region, but what drives it lies in a diverse range of interacting complex factors including political, cultural, economic, demographic, environmental, and social factors (which are difficult to unravel). There is hardly any evidence that climate change has contributed to forest loss in the last 30 years. Higher temperatures and lower precipitation would potentially contribute to increased tree dieback, essentially changing the vegetation structure, creating – for instance – savanna landscapes from previously forested areas; and from savanna to open and bare land. However longitudinal studies are required to understand if there are effects of climate change on the protected forests – but this is unlikely to be an issue for forests on private land where nearly all of them have been cleared. However, climate change and vegetation models may be useful in predicting future forest cover in the landscape under the different scenarios. This Ph.D. project set out with clear objectives (see Chapter 1) and has unearthed some interesting findings (Chapters 2, 3, and 4), but as with such time-bound projects, it could only attempt a few questions. The investigation has been able to raise some important questions that would benefit from further analysis, where controlled quasi-experimental designs, longitudinal studies and advanced modelling would make more revelations, important for further planning and protection of the endangered forestry resource. The findings are useful for developing countries grappling with intricate deforestation and land use changes at the heart of development agendas, and the survival of their populations. While forest loss and other unsustainable land use activities are local, the impacts are potentially global, and partly contribute to climate change. The solutions may lie in focused and perhaps unconventional interventions (suggested in the recommendations section), where the local and national governments make drastic steps to engage in global initiatives. There is, for instance, growing climate change finance targeted at Reducing Emissions from Deforestation and forest Degradation (REDD) under the UN-REDD program, World Bank Forest Carbon Partnership Facility, Norwegian Government funding under the Nordic Climate Facility, among others, which could be tapped into. While this is a finance-based initiative, enabling knowledge and institutional arrangements would need to be strengthened for wider benefits.
Table 5.1 Modelling land use and vegetation cover change techniques

<table>
<thead>
<tr>
<th>Model</th>
<th>Description</th>
<th>Pros</th>
<th>Cons</th>
</tr>
</thead>
<tbody>
<tr>
<td>Logistic regression and</td>
<td>Regression is a means to ascertain empirical relationships between binary dependent, and categorical or continuous variables. The dependent variable is binary, meaning that, in this context, a certain land use type occurs at a certain location (value 1) or not (value 0). (Braimoh and Onishi 2007). The common land use/cover dependent variables include distance to main roads, markets, river; slope, elevation and population pressure. The equation of linearised form of the logistic response also referred to as “logit response function” is given below (Overmars 2006).</td>
<td>-Efficient for explicit incorporation of drivers of land use/cover change for prediction of changes</td>
<td>-It assumes that all people in the area respond to the variables in a similar way (giving a linear response)</td>
</tr>
<tr>
<td>Generalised Linear Models</td>
<td></td>
<td></td>
<td>A regression model that fits well in the region of the variable space corresponding to the original data can perform poorly outside that region (Lambin et al. 2000).</td>
</tr>
</tbody>
</table>

\[
\log \left( \frac{p}{1-p} \right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n
\]

Where \( p \) is the probability for the occurrence, \( \beta_0 \) is an intercept and \( \beta \) are regression coefficients to be estimated, and the \( Xn \) are a set of exogenous explanatory variables. The ratio \( p/(1-p) \) is called the odds, \( \log \left( \frac{p}{1-p} \right) \) is the log odds, also named ‘logit’.

The output of a logistic model is a probability surface of dependent variable occurrence indicating land use/cover change. This is a map showing the probability of each cell changing based on the parameters used (Arsanjani et al. 2013). This map could then be integrated with the CA-Markov maps to show location of predicted changes.

| CA-Markov Chain Models                | The CA-Markov model is used to predict future land use patterns based on transitional probabilities of land use change between the past and present states. A land use in a future time (\( LU_{t1} \)) is a function of developing potential scores (\( S_{t0} \)), the land use in previous time (\( LU_{t0} \)), the neighbouring land use states (\( N \)), and time interval (\( T \)) between \( LU_{t1} \) and \( LU_{t0} \). \( LU_{t1} = f\{S_{t0} \cdot LU_{t0}, N, T\} \)
|                                      | The transition probability matrix \( P_{ij} \) is described as follows (Balzter 2000). \( P_{ij} = \begin{bmatrix} LU_{11} & LU_{12} & \ldots & LU_{1n} \\ LU_{21} & LU_{22} & \ldots & LU_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ LU_{n1} & LU_{n2} & \ldots & LU_{nn} \end{bmatrix} \) \( \sum_{j=1}^{n} LU_{ij} = 1; \ i = 1, 2, \ldots, n \)
|                                      | Where \( LU_{ij} \) is the probability of change from land use type \( i \) to \( j \), the sum of each row always equals to 1. Next, by multiplying the matrix by the total areas of each kind of land use (\( A_i \)) in the target year, the land use demand (\( A_{in} \)) in the simulation process can be defined. Based on the Markov chain analysis, the quantity of transition between each kind of land use can then be used in the allocation process to decide their location. |
|                                      | -The grid-based system could easily be coupled with GIS software making raster-based analysis possible.                                                                                   | -The transitional probabilities are insensitive to spatial heterogeneities and dynamics.                                               |
|                                      | -The changing probabilities between specific kinds of land uses can be explored, providing a better understanding of changing processes between different time periods |                                                                                                                                    |
During the simulation, a GIS-based Multi-Criterion Evaluation (MCE) method is used to calculate the developing potential scores of each kind of land-use for determining the most suitable sites (Nourqolipour et al. 2014).

**CA-based Artificial Neural Networks**

Artificial Neural Networks (ANN) is a “brain-like” structure that consist of neurons which provide both learning and recalling processes, where surrounding cell effects in the neighbouring land use are calculated and used as an explanatory factor to the input neuron, as illustrated below (Mas 2004). Essentially, ANN is a non-linear model which trains and learn from data based on numerous runs in order to automatically get the best fit, hence good at handling multivariable data (Mas 2004). Parameter values are automatically determined by a learning process which is based on a back-propagation algorithm (Marshall and Randhir 2008). The output layer represents the possibility of change between land-use type \( i \) and \( j \), and the input layer consists of several factors that could explain the land-use changes. The ANN-CA model acquires the parameters by fitting the input and output layer based on numerous sets of non-linear models. There is no need for researchers to predefine the transition rules which are mostly required in other CA-based models. The study argues that this technique gives us a more objective view of understanding the relationship between land-use changes and different socioeconomic and environmental factors.

- Reliable way to estimate the relative explanatory power of each factor that might influence land-use change as the parameter values are automatically determined by a learning process.
- The model can deal with the complex relationships among variables because of its excellent non-linear calculating abilities. This is especially useful when there are many parameters that need to be defined in the simulation of a complex system.
- The simulated future land-use changing pattern is sorely based on the changing trend in the past. And the parameter is derived from “the results of changes” instead of change processes. It fails to consider the process of land-use changing especially when it comes to decision-making processes.
- The process of finding the best fit would become extremely time-consuming when the amount of variables increase, which makes it inefficient in terms of real-world applications.
5.7 General Conclusions

The conclusions in this section are generally drawn from the work in this project, and more succinct (and/or elaborate) summaries can be found at the end of each results’ chapter (2, 3 and 4).

1. Remote sensing data analyses show that forest cover in the region has declined overall in the last 30 years, mostly on private land, although the protection of the large blocks, Budongo and Bugoma has been largely successful albeit with undetectable illegal logging.

2. Remote sensing data analyses further show that the areas where loss of forest cover in the corridors has occurred is now dominated by agricultural activities: sugarcane growing around Budongo and small-scale farming around Bugoma.

3. Household surveys suggest that poorer households are located nearer to the protected forests than the peri-urban areas, and are more dependent on forest products than their peri-urban counterparts.

4. There is wide agreement in the data collated and analysed on the trends and status of forest cover and livelihoods in the landscape.

5. Agricultural expansion, population growth, and migration are agreed to be the leading underlying and proximate drivers of deforestation in the region respectively, although they operate in complex political, social, economic, and cultural contexts.

6. This study provides the much needed data for future analyses, including the suggested, more sophisticated, agent-based modelling, which promises to unearth likely land use and forest cover patterns under plausible future landscape scenarios.
5.8 Policy Recommendations

These are a set of interrelated recommendations arising from this project that could improve use of resources in the Northern Albertine Rift region in a manner that would favour both people and nature. The policy recommendations are based on the findings of this thesis backed by literature, but are presented in no particular order of importance. What is exclusively from this research or literature or the position of the author (or a combination) are indicated in parentheses at the end of recommendation.

1. **Maintain protection status of the gazetted forests**: considerable effort is required for continued maintenance of the protection status of the gazetted Central Forest Reserves (Budongo, Bugoma and Wambabya); this has been largely successful in the last 30 years albeit with resource constraints (evidence from this thesis).

2. **Promote agro-forestry**: erosion of all tree cover on the private landscapes poses a major threat, and increases pressure on the protected forests. The analyses have shown that the majority of the households are poor (living below poverty line), and seek to supplement their livelihoods from “freely available” natural resources. This includes seeking fuel wood, building material, medicinal plants, among others from forests (among other areas). Considerable effort is required to promote co-existence of trees and food crops on their landscapes: fruit trees that have additional benefits (e.g. shed and fruits) could be promoted, compared to pine and eucalyptus, although the latter provide better fuelwood and timber and mature faster. The judgement on species to be adopted should be based on consultations with the local communities. Seedlings should then be made available at an affordable cost (evidence from this thesis, with author’s own interpretation).

3. **Promote carefully controlled yield enhancement**: interrelated to the second, mechanisms to improve yields sustainably need to be considered. The data from the surveys show that agricultural inputs, both synthetic and organic, are minimal. To be able to meet the rising national food demands, extra effort is required to roll out sustainable agricultural enhancement programs: including the use of fertilisers, control of soil erosion, improved and adaptable seed, pest and weed control. This should be carried out in a way that intensification for instance does not lead to eutrophication. Institutional arrangements at the local level could be put in place to monitor this
possibility (this recommendation is backed by results of this thesis, and the literature although further studies are required before it could be implemented).

4. **Trial of small field amalgamation, joint use of agricultural implements and equitable sharing of benefits**: farmers spend considerable amounts of time on agricultural activities particularly because they use low input implements. Programs to explore joint production schemes where their small pieces of land could be amalgamated (to provide sizeable pieces), and higher input implements used, while food and proceeds from crop sales are shared, could be piloted. This may be a useful way to increase food production in the presence of population pressure and food insecurity. Similar to 3, careful thoughts of the outcomes of intensification should be considered (author’s suggestion for pilots: success cannot be guaranteed without further research).

5. **Explore and roll out collaborative government–local community forest management schemes**: collaborative Forest Management (CFM) has registered some success around Budongo and could be rolled out to other areas of the landscape (e.g. Bugoma). This would require extra district staffing and funding to supervise the projects, whilst empowering the locals to engage in resource planning and revenue management. Other forestry governing institutions (e.g. National Forest Authority, Uganda Wildlife Authority, District Forestry Services, Forestry Inspection Division, and the Ministry of Water and Environment) should be better coordinated to support forest conservation efforts on ground (author’s position based on field experience in the region).

6. **Holistic approaches to managing forest loss in the landscape**: as the drivers of deforestation in the region are driven by multi-faceted factors, programs to avoid future deforestation should be integrated, and holistic, ranging from agricultural to market to social services and to other development needs. They should be needs-based, and largely site-specific. While this is likely to be a much more expensive approach in terms of required resources, it seems to be the most plausible way to deal with the problems in this socially- and economically-diverse landscape. Particularly, there is need to bridge the social inequity gap between the rural poor and urban population. The government has local governments through which state-funded programs could be
channelled. This is a more generalised policy recommendation that allows easy and wide assimilation (supported by the data from this thesis).

7. **Engage in international initiatives to control forest loss:** given that Uganda operates on a limited budget (from state-generated funds, supplemented in part by donor funding), and thus allocates a dismal proportion to the Environmental sector due to other pressing development agendas (including security, health, education), conservation efforts could be enhanced through seeking external funding, either through government or non-government organisations. The country should participate in globally-funded climate change resilience and adaptation initiatives to tackle local problems. For instance, the national REDD (Reducing Emissions from Deforestation and forest Degradation) program that has stalled at the scoping phase could be developed to full. Extra efforts should ensure that such large-scale funding is secured, and appropriately used to enhance the future safeguard of the highly threatened forests (author’s position from synthesis of the results).

8. **Development projects in the region should carefully consider and mitigate their impacts on the environment as far as possible:** new economic activities (e.g. the oil industry) in the landscape need to be carefully drafted into the conservation objectives, to harness long-term protection of the gazetted forests. Even though oil exploration and production are of much importance to the development of the national economy, substantial efforts will be required to ensure environmentally friendly development success. A certain percentage (at least 7%) of proceeds from the oil revenues should be deliberately reinvested into improving the rural people’s livelihoods, as well as to promote conservation goals in the region (author’s oversight suggesting holistic environmental friendly development).

9. **Environmental education is necessary** to sensitise the communities in these regions on the importance of forests, and the future plans of conservation and development processes. This could be achieved through deliberate radio talk shows, extension rallies, incorporating conservation planning and practice into the education curriculum at various levels, including at least primary and secondary schools. Institutions of higher learning should be allocated more funding for research to inform evidence-based policy formulation (supported by data from this thesis and the literature).
References


SNV, 2012. *Agrarian Diagnosis Buliisa: summary on landscape and farming dynamics,*


## Appendices

### Appendix 2.1 Bands and what they best classify (source: USGS, 2013)

#### Landsat Multi-spectral Scanner (MSS)

<table>
<thead>
<tr>
<th>Landsat MSS 1, 2, 3 Spectral bands</th>
<th>Landsat MSS 4, 5 Spectral bands</th>
<th>Wavelength</th>
<th>Useful for mapping</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 4 - green</td>
<td>Band 1 - green</td>
<td>0.5-0.6</td>
<td>Sediment-laden and shallow water</td>
</tr>
<tr>
<td>Band 5 - red</td>
<td>Band 2 - red</td>
<td>0.6-0.7</td>
<td>Cultural features</td>
</tr>
<tr>
<td>Band 6 - Near Infrared</td>
<td>Band 3 - Near Infrared</td>
<td>0.7-0.8</td>
<td>Vegetation boundary between land and water, and landforms</td>
</tr>
<tr>
<td>Band 7 - Near Infrared</td>
<td>Band 4 - Near Infrared</td>
<td>0.8-1.1</td>
<td>Penetrates atmospheric haze best, emphasizes vegetation, boundary between land and water, and landforms</td>
</tr>
</tbody>
</table>

#### Landsat 4 and 5 Thematic Mapper (TM) and Landsat 7 Enhanced Thematic Mapper Plus (ETM+) (Highlighted are selected bands used in the classification)

<table>
<thead>
<tr>
<th>Band</th>
<th>Wavelength</th>
<th>Useful for mapping</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 1 - blue</td>
<td>0.45-0.52</td>
<td>Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation</td>
</tr>
<tr>
<td>Band 2 - green</td>
<td>0.52-0.60</td>
<td>Emphasizes peak vegetation, which is useful for assessing plant vigour</td>
</tr>
<tr>
<td>Band 3 - red</td>
<td>0.63-0.69</td>
<td>Discriminates vegetation slopes</td>
</tr>
<tr>
<td>Band 4 - Near Infrared</td>
<td>0.77-0.90</td>
<td>Emphasizes biomass content and shorelines</td>
</tr>
<tr>
<td>Band 5 - Short-wave Infrared</td>
<td>1.55-1.75</td>
<td>Discriminates moisture content of soil and vegetation; penetrates thin clouds</td>
</tr>
<tr>
<td>Band 6 - Thermal Infrared</td>
<td>10.40-12.50</td>
<td>Thermal mapping and estimated soil moisture</td>
</tr>
<tr>
<td>Band 7 - Short-wave Infrared</td>
<td>2.09-2.35</td>
<td>Hydrothermally altered rocks associated with mineral deposits</td>
</tr>
<tr>
<td>Band 8 - Panchromatic (Landsat 7 only)</td>
<td>.52-.90</td>
<td>15 meter resolution, sharper image definition</td>
</tr>
</tbody>
</table>
### Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)

<table>
<thead>
<tr>
<th>Band</th>
<th>Wavelength</th>
<th>Useful for mapping</th>
</tr>
</thead>
<tbody>
<tr>
<td>Band 1 – coastal aerosol</td>
<td>0.43-0.45</td>
<td>Coastal and aerosol studies</td>
</tr>
<tr>
<td>Band 2 – blue</td>
<td>0.45-0.51</td>
<td>Bathymetric mapping, distinguishing soil from vegetation and deciduous from coniferous vegetation</td>
</tr>
<tr>
<td>Band 3 - green</td>
<td>0.53-0.59</td>
<td>Emphasizes peak vegetation, which is useful for assessing plant vigor</td>
</tr>
<tr>
<td>Band 4 - red</td>
<td>0.64-0.67</td>
<td>Discriminates vegetation slopes</td>
</tr>
<tr>
<td>Band 5 - Near Infrared (NIR)</td>
<td>0.85-0.88</td>
<td>Emphasizes biomass content and shorelines</td>
</tr>
<tr>
<td>Band 6 - Short-wave Infrared (SWIR) 1</td>
<td>1.57-1.65</td>
<td>Discriminates moisture content of soil and vegetation; penetrates thin clouds</td>
</tr>
<tr>
<td>Band 7 - Short-wave Infrared (SWIR) 2</td>
<td>2.11-2.29</td>
<td>Improved moisture content of soil and vegetation and thin cloud penetration</td>
</tr>
<tr>
<td>Band 8 - Panchromatic</td>
<td>.50-.68</td>
<td>15 meter resolution, sharper image definition</td>
</tr>
<tr>
<td>Band 9 – Cirrus</td>
<td>1.36 -1.38</td>
<td>Improved detection of cirrus cloud contamination</td>
</tr>
<tr>
<td>Band 10 – TIRS 1</td>
<td>10.60-11.19</td>
<td>100 meter resolution, thermal mapping and estimated soil moisture</td>
</tr>
<tr>
<td>Band 11 – TIRS 2</td>
<td>11.5-12.51</td>
<td>100 meter resolution, Improved thermal mapping and estimated soil moisture</td>
</tr>
</tbody>
</table>
Appendix 2.2 Management zones of Budongo (above) and Bugoma (below) forests
(Source: MWE, 2012, 2013)
Appendix 2.3 A classified Landsat image affected by the Scan-line corrector error
(wedge-shaped gaps at the edges of the image introduce gaps, and continuous areas of land uses affected are erroneous: development of an interpolation algorithm to fill the gaps is required, but is beyond the scope of this investigation)
Appendix 3.1 Household Questionnaire administered, October 2013–March 2014

Modelling of household land and energy utilisation, and emergent forest cover patterns in Western Uganda

Author: Ronald Twongyirwe
Ph.D. student, Department of Geography, University of Cambridge, UK.

Pre-interview details (filled in after consent of the respondent has been granted)

<table>
<thead>
<tr>
<th>Field assistant’s name:</th>
<th>........................................................................................................</th>
</tr>
</thead>
<tbody>
<tr>
<td>District:</td>
<td>........................................................................................................</td>
</tr>
<tr>
<td>Parish:</td>
<td>........................................................................................................</td>
</tr>
<tr>
<td>Village:</td>
<td>........................................................................................................</td>
</tr>
<tr>
<td>Household coordinate:</td>
<td>........................................................................................................</td>
</tr>
<tr>
<td>Respondent’s gender and age:</td>
<td>........................................................................................................</td>
</tr>
<tr>
<td>Position of respondent in the household:</td>
<td>........................................................................................................</td>
</tr>
<tr>
<td>Position of respondent in the village (if applicable):</td>
<td>........................................................................................................</td>
</tr>
<tr>
<td>Date of interview:</td>
<td>........................................................................................................</td>
</tr>
<tr>
<td>Household code:</td>
<td>........................................................................................................ (Filled in by RT before each day’s work)</td>
</tr>
</tbody>
</table>

Interview Quality Assessment

1. Excellent (80–100%)
2. Very good (70–79%)
3. Good (60–69%)
4. Fair (50–59%)
5. Poor (0–49%)

Interviewer self assessment:..........

Overall assessment by RT:..........
(Completed per interview at the end of each working day)

Questionnaire Content

1.0. Household biographical data and livelihood quality indicators
2.0. Household land use (crop inventory and management)
3.0 Household land use (livestock inventory and management, and land tenure)
4.0. Household energy sources and utilisation, and policy knowledge
5.0 Household day–to–day time budget
## 1.0. Household biographical data and livelihood quality indicators

<table>
<thead>
<tr>
<th>1.1. Age composition a</th>
<th>1.2. Gender (Male=1, Female=2)</th>
<th>1.3. Highest level of learning b</th>
<th>1.4. Occupation c (specify if 2 or 3) Note all who provide on-farm HH labour</th>
<th>1.5. Monthly income d (UGX) from Off-farm employment</th>
<th>1.6. Household nativity</th>
<th>1.7. Source of water</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mother</td>
<td></td>
<td></td>
<td></td>
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<td>Biological children</td>
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<td>1.</td>
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<tr>
<td>Other relatives (list)</td>
<td></td>
<td></td>
<td>Is off-farm income used to pay for farming activities?</td>
<td></td>
<td></td>
<td>a) For farming</td>
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<td>5.</td>
<td>If 1, what is the percentage 2. Migration 2. Other 8.</td>
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<td>6.</td>
<td>a) for current year 3. Other 3.</td>
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<td>8.</td>
<td>b) for previous year</td>
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</tbody>
</table>

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*Age composition a: Note household with one parent, child headed; list all relatives to household head living in household at the time of the interview*

*Highest level of learning b: 1. No education 2. Primary 3. Secondary (O’ level) 4. Secondary (A’ level) 5. Tertiary (indicate specific class if known)*

*Occupation c: 1. Subsistence farming 2. Employed in a government sector 3. Employed in private sector 4. Dependent (all categories not working)*

*Monthly income d: income from every member of the family can be entered if known (from a specified occupation) in Uganda shillings*
### 1.0. Household biographical data and livelihood quality indicators

<table>
<thead>
<tr>
<th></th>
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<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>What is the distance from the household to the nearest: (circle correct)</td>
<td>What type of house does household live in? (circle correct)</td>
<td>Who makes decisions on: (Husband=1, wife=2, Other=3)</td>
<td>Does the HH own any of the following? (Yes=1, No=2)</td>
<td>What is the HH main source of information? (circle correct)</td>
<td>Does the household own any of the following (Yes=1, No=2)</td>
</tr>
<tr>
<td>0.5 to 1 km 2.</td>
<td>Temporary 3.</td>
<td>c) Fuelwood collection Mobile phone 3.</td>
<td>Print media 3.</td>
<td>Bicycle 3.</td>
<td></td>
</tr>
<tr>
<td>&gt; 5 km 4.</td>
<td>1 to 5 km 3.</td>
<td>to the next (insert code) Fixed phone 4.</td>
<td>Post mail 4.</td>
<td>Canoe/boat 4.</td>
<td></td>
</tr>
<tr>
<td>b) Source of water?</td>
<td>Permanent house? 1.</td>
<td>d) Buying new land? Other (specify) 2.</td>
<td>Other (specify) 2.</td>
<td>E-mail address 5.</td>
<td></td>
</tr>
<tr>
<td>&lt; 0.5 km 1.</td>
<td>0.5 to 1 km 2.</td>
<td>(insert code)</td>
<td>Hand mail 5.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 to 5 km 3.</td>
<td>&gt; 5 km 4.</td>
<td>(insert code)</td>
<td>Donkey 5.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>c) Health facility?</td>
<td>How far is the HH 1.</td>
<td>e) Disposal of land? Other (specify) 2.1.</td>
<td>Fixing phone 4.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 0.5 km 1.</td>
<td>1 to 5 km 3.</td>
<td>Do you share farming Do you transport 2.</td>
<td>Yes 1.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1 to 5 km 3.</td>
<td>&gt; 5 km 4.</td>
<td>f) Forest product use? (insert code)</td>
<td>No 2.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>d) Market? / Town?</td>
<td>How far is the HH 1.</td>
<td>g) Labour allocation? No 2.</td>
<td>Yes 1.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 0.5 km 1.</td>
<td>1 to 5 km 3.</td>
<td>How far is the HH 1.</td>
<td>Yes 1.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&gt; 5 km 4.</td>
<td>1 to 5 km 3.</td>
<td>to the next (insert code)</td>
<td>Informal chat 1.</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; 0.5 km 1.</td>
<td>0.5 to 1 km 2.</td>
<td>Discussion farming e.g. fuelwood/charcoal? 3.4.</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>0.5 to 1 km 2.</td>
<td>1 to 5 km 3.</td>
<td>to the next information? Yes 1.</td>
<td></td>
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</tr>
<tr>
<td>1 to 5 km 3.</td>
<td>to the next (insert code)</td>
<td>If 1. Specify transport 4.</td>
<td></td>
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</tr>
<tr>
<td>&gt; 5 km 4.</td>
<td>1 to 5 km 3.</td>
<td>Other (specify) 5.</td>
<td></td>
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</tr>
</tbody>
</table>

House type e: 1. Permanent is built with bricks and iron sheet roof, 2. Semi-permanent is built with mud and wattle with an iron sheet roof 3. Temporary is made of mud and wattle, and grass thatched.
2.0. Household Land use (Crop inventory and management)

| 2.1. Agricultural implements owned | 2.2. Crops grown inventory | 2.3. Land sizes for crop cultivation for 2 seasons | 2.4. Yields per crop (for 2 seasons) | 2.5. Income obtained from cropping activities for 2 seasons | 2.6. Management practices

<table>
<thead>
<tr>
<th>Record the number of implements in a HH (for all applicable)</th>
<th>Annuals</th>
<th>Perennials</th>
<th>Area under each annual crop</th>
<th>Annual crop yield</th>
<th>Income from each annual crop</th>
<th>On annual crops (List all codes, and attach amount and costs where applicable)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Previous and current season (Yes=1, No=2)</td>
<td>Previous and current season (Yes=1, No=2)</td>
<td>x y</td>
<td>x y</td>
<td>x y</td>
<td>List Amount and cost</td>
</tr>
<tr>
<td>1. Hoe (jembe)</td>
<td>1. Beans</td>
<td></td>
<td></td>
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<tr>
<td>2. Forked hoe</td>
<td>2. Maize</td>
<td></td>
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<tr>
<td>3. Panga</td>
<td>3. Sorghum</td>
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<tr>
<td>4. Slash</td>
<td>4. Wheat</td>
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<tr>
<td>5. Sickle</td>
<td>5. Barley</td>
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<tr>
<td>7. Axe</td>
<td>7. Groundnut</td>
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<tr>
<td>8. Tractor</td>
<td>8. Peas</td>
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<tr>
<td>10. Tractor plough</td>
<td>10. Tobacco</td>
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<tr>
<td>11. Harrow</td>
<td>11. Vegetable</td>
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<tr>
<td>12. Planter</td>
<td>12. Others</td>
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<tr>
<td>13. Wheelbarrow</td>
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<td>14. Secateurs</td>
<td>1. Tea</td>
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<td>15. Storage</td>
<td>2. Coffee</td>
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<td>16. Fencing</td>
<td>3. Cotton</td>
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<td>17. Spray pump</td>
<td>4. Bananas</td>
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<td>18. Milk cans</td>
<td>5. Sugarcane</td>
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<td>19. Milking machine</td>
<td>6. Fruit trees</td>
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<td>20. Feeding troughs</td>
<td>7. Shed trees</td>
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<td>21. Other (specify)</td>
<td>8. Other</td>
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</tbody>
</table>

*Areas and yields can be reported in units farmers can understand (acres/ha), but this has to be carefully recorded. *Yields can be reported in bags or kg *Management practices: 1= Mulching, 2= Crop rotation, 3= Crop residues, 4= Fallowing, 5= Farmyard manure, 6= Compost manure, 7= Fertilisers (specify), 8= other (specify)
### 3.0. Household Land use (Livestock inventory and management, and land tenure)

<table>
<thead>
<tr>
<th>2.7. Cropping decision criteria</th>
<th>3.1. Livestock on-farm inventory</th>
<th>3.2. Income from livestock &amp; products</th>
<th>3.4. Livestock management system</th>
<th>3.5. Land tenure</th>
<th>3.6. Land disposal procedure</th>
</tr>
</thead>
<tbody>
<tr>
<td>How do you choose crops to grow? (Yes=1, No=2)</td>
<td>Number of livestock Previous(^x) &amp; current(^y) year</td>
<td>Income from each entity in previous(^x) current(^y) yrs</td>
<td>1=Zero grazing,  2=Tethering, 3=Communal grazing, 4=Free range, 5=Paddocks, 6=Other</td>
<td>Under what tenure system is the HH largest percentage of land? (1=Yes, 2=No)</td>
<td>Under what circumstances is land disposed of?</td>
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<tr>
<td><strong>Annuals: Based on</strong></td>
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<tr>
<td>1. Previous yields</td>
<td>1. Cattle</td>
<td></td>
<td>1. Freehold</td>
<td>1. Shifting to a new place</td>
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<tr>
<td>2. Neighbour’s use</td>
<td>2. Goats</td>
<td></td>
<td>2. Leasehold</td>
<td>2. Reduced productivity</td>
<td></td>
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<tr>
<td>5. Easy management</td>
<td>5. Rabbits</td>
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<td>5. Pests and disease prone</td>
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<tr>
<td>6. Agric. credit/cost</td>
<td>6. Donkeys</td>
<td></td>
<td>Did the HH acquire additional land for</td>
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<td>7. Purely random</td>
<td>7. Horses</td>
<td></td>
<td>If household head dies, is</td>
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<td>8. Rainfall projection</td>
<td>8. Camels</td>
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<tr>
<td><strong>Perennials: Based on</strong></td>
<td>9. Bee hives</td>
<td></td>
<td>in the last 2 years?</td>
<td>the land passed on to a</td>
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<tr>
<td>1. Previous yields</td>
<td>10. Poultry</td>
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<tr>
<td>2. Neighbour’s use</td>
<td>11. Other</td>
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<tr>
<td>3. Extension advice</td>
<td></td>
<td></td>
<td>1. Yes</td>
<td>1. Yes member of the family?</td>
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<tr>
<td>4. Seed available</td>
<td></td>
<td></td>
<td>2. No</td>
<td>2. No</td>
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<tr>
<td>5. Easy management</td>
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<tr>
<td>6. Agric. credit/cost</td>
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<td>7. Purely random</td>
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<td>8. Rainfall projection</td>
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<tr>
<td><strong>Management strategy: Based on</strong></td>
<td>2.8. Cost of crop production (in UGX)</td>
<td>3.3. Cost of livestock production (in UGX)</td>
<td>If 1. How much more land was needed?</td>
<td>If 1. Who is it passed to?</td>
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<tr>
<td>1. Previous yields</td>
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<tr>
<td>2. Neighbour’s use</td>
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<tr>
<td>3. Extension advice</td>
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<td>4. Seed available</td>
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<tr>
<td>5. Easy management</td>
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<tr>
<td>6. Agric. credit/cost</td>
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<td>7. Purely random</td>
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<tr>
<td>8. Rainfall projection</td>
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<tr>
<td>Buying seedlings</td>
<td></td>
<td></td>
<td>Under what tenure system is the acquired land?</td>
<td></td>
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<tr>
<td>Fertilisers</td>
<td></td>
<td></td>
<td>Under what tenure system is the</td>
<td>1. Freehold</td>
<td></td>
</tr>
<tr>
<td>Livestock treatment</td>
<td></td>
<td></td>
<td>acquired land?</td>
<td>2. Leasehold</td>
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<tr>
<td>Pest control</td>
<td></td>
<td></td>
<td>1. Freehold</td>
<td>3. Customary</td>
<td></td>
</tr>
<tr>
<td>Livestock shelter</td>
<td></td>
<td></td>
<td>Under what tenure system is the</td>
<td>4. Mailo</td>
<td></td>
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<tr>
<td>Land acquisition</td>
<td></td>
<td></td>
<td>acquired land?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Land acquisition</td>
<td></td>
<td></td>
<td>3. Customary</td>
<td></td>
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</tbody>
</table>
### 4.0. Household Energy sources and utilisation, and policy knowledge

#### 4.1. Main energy source for cooking

<table>
<thead>
<tr>
<th>Question</th>
<th>Yes</th>
<th>No</th>
</tr>
</thead>
<tbody>
<tr>
<td>What does the HH use mainly for cooking? (Yes=1, No=2)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>How much is used per month? (quote electricity bill)</td>
<td></td>
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</tr>
<tr>
<td>How much firewood is used per day?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>How many bags of charcoal are used per month?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Does the HH obtain any products from the natural forest?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Are you aware of policies affecting your decisions on energy and land use choices?</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### 4.2. If electricity is the main energy source for cooking

<table>
<thead>
<tr>
<th>Question</th>
<th>Yes</th>
<th>No</th>
</tr>
</thead>
<tbody>
<tr>
<td>Is the firewood collected daily? (how many times in a week)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Where is charcoal obtained from?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If Yes, which ones?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If 1, give examples?</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### 4.3. If firewood is the main energy source for cooking

<table>
<thead>
<tr>
<th>Question</th>
<th>Yes</th>
<th>No</th>
</tr>
</thead>
<tbody>
<tr>
<td>Why do you prefer electricity to other energy types?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Where is the firewood obtained from?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Home made</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Bought from vendors</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. From charcoal markets</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Bamboo</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### 4.4. If charcoal is the main energy source for cooking

<table>
<thead>
<tr>
<th>Question</th>
<th>Yes</th>
<th>No</th>
</tr>
</thead>
<tbody>
<tr>
<td>Does the HH use a stove for cooking?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>What is the distance of firewood collection from the household?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>What quantity of each of the items is got from the forest/year?</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### 4.5. Forest products

<table>
<thead>
<tr>
<th>Question</th>
<th>Yes</th>
<th>No</th>
</tr>
</thead>
<tbody>
<tr>
<td>Which cooking stove?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>What is the type of cooking stove?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>If charcoal is bought, what is the cost of each bag?</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Would you allow more of your HH members to obtain more income from off-farm jobs?</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Firewood can be reported by number of logs or number of bundles (estimates of average volume of log/bundle per parish were made)

** Quantities of forest products should be estimates by numbers and can be stated per month, and later extrapolated to a year (units should be carefully recorded)
## 1. Hire more labour 2. Postpone the activity until time/labour is available 3. Maximise time/labour for future availability of product/service 4. Abandon activity

### 5.0. Household day-to-day time budget

<table>
<thead>
<tr>
<th>Dry season</th>
<th>Wet season</th>
<th>Wet season</th>
<th>Dry season</th>
<th>Wet season</th>
<th>Dry season</th>
<th>Additional notes/comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>HH</td>
<td>Ext</td>
<td>HH</td>
<td>Ext</td>
<td>HH</td>
<td>Ext</td>
<td></td>
</tr>
<tr>
<td>1. Opening agric. land</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1. Agricultural expansion</td>
</tr>
<tr>
<td>2. Fetching water</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2. Population growth</td>
</tr>
<tr>
<td>4. Grazing animals</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>4. Poor agronomic practices</td>
</tr>
<tr>
<td>5. Extension meetings</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>5. Land fragmentation</td>
</tr>
<tr>
<td>6. Food preparation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>6. Poor policy implementation</td>
</tr>
<tr>
<td>7. Weeding</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>7. Poverty (dependence on forests)</td>
</tr>
<tr>
<td>8. Harvesting</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>8. Other (specify)</td>
</tr>
<tr>
<td>9. Pest control</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10. Post-harvest handling</td>
<td></td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>11. Tree growing</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>12. Selling agric. produce</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Specific to commercial farming: what are the reasons for commercial farming</td>
</tr>
<tr>
<td>13. Trading (own shop)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1. Income</td>
</tr>
<tr>
<td>14. Grocery shopping</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>2. Incentives from companies</td>
</tr>
<tr>
<td>15. Other off-farm jobs</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>3. Low annual crop yields</td>
</tr>
<tr>
<td>17. Other activities</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>5. Other (specify)</td>
</tr>
<tr>
<td><strong>Monthly/Annual events</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Sick days</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Annual leave</td>
<td></td>
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<tr>
<td>3. Hospital visits</td>
<td></td>
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<tr>
<td>4. Animal vaccination</td>
<td></td>
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<td></td>
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</tr>
<tr>
<td>5. Purchasing agric. inputs</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Appendix 3.2 Ethical considerations

The main ethical issues arising from the proposed study include: 1) Free Prior Informed Consent (FPIC) for participation in the household surveys, 2) data safety and handling, 3) ethical nature of the deforestation subject, 4) recruitment and working with field assistants, 5) recruitment and working with local resource users (guides) per parish, and 6) the extractive nature of the proposed research. I discuss these in turn, providing variances of how each were addressed.

1) FPIC is particularly a vital consideration where the respondent’s and the researcher’s interests may be conflicting or where the data required is characteristically sensitive. There is indeed a subtle delineation between both, and a clear distinction is not obvious. In the proposed project, questionnaires and interviews form the largest percentage of the required primary data. The questionnaires sought information on household biographical data, livelihood indicators (e.g. on– and off–farm income, access to basic needs, social amenities), crop and livestock inventories and management, energy sources and utilisation, policy knowledge, and their seasonal time budgets for the different routine activities. To forestall the problem of potential unwillingness by some respondents to disclose their income for instance or time budgets for fear of portraying their poverty status, prior to the interview, the project goals were thoroughly explained and the participants requested for their consent to take part, with the possibility to withdraw at any stage they feel like, or not to respond to any questions they may not feel comfortable about. Consent to participate was however by word–of–mouth since signing any documentation (the consent statement) was considered counterintuitive especially if the respondents are illiterate as they would have difficulty understanding it; but also to avoid biasing the interview session if they thought it would be ‘legally binding’ participation.

Although GPS coordinates for the participating households were taken, these cannot be used to link the responses to any individual for two main reasons: 1) the household is made of many members, and participation was based on a willing adult involved in decision making in the household, and 2) GPS coordinates are accurate to up to ~2m.
Whenever the data were plotted showing spatial patterns, care was taken not to show the geographical coordinates, and the scale was made coarse to avoid identifying them.

2) Following on from FPIC is how the data from the surveys was handled. The respondents were assured of anonymity, and that the data gathered would be used for scientific purposes (to generate a model), write publications and a Ph.D. dissertation. Since the data were anonymous, there is no necessity to destroy it, and could be stored in perpetuity or even sharable with other projects upon request (following completion of the Ph.D.). The data is primarily stored on the Ph.D. student’s laptop (and backed up on an external hard disk), and secured with a password.

3) Deforestation is in itself an ethical issue particularly if it is the main source of (illegal) livelihood. The ethical nature of deforestation therefore posed a challenge as to how the questions were presented to the participants without them feeling they are being held responsible for environmental degradation. In response to this, questions were phrased in a generic manner, concentrating on land and energy use, and probing for resources that are obtained from forests (if any). They were also asked about their knowledge of the forest cover trend in their parish but this question was optional; if the respondent felt free to talk about deforestation in the course of the discussion, then related questions were raised. This approach avoided the sensitivity of the problem in case they feared that our results may expose them to authorities.

4) As a corollary to the extensive nature of the field activities, especially targeted towards generating a statistically robust data-set to understand the underlying and proximate drivers of deforestation and land use change, this project hired four field assistants to administer questionnaires and take ground true coordinates. Because of the need of a competent and enthusiastic team, field assistants were recruited through a competitive application process (targeting graduates, fluent in both English and Runyoro – a local dialect). Adverts were run on the Makerere University College of Agricultural and Environmental Sciences and ITFC notice boards, requesting for expression of interest and CVs. Interviews were held for the competitive applicants a month before the start of fieldwork. Successful applicants signed a Memorandum of Understanding (MoU) with the project leader (Ph.D. student) which highlighted their
roles and deliverables. They were then thoroughly trained on ethical requirements of the project and how to execute their jobs as part of the field team for an entire week. This was followed by actual field training, which will involve hands-on questionnaire pre-testing, recording, and use of hand-held GPS units. A good working relationship with all involved was emphasised as well as the need for high quality data (among other project deliverables), and professionalism.

5) Additionally, four local resource users (local guides – influential people or leaders in the village/parish) whose role was to introduce the field team were hired per parish surveyed. The local leaders were influential in identifying these (guides), and each worked with one field assistant. These (guides) also provided a rich knowledge base of the study area improved the confidence of participants in taking part in the surveys. The study region has particularly attracted extensive interest (due to its rich oil reserves, and biodiversity importance) from diverse stakeholders, some of whom have wrongly evicted locals in land grabbing scoundrels. The scepticism of locals is therefore enormous and somewhat well founded. Working with the guides therefore increased project success; they were compensated for their time at prevailing local NGO rates.

6) Last but not least, the ‘extractive’ nature of the research is another key ethical issue that arises from this project. Data extraction may be viewed as unfair as it may not be immediately obvious to participants how their contribution would be beneficial to them. In response to this, a follow up field trip at the end of the Ph.D. is planned to share results with the stakeholders (if funding becomes available). The dissemination of results (and the model) would increase understanding of how their actions affect the environment, and could trigger useful discussions as to how they could deal with their problems at the local level.
Appendix 3.3 Department of Geography Ethics Review Approval

27th May, 2013

Ronald Twongyirwe
PhD student, Department of Geography

Dear Ronald,

I am writing formally in response to your submission of material to the Department’s Research Ethics Review Group for an assessment of the research ethics associated with your PhD investigation on ‘Quantifying anthropogenically-driven changes in forest cover and rural land use dynamics in the Northern Albertine Rift Landscape, Western Uganda: An Agent Based Modelling approach. You submitted a completed Self Assessment form in which you identified that the study will involve the informed consent of your research participants as an area where your research methods might raise ethical issues. You also provided a summary of your research proposal and a detailed ethics statement.

Your ethics statement identified issues relating to free prior informed consent, data safety and handling, the ethical nature of the subject of deforestation, recruitment and working with fieldwork assistants and local resource users and the ‘extractive’ nature of the research. Each of these is given careful consideration and the Review Group noted the appropriateness of obtaining oral rather than written consent from your research participants. You have given detailed thought to questions of anonymity and data protection (including video recordings), the need for sensitivity in framing your questions, the training of research assistants in ethical practices and the dissemination of findings to your research participants. Thus your ethics statement shows that you have fully engaged with the ethical issues raised by your proposed research, and have provided detailed information to demonstrate that you have thought about how to minimize harm to your research participants. On behalf of the Review Group, I should like to commend you for the care which you have afforded to this process and am therefore pleased to give ethics approval for your research. Your project sounds really interesting and I wish you well with your fieldwork.

Yours sincerely,

Molly Warrington
Chair, Ethics Review Group

Downing Place, Cambridge, CB2 3EN, England
Tel: (01223) 333399 • Direct line (01223) 333370 • Fax: National (01223) 333392 • International: +44 1223 333392
Email: mjw29@cam.ac.uk
Appendix 3.4 Histograms of household livelihood characteristics: continuous variables (all data, N=706)
Household livelihood characteristics: continuous variables (continued)

- **Education Level Father**: Mean = 5.66, Std. Dev. = 4.769, N = 701
- **Education Level Mother**: Mean = 4.5, Std. Dev. = 4.111, N = 701
- **Mean Education Level Biological Children**: Mean = 3.92, Std. Dev. = 3.796, N = 701

- **Off farm income father**: Mean = $2948595.42, Std. Dev. = $2743225.421, N = 262
- **Off farm income mother**: Mean = $2300062.5, Std. Dev. = $1780292.926, N = 96
- **Mean Education other relatives**: Mean = 103903.68, Std. Dev. = 701530.3, N = 706

- **Off farm income Biological Children**: Mean = $18.3, Std. Dev. = $1.952, N = 706
- **Tot Off farm income Biological Children**: Mean = $20.48, Std. Dev. = $3.222, N = 706
- **HH total off farm income**: Mean = $5.19, Std. Dev. = $6.084, N = 377

- **Clan marriage age girls**: Mean = 15, Std. Dev. = 6, N = 706
- **Clan marriage age boys**: Mean = 20, Std. Dev. = 10, N = 706
- **No. HH with which respondent shares farming info.**: Mean = 5, Std. Dev. = 10, N = 377
Land use and cropping characteristics: continuous variables

- **No Hoes**: Mean = 3.13, Std. Dev. = 2.43, N = 705
- **No Forkedhoes**: Mean = 0.12, Std. Dev. = 0.546, N = 705
- **No Pangas**: Mean = 1.52, Std. Dev. = 1.858, N = 705
- **No Slasher**: Mean = 0.86, Std. Dev. = 1.471, N = 705
- **No Sickle**: Mean = 0.44, Std. Dev. = 0.941, N = 704
- **No Axe**: Mean = 0.74, Std. Dev. = 0.78, N = 705
- **No Wheelbarrow**: Mean = 0.11, Std. Dev. = 0.388, N = 705
- **No Secateurs**: Mean = 0.02, Std. Dev. = 0.167, N = 705
- **No Storage facilities**: Mean = 0.11, Std. Dev. = 0.331, N = 705
- **No Spraypumps**: Mean = 0.1, Std. Dev. = 0.379, N = 705
- **No Milkcans**: Mean = 0.01, Std. Dev. = 0.176, N = 705
- **HH_tot_lowinput_agric Implements**: Mean = 1.0, Std. Dev. = 6.1, N = 706
Land use and cropping characteristics: continuous variables (continued)

- **HH_tot_highinput_agric Implements**
  - Mean = 0.39
  - Std. Dev. = 1.269
  - N = 706

- **HH_Tot_Implements**
  - Mean = 7.59
  - Std. Dev. = 6.765
  - N = 706

- **Landsize_Beans_current season**
  - Mean = 0.10
  - Std. Dev. = 0.164
  - N = 706

- **Landsize_Maize_current season**
  - Mean = 0.14
  - Std. Dev. = 0.262
  - N = 705

- **Landsize_Ganut_current season**
  - Mean = 0.03
  - Std. Dev. = 0.121
  - N = 705

- **Landsize_Peas_current season**
  - Mean = 0.01
  - Std. Dev. = 0.041
  - N = 704

- **Landsize_Potato_current season**
  - Mean = 0.04
  - Std. Dev. = 0.069
  - N = 705

- **Landsize_Tobacco_current season**
  - Mean = 0.01
  - Std. Dev. = 0.046
  - N = 706

- **Landsize_Cassava_current season**
  - Mean = 0.13
  - Std. Dev. = 0.219
  - N = 704

- **Landsize_Coffee_current season**
  - Mean = 0.02
  - Std. Dev. = 0.084
  - N = 705

- **Landsize_Bananas_current season**
  - Mean = 0.04
  - Std. Dev. = 0.164
  - N = 705

- **Landsize_Sugarcane_current season**
  - Mean = 0.08
  - Std. Dev. = 0.424
  - N = 703
Land use and cropping characteristics: continuous variable (continued): land size in ha, yield in kg

- **Landsize_fruittrees_current season**
  - Mean = 0.01
  - Std. Dev. = 0.044
  - N = 706

- **Landsize_rice_current season**
  - Mean = 0.02
  - Std. Dev. = 0.084
  - N = 706

- **Tot_farmed_land_previous season**
  - Mean = 0.64
  - Std. Dev. = 0.889
  - N = 706

- **Tot_farmed_land_current season**
  - Mean = 0.63
  - Std. Dev. = 0.887
  - N = 706

- **Yield_Beans_current season**
  - Mean = 102.12
  - Std. Dev. = 153.676
  - N = 301

- **Yield_Maize_current season**
  - Mean = 391.14
  - Std. Dev. = 769.095
  - N = 255

- **Yield_Gnut_current season**
  - Mean = 141.52
  - Std. Dev. = 192.012
  - N = 66

- **Yield_peas_current season**
  - Mean = 38.89
  - Std. Dev. = 27.789
  - N = 18

- **Yield_potato_current season**
  - Mean = 230.55
  - Std. Dev. = 279.287
  - N = 100

- **Yield_tobacco_current season**
  - Mean = 1370
  - Std. Dev. = 1545.801
  - N = 5

- **Yield_cassava_current season**
  - Mean = 744.76
  - Std. Dev. = 1140.645
  - N = 150

- **Yield_coffee_current season**
  - Mean = 342.78
  - Std. Dev. = 779.954
  - N = 41
### Land use and cropping characteristics: continuous variable (continued): yield in kg, income in UGX (1USD=UGX2500)

<table>
<thead>
<tr>
<th>Crop Type</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yield_bananas_current season</td>
<td>465.5</td>
<td>826.924</td>
<td>120</td>
</tr>
<tr>
<td>Yield_sugarcane_current season</td>
<td>74287.93</td>
<td>101866.577</td>
<td>29</td>
</tr>
<tr>
<td>Yield_fruit trees_current season</td>
<td>72.71</td>
<td>161.989</td>
<td>28</td>
</tr>
<tr>
<td>Yield_rice_current season</td>
<td>1082.69</td>
<td>1164.383</td>
<td>26</td>
</tr>
<tr>
<td>Total_yield_previous season</td>
<td>4060.33</td>
<td>26674.39</td>
<td>706</td>
</tr>
<tr>
<td>Total_yield_current season</td>
<td>3638.49</td>
<td>25170.29</td>
<td>706</td>
</tr>
<tr>
<td>Income_Bean current season</td>
<td>49238.56</td>
<td>273033.965</td>
<td>306</td>
</tr>
<tr>
<td>Income_Maize current season</td>
<td>79460.32</td>
<td>301039.739</td>
<td>315</td>
</tr>
<tr>
<td>Income_Gnut current season</td>
<td>34179.1</td>
<td>107575.333</td>
<td>67</td>
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<tr>
<td>Income_peas current season</td>
<td>14900</td>
<td>58094.207</td>
<td>20</td>
</tr>
<tr>
<td>Income_potatoes current season</td>
<td>9877.05</td>
<td>59365.752</td>
<td>183</td>
</tr>
<tr>
<td>Income_tobacco current season</td>
<td>3361250</td>
<td>5848169.223</td>
<td>8</td>
</tr>
</tbody>
</table>
Land use and cropping characteristics: continuous variable (continued): income, costs in UGX (1USD=UGX2500)
Livestock inventory

- **Tot_Expenditure_crop_previous season**
  - Mean = 85852.62
  - Std. Dev. = 268814.481
  - N = 706

- **Tot_Expenditure_crop_current season**
  - Mean = 83897.17
  - Std. Dev. = 296956.795
  - N = 706

- **No_cattle_2013**
  - Mean = 0.93
  - Std. Dev. = 4.334
  - N = 704

- **No_goats_2013**
  - Mean = 1.77
  - Std. Dev. = 3.41
  - N = 705

- **No_sheep_2013**
  - Mean = 0.12
  - Std. Dev. = 0.788
  - N = 704

- **No_pigs_2013**
  - Mean = 0.39
  - Std. Dev. = 1.142
  - N = 706

- **No_rabbits_2013**
  - Mean = 0.05
  - Std. Dev. = 0.719
  - N = 706

- **No_beehives_2013**
  - Mean = 0.06
  - Std. Dev. = 0.581
  - N = 705

- **No_poultry_2013**
  - Mean = 4.47
  - Std. Dev. = 11.946
  - N = 706

- **Tot_largeruminants_2013**
  - Mean = 0.93
  - Std. Dev. = 4.328
  - N = 706

- **Tot_smallruminants_2013**
  - Mean = 2.32
  - Std. Dev. = 3.984
  - N = 706
Livestock inventory (continued): income, costs in UGX (1USD=UGX2500)
Livestock inventory (continued) and Household Energy and forest product use inventory

- **Cost_Shelter_2013**
  - Mean = 895.74
  - Std. Dev. = 13468.569
  - N = 681

- **Tot_Expenditure_livestock_2013**
  - Mean = 15989.38
  - Std. Dev. = 91352.875
  - N = 706

- **Size_acquired_land_in_last_2_years_in_ha**
  - Mean = 0.48
  - Std. Dev. = 0.801
  - N = 72

- **Tot_Expenditure_livestock_2012**
  - Mean = 511023.25
  - Std. Dev. = 1912647.635
  - N = 706

- **Tot_on_farm_income_2012**
  - Mean = 408533.88
  - Std. Dev. = 1911418.04
  - N = 706

- **Tot_on_farm_income_2013**
  - Mean = 3.36
  - Std. Dev. = 2.407
  - N = 576

- **No_of_days_firewood_is_collected_in_week**
  - Mean = 35.84
  - Std. Dev. = 90.138
  - N = 705

- **Annual_volume_firewood_obtained**
  - Mean = 100.4
  - Std. Dev. = 703.17
  - N = 120

- **Quantity_charcoal_used_per_annum_in_kg**
  - Mean = 393860.87
  - Std. Dev. = 264090.728
  - N = 115

- **Amount_spent_on_charcoal_per_annum_UCK**
  - Mean = 1.14
  - Std. Dev. = 9.655
  - N = 784

- **Volume_timber_obtained_cubic_m**
  - Mean = 1.10
  - Std. Dev. = 8.895
  - N = 704

- **Volume_poles_obtained_cubic_m**
Household time budgets: based on data for 2013
Household time budgets (continued): based on data for 2013

- Hrs_weeding_dry_season
  - Mean = 47.99
  - Std. Dev. = 58.443
  - N = 702

- Hrs_weeding_wet_season
  - Mean = 51.16
  - Std. Dev. = 60.642
  - N = 702

- Hrs_harvesting_dry_season
  - Mean = 21.01
  - Std. Dev. = 20.233
  - N = 702

- Hrs_harvesting_wet_season
  - Mean = 21.25
  - Std. Dev. = 21.329
  - N = 702

- Hrs_pest_control_dry_season
  - Mean = 0.68
  - Std. Dev. = 3.637
  - N = 702

- Hrs_pest_control_wet_season
  - Mean = 0.76
  - Std. Dev. = 3.873
  - N = 702

- Hrs_post_harvest_handling_dry_season
  - Mean = 18.71
  - Std. Dev. = 20.851
  - N = 702

- Hrs_post_harvest_handling_wet_season
  - Mean = 23.98
  - Std. Dev. = 29.491
  - N = 702

- Hrs_tree_growing_dry_season
  - Mean = 1.41
  - Std. Dev. = 15.508
  - N = 692

- Hrs_tree_growing_wet_season
  - Mean = 1.9
  - Std. Dev. = 16.566
  - N = 692

- Hrs_selling_agrc_produce_dry_season
  - Mean = 3.75
  - Std. Dev. = 12.002
  - N = 702

- Hrs_selling_agrc_produce_wet_season
  - Mean = 4.06
  - Std. Dev. = 15.118
  - N = 702
Household time budgets (continued): based on data for 2013

- Hrs_trading own shop_dry season: Mean = 113.36, Std. Dev. = 459.037, N = 702
- Hrs_trading own shop_wet season: Mean = 113.3, Std. Dev. = 459.511, N = 702
- Hrs_grocery shopping_dry season: Mean = 39.55, Std. Dev. = 54.648, N = 702
- Hrs_grocery shopping_wet season: Mean = 346.39, Std. Dev. = 575.141, N = 634
- Hrs_off-farm jobs_dry season: Mean = 1.65, Std. Dev. = 9.829, N = 687
- Hrs_off-farm jobs_wet season: Mean = 1.43, Std. Dev. = 8.324, N = 687

- Hrs_animal vaccination_dry season
- Hrs_animal vaccination_wet season
Household labour budgets: based on data for 2013
Household labour budgets (continued): based on data for 2013

- No. HH members providing labour_Opening_agric.land_wet season
  - Mean = 1.88
  - Std. Dev. = 1.576
  - N = 705

- No. External Labour_Opening_agric.land_wet season
  - Mean = 0.88
  - Std. Dev. = 1.993
  - N = 685

- No. HH members providing labour_Opening_agric.land_dry season
  - Mean = 1.87
  - Std. Dev. = 1.574
  - N = 705

- No. External Labour_Opening_agric.land_dry season
  - Mean = 0.87
  - Std. Dev. = 1.969
  - N = 685

- No. HH members providing labour_fetching water_wet season
  - Mean = 1.68
  - Std. Dev. = 1.332
  - N = 703

- No. External labour_fetching water_wet season
  - Mean = 0.01
  - Std. Dev. = 0.132
  - N = 681

- No. HH members providing labour_fetching water_dry season
  - Mean = 1.68
  - Std. Dev. = 1.331
  - N = 705

- No. External labour_fetching water_dry season
  - Mean = 0.01
  - Std. Dev. = 0.132
  - N = 681

- No. HH members providing labour_gathering firewood_wet season
  - Mean = 1.22
  - Std. Dev. = 1.072
  - N = 676

- No. External labour_gathering firewood_wet season
  - Mean = 0.02
  - Std. Dev. = 0.187
  - N = 676

- No. HH members providing labour_gathering firewood_dry season
  - Mean = 1.21
  - Std. Dev. = 1.071
  - N = 676

- No. External labour_gathering firewood_dry season
  - Mean = 0.02
  - Std. Dev. = 0.205
  - N = 676
Household labour budgets (continued): based on data for 2013

- No. HH members providing labour, harvesting, wet season: Mean = 1.86, Std. Dev. = 1.592, N = 674
- No. HH members providing labour, harvesting, dry season: Mean = 0.49, Std. Dev. = 1.738, N = 674
- No. External labour, harvesting, wet season: Mean = 1.86, Std. Dev. = 1.605, N = 674
- No. External labour, harvesting, dry season: Mean = 0.49, Std. Dev. = 1.744, N = 674
- No. HH members providing labour, pest control, wet season: Mean = 0.12, Std. Dev. = 0.56, N = 677
- No. HH members providing labour, pest control, dry season: Mean = 0.11, Std. Dev. = 0.532, N = 677
- No. External labour, pest control, wet season: Mean = 0.04, Std. Dev. = 0.401, N = 677
- No. External labour, pest control, dry season: Mean = 0.03, Std. Dev. = 0.329, N = 677
- No. HH members providing labour, tree growing, wet season: Mean = 0.08, Std. Dev. = 0.368, N = 688
- No. HH members providing labour, tree growing, dry season: Mean = 0.04, Std. Dev. = 0.259, N = 688
- No. External labour, tree growing, wet season: Mean = 0.02, Std. Dev. = 0.241, N = 688
- No. External labour, tree growing, dry season: Mean = 0.01, Std. Dev. = 0.132, N = 688
Household labour budgets (continued): based on data for 2013
Household labour budgets (continued): based on data for 2013
Appendix 3.5 Histograms of household livelihood characteristics: categorical variables (all data, N=706)
Household livelihood characteristics: categorical variables (continued)
Household livelihood characteristics: categorical variables (continued)
Land use and cropping characteristics: categorical variable

- Taking agric. products to market: 413, 163
- Obtaining energy used for cooking: 538, 146

Frequency of crops taken on foot:
- Beans: 453
- Beans curr: 427
- Maize: 361
- Maize curr: 346
- Groundnut: 131
- Cassava: 148
- Peas: 35
- Peas curr: 31
- Potatoes: 252
- Tobacco: 249
- Tobacco curr: 305
- Cassava curr: 315

Dominant crops grown in previous and current seasons:
- Coffee: 72
- Coffee curr: 79
- Banana: 216
- Banana curr: 226
- Sugarcane: 74
- Sugarcane curr: 74
- Fruit trees: 185
- Fruit trees curr: 181
- Rice: 41
- Rice curr: 40

Criteria on which growing annual (and perennial) crops are based:
- Previous yield: 215
- Neighbour yield: 72
- Extension advice: 97
- Seed availability: 97
- Ease of management: 97
- Agricultural credit: 97
- Purely random: 97
- Rainfall prediction: 97

Frequency of land tenure systems:
- Freehold: 385
- Leasehold: 244
- Customary: 77
Land use and cropping characteristics: categorical variables

- Shifting to a new place: 93
- Reduced productivity: 123
- Prime land for development: 14
- Death of owner: 10
- Pest and disease prone: 8
- Land can’t be sold: it is passed on to the next generation: 135
- Poverty in need of money to meet urgent needs (e.g., children’s tuition fees): 62

Circumstances under which land is disposed of

- Did the household acquire land in the last 2 years:
  - Yes: 88
  - No: 614

Main use of acquired land:
- Crop production: 85
- Livestock production: 1
- Mixed farming (crop + livestock): 2

Tenure system of acquired land:
- Freehold: 33
- Short-term lease: 55
Energy and forest product use, policy awareness: categorical variables

- **Main energy source for cooking**
  - Gas: 1
  - Firewood: 588
  - Charcoal: 116

- **Type of stove used for cooking**
  - 3-stone-stove: 582
  - Stove built-in kitchen: 7
  - Charcoal-stove: 109
  - Improved cookstove: 6

- **Household member that gathers firewood**
  - Mother: 379
  - Children: 64
  - Father: 23
  - Mother + children together: 76
  - Hired labour: 4
  - Other: 5

- **Main source of firewood**
  - Forest (natural and protected): 173
  - Bushland/scrub: 264
  - Gardens: 82
  - Bought from vendors: 37
  - Plantation forest: 27
Energy and forest product use, policy awareness: categorical variables (continued)

**Proximity to main source of fuel for cooking**

- Distance to charcoal source
- Distance to source of firewood

**Criteria for selection of firewood gathering sites**

- Known/previous sites visited until exhausted
- Information from neighbours
- Other

**Would HH switch from firewood to other energy sources given incentives**

- Yes
- No

**Products obtained/extracted from the forest by households**

- Timber
- Poles
- Bamboo
- Firewood
- Medicinal plants
- Papyrus reeds
Energy and forest product use, policy awareness: categorical variables (continued)
Household time- and labour- budgets
Appendix 3.6 Summary: descriptive statistics of continuous variables
Variable
Household
demographic data

Raw–data
Mean

Lower
B

Upper B

Median

St.dev

Min

Max

Skewness

Respondent’s age
Father’s age
Mother’s age
Total household size
No. biological children
No. of boys (biological)
No. of girls (biological)
No. other relatives: Male
No. other relatives: Female
Mean age biological Ch.
Mean age other relatives
Respondent’s educ. level
Father’s educ. level
Mother’s educ. level
Biological Ch. educ. level
Other rel. Educ. level
Off–farm inc. father (x105 UGX)
Off–farm inc. mother (x105
UGX)
Off–farm
inc.
biological
children ( x 105 UGX)
Off–farm inc. other relatives
(x105 UGX)
Tot. HH. Off–farm inc. (x105
UGX)
Clan marriage age for girls
Clan marriage age for boys
No. HH with which respondent
shares farming information

38.95
43.26
39.37
6.34
3.57
1.97
1.60
0.52
0.48
13.32
17.62
5.85
5.66
4.50
3.92
4.27
29.49
23.00

37.74
42.00
38.24
6.11
3.39
1.85
1.50
0.44
0.40
12.48
15.75
5.54
5.31
4.19
3.64
3.79
26.14
19.39

40.17
44.52
40.50
6.56
3.74
2.09
1.70
0.61
0.55
14.17
19.49
6.17
6.01
4.80
4.20
4.74
32.82
26.61

35.50
40.00
37.00
6.00
3.00
2.00
1.00
0.00
0.00
11.00
13.67
6.00
6.00
5.00
3.43
4.00
24.00
20.10

16.46
15.30
15.04
3.03
2.36
1.56
1.40
1.10
1.02
11.39
14.87
4.24
4.77
4.11
3.80
3.68
27.43
17.80

15.00
15.00
16.00
1.00
0.00
0.00
0.00
0.00
0.00
0.00

0.00
1.20

93.00
96.00
91.00
22.00
10.00
7.00
7.00
7.00
8.00
63.00
90.00
16.00
17.00
16.00
2.18
1.60
180.00
70.8

0.83
0.70
0.79
0.91
0.50
0.63
0.87
2.71
2.84
1.14
2.26
0.28
0.29
0.52
0.86
0.69
2.45
0.75

0.37

0.01

0.73

0.00

4.86

0.00

108.00

17.91

Mean

18.16
20.24
4.57

No. hoes
No. forked hoes
No. panga
No. slashers
No. sickles
No. spades
No. axe
Tot. No. HH. low farm
agricultural Implements
No. tractor
No. animal plough
No. tractor plough
No. disc harrows
No. planters
No. wheelbarrows
No. secateurs
No. stores
No. farm fences
No. spray pumps
No. milk cans
No. feed troughs
Tot. No. HH. high farm
agricultural Implements
Tot. No. all farm agricultural
Implements
Land size beans prev.S (ha)
Land size beans curr.S (ha)

3.13
0.12
1.52
0.86
0.44
0.40
0.74
7.20

7.79

Land use/cropping

Land size maize prev.S (ha)
Land size maize curr.S (ha)
Land size g.nuts prev.S (ha)
Land size g.nuts curr.S (ha)
Land size peas prev.S (ha)
Land size peas curr.S (ha)
Land size potato prev.S (ha)
Land size potato curr.S (ha)

1.04

15.47
18.30
20.48
5.19

0.00
0.00
0.00
0.00
0.00
0.11
0.02
0.11
0.01
0.10
0.01
0.02
0.39
0.10
0.10
0.15
0.14
0.03
0.03
0.01
0.01
0.04
0.04

0.52

13.39

1.56

17.56

0.00

7.02

28.25

0.00
0.00

108.00
225.60

9.50
3.02

Upper B

18.00
20.00
4.00

Median

2.00
3.22
6.08

St.dev

12.00
14.00
1.00

Min

30.00
57.00
50.00

Max

0.68
3.34
4.26

2.95
0.08
1.38
0.75
0.37
0.33
0.68
6.75

3.31
0.16
1.66
0.97
0.51
0.47
0.80
7.65

2.00
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1.00
1.00
0.00
0.00
1.00
6.00

2.43
0.55
1.86
1.47
0.94
0.91
0.78
6.10

0.00
0.00
0.00
0.00
0.00
0.00
0.00
0.00

20.00
10.00
40.00
30.00
8.00
15.00
10.00
75.00

2.21
10.13
13.28
11.82
3.71
8.15
5.25
4.55

7.09

8.09

6.00

6.77

0.00

87.00

4.67

Lower
B

0.00
0.00
0.00
0.00
0.00
0.08
0.01
0.08
0.00
0.07
0.00
0.00
0.30
0.09
0.08
0.13
0.12
0.02
0.02
0.00
0.00
0.03
0.03

18.45
20.71
5.80

0.00

0.00
0.00
0.00

0.01
0.00
0.00
0.01
0.00
0.14
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0.13
0.02
0.13
0.03
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0.01
0.04
0.04

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0.00
0.00

0.05
0.04
0.04
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1.00
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5.00
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4.00
12.00
18.00
1.62
1.42
3.24
3.24
2.00
2.00
1.00
1.00
0.50

Skewness

18.75
26.55
26.55
18.74
26.55
5.26
11.19
3.69
9.91
5.74
17.98
25.36
7.87
3.96
3.65

5.68
5.44
10.80
9.64
11.90
13.95
2.50
2.70

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### Livestock inventory

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## Appendix 4.1 List of Key Informants

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<tr>
<td>1.</td>
<td>Mr. Simon Biryetga</td>
<td>Masindi District Local Government</td>
<td>District Forestry Officer</td>
<td>Masindi</td>
<td>Gov’t, *District</td>
<td>07.10.2013</td>
<td><a href="mailto:biryetegafdo@yahoo.com">biryetegafdo@yahoo.com</a></td>
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<tr>
<td>2.</td>
<td>Mr. Amnon Mitumbi</td>
<td>Busingiro ecotourism site, National Forest Authority</td>
<td>Conservation Area Manager and guide</td>
<td>Masindi</td>
<td>Gov’t, *Local</td>
<td>08.10.2013</td>
<td><a href="mailto:urusaraai@gmail.com">urusaraai@gmail.com</a></td>
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<tr>
<td>3.</td>
<td>Dr. Ramesh Bollampalli</td>
<td>Kinyara Sugar Works</td>
<td>Entomologist and Estate Agronomist</td>
<td>Masindi</td>
<td>Gov’t/private (PPP), *Local</td>
<td>11.10.2013</td>
<td><a href="mailto:bollampallir@kinyara.co.ug">bollampallir@kinyara.co.ug</a></td>
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<td>4.</td>
<td>Mr. Kaahwa Tadeo</td>
<td>Budongo Conservation Area, National Forest Authority</td>
<td>Deputy sector manager</td>
<td>Masindi</td>
<td>Gov’t, *Local</td>
<td>10.10.2013</td>
<td><a href="mailto:kaahwatadeo@yahoo.com">kaahwatadeo@yahoo.com</a></td>
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<td>5.</td>
<td>Mr. Gift O. Okojja</td>
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<td>Deputy Principle</td>
<td>Masindi</td>
<td>Gov’t, *National</td>
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<td>6.</td>
<td>Hon. Proscovia Bamutura</td>
<td>Bunyoro Kitara Kingdom</td>
<td>Community Mobiliser and Cultural leader</td>
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<td>Cultural Institution, NGO *Regional</td>
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<td>District Population Officer</td>
<td>Masindi</td>
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<td>Biodiversity supervisor</td>
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Appendix 5.1 Agent-based Model Conceptual Framework for Simulating Deforestation (Dotted lines indicate potential feedback loops amongst the components; feedback is loosely defined – input of one component could affect activities, or output of another component and vice versa)

- **Resource access**
  - Land use (patch sizes, ownership)

- **Economic dynamics**
  - Income (on and off-farm)
  - Expenditure (aggregate)
  - Savings / deficit

- **Social dynamics**
  - Household demography
  - Household location
  - Cultural context

- **Bio-physical dynamics**
  - Physical characteristics
  - Cropping dynamics
  - Forest cover dynamics

- **World-policy constraint**
  - REDD+ implementation (fuel switch, introduction of improved cookstoves)
  - Oil revenue investment (household labour in oil industry)
  - Increased agricultural–technological investment (increased fertiliser use)

- **Emerging regional deforestation patterns**

- **Agent environment assessment**

Feedback loops encompass:
- Income (on and off-farm)
- Expenditure (aggregate)
- Savings / deficit
- Household demography
- Household location
- Cultural context
- Physical characteristics
- Cropping dynamics
- Forest cover dynamics
- REDD+ implementation
- Oil revenue investment
- Increased agricultural–technological investment
Appendix 5.2 Modelling framework: Description of the ABM based on the ODD protocol

In this section, a description of some of the early stages of the ABM development is provided. The aim here is not to present the detailed algorithms (as these are still under construction). The widely advocated “Overview, Design concepts and Details” (ODD) protocol (Railsback and Grimm 2011) (Figure 5.3a) is used to provide a succinct summary of each of the model components. The conceptual framework (Appendix 5.1) provides a summary of what key components the model will be comprised of. The final detailed parameter set to run the ABM can only be confirmed after the initialisation phase to assess which parameters will pass the parsimony criteria to represent the socio-ecological system in a meaningful way (as the model is empirically–based).

Figure 5.3a An overview of the ODD protocol (adapted from Railsback and Grimm, 2011, pg. 37)
Appendix 5.2.1 Overview

The overview provides the purpose of the model with a quick outlook to the model’s focus, resolution and complexity. The ‘design concepts’ are not a description of the model but general concepts related to complexity theory underpinning the model. The ‘Details’ section describes the sub–models and all information to set–up and run the model (Grimm et al. 2006).

Purpose

The Northern Albertine Rift region Agent Based Model (NAR–ABM) is designed to understand the dynamics of deforestation (primarily based on decisions on agricultural land use/expansion, and settlement patterns) as a function of the complex interaction of the bio–physical and socio–economic factors, influenced by emerging policy constraints within the landscape and country at large.

Entities, State variables and Scales

Decisions on land use are made at the household (HH) level as a function of 6 selected components: 1) Social dynamics, 2) Economic dynamics (components 1 and 2 will be merged following rigorous statistical analysis during categorisation of the agents), 3) Resource access, 4) Bio–physical dynamics, 5) Agent–environment assessment, and 6) World–policy constraint (Equation 1). The key assumption is that these components interact to produce the observed emergent patterns of deforestation at the regional scale.

\[
\text{HHDecision} = f \{\text{Social dynamics, Economic dynamics, Bio–physical dynamics, Resource access, Agent–environment assessment, World–policy constraint}\} \ldots \ldots \ldots \text{Equation 1}
\]

Social dynamics component

This component considers the household demographic structure, the relative location of the household in the landscape (a key influence on social interactions) and the cultural context. The social dynamics are primarily at household–level (with an assumption that
the key decision makers are organised in households), and these could be modelled alongside the economic dynamics (at household-level) to understand the regional–level emergent population socio-economic dynamics (Figure 5.3b). The data to parameterise these components is primarily based on the household surveys.

\[ \text{HH social dynamics} = \text{f} \{ \text{HH demographics, HH location social attributes, HH cultural context} \} \ldots \text{Equation 2} \]

\[ \text{HH Demographics} = \text{f} \{ \text{HH size (total), HH gender composition, HH age structure, HH member occupation, HH nativity (immigration/emigration), HH social dynamics/networks, HH dependence ratio, HH births, HH deaths} \} \ldots \text{Equation 3} \]

\[ \text{HH location social attributes} = \text{f} \{ \text{HH proximity to education centres, HH proximity to roads, HH proximity to markets, HH proximity to water sources, HH proximity to forests, HH land sizes, HH land ownership, HH next of kin relationships, HH social networks (friendship groups), HH Interaction across principal components} \} \ldots \text{Equation 4} \]

\[ \text{HH cultural context} = \text{f} \{ \text{HH key decision maker, HH inheritance criteria, HH criteria for new household creation and deletion (through marriages, abandonment), HH ancestral sites located in forests} \} \ldots \text{Equation 5} \]

**Economic dynamics component**

The economic state variables considered in this model are those that are pertinent to land use in the landscape. The household economic decisions are utility-based as a starting point, modelled around annual household income (on and off-farm), annual expenditure (aggregate on- and off-farm activities), and annual savings / deficits.

\[ \text{HH Economic dynamics} = \text{f} \{ \text{HH annual income (on and off-farm) - HH expenditure (aggregate)} \} \ldots \text{Equation 6} \]

\[ \text{HH income (on and off-farm) = f} \{ \text{HH income from annual crops, HH income from perennial crops, HH income from livestock and products, HH agricultural credit (loan), HH aggregated income from off-farm employment} \} \ldots \text{Equation 7} \]

\[ \text{HH expenditure} = \text{f} \{ \text{HH labour, HH agricultural inputs (improved seed, mechanisation, fertiliser)} \} \ldots \text{Equation 8} \]
Figure 5.3b Landscape–level socio-economic population dynamics

Notes:

1. Households are categorised based on real–world socio–economic data from the field survey based on principal component and cluster analysis (in Chapter 3).
2. Communication amongst household agents could initially be limited to the cluster for simplicity, although a random float error is included to cater for communication with other clusters.
3. The model is flexible, providing for a possibility for household livelihood status to change (as a result of the dynamic processes) – obtain properties to move to another cluster after a given period.
4. New households can gain properties similar to the clusters where they are born, and could evolve to gain characteristics to move another cluster.
5. Partial information could be observed or perceived, and through interaction.
Resource Access

A number of factors influence access to land resources, some of which overlap with the other model components, such as duplicated here.

**Resource access_{Land} = f \{proximity to forest, roads, towns, markets, price\} \ldots \ldots \textbf{Equation 9}**

**Landscape bio-physical dynamics component**

This represents the physical environment static (mostly generated with ArcGIS spatial analysis tools) and dynamic variables (e.g. agricultural land use, forest patch conversion) (Figure 5.3c). The area of forest loss to crop land and settlements and volume of fuel wood extraction could be modelled. The landscape can be represented as patches in Netlogo through a scaling transformation from the GIS layers yet to be determined.

**Landscape bio-physical dynamics = f \{Patch_{Physical characteristics}, Patch_{Cropping dynamics}, Patch_{Forest cover dynamics}, Patch_{Hydrological variables}\} \ldots \ldots \textbf{Equation 10}**

**Patch_{Physical characteristics} = f \{Patch_{Land use/cover}, Patch_{Slope}, Patch_{Aspect}, Patch_{Nitrogen}, Patch_{Phosphorous}, Patch_{Potassium}, Patch_{Organic Carbon}, Patch_{Soil moisture}, Patch_{Soil texture}, Patch_{Soil type}, Patch_{Distance to road}, Patch_{Distance to forest}, Patch_{Distance to town (market), Patch}_{Distance to water body, Patch}_{Distance to settlement}\} \ldots \ldots \textbf{Equation 11}**

**Patch_{Cropping dynamics} = f \{Patch_{Annual crop type (maize, beans, tobacco), Patch}_{Perennial crop type (sugarcane, tea), Patch}_{Crop yield (per season), Patch}_{Soil nutrient management options (fertiliser application, crop rotation, fallowing), Patch}_{Cropping history, Patch}_{distance to National Park}\} \ldots \ldots \textbf{Equation 12}**

**Patch_{Forest cover dynamics} = f \{Forest logistic growth, Fuelwood extraction, Patch_{Clearance for agriculture, Adjacent crop patch conversion to forest, forest patch tenure, illegal logging}\} \ldots \ldots \textbf{Equation 13}**

**Patch_{Hydrological variables} = f \{Patch_{Mean seasonal Rainfall}, Patch_{Runoff rate, Patch}_{Evapotranspiration rate}\} \ldots \ldots \textbf{Equation 14}**
Figure 5.3c Bio–physical dynamics component (Solid lines indicate possible changes in land use after a given period; dotted lines without arrows show inter-linkages between attributes and landscape)
Agent–environment assessment component

Through a series of rules (in a decision–making module), the agents make decisions on land use. This component can be developed during the initialisation phase.

World policy constraint component

This ABM could be used to run experiments on at least three policy scenarios that are likely to play an important role in shaping decisions on land and energy use in the next 30 years in the Northern Albertine Rift region. These include 1) Reducing Emissions from Deforestation and Forest Degradation (REDD) implantation – potential of improved cookstoves scenario, 2) Oil revenue investment (household labour in oil industry), and 3) Increased agricultural–technological investment (increased fertiliser use).

Reducing Emissions from Deforestation and Forest Degradation (REDD) implantation – potential of improved cookstoves scenario

Although an international deal on REDD has not yet been struck, the World Bank Forest Carbon Facility (FCPF) and UN–REDD programmes have made substantial investments in preparing countries for REDD (Cerbu et al. 2011). Uganda is at the scoping phase of REDD–Readiness supported by World Bank FCPF in anticipation of future carbon funding. Although the REDD scheme promises to strengthen forest and biodiversity conservation, and improve livelihoods (Agrawal et al. 2011), how it will be implemented at an international level remains far from clear, and these ambiguities are self–evident at the national and regional levels (Blom et al. 2010). A number of REDD and other forest–carbon Payment for Ecosystem Services (PES) projects (under the voluntary market schemes) are being designed for the region by several NGOs. Of interest is the potential of improved cookstoves to reduce deforestation and forest degradation in the region.

Many rural households in the Albertine Rift rely solely on fuelwood collected from the forest for their domestic energy supply (Wallmo and Jacobson 1998; and this thesis). Traditionally, a three–stone–stove is assembled and fuelwood combusted in the open during cooking; this is highly wasteful and increases deforestation pressure (Okello et
Fuel-saving stoves (or improved cookstoves), are being supplied to households in the region by a local NGO, Ugastoves, at a subsidised cost (with extra costs obtained from carbon funding), with the aim of reducing fuelwood consumption and alleviation of deforestation. The ABM could be used to run simulations on this ‘what if’ scenario to understand how improved cookstoves would impact on deforestation in the face of the growing population, increased fuel demand, and poverty. The model could have an adjustable scenario bar (level of improved cookstove use) which could be moved to show different levels of adoption and the model run to enable us understand how agents would adapt to their environment in order to survive, and what the long term impacts on forest loss/conservation could be.

**Oil revenue investment (household labour in oil industry)**

Oil was discovered in the Albertine graben in the last decade, and the oil and petroleum bill was passed in December, 2012 amidst political protests of lack of transparency in the award of oil contracts and the sharing of the accruing revenues. Oil companies have since completed exploration and plans of production and processing are underway. A few oil wells are located in sections of the national protected reserves, and many are not distant from the protected forests of aesthetic and biodiversity importance. Land wrangles have been on the rise, and a number of people are being compensated to relocate to other regions in the country. This region is faced with one of the highest poverty rates in the country despite being endowed with natural resources. Some of the issues presented here are very sensitive and could not be thoroughly (and ethically) investigated through household surveys and interviews, although a hypothetical question on household involvement in the oil industry if given opportunity was included. The results show nearly all households are willing to participate, and there is great enthusiasm, and perceived potential benefits are high.

The oil policy provides for employment of local residents in both odd and professional jobs. The ABM therefore provides an excellent and timely platform to explore the potential reaction of the agents (to a set of rules) to test potential futures of shifts in employment patterns in the landscape. Simulations could be run to understand how a shift in employment and increased off-farm revenues is likely to impact on land use, or land abandonment, and emergent deforestation patterns in the landscape.
Increased agricultural–technological investment (increased fertiliser use)

Given that agriculture is the backbone of Uganda’s economy, the government has primarily attempted to improve household incomes through increased agricultural productivity and value addition. While there have been efforts to achieve this, funding and political instability have obscured such objectives in the past decades. The region is peaceful and stable (and even hosts displaced communities in camps from war-torn areas in the neighbouring countries, Sudan, DRC, and Rwanda). The agricultural productivity enhancement policies through for instance fertiliser application are likely to spur increased production and development; however, a proper evaluation of their potential impacts on the ecosystem remains largely unknown. The ABM could run experiments to understand the consequences of increased fertiliser application on land use, and the emergent land productivity and deforestation patterns in the landscape in the next 30 years.

Appendix 5.2.2 Process overview and scheduling

Each component of the ABM has processes that could form data processing requirements for others, or feedback loops. Next, the proposed processes are briefly listed (although without a full description).

a) Socio dynamic component: ageing, death, creation of new households (marriage, inheritance), deletion of households (death and abandonment), formation of social networks (information sharing, hierarchies).

b) Economic dynamic component: production resource allocation (agricultural credit, labour, fertiliser)

c) Resource accesses: fuelwood gathering, land allocation (to different farming activities), (illegal) deforestation.

d) Bio–physical dynamics: crop growth, tree regeneration at the forest edges.


The policy constraints could include direct tweaking of resource allocation, or have standalone buttons in the model frame for adjusting the level of inputs. To begin a simulation, households would have to be filled with a representative agent population, and allocated land patches. Most of the scheduling can be determined from the survey
data, and key informant interviews to get representative information on how processes follow up on each other (daily, monthly, seasonally or annually).

**Design concepts**

The design concepts are general concepts related to complexity theory underlining the model.

**Emergence**: The emergent system dynamics explicitly expected from this model include: land use patterns, population growth (e.g. through birth and immigration), deforestation patterns, land productivity, livelihood status (based on income generation) – evaluated against varying policy constraints.

**Adaptation**: Farmers switch to new energy use when it is no longer practically feasible to continue with the old fuel (e.g. when distance to wood gathering places are depleted, or get farther, or when cost of electricity is very high). Land could be adapted to use where there are more incentives (e.g. to a cash crop when offered inputs in an out grower’s scheme). Farmers must adapt to prevailing conditions for them to survive, and to thrive in the landscape.

**Learning**: The main form of learning for the farmers could be through interaction in the social networks, and based on past experiences (in similar situations).

**Sensing**: Farmers have a rough idea what the soil conditions are (based on yields), and switch to other alternatives when the policy constraints are demanding or if activities (e.g. illegal logging) become too risky.

**Interaction**: Households interact within a similar cluster, although with possibilities of communication with other clusters. Marriages can only take place amongst members of different clans. Other forms of interaction could be considered during the model development based on household survey data.

**Stochasticity**: The model is mainly stochastic, except for variables that are relatively constant.

**Collectives**: Farmers in the landscape are autonomous and make independent decisions, although seldom collective decisions in the cluster may influence actions to
be taken, for instance on fuelwood gathering and crops grown (supported by empirical data).

**Observation:** The results of some of the model components (e.g. crop yield, population dynamics, rainfall amounts) could be tested against observation data (where it exists). Particularly, the reconstructed trend of land use and vegetation cover patterns could be reproduced by the ABM before it can be confidently used to predict future patterns.

**Appendix 5.2.3 Details**

*Initialisation*

The model is initialised with data from a synthetic agent population (mechanism is in design phase) occupying patches within the landscape, based on initial analyses from satellite imagery. The initialisation process could take two forms. First, from the reconstructed historically observed pattern, and as such initial parameters (e.g. population, socio-economic and bio-physical) would be stochastically estimated, and land use/vegetation cover map of 1985 could be used (land use/cover maps of the different times will be used to assess whether rates of change are captured). The second initialisation could be based mainly on the recent household survey data and the 2014 land use/vegetation cover map to project the future 30 year deforestation and land use pattern.

*Input data*

The aim is to use mainly empirical data, although secondary data from census and published literature could be sought to parameterise (some parts) the model. The variables highlighted per component would form the basis for the selection of the input for each of the algorithms to achieve each of the required objectives.

*Sub-models*

Each of the components is comprised of sub-models that have underlying processes described. Again, the full algorithms are not presented in this section; rather a summary of the propositions is provided, essentially in two categories: 1) Household (socio-economic) sub-models and 2) Landscape (ecological) sub-models.
Household (social) sub-models
1. Kinship (ethnic and marriage) relationships
2. (Mapping) Social networks of interaction within (and outside) socio-economic clusters
3. Fuelwood gathering
4. Income–expenditure on agricultural related activities
5. Land ownership and acquisition (agricultural land demand function)

Landscape (ecological) sub-models
1. Crop growth (plant water–nutrient uptake) based on CROPWAT and CLIMWAT
2. Forest regeneration/growth (customised logistic model)
3. Water balance (hydrological model) focusing on rainfall–runoff modelling
4. Partial nutrient budgets for main nutrient flows (and requirements) N, P, K
5. Deforestation sub-model (Anthropogenic forest cover transformation model)

Appendix 5.3 ABM platform: Rationale for use of Netlogo

Although several platforms (e.g. Mason, Swarm and Repast) have been developed and used to run ABMs, Netlogo, an interpreted language that has been suggested as the highest level platform for running ABMs, with ease of addition and deletion of agents (Railsback et al. 2006), and which has many high-level structures and primitives that are easy to use, and provides an error checker and extensive documentation (Le 2005), is suggested for the next phase of analyses. It however lacks a stepwise debugger (Railsback et al. 2006), and could struggle (become extremely slow) as the number of agents becomes large (e.g. more than 500,000), at a high spatial resolution. It is not yet clear how many agents will be involved in the model development for the region, and given the numerous advantages and recommendations over the other platforms, Netlogo will form the starting point for programming, however, if the platform does not perform to the required expectation, Repast, a compiled Java based language that could easily read into Netlogo could be adopted.