Quantifying deforestation rates in a cocaine source region in Bolivia: A study to verify rates of land-use change under pro-coca policies

Thesis submitted by

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Declaration

I **Edmond Nagombi**, certify that this thesis does not incorporate without acknowledgment any material previously submitted for a degree or diploma in any university; and that to the best of my knowledge and belief it does not contain any material previously published or written by another person except where due reference is made in the text.

Signed:

Date: 09th of September, 2017

Abstract

This thesis focuses on humid tropical deforestation in one of the most important coca growing regions in central Bolivia, Chapare. On the one hand, the cultivation of coca leaves which is the source of cocaine paste, their processing and narcotrafficking are global, social and legal issues that lead to violence, corruption, and instability in foreign policy frameworks. On the other hand, their cultivation has local environmental and economic repercussions that are not always negative.

The project is grounded in geospatial science and the methodology comprises of three main sections: image pre-processing, land-use and land-cover classification aimed at forest/non-forest mapping, and the generation of forest and non-forest statistics for individual farms in four communities in Chapare. Landsat 4 & 5 (TM) (2011) and Landsat 8 (OLI) satellite (2015 and 2016) image data were used. Pre-processing steps covered verification of geometric and radiometric parameters, image mosaicking and, for the 2015 data, pan sharpening. Thus, the images were classified using unsupervised classification to map major land-use and land-cover types from 2015 imagery. These were verified with reference to field data collected in 2015 that was made available to this research project. Forest and non-forest classification was carried out for the 2011, 2015 and 2016 image data. All geospatial analyses were done in ERDAS Imagine 2015 and ArcGIS version 10.4.

The results of the three classified images for 2011, 2015 and 2016 shows overall accuracies of 84.51%, 87.84% and 98.42% respectively. Comparing the four different communities investigated in detail in the study area, the areas in the Community I and Community II shows regrowth of forest areas while areas in Community IV shows increased rate of deforestation. Community I with an average

of 20 ha of land parcels and a standard deviation of 3 hectares has a current average regrowth rate of 204.73 ha/year which is 2 ha/year per farm at the end of the study period in 2016. Community II with mix grazing and farming land parcels indicated by its size of 50 ha (50 hectare land parcels are meant for pastures) have a regrowth of 786 ha/year which is 8.46 ha/year per farm in 2016. Community III and IV has a clearance rate of 25.18 ha/year which is 0.42 ha/year per farm and 79.56 ha/year which 1.99 ha/year per farm.

However, there is 50% decrease in deforestation rate for the communities mapped in detail compared to statistics generated for the 1980s and 1990s. This is indicative of the Bolivian government's pro-coca policies and legislation since they were first elected in 2006, and their increasing influence since c. 2000. The quantitative data reaffirms the hypothesis that weak anti-coca polices lead to less deforestation in Chapare.

A key recommendation arising from the use of pan-sharpening technique used in this study shows improvement of the quality of the image and its spatial resolution in the 2015 classification discriminating individual forest degradation needs to explored. That is recommended as an advantage that must be employed on newly available sources of high spatial resolution imagery, to more accurately map and monitor fluctuations in the rates of deforestation in different communities and different farmers in each community under policies that either promote or discourage coca cultivation in future researches.

Dedication

I wish to dedicate this work to the memory of my late brother – Marceline Nagombi.

1 Thessalonians 4:17- "After that, we who are still alive and are left will be caught up together with them in the clouds to meet the Lord in the air. And so we will be with the Lord forever."

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I sincerely would like to extend my acknowledgement to all the people who contributed in many ways directly or indirectly to make this thesis project a success. Firstly, I would like to take this time to thank the heavenly God for this gift of life.

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Acronyms and abbreviations

AOI	Area Of Interest
CDRP	Cochabamba Regional Development Program;
CONCADE	Counter Narcotics Consolidation of Alternative Development Program
CORDEP	Chapare Regional Development Program
EKC	Environmental Kuznets Curve
EU	European Union
FAO	Food and Agricultural Organisation
FCC	False Colour Composite
GCV	Generalized Cross Validation
GDP	Gross Domestic Product
GIS	Geographical Information Systems
GMO	Genetically Modified Organism
GNP	Gross National Product
GPS	Global Positioning Systems
IBTA	Bolivian Institute of Agricultural Technology
IPPC	International Plant Protection Convention
ISODATA	Iterative Self-Organising Data Analysis Technique
LAI	Leaf Area Index
Landsat TM	Landsat Thematic Mapper
Landsat ETM+	Landsat Enhanced Thematic Mapper
Landsat OLI	Landsat Operational Land Imager
LEDAPS	Landsat Ecosystem Disturbance Adaptive Processing System
LULC	Land Use & Land Cover
LULCC	Land Use Land Cover Change
MAS	Morales Movement to Socialism
NDVI	Normalised Difference Vegetation Index
NEP	New Economic Policy
NIC	Institute Nacional de Colonización
NIR	Near infrared
PS	Polar Stereographic
RGB	Red Green Blue

ROC	Receiver Operator Characteristics
SW1	Short Wave 1
TIPNIS	Isiboro Sécure Indigenous Territory and National Park
USGS	United States Geological Survey
UN	United Nations
UNCED	United Nations Conference on Environment and Development
UNHCR	United Nations High Commission for Refugees
UNODC	United Nations Office of Drug and Crime
USA	United States of America
UTM	Universal Transverse Mercator
UK	United Kingdom
WGS	World Geodetic System
WRS	Worldwide Reference System

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CHAPTER 1

1 INTRODUCTION

1.1 Deforestation and Land-use

Deforestation is the clearing of the forest and its conversion to other land-uses according to Luca *et al.,* (2016), who also define it as a land-use trade-off between conservation and land development for economic profit. Deforestation has taken place throughout the world for millennia (Millington and Jepson, 2008). Tropical forests across the globe have been under pressure since the 1950s, whereas deforestation and forest degradation was commonplace in the industrialized countries up to in the twentieth century (Palo and Lehto, 2012).

The UN Food and Agricultural Organisation (FAO) was established to take stock of global forest resources. Globally, deforestation currently occurs at a rate of 13 million hectares per year (FAO, 2005a), but the rate varies from year to year and place to place. Much of the forest being lost currently in countries in the three tropical humid forest blocks on either side of the Equator—an archipelago of countries extending from South Asia to island nations in the Pacific, the central African forest block, and Mesoamerica to the Amazon Basin–due to economic development (Ehrhardt-Martinez *et al*., 2002) and urbanisation including rapid population growth (Redo *et al*., 2012). Countries encompassed by these areas generally experience high levels of poverty which is an under-laying pressure causing deforestation as people rely on forests and their land resources to alleviate privation. Nearly 600 million people around the world depend on forest for their livelihood, of which 200 million are indigenous people (Byron and Arnold, 1999; Chao, 2012). However, commercial interests are also significant deforesters, e.g., timber extraction globally, plantation (e.g. oil palm in Indonesia and Malaysia) and other commercial agriculture (e.g., soy in Brazil), mining and oil extraction.

Reflecting on the causes of deforestation, some land clearance is inevitable because of social and sustainable economic development. However, the rate at which this is occurring , its` causes and whether it can be avoided is a current issue at the forefront of academic and policy debates (Palo and Lehto, 2012). There is an implicit relationship between deforestation and post-deforestation land uses. Large-scale deforestation, whatever the purpose, can have severe impacts on socio-economic factors such as a decline in local timber supplies, soil erosion, flooding, decreased agricultural productivity, loss of cultural values and hunting grounds, loss of biodiversity and a reduced capacity to sequester carbon (Peter *et al*., 2015, Sandro *et al*., 2015). Others argue that these costs need to be offset by the benefits in terms of economic development, sustainability and development; e.g., Babin (2004) wrote about the research, management and development perspectives of forests and land-use in tropical countries that is occurring at a faster rate for the sake of sustainable development.

There is global pressure to arrest deforestation and this has brought together global environment organisations such as UNE (United Nation Environment), WEO (World Environment Organisation), and GEO (Global Environment Organisation) e.t.c to agree on common principles. This pressure led the United Nation to address deforestation at the Conference on Environment and Development (UNCED) in Rio de Janeiro in 1992 (Nations, 1992, Grubb, 1993). However, from the developing countries' perspective, government need to initiate development and food security: agricultural sustainability is key to the latter but to achieve development goals much forest is being converted to produce oil palms and cocoa amongst the many plantations crops. Therefore, there continues to be an ongoing link between deforestation and land-use. It is estimated that approximately one fifth of the world's tropical forest was destroyed over the 30 years from 1970-2000 and that it all will be gone by the end of the 21st century (IPCC, 2000).

There are hundreds of research studies on deforestation in the context of land-use and land-cover change in developing countries. Therefore, the meta-analysis of the research articles up to *c.* 2000 that was published in the seminal Geist & Lambin (2001) paper is an important introduction to key themes, particularly the distinction between local drivers and underlying causes (See Figure 1.1-1) which operate at national and global scales. More of it is elaborated as driving factors in section 2.3.

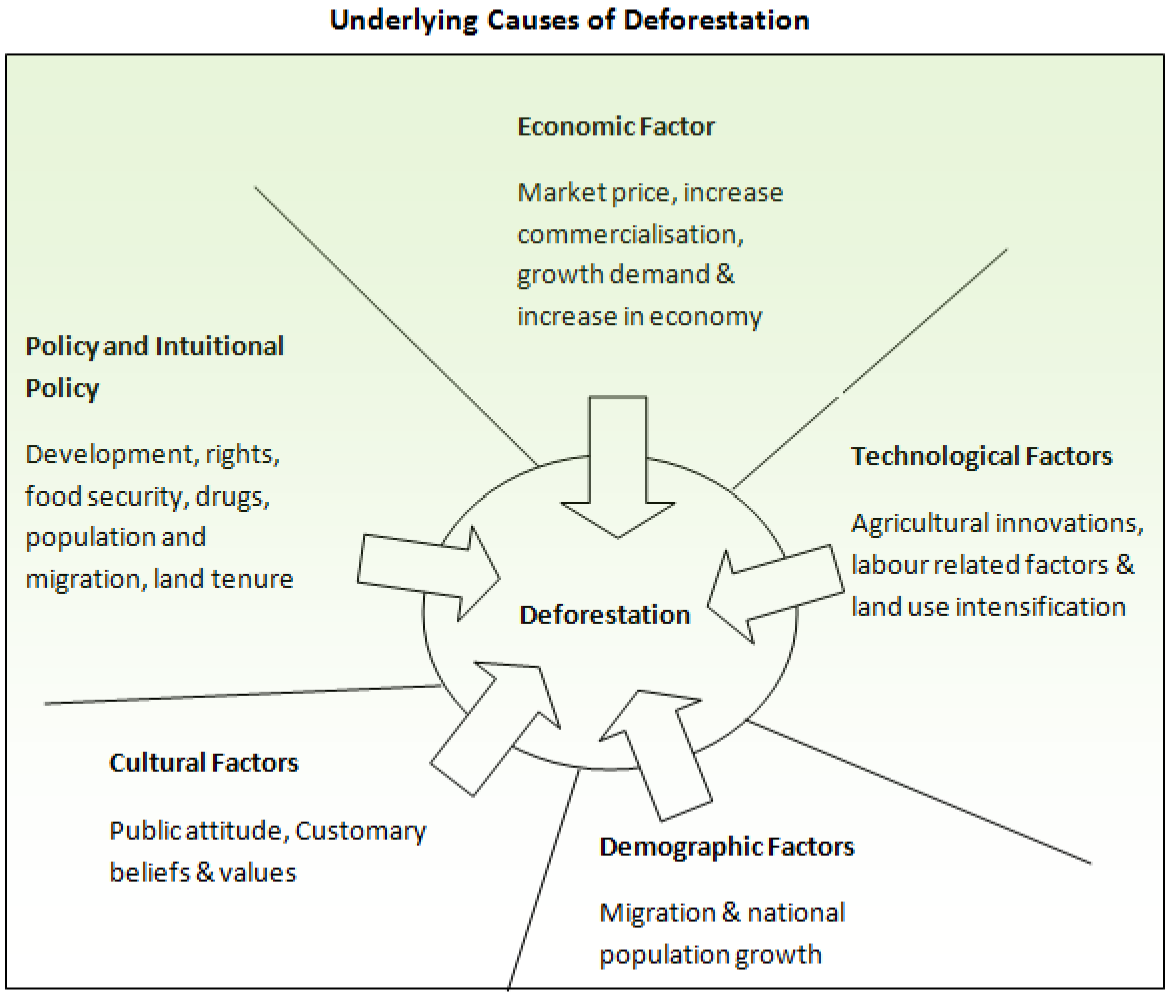

Figure 1.1-1 Factors seen as the underlying causes of deforestation (based on Geist & Lambin, 2001)

Research since then has incorporated new themes (Basiron, 2007, Chao, 2012, Gibbs *et al.*, 2010, Luca *et al*., 2016, Zimmerer, 2013, Hameleers *et al*., 2016) such as food and water security, deforestation in the framework of global climate change, and reprised old themes such as soil degradation (Young, 2009), while simultaneously deepening understanding of deforestation using Geist & Lambin’s (2002) drivers-and-causes framework. Government policies and regulations are key causes of deforestation, e.g., the role of government policies that encourage the illegal timber trade leading to increasing deforestation (Meyfroidt and Lambin, 2009). However, policies are, perhaps, the least understood major cause of forest loss.

1.2 Focus of this study

The focus of this study is in one area of the Amazon Basin tropical forest block indicated in Section 2.2. It is, therefore an example of what is occurring in one part of the tropics. It is a detailed case study, which looks at land-use activities in relation to forest dynamics and driving factors with an emphasis on policy drivers. National deforestation rates in selected tropical countries including most Amazon countries are presented in Figure 1.2-1. Although, the data may arguably be from 2000 to 2005, and the accuracy of data from some may be disputed (Keenan *et al*., 2015), it illustrates the dimensions of pressing major environmental problem of global proportions. It is expected to continue at that rate provided with a rapid decline in forest areas in tropical developing countries as predicted (Ehrhardt-Martinez *et al.*, 2002) .

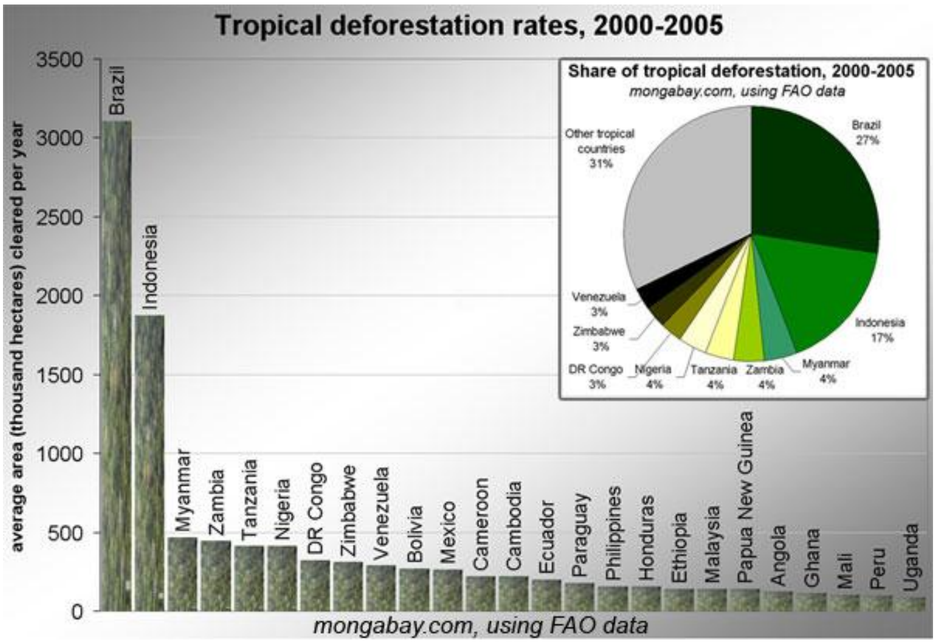

Figure 1.2-1 Deforestation rates of tropical developing countries from 2000 – 2005 (Source: Mongabay.com)

In 1980 the rate of tropical deforestation was estimated to be 11 million ha/year. By 2005 this had increased to 12 million ha/year and 80% of the deforestation incorporated in the current global deforestation rate was occurring in the tropics (FAO, 2005b). Bolivia, a tropical country with extensive lowland tropical and sub-tropical forests has the seventh largest contemporary deforestation rate of 430, 000 ha/year (Andersen *et al.*, 2016). The land use in lowland Bolivia is like many other tropical countries that are rapidly converting forest through “slash and burn” to i) farmland, ii) grazing, iii) other forms of economic development` such as roads, plantations, and iv) settlements and infrastructure. Chapare, in the Department of Cochabamba and Santa Cruz have been extensively deforested in the last 30 years because of agriculture and forestry policies that encourages extensive agricultural activities (Andersson and Gibson, 2007). Deforestation in Santa Cruz, which are known for various forms of commercial agriculture such as banana and soya, can be liked to neoliberal agricultural and trade polices (Redo *et al*., 2011). In Chapare, a chief crop is coca and cocaine frontier, the link is between deforestation and narcotics policies. Much of the deforestation in these two areas of Bolivia are linked to government policies that focuses on the eradication of coca.

Coca production has a particular place in understanding the links between society, agricultural production and forest dynamics in contemporary Bolivia. Around 200 million people consume illicit drugs daily (Ware, 2007) and all the cocaine consumed comes from Bolivia, Colombia and Peru. Many studies on coca cultivation and its trade have been carried out in Bolivia (Marcy, 2010, Steinberg *et al*., 2004) and in neighbouring countries, but very few have analysed this trade as a driving factor in deforestation.

1.2.1 Agriculture and natural resources policy

Agricultural and natural resources policies are linked to deforestation through decisions made in developing countries about their contemporary attempts to achieve sustainability in areas like agriculture, rural development and biodiversity conservation. For example, Malaysia's oil palm industry is focusing on achieving universally accepted agricultural standards (Basiron, 2007) and the Round Table of Sustainable Oil Palm is a global effort with the same objectives (Schouten and Glasbergen, 2011). That is to minimise the rate of deforestation while maximising the use of agricultural land and its sustainability. In Latin America recent research has been carried out in ten countries aimed at developing policies that promote sustainable farming while simultaneously stimulating rural economies (Elsner, 2016). This was done by encouraging local economic growth that is socially inclusive and promoting regrowth and protecting biodiversity.

The importance of the agricultural sector in Bolivia is underlined by the fact that it accounts for 15% of the nation's GNP (Hameleers *et al.*, 2016). Agricultural land uses are estimated to be close to 2.5 million hectares in total; of which local farmers growing agro-industrial crops use more than half (1.4 million hectares). Land-use change is most dynamic in the new agricultural areas where forest being is converted to agriculture, e.g., the conversion of the eastern lowland forests to soy grown in large mechanised farms (Redo *et al.*, 2012), and by peasant farms in colonization zones (Bradley and Millington, 2008a, Peter *et al*., 2015, Redo *et al*., 2012, Redo, 2012, Killeen *et al.*, 2007).

Some other tropical developing countries have implemented macroeconomic policies, often with the intention of paying off international debts and loans from financial institutions like World Bank (Victor *et al*., 1995), that unintentionally has impact on deforestation. These policies often marginalize the agriculture sectors by favouring the industrial sectors. That is done so by prioritising on developing various industries like livestock and commercial plantations together with other infrastructure industries while no or less emphasis being placed on forest and its biodiversity. Focusing more on the area of this study, cash crops like cocoa, banana, citrus and coca are very important to the Bolivian agricultural economy (Crabtree and Chaplin, 2013). Previous studies have focused on Bolivia as an example of how agricultural technology has encouraged deforestation (Angelsen and Kaimowitz, 2001, Kuiper and Hudak, 2000, Morales, 1991), but they have failed to quantify how much forest disappeared over time as well as identifying other driving factors such as pro-coca policies, advance agricultural equipments, market price, food security and population growth.

1.3 Aims and objectives

The research in this thesis has the overall aim of examining policy drivers on tropical deforestation (Geist and Lambin, 2001) using a case study from Bolivia.

From previous work by Bradley (2005) highlighted that the impact of international and national narcotics policies influencing clearance of humid tropical forest like the one in the study does affects the environment, economy and social aspects of land use management. It will achieve this by examining recent forest dynamics in Chapare, Bolivia; an area where international and national narcotics policies have been very furiously debated, sometimes resulting in political unrest since the 1970s and where policies have swung between strongly enforced anti-coca and cocaine policies to positive encouragement to cultivate coca. Specifically, the project will address the following objectives:

a) To map forest and other non-forest land covers for 2011, 2015 and 2016 for the study area.
b) To test the hypothesis (Bradley and Millington, 2008a) that deforestation rates are significantly less under conditions where coca is encouraged than under well-enforced anti-coca policies.

1.4 The research in a wider context

The narrow aim of the study is to address issues of deforestation rate in Bolivia and the cultivation of coca, production of, and trade in cocaine. It addresses three factors that form the basis of human communities and societal cohesion: economics, society and culture, and the environment (Marcy, 2010). They co-exist together where as one have to be marginalized for the sake of other in which the environment is always at the losing end. Looking at the issue from a global perspective, the actions around cultivating drug plants, processing them and narcotrafficking leads to conflict, violence, corruption, and instability in foreign policy frameworks (Steinberg *et al*., 2004).

1.4.1 Environmental impacts

This research examines links between coca farming and the cultivation of substitute crops, and rates of deforestation. It will quantify the pressure being put to the environment by coca cultivation under different policy regimes and could be a key input to future policy-making and planning. Coca cultivation and cocaine processing pose environmental problems from cultivation right through to the process of producing cocaine. The process of producing cocaine involves many harmful acids and other chemicals, which are disposed in river systems and into groundwater aquifers. The environmental effects of coca farming are mainly related to the loss of habitat, native flora and fauna species and the water pollution (Sandro *et al*., 2015, Peter *et al*., 2015). In a study of coca cultivation in Peru it was noted that when forest had been cleared, there was a decline in water quality (Steinberg *et al*., 2004). Another observation been made with regard to montane rainforest biodiversity in Colombia (Dávalos *et al*., 2011). Similar observations have been made in Peru (Young, 2009), and coca cultivation has been blamed as the main cause of deforestation, and loss of biodiversity, in Colombia by other researchers (Álvarez, 2007, Dávalos *et al.*, 2009, Dávalos and Bejarano, 2008), and it is argued that this will be the case for Peru and Bolivia (Dávalos and Bejarano, 2008).

1.4.2 Economic impacts

Coca and other illicit drug plants attract growers to cultivate them because of their market demand and high prices. The global market for the illicit drug cocaine increased dramatically around the world in the 1970s (though there was a well-established illegal trade from the 1950s onwards in Bolivia – (Millington, in press) and (Gootenberg, 2008). The two main coca growing countries in the 1950s – Bolivia and Peru – responded to the global market stimulus simultaneously (Steinberg *et al.*, 2004, Bradley and Millington, 2008a), while Colombia became the main producer two decades later (UNODC, 2016a).

At the local scale the economic stimulus from coca and cocaine complicated land cover changes that were driving tropical deforestation (Bradley and Millington, 2008a). Colonist farmers saw coca as an income-generating crop requiring less labour compared to other crops and livestock farming. It also boosted local economy in the region because of the high prices paid by drug smugglers and some basic processing of coca leaf was done in areas where coca was grown.

Soares (2011) noted that coca, oil and other forms of agriculture make up 25 % of Bolivia's GDP, but his statement needs to be dissected. While the oil industry and agricultural enterprises pay taxes, the illicit commerce in coca and cocaine does not benefit national revenue streams. As a consequence of this, the Bolivian government developed policies that would enable farmers to grow crops that would generate taxable revenue while simultaneously marginalizing the coca trade. This is also an intentional move to eradicate coca (Bradley and Millington, 2008a). Though the introduction of alternative crops is not solely an economic issue. The major push for these policies in the 1980s and 1990s came from international anti-narcotics policies which came into force under the globally recognized Single Convention on Narcotic Drugs in 1961 (UNODC, 1961)

1.4.3 Political and social impacts

Drug use and narcotrafficking are related social and political problems of global proportions (Ware, 2007, Soares, 2011). In terms of botanical drugs like cocaine, heroin and marijuana, social problems occur in the countries where they are grown, as there is always a nascent drug sub-culture, and amongst consumers elsewhere. In the case of cocaine, the main consumers in 2014 were the USA; Argentina, Brazil and Chile; Australia; and most western European countries, especially the UK, Ireland, Belgium and Spain (UNODC, 2016a). According to the latest World Drug Report, 247 million people used drugs, of which 29 million suffered from medical disorders related to drug use. In 2014 alone, the agency reported an estimated of 207,400 drug-related deaths (UNODC, 2016a).

Locally, there are other less important consumers in the region apart from selling it to drug syndicates and these have changed over time. A further social issue that re-appears from time-to-time is that chewing coca leaf is a social and medical problem, but this has never gained much traction for long and in Bolivia. However, currently chewing is considered part of the national heritage of Bolivia as well as its medicinal uses and other social interactions and religious ceremonies.

Over time, there has been an increase violence and social disturbances related to the coca and cocaine trade that has increased crime rates (which have prompted various law-and-order and alternative pathway initiatives) and the disintegration of cultural lifestyle; i.e., normal socialising activities such as sports and entertainment that promote population mobility and provide places where money can be spent. This has occurred in all three Andean coca growing countries (Sorrell, 2010). The Bolivian Vice Minister of Social Defence was quoted in 2006 as saying *" We decided to leave machine guns, bullets and bombs,"*(Farthing and Ledebur, 2014). That was a strong statement because it meant an end to the violence associated with the implementation of anti-narcotics policies in Bolivia. In any society, there is always social problems that needs to be taken into consideration in any decision-making.

1.5 Thesis Structure

This thesis has seven chapters in total. Chapter 1 provides and introduction and elaborates on the aim of this study. The chapter also outlines the aim and objective of this study with anticipated impacts. Previous research, which is pertinent to the topic, is reviewed in Chapter 2. In addition to this, Chapter 2 has a section that introduces Chapare—the study area. It covers briefly major areas and aspect of the study area in setting the scene for readers. This major areas and aspects includes geology, climate deforestation and policies that are combined to nurture deforestation in the study area. The methods are introduced in Chapter 3 and the results are presented in Chapter 4. The methods involve remote sensing skills and geospatial techniques to derive Land Use and Land Cover Classification (LULCC) maps for analysis. The method starts from image downloads and pre-processing to final LULCC. The results and findings are discussed in Chapter 5 and 6 that compare, argue and validate the aim and objectives of this thesis, all in the context of remote sensing. Chapter 5 covers the image analysis discussion, while chapter six elaborate on LULCC and policies. Both chapters deliberate to the extent that the research questions posed in the first chapter have been answered. Chapter 7 provides a conclusion and recommendation for future research. Much of the recommended future research was based on keeping to finer resolution and this can be a transition moving from a course to finer resolution.

CHAPTER 2

2 : DEFORESTATION AND ITS DRIVERS INCLUDING COCA IN CHAPARE

This chapter provides background material on coca and cocaine in South America. It also introduces the study area in Bolivia—Chapare–and discusses drivers of deforestation. Drivers of deforestation can be the direct cause or influence driving the forest areas into other land use. Like most tropical countries, humid tropical deforestation occurs through various policies change for the sake of sustainable development and standard of living.

2.1 Coca and cocaine

Coca is the common name given to two species of shrubs from the pan-tropical family of trees and shrubs Erythroxlylaceae. The two species*, E. coca* and *E. novogranatense* (both of which have two varieties), that have historically been grown to produce leaves for chewing and, since the early 20th Century to produce cocaine, are native to north western South America (Bradley, 2005). Although coca leaves are a home remedy, a locally used stimulant through habitual chewing herb and an infusion that can be drunk like tea, its recreational product is psychoactive drug, cocaine, which is very addictive. The traditional domestic and illegal cocaine trades mean that coca has been a cash crop for centuries, but its rise to the recreational drug of choice in the 1970s boosted its economic significance both in producer countries like Bolivia and globally.

Unlike many other cash crops, where when demand increases the price of the cash crop increases, coca prices do not obey normal supply and demand rules because the international market is imperfect in international terms. This is because of factors around the international prohibition on cocaine which has been in force since the Single Convention on Narcotic Drugs, 1961 (UNODC, 1972) . Coca cultivated to supply the domestic chewing markets is not illegal, but it has been almost impossible for the authorities in Bolivia and Peru, where large numbers of people chew coca leaf on a daily basis, to differentiate between coca being grown for chewing and cocaine production.

Illegal coca cultivation for illegal cocaine production is seen as the major driver that has stimulate cultivation in the coca producing regions in South America (Soares, 2011, Steinberg *et al*., 2004, Ware, 2007, Sorrell, 2010), and since 2004 the UN Office of Drugs and Crime has monitored coca cultivation in Bolivia, Colombia and Peru providing annual reports (e.g., the latest survey for Bolivia: UNODC, (2016b)). The trade routes (more often called narcotrafficking routes) for cocaine smuggling from South America to the rest of the world are of course not known until drugs are interdicted, and are known only to complicated secretive network of gangs and money launders. In the context of this research the study area - Chapare (Section 2.2) - is a major source of coca leaf for the global cocaine trade at the present time, and has been since the 1950s (Millington, in press).

Psychoactive plants have always played important roles in local ethnical communities in developing countries (Steinberg *et al*., 2004). Local indigenous communities tend to use these plants to elevate them to a different consciousness level to fight demons and for healing purposes. Coca is no exception in Bolivia and much historical and cultural significance is attached to this aspect. So much so that coca and coca chewing in Bolivia is often talked about in terms of national heritage.

Legal coca chewing and arguments around heritage provide a kind of blanket cover under which the illegal cocaine trade is hidden.

2.2 Chapare

This section introduces the background of the study area, Chapare, in terms of its locality, climate and agricultural aspects.

2.2.1 Location and administrative divisions

The study area extends for approximately 300 km from Isinota to Entre Rios and occupies the low hills in the south to the inundated lowland swamplands up in the north. The figure taken from Bradley and Millington (2008) clearly outlines the study area (Figure 2.2-1). Moreover, the study area covers the southernmost fringes of Beni Department, central Cochabamba Department and the extreme west of Santa Cruz Department (See Figure 2.2-1). Departments are the primary administrative division in Bolivia. Each department is subdivided into provincias[1], each of which has its own capital, which is administered by an alcalde[2] and municipal council. The study area comprises three provincias and a number of smaller subdivisions called *municipos* or municipalities (Table 2.2-1 below)

[1]Provincia is the Latin word for province which is an administrative division forming a state or country.
[2]AlcaldeordinaR, is the traditional Spanish municipal magistrate, who had both judicial and administrative functions over the town and they are elected annually

Table 2.2-1: Cochabamba Department: provinces with municipalities in the Chapare lowlands at the 2012 census (from Millington, in press)

Province [1]	Municipalities [2[predominantly in the Cochabamba *yungas*, cordillera or high valleys	Municipalities predominantly in the Chapare lowlands
Chapare	Sacaba Colomi	Villa Tunari
Tiraque	Tiraque	Shinaota
Carrasco	Totora Pocona Pojo	Chimoré Entre Rs Puerto Villarroel

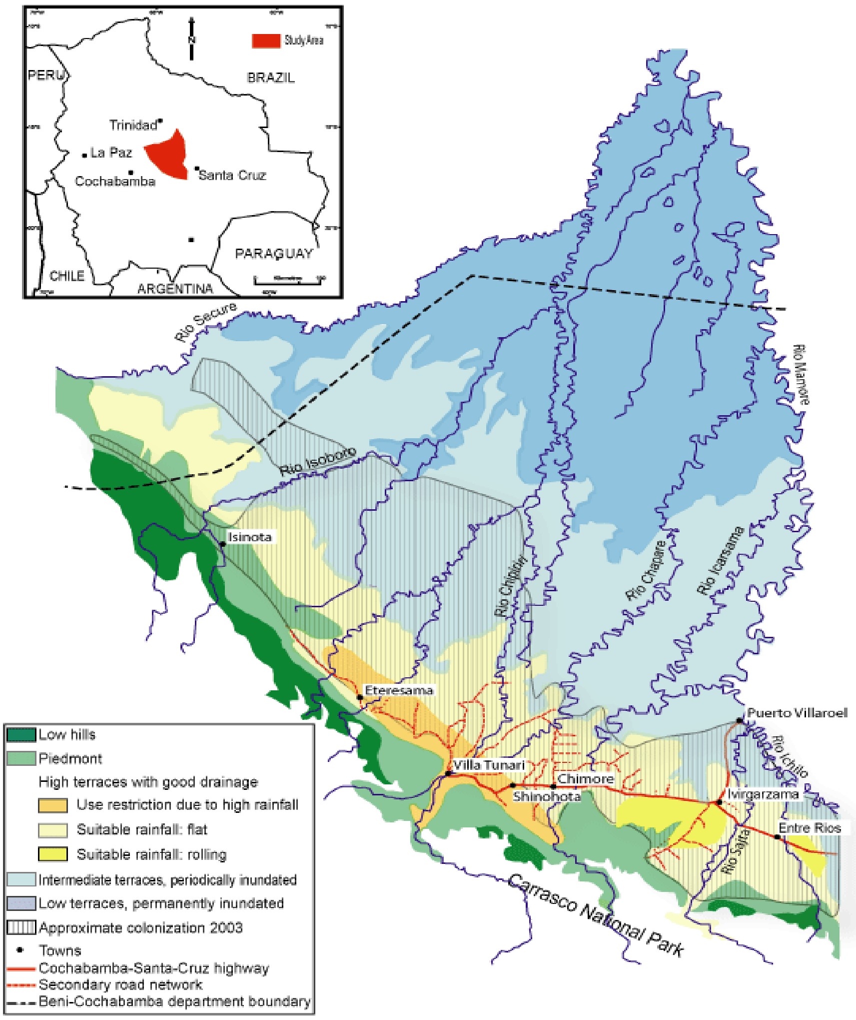

Figure 2.2-1 – Bolivia: location extending south-east from Isinota to Entre Rs and shaded relief outlining the low hills to swamplands up north: (Source – Bradley & Millington, 2008)

2.2.2 Geology

Bolivia can be approximately divided into two main regions. The high mountainous Andes to the west, which includes the high-level desert known as the Altiplano, and the lowlands to the east, which are mainly seasonally flooded floodplains of rivers that ultimately drain into the Amazon. Thus, between Andes and Amazon Basin is a narrow zone, approximately 100 km wide, where elevations change from > 4000 m.a.s.l to around 200 m.a.s.l. These are the forest eastern slopes of the Andes, and at the foot the Andes at the margin of the Amazon Basin there are a number of colonization zones, including Chapare, where the Bolivia Government has undertaken planned settlement since the 1920s (Fifer, 1967, Millington, in press).The terrain in Chapare mainly comprises floodplains of major rivers like the Sécure, Isiboro, Chapare, Chimoré, Sajta, Ichoa and Ichilo. However, close to the Andes there is a hilly zone of dissected alluvial fans and in the extreme northwest and southeast of the study area there are low fold mountain ranges where natural gas deposits are exploited.

2.2.3 Climate

The climate in Bolivia is strongly influenced by the location of the topography of the country. The northern part of the country is located in the tropics, while it is sub-tropical in the south. In the Andes and Atilplano, a cold arid climate prevails. In the Köppen-Gieger climate classification system Chapare is classified as Am in the north and Aw in the south (Peel *et al*., 2007) (Figure 2.2-3 below). An Am climate is a wet monsoonal regime, and Aw is tropical savannah climate. The Aw climate only represented in the southeast of Chapare. The area experiences a wet season from

November to May, with a drier season from June to October. Mean annual rainfall in Chapare varies from approximately 6500 mm in central Chapare between Villa Tunari and Chimoré, with the lowest rainfall total occurring in the southeast on the border between Cochabamba and Santa Cruz Departments. Andrew Bradley (2005) in his thesis gave the amount of precipitation with an average annual amount of rainfall calculated from 20 years of rainfall data (Figure 2.2-2)

Station	Altitude (m.a.s.l.)	Annual Precipitation (mm)	Temp range (ºC)	Latitude (degrees)	Longitude (degrees)
**Chipiriri	411	4,800	-	16º 55'	65º 19'
**La Jota	226	4,100	-	16º 58'	64º 57'
**San Isidro	327	2,050	-	17º 28'	63º 32'
*Ivirizu en Sehuencas	1,980	3,541	2.47	-	-
*Planta Corani	2,740	2,969	3.48	-	-
*Pojo	2,600	547	4.34	-	-
*Arani	2,740	454	4.7	-	-

Figure 2.2-2 Figure of table taken from Bradley (2005) outlining average annual rainfall in the study area collected in a peRd of 20 years.

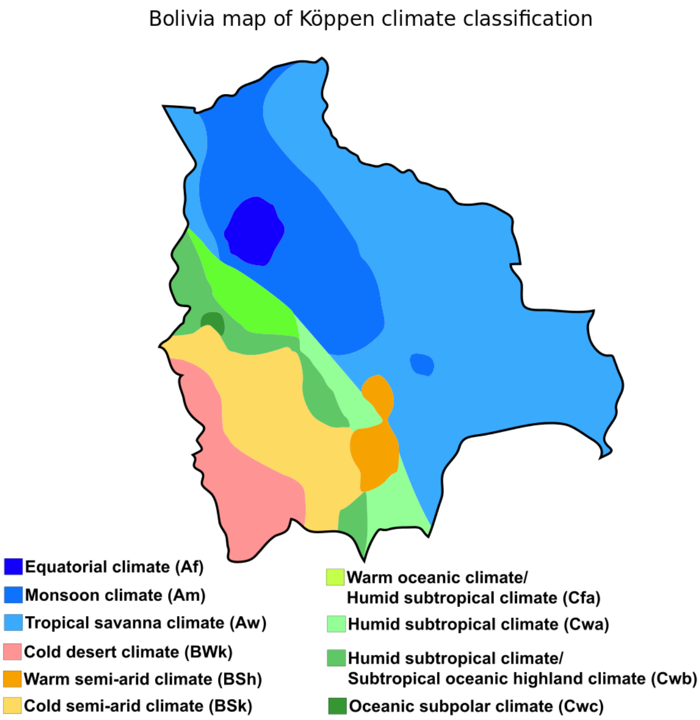

Figure 2.2-3 Köppen-Geiger climate classification for Bolivia. (Source: Derived from [World Koppen Classification.svg](), Wikimedia Commons Licence)

The vast resource-rich tropical areas of South America ideal for agricultural activities (Gibbs *et al*., 2010) and this is no exception in Chapare. The whole of the lowlands of Bolivia, including the study area, have been devoted to either subsistence agriculture or cash crop farming. The cash crop farming in Chapare mainly involves banana, citrus, pineapple and palmetto (Crabtree and Chaplin, 2013). Banana and citrus are the greatest crops by area, but cash returns to farmers from coca far outweigh the next most profitable crop, which is palmetto (Bradley, 2005). Perhaps the major agricultural land use in Chapare is improved pasture for cattle rearing. In addition to these commercial crops, subsistence crops such as rice, maize and cassava are grown.

Most families in the region live under poverty line and depend on a mix of rain-fed subsistence farming and either rain-fed commercial crops or livestock (Kuiper and Hudak, 2000). The cultivated area per farm size is less than five hectares in the 20 ha land parcels allocated to each farmer. While early settlers in Chapare, in the 1950s, were encouraged to produce rice for the Bolivia domestic market, they soon developed commercial ventures through citrus and coca. This situation continued throughout the 1960s, but when cocaine became the international drug of choice during the 1970s, farmers began to convert more land to coca production to be able to meet the demand from local cocaine paste processing ‘factories’ as a result of national and international reaction. There have been a number of anti-narcotic policy responses to the coca and cocaine trade in Bolivia. These will be further discussed in this thesis, as they are the driver of forest change that is being investigated (Sections 2.3 and 2.4). However, in terms of agriculture, these policies often encouraged farmers to grow alternative crops, such as banana and pineapple, to alleviate stagnating local economic growth when coca was eradicated (Morales, 1991).

2.3 Deforestation and its Driving factors

Geist and Lambin (2001, 2002) carried out seminal research that introduced a drivers-approach to humid tropical deforestation based on a metadata analysis of their studies (Figure 2.3-1). This is a similar approach used in this research and frames the discussion in the remainder of this chapter. Gibbs *et al.*(2010) also state some of the driving factors strongly pointing out conversion of forest to agricultural lands.

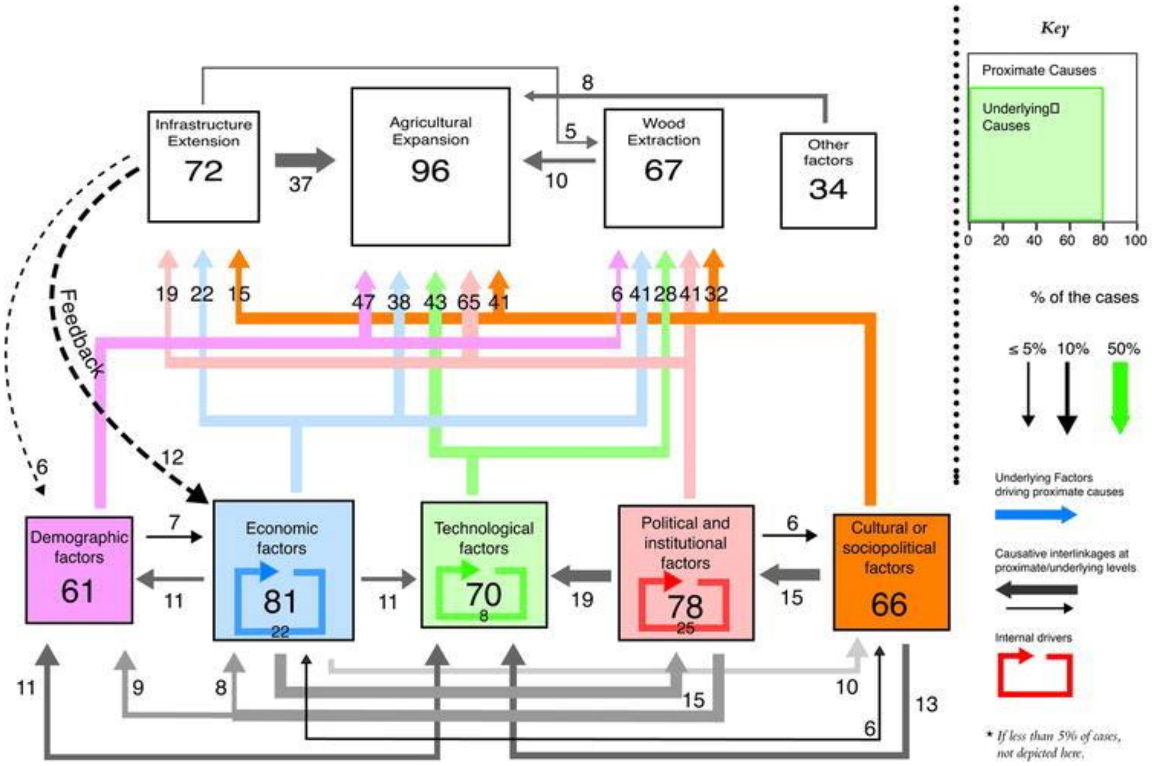

Figure 2.3-1; Land use dynamics identifying deforestation drivers for humid tropical forest ranging from demographic on the left to cultural factors on the right including the land cover conversions at the top. (Source: Geist and Lambin, 2001)

2.3.1 Demographic factors, infrastructure development and agricultural expansion

According to Geist and Lambin (2001) demographic factors are underlying causes of tropical deforestation (Figure 2.3-1). The main factors are population growth and migration. Once people move into an area like Chapare, where the initial demographic factor was migration from the Bolivian highland farms (agricultural expansion) and infrastructure development is necessary to support these people. Agricultural expansion and infrastructure are proximate causes of deforestation (Figure 2.3-1). Of course, once settlement occurred in Chapare, the population grew through normal reproduction processes, but also migrants continued to have arrived. This way of expansion of communities in areas of settlement and farming is commonplace throughout most tropical developing countries (Dimobe *et al*., 2015).

Most rural colonists in tropical agricultural communities depend on balance subsistence agricultural farming as one of their main food sources with an element of commercial cash cropping: this is the case in Chapare. People moving into new areas to cultivate often clear large amounts of primary forest initially to grow food crops that they can consume and sell on the domestic market before moving into other commercial crops. In Chapare the initial crop for most settlers was rice (Weil, 1983). The conversion of forest to farmland accounts for most forest area lost in most parts of the tropics if only proximate causes are considered, and it the most important proximate cause being cited in 96 studies analysed by Geist and Lambin (2002) (Figure 2.3-1). Settlers in Chapare also used timber from forest clearance to build their houses. In doing so they destroyed habitat for native flora and fauna (Crabtree and Chaplin, 2013): though habitat loss in a biological sense is not the main focus of this research.

The expansion of infrastructure accounts for a smaller area of forest loss than the expansion of agriculture, and is the second-most important proximate cause of deforestation being implicit in 72 case studies that Geist and Lambin (2001) reviewed (Figure 2.3-1). Infrastructure development in Chapare involves the expansion of the main road and feeder road network and the establishment on towns of 2000-5000 people that provides services to the dispersed farming communities. The main towns from west to east are Isinota, Eterasama, Villa Tunari, Shinaota, Chimoré, Ivigarzama, Puerto Villaroel and Entre Rios. The push to increase the road network has been considered the main cause of deforestation in parts of Chapare by Gils and Ugon (2006)

More recently, the possibility of extending the road network in the northwest of the study area has caused uprisings amongst the indigenous people over the Isiboro-Sécure Indigenous Territory and National Park (TIPNIS). If this occurs it will concentrate significantly to the rate of deforestation in TIPNIS (Crabtree and Chaplin, 2013), and part of Chapare that has already seen settlement along access lines cuts into the primary forest for oil and gas exploration.

2.3.2 Food Security

Food security is another important factor to consider in understanding how agriculture develops and can be considered to encompass the proximate cause of agricultural expansion and two underlying causes, economic factors and political and institutional factors (Figure 2.3-1). Food security has become a key global issue with a greater visibility than when the research papers that Geist and Lambin (2002) analysis were carried out. This is a particular issue where there is not enough money to sustain dietary needs because of families living below the poverty line, and people depend entirely on farming. This is widespread in Bolivia (Devere *et al*., 2017) where it is related to indigenous land rights in Bolivia because of political land reforms in the 1950s.

The combination of proximate causes and underlying drivers that food security implies leads to agricultural expansion but also demographic growth, which in turn increases demand for agricultural produce. The linkages outlined above are also indirect as they increase global agricultural flows (Morales, 1991, Millington and Jepson, 2008, Kuiper and Hudak, 2000, Devere *et al.*, 2017, Angelsen and Kaimowitz, 2001, Hellin, 2013, Dimobe *et al*., 2015). The population is still expanding and this is putting pressure for farmers to self-sustain themselves as well as encouraging the communities to develop sources of external income. Hellin (2013) stated that, there is a need for the promotion of agricultural products including coca in the area, as it exposes farmers to new challenges and opportunities.

2.3.3 Increased technology

Technological change is an underlying driver of deforestation (Geist and Lambin, 2001, Geist and Lambin, 2002) that has contributed towards much of the deforestation that has happened in the second half of the 20th Century. In the 1960s and 1970s, that was mainly limited advances in agricultural equipment, fertilisers and agrochemicals. This now includes further advances in these areas and GMOs. Technological advances have had two main impacts: reduced labour inputs and increased crop yields. Such technologies included chain saws for felling trees and tractors for ploughing fields.

Furthermore, because of the availability of new technologies, farming household see the opportunity for increasing their living standard (Angelsen and Kaimowitz, 2001).

They have shown how soybeans have taken large parts of the Amazon Basin in both Brazil and Bolivia. This is, in part, because it takes less labour, improved technology to control weeds and market prices that allowed to grow soybeans than coffee, banana or other crops. An example from the area studied are banana farms where complete infrastructure have been installed by farm cooperatives and banana fruits cut in the field are transported to washing and packing facilities using a network aerial rails along which bunches of bananas are pulled (Appendix 2.1) resulting in less labour.

2.3.4 Agricultural market prices

There is evidence that patterns of farming and the crops grown can change with fluctuations in farm gate prices. This can be seen as a catalyst to either encourage or discourage farmers from growing certain crops and it plays an import role in farmers deciding which crop to grow commercially (Perez-Verdin *et al*., 2009). These researchers concluded that deforestation rates and economic marginality index are proportional, and more poor famers convert more forest areas to farmland mainly because of the opportunity to earn more money. That is probably true for coca in the region where people turn to it to earn more money with less labour input compared to other crops (Bradley, 2005).

2.3.5 Policies and legislation

Policy issues that drive deforestation are consider underlying drivers by Geist and Lambin (2001, 2002). Policies and legislation to enable large haciendas to be subdivides into smallholder production systems under lease agreements were introduced in the 1950s in Bolivia with the Agrarian Reform of 1952 (Hellin, 2013).

That is through agriculture innovative systems that includes infrastructure and organisational improvements to produce land estates in manageable sizes.

That led to former miners and farmers from the impoverished highlands to settle in Chapare. These regulations, along with the formation of the National Colonization Institute in 1963 led to forest being allocated and cleared for farming and settlement in colonization zones in Bolivia, like Chapare. Another example of a policy that led to changes in deforestation rates in Bolivia was the introduction of the New Economic Policy in 1985 (NEP) which promoted improved farming techniques in a political framework that would improve economic performance and stabilise markets. Thus, it consisted of an “orthodox program relying on fiscal policies” (Morales, 1991).

The introduction of agricultural reforms in countries like Bolivia was underpinned by the perception that tropical forests were seen as suitable areas for farmland and major shifts in replacing forests with agriculture occurred from the 1950s onwards in South America, and elsewhere in the tropics (Gibbs *et al*., 2010) for sustainability and development. This shift came about at time when there was limited environmental regulation. It was clearly a global trend in agricultural reforms which is one of the factor that drives forest clearance and the conversion to agricultural land. It applies in Chapare, but because the main crop in this area was also illegal, another important policy dimension comes into play. That is anti-narcotics policies, often promoted and funded by the United States. These provide an unusual policy framework, and one that is explored in this research. It is explained in more detail in the following section below.

2.4 Anti-coca policies

Growing and harvesting coca leaves became a lucrative farming enterprise compared to other agricultural crops in parts of Bolivia and Peru as far back as 1950s (Walsh, 2004). However, the high demand globally for cocaine since the 1970s created an acceleration on the flows of cocaine paste from Bolivia and Peru—the two main producers–mainly to North America and Western Europe. Much of this cocaine was routed through Colombia, but during the 1980s, Colombia started to cultivate coca and became the major producer (UNODC, 2016). Bolivia has fluctuated between being the second and third largest coca-producing country in the 21st (UNODC, 2016), alternating its ranking behind Colombia with Peru. In Bolivia, Chapare became the main coca producing area in the mid-1960s (Millington, in press) and continues to be so half a century later.

The rise of coca cultivation, cocaine processing and narcotrafficking saw the launch of a war on drugs in Latin America targeting coca cultivation as part of a raft of measures. That led to airborne fumigation exercises in Columbia (LeoGrande, 2005), while in Bolivia ground based activities included forcing farmers to pull up bushes and spraying with herbicides.

The first signs of policies and legislation focussed on coca and cocaine was the establishment of UN Commission of Enquiry into the Coca Leaf in the 1950s which investigated the social and health implications of coca leaf chewing in 1950, but was thinly veiled initiative by the international community led by the USA to get its teeth into cocaine smuggling into cities of the east coast of the USA. The Single Convention on Narcotic Drugs that was passed by most countries of the world in

1961 stipulated the ban on coca leaves grown for the drug trade which was growing in response to an increasing demand for coca and cocaine trafficking in 1960.

Whilst embassy officials noted a rise in arrests by Bolivian authorities for running cocaine processing factories and drug smuggling in the 1960s, it was not until the 1970s that anti-narcotics policies begun to be developed in Bolivia, at the behest of the US Government and supported by them with funds and logistical support. The adoption of externally driven and funded policies by Bolivia has a chequered history. This enabled Blanco (2008) to divide the six decades from 1960 into five periods of policy effort in Chapare (Table 2.4-1).

This is somewhat generalised and suggests that the 1960s through to 2003 that the anti-narcotics policies prevailed in Chapare and since a pro-coca regime has been in place. Bradley and Millington (2008b) show that during the 1980s and 1990s, when many anti-coca policies that targeted Chapare were being developed and launched in Bolivia (Table 2.4-2) they were not always enforced. This enabled them to identify anti-coca and pro-coca periods in these two decades.

A key element of successive anti-coca policies were initiatives to introduce alternative crops (Sturm and Smith, 1993). These were usually combined effort from Bolivian government and US government to replace coca with crops like banana, palmetto and pineapple; and later black pepper and passion fruit that either had external markets (e.g., bananas) or could be processed and exported. This had little impact on the overall levels of coca leaf production because of the vast areas of forest, which could be cleared at the peripheries of Chapare. As the numbers of settlers increased during the 1970s, 1980s and 1990s, and more land was cleared at the margins, so the focus of coca cultivation generally shifted from the centre to the

Table 2.4-1 **Retrospective and situation of Chapare with respect to coca cultivation. Based on a tabular representation of Blanco's (2008, p 41, 43) research. (Translator: Andrew Millington)**

	1960 – 1976 (16 years)	1976 – 1992 (16 years)	1992 – 2003 (11 years)	2003 – 2005 (2 years)		2005 – 2012 (7 years)
Demographic, administrative and coca responses	Colonization programs in lowland tropics. Migration to Villa Tunari*.	Population growth and migration to Villa Tunari	Tiraque, Chimoré, Entre Rs and Puerto Villaroel created	Coca cultivation increased, mainly in Villa Tunari	**CHANGE OF VISION**	Increase in coca cultivation and leaf sales.
Attitude to /legal status of coca cultivation	Commitment to eradicate coca cultivation and the habit of 'aculico'	From the beginning of 1998 voluntary eradication programs under Law 1008 and alternative development programs.	Forced coca eradication and alternative development programs	Proposed revision and modification of Law 1008		Decriminalization of cultivation coca leaf surpluses
Main presidential administrations**	Paz Estenssoro, Banzer	Paz Zamora	Banzer, Sanchez de Lozada	Mesa		Morales
Overarching vision	**Eradication of coca cultivation**	**Eradication of coca cultivation**	**Eradication of coca cultivation**	**Conciliatory government**		**Support for coca cultivation**

*Places refer to municipos, rather than urban centres. ** There have been 10 other presidential administrations and 8 military administrations between 1960 and 2012 margins of Chapare. This coincided with a ramping up of US government imposed programs, strategies and anti-narcotics policies between the 1980s and the 1990s as part of the "War on Drug" (Xie, 2011). The "War on Drugs" enabled the US gain momentum from other countries and international organisations to help halt the cultivation of coca leaves in the region, as well as other drugs elsewhere around the world.

Table 2.4-2 Main periods during which anti-narcotics policies were introduce with military action to enforce eradication of coca (Source: Bradley & Millington, 2008b)

Year(s)	Policy instrument	Enforcement action
1981	Law 18265 Law 18741	Option of compensation to farmers in forfeiting their coca plots, otherwise forced removal of coca crop when discovered
1986	Operation blast furnace	Military operation unit selecting localized hotspot areas to destabilize local economies based on coca.
1986–1989	Plan Trienial	Intense military action to eradicate coca, which was abandoned after 12 months because of a civil unrest relating to this exercise.
1988	Law 1008	Legalization of 12 000 ha of coca for cultural purposes—mainly in the Yungas of La Paz. Coca bushes in excess in the remaining areas to be removed within 8 years.
1998–2003	Plan Dignidad	Five-year plan to remove all illegal coca—this target was claimed to be met in 2000.

This included more than trying to control production. According to UNODC (2004) there was a major drive in rehabilitating drug-related criminals by the United Nations Office of Drug and Crime, through a project called PREDEM to try and tackle demand reduction. The overall aim remains to generate public policy and strategies to reduce drug demand (UNODC, 2015). A major player in this effort globally has been European Union (EU), who through a range of coca-related programs in the region generally, with specific projects in Chapare aimed at developing agro-industries based on alternative crops. A key piece of legislation that is relevant to restricting coca in Bolivia was Law 1008. This law, which was passed in 1998, demarcated how much coca a household could grow, one cato[3] per household, and designated areas in which 'traditional' cultivation for leaves for chewing as legal cultivation areas. In all other parts of Bolivia coca cultivation was declared illegal, this included Chapare.

Amazingly, Human Rights Watch and the UN High Commission for Refugees (UNHCR) has monitored the violations of human rights issues, which have been an outcome of imposing anti-coca policies. Xie (2011) reported that in 2011, almost 35,000 families who depended on coca as a source of income were forced into poverty when their coca fields were destroyed and no economic alternatives offered (Law 1008).

The situation with respect to coca in Bolivia, and Chapare in particular, began to change with Evo Morales' Movement to Socialism (MAS) started to wield influence in the early 2000s (Table 2.4-1). MAS is a Spanish acronym where 'a' means 'to' in Spanish. When Morales become president in 2006, there is a major shift in policies which went under the mantra "*Coca si, Cocaine non*" giving coca farmers flexibility in growing coca plants but still limiting it to one cato per family (Farthing and Ledebur, 2014, Dangl, 2010). Specific policies recognised traditional uses of coca leaves in 2009. In 2017 Morales announced the expansion of the area of legal cultivation (BBC, 2017) .Coca farmers are closely monitored to meet the international obligations of not supporting the use of cocaine. Thus in 2013, there is 50,000 registered growers using well over 1.2 million acres of land. While UN uses satellite and surveillance to monitor coca growing in the study area, work is in place to register and monitor them electronically (Farthing and Ledebur, 2014).

[3] One cato is approximately 1,600 square meters and thus one cato of coca was estimated to earn around 70 to 100 dollars per month.

2.4.1 Alternative Farming and Deforestation

Alternative crops and farming methods were introduced in Chapare to encourage farmers to grow other cash crops apart from coca as one of the measures to reduce coca cultivation. The US government and the Bolivian government started promoting the establishment of alternative cropping system in 1975 shortly before the *Coca and Controlled Substances Regulation Law* (Law 1008 of 1998) came into effect (Sturm and Smith, 1993). The farmers were given technical assistance, in terms of aid and infrastructure that was fully funded by US AID. The main Bolivian organisation tasked to deliver this program was the Bolivian Institute of Agricultural Technology (IBTA). The major alternative crops cultivated in the study area were banana, palmetto, pineapple, black pepper and passion fruit (Table 2.4-3)

Table 2.4-3 Duration for the project and its aim to be used as anti-narcotics policy targeting coca. (Source; Bradley & Millington (2008b). CDRP = Cochabamba Regional Development Program; CORDEP = Chapare Regional Development Program; CONCADE = Counter Narcotics consolidation of Alternative Development Program.

Years	Projects	Aims
1984-1987	CDRP	Alternative crop were researched and introduced. Creation of micro regions centred around the coca growing areas.
1987-1990	CDRP (amended)	Crop substitution, research, and development into 40 years substitute crops in Chapare
1991-1999	CORDEP	Marketing and subsidizing of few specific coca alternative crops such as palm hearts, banana, and pineapples.
1999-2004	CONCADE	Support for Plan Dignidad, aimed at encouraging alternatives and stabilize alternative markets to coca bushes as they were eradicated.

Therefore, the crop mix in Chapare changed considerably as these were added to citrus, cassava, rice and livestock rearing. Coca was retained in the crop mix in many communities, illegally by this time. In 2002 the Bolivian Government announced the eradication of coca in Chapare (Bradley and Millington, 2008a),. That has drawn interest from other researchers who have looked at the coca policy arena in Bolivia, thus (Elsner, 2016) states that *“is one of the first Latin American county to implement economic adjustment programs in the farming sector”*

However, farmers growing alternative crops to meet the international demand were faced with a number of problems. The market prices from their products fluctuated, when subsides provided by USAID depleted and the crops were often uneconomic. They required more labour and large areas of land to respond to the market as well as meeting their household needs. Thus farmers formed cooperatives to address those issues to try and stabilise prices to provide for local economic security and to have a voice at a political level (Ofstehage, 2012). Farmers’ income from those alternative-farming crops still do not match with what coca had to offer: hence, coca remained part of the crop mix.

Bradley and Millington (2008b) examined forest clearance rates from forest and non-forest maps of farms in three communities in Chapare during the 1980s and 1990s. These were calibrated by interviews with farmers (Bradley 2005). Their finding was that when anti-coca policies were in force and alternative crops were actively promoted and supported financially deforestation rates were 0.9-1.1 ha/year per farm, whilst when policies were weakly enforced deforestation rates were much lower 0-0.4 ha/ year per farm. Their analysis did not include the strongly pro-coca vision that has been in place since 2003 (Table 2.4-1) and this research takes the opportunity to see if, after a decade of more of pro-coca policies and legislation, their hypothesis is correct. If it is, it would be expected that deforestation rates would be very low in the communities studied by Bradley and Millington (2008a) and forest cover would have stabilised or possibly even increased.

CHAPTER 3

3 : METHODOLODY

This chapter outlines what has been done in a sequential process. It also justifies why certain processes were chosen and how they were used. The chapter has three main sections grouped around the major steps in the work: image pre-processing, land-use and land-cover classification aimed at forest/non-forest mapping, and the generation of forest/non-forest statistics for individual communities.

The data collection and analysis is focussed on remote sensing, and various remote sensing techniques were applied and are outlined in the sections on pre-processing of imagery and land-cover and land-cover classification and mapping. This project used ERDAS Imagine 2015 and ArcGIS Version 10.4.1 software. There are various software packages for image processing and GIS, however the two were chosen because they are applied widely in the many areas of remote sensing and land-cover classification and are available in the institution where the study was conducted. The image data used were from the USGS (United States Geological Survey); this elaborated on further in Section 3.1. These data were acquired at no cost, which is an advantage.

The study focuses on a time series of images to detect and map land-cover changes and therefore, it uses of similar images in terms of the satellite-sensor series—Landsat–from 2011, 2015 and 2016 images. No cloud free imagery was available from 2012 or 2013, and Landsat data from 2014 for this area has already been analysed at Flinders University by Morgan (2015). Images between 1996 and 2003 were analysed by Bradley (2005), this was updated to 2006 (Bradley and Millington 2008a, 2008b), and CBERS imagery was investigated from 2007-2009 because of the problems with the series of Landsat satellite-sensors (Millington *et al*., 2009).This project therefore fills gaps and updates a time series of data for Chapare. Ground observations of land use and land cover, which were made available for this thesis for accuracy assessment purposes, were collected by Professor Andrew Millington in 2015. Much of what was done methodologically is summarised in Figure 2.4-1.

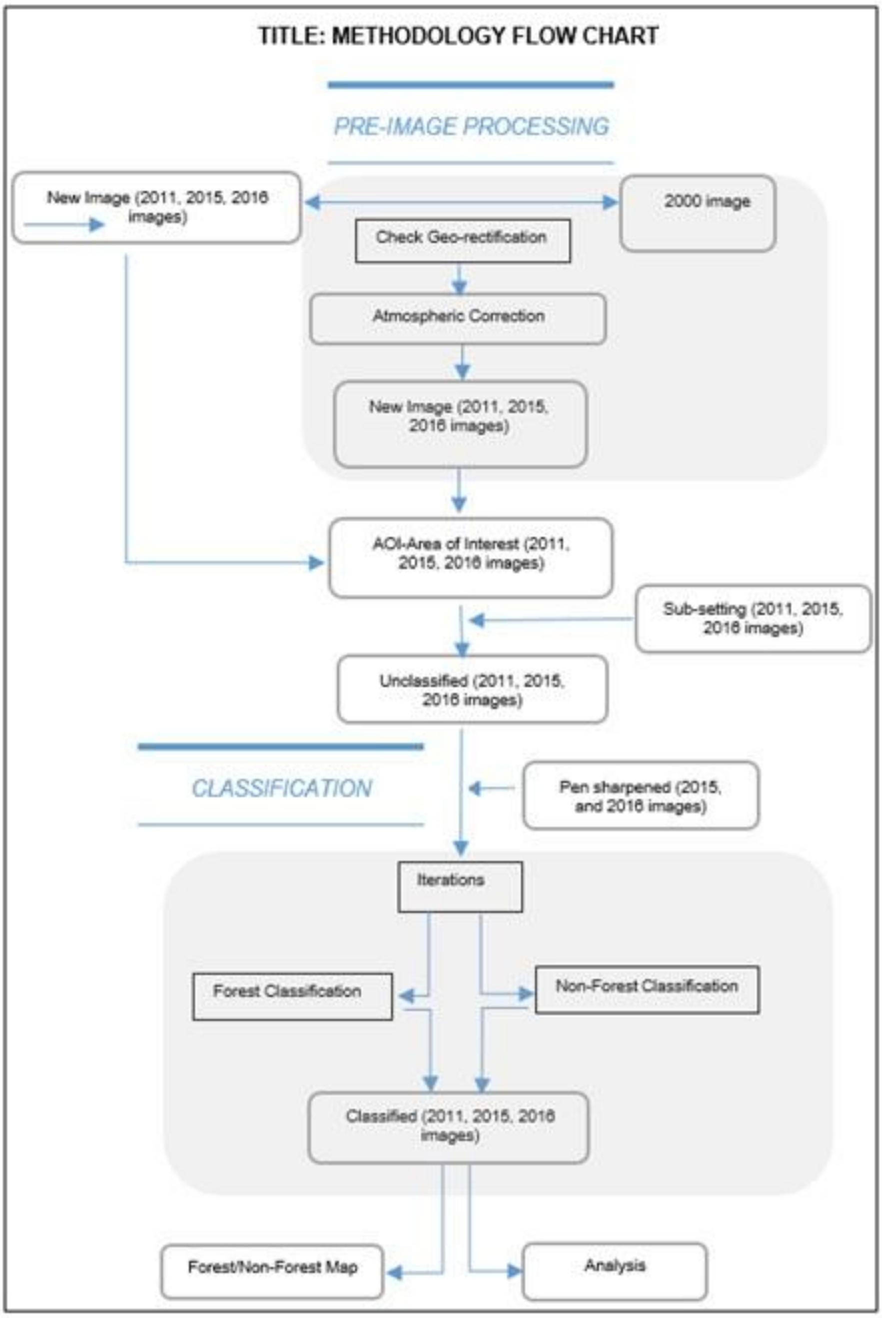

Figure 2.4-1; Flow chart of the methods used in this study from the image pre-processing of the images to forest/non-forest mapping and analysis.

3.1 Image pre-processing

3.1.1 Image downloads and image quality

The images were downloaded from the USGS through the *LansatLook* portal (https://landsatlook.usgs.gov/viewer.html). USGS is a scientific agency of the United States government, which focuses on studying the Earth's natural resources and natural hazards. One of the data sources it provides are images from the Landsat series of satellites. This series was designed to map and monitor earth resources for research and educational purposes. The first satellite, now known as Landsat 1, was launched in 1972. Its original name was the 'Earth Resource Technology Satellite 1'. The latest satellite in the series—Landsat 8–was launched in 2013 and is still in orbit. It is the longest series of remote sensing satellites and therefore has the longest archive of medium spatial resolution multispectral data. These characteristics make Landsat image data the clear choice for historical land-use and land-cover change studies. According to the USGS (2017) in the first three months of 2017, the biggest use of Landsat data (24.2%) was for land-use and land-cover change research. The sensors on board Landsat satellites have changed over time, but since the 1980s, channels have covered the visible, near infrared, short wave infrared and thermal infrared parts of the electromagnetic spectrum. The images used in this study were from Landsat 5 Thematic Mapper (TM) and Landsat 8 (ETM+ OLI). The images have a 30-m spatial resolution and are projected onto the WGS datum. The Enhanced Thematic Mapper sensors have two spectral bands not found on the Thematic Mapper, deep ultra-blue visible (0.43µm – 0.45µm) and a short wave infrared cirrus band (1.36µm – 1.38µm), as well as including a panchromatic (0.5µm – 0.6µm) band. The cirrus band was designed for cloud cover studies because it can detect cirrus cloud formation in the short wave infrared wavelength (Makarau *et al*., 2016). The data were downloaded as 8-bit quantized radiance data. Table 3.1-1 specifies the details of the Landsat satellites and sensors used.

Table 3.1-1 Tables outlining the bands for Landsat4-5 & Landsat 8 (OLI) (Source; https://landsat.usgs.gov)

Landsat 4-5 Thematic Mapper ™

Bands	**Wavelength (μm)**	**Spatial resolution (m)**
Band 1 –Visible Blue	0.45-0.52	30
Band 2 – Visible Green	0.52-0.60	30
Band 3 –Visible Red	0.63-0.69	30
Band 4 - Near Infrared (NIR)	0.76-0.90	30
Band 5 - Shortwave Infrared (SWIR) 1	1.55-1.75	30
Band 6 - Thermal	10.40-12.50	120* (30)
Band 7 - Shortwave Infrared (SWIR) 2	2.08-2.35	30
The approximate scene size is 170 km north-south by 183 km east-west (106 mi by 114 mi).		
Landsat 4 and 5 orbit height = 705.3 km		
Repeat interval = 16 days		

Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)

Bands	**Wavelength** (μm)	**Resolution (m)**
Band 1 – Visible Ultra Blue (coastal/aerosol)	0.43 - 0.45	30
Band 2 –Visible Blue	0.45 - 0.51	30
Band 3 –Visible Green	0.53 - 0.59	30
Band 4 –Visible Red	0.64 - 0.67	30
Band 5 - Near Infrared (NIR)	0.85 - 0.88	30
Band 6 - Shortwave Infrared (SWIR) 1	1.57 - 1.65	30
Band 7 - Shortwave Infrared (SWIR) 2	2.11 - 2.29	30
Band 8 - Panchromatic	0.50 - 0.68	15
Band 9 - Cirrus	1.36 - 1.38	30
Band 10 - Thermal Infrared (TIRS) 1	10.60 - 11.19	100 * (30)
Band 11 - Thermal Infrared (TIRS) 2	11.50 - 12.51	100 * (30)
The approximate scene size is 170 km north-south by 183 km east-west (106 mi by 114 mi).		
Landsat 8 orbit height = 705 km		
Repeat interval = 16 days		

The improved features of Landsat 8 OLI, including its aerosol bands, have greatly improved the quality and features in coastal studies (Finkl, 2016, Finkl and Makowski, 2014). However, the focus of this study on land-cover mapping in humid tropical forested environments was proven with Landsat TM and ETM+ (Foody *et al.*, 2010, Hyde *et al.*, 2006, Sobrino *et al*., 2004).

The images downloaded for this research had (i) less than 10 percent of cloud cover and, (ii) given that four images were required to create a mosaic that covered all of Chapare, a limit of no more than two months apart was set to avoid issues related to regrowth after crops had been harvested or new land cleared. These images were mostly acquired during the May and October dry season, the best images in terms of cloud cover and spectral contrast were from August and September. For a humid tropical country, the ability to obtain cloud-free satellite scenes involves an element of luck and the option to revert to radar data did not have to be exercised. Table 3.1.-2 presents a list of the images acquired with their dates of acquisition and cloud cover statistics.

All the images acquired had been geometrically and radiometrically corrected by the USGS. Radiometric correction involves corrective measures to compensate for the errors and distortions due to sun's azimuth, atmospheric conditions, aerosols in the atmosphere and changes in sensor response. Geometric correction relates to geometric distortion of the image and the projection of the image. Good GIS practice suggest that all data must be verified for geo-rectification and that has been done, and this is essential when changes in boundaries, e.g., forest/non-forest boundaries, are being analysed. Thus, the images were correctly geometrically and ready for use as follows, images acquired in row 233 are projected to WGS 84 UTM Zone 19S while those on rows 232 and 231 images are projected on WGS 84 UTM Zone 20S.

Table 3.1-2 ; Images used in this research project

2016

Scene ID	Sensor	Path	Row	Cloud Cover	Scene time (GMT)	Date
LC83230722016168LGN00	OLI	232	072	8%	14:22:32	16-Jun
LC83230712016168LGN00	OLI	232	071	0%	14:22:08	16-Jun
LC83210722016305LGN00	OLI	231	072	2%	14:17:00	31-Oct
LC82320722016200LGN00	OLI	232	072	16%	14:22:48	18-Jul
LC82320722016216LGN00	OLI	232	072	16%	14:22:51	3-Aug

2015

Scene ID	Sensor	Path	Row	Cloud Cover	Scene time (GMT)	Date
LC82320722015293LGN00	OLI	232	072	0%	14:22:29	20-Oct
LC82320712015293LGN00	OLI	232	071	6%	14:22:53	20-Oct
LC82330712015316LGN00	OLI	233	071	3%	14:16:27	12-Nov
LC82310722015238LGN00	OLI	231	072	15%	14:28:43	26-Aug

2011

Scene ID	Sensor	Path	Row	Cloud Cover	Scene time (GMT)	Date
LT52330712011193CUB01	TM	233	071	3%	14:17:49	12-Jul
LT52320712011218CUB01	TM	232	071	0%	14:11:23	6-Aug
LT52320722011218CUB01	TM	232	072	6%	14:11:47	6-Aug
LT52310722011259CUB01	TM	231	072	0%	14:05:11	16-Sep

The radiometric and geometric correction was done prior to the image data being downloaded through the *LandsatLook* portal. This is because they are from a relatively new source of atmospherically corrected imagery for land-change detection and environmental monitoring—the Surface Reflectance Calibrated Image Archive` (USGS, 2015a, Feng *et al*., 2013, Vuolo *et al*., 2015). This is part of the Landsat Surface Reflectance Climate Data Record (Landsat CDR), which is part of the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) ((Vuolo *et al.*, 2015).

The images in this archive have been calibrated to surface reflectance by applying a model that uses physically based measurements of land surface properties. It converts to top-of-atmosphere reflectance values before atmospheric effects are removed, thereby producing at-surface reflectance values (USGS, 2015b). Data are supplied in either a Universal Transverse Mercator (UTM) or Polar Stereographic (PS) format (Masek *et al*., 2006). Ross *et al*., (2017) have argued that these data are well suited to observing and analysing land-cover change because (i) Landsat image data have been used extensively in land-cover analyses, and (ii) these data are atmospherically-corrected and georectified significant amounts of image processing time and effort by researchers has been saved. The archive includes TM, ETM+ and OLI imagery at 30 m spatial resolution, MSS data are not included in the archive at the present time. Despite the fact that corrections have been done prior to the images being downloaded, they were checked before being processed further.

3.1.2 Haze Correction

Most satellite imagery acquired over tropical countries are not free of cloud cover and therefore it can cause the acquired imagery to have reduced contrast and can lead to land-cover misclassification. This is a result of atmospheric scattering and absorption in high humidity regions (Richards, 2012), thus it cannot be completely eradicated as argued earlier (Chavez, 1988). Thus, the images used required haze reduction to sharpen them. This correction was done by using the tasselled cap transformation in which the component that correlates with haze is transformed back into RGB space; this technique has been widely applied in studies focusing on crop development cycles (Dave, 1981). This is because when crops emerge, they tend to cast shadows over the ground but the soil still dominates reflectance values. Later, when they mature, they tend to cover the soil increasing NIR reflectance and then when they wilt and turn yellow NIR reflectance declines in a manner depicted by the tasselled cap model itself (Richards, 2012). As the focus was on cropped and forested land, and because (i) the images in any single annual image can cover up to 13 weeks, and (ii) because cropping cycles vary slightly between years. Even though this technique is widely used in cropping cycle, it is commonly used in haze correction as stated earlier as it is a spectral transformation technique because of the low frequencies where haze is normally distributed (Hu *et al*., 2009).

3.1.3 Sub-setting the area of study

The Chapare colonization zone or area of interest (AOI) overlaps four different images (Table 3.1-2). Therefore, the specific areas on each image that make up the AOI had to be cut from the individual images before they could be mosaicked together to reduce larger image processing effort and to minimize variance in radiance over the ~500 x ~300 km combined of the four images that would distort results from information extraction algorithms.

The ERDAS Image subset and chip tool was used to subset the component parts of the AOI from each image. The output file is continuous raster data, sometimes called non-discrete data.

3.1.4 Mosaicking

Mosaicking was done to stitch together the different components of the AOI from the four geo-referenced images. This was done separately for each of the 'years' (Table 3.1-2). The input files for mosaicking are the output files from the subset and chip algorithm. The have the same projection and number of bands as the original images they were subset from originally.

The four images used to create the mosaic for any one year were acquired on different dates from the low rainfall season (Table 3.1-2). This is done by setting a low land cover change threshold for data downloading. Nonetheless, contrast between some images indicates differences in radiometric properties between dates and across the entire extent of the imagery. In addition, and despite the use of the tasselled cap transformation, there will be some areas in one image of a mosaic where crops may have been harvested but not in another image acquired at an earlier date; or where land preparation (cutting secondary regrowth and burning) has taken place in a later image but not in an earlier image. Overall, the land cover will still be agricultural and not regrowth forest.

The radiometric issue in mosaicking was dealt with at his stage in the processing chain. The methods tested were i) colour balancing, ii) illumination correct and iii) histogram matching. All those methods tested to identify the best method that does not change the radiometric properties of pixels before they are classified. Illumination correction and histogram matching were used to accomplish this. Illumination correction was chosen because it increases illumination levels in dark (low reflectance) pixels, while simultaneously decreasing illumination in bright (high reflectance) pixels, using an image as a reference, to provide a uniform correction to the other three images as far as possible.

Mosaicking uses an algorithm that stitches together images as well as correcting the colour and illumination levels. Various options are available for image mosaicking. The one used in this research was histogram matching. In this, a histogram of the image, which is unambiguously clear of cloud, was used to match to the other three images. It was used in this research because the images selected were a few months apart in their dates of acquisition and their radiance characteristics will have some differences. Therefore, histogram matching was used to obtain uniformity in radiance over the entire stitched image mosaic. This does possibly introduce noise but it proved to produce a better output compared to the other options for mosaicking as compared. The other options compared were image dodging, illumination equalization, and colour balancing as stated.

3.1.5 Sharpening

Pan (panchromatic) sharpening is an image enhancement technique that improves the image quality from low- to a high- spatial resolution. With OLI data, it transforms and enhances an image created from the multispectral bands by merging the high spatial panchromatic band (Table 3.1-1) to create high spatial resolution colour bands reveal finer spatial detail. In doing so, it retains the radiometric quality from the 30 m spatial resolution data while incorporating the spatial details of the 15 m panchromatic band. It was applied to 2015 image after mosaicking for the purpose of improving the definition of the pixel boundaries (Tarolli *et al*., 2014) so that small agricultural plots of, and possibly even coca plots classes, could be defined and mapped.

Using pan sharpening does lead to a trade-off between the spectral resolution and the spatial resolution, with the image being resampled back to the spatial resolution of the panchromatic image (Richards, 2012). This is the reason why most recent commercial satellites like IKONOS, WolrdView2, WorldView3, SkySat1 provide three or more relatively coarse spatial resolution multispectral bands along with a finer spatial resolution panchromatic band.

In the pan-sharpening algorithm in ERDAS Imagine, the panchromatic band is overlain on the multispectral image, and adjusts the saturation and brightness levels to enhance the spatial resolution of the multispectral image. Pan sharpening was deemed essential to bring out the features and increase the resolution of the colour information before classification.

3.2 Classification

Land-use and land-cover classification generally relies on supervised classification or unsupervised classification techniques. Supervised classification is used when the user guides the image processing steps used in determining the land cover classes. In particular, the user decides on the following key steps, selecting training data and training the classification algorithm (Richards and Jia, 2006) and in deciding which technique, usually maximum likelihood classification, minimum distance or parallelepiped classification, to use. Unsupervised classification differs from supervised classification in that training, which is not undertaken by the operator before the algorithm, which clusters image pixels into unknown but statistically defined classes, is applied. Nonetheless, the onus is on the user to identify the classes at the end of the classification.

Unsupervised classification was used for all three images for two reasons as a result of the algorithm (tasselled cap) used in the classification.

1. Consistency of methods, so that results are comparable like the statistics from Bradley, (2005) used in this research study. The image processing protocol used (Bradley, 2005), was followed and modified by Dr. Danny Redo and Dr. Mlenge Mgendi when they analysed 2006, 2007 and 2008 data for this area at Texas A & M University. This protocol was followed again by Andrew Morgan in an undergraduate BAGIS thesis at Flinders when analysing 2014 imagery (Morgan, 2015)

2. As forest/non-forest maps were the ultimate product required for the community-scale quantitative analysis, robust land-use and land-cover classifications are perfectly adequate. Forest and non-forest classes can be derived by merging land-use and land-cover classes derived from unsupervised classification by references to the 400+ ground observations that were made in Chapare in 2003 by Andrew Bradley, 2007 by Danny Redo and, importantly for this thesis in 2015 by Andrew Millington.

3.2.1 Unsupervised Classification

The steps in the unsupervised classification process adopted for this research are outlined in Figure 3.2-1 and Figure 3.2-2.

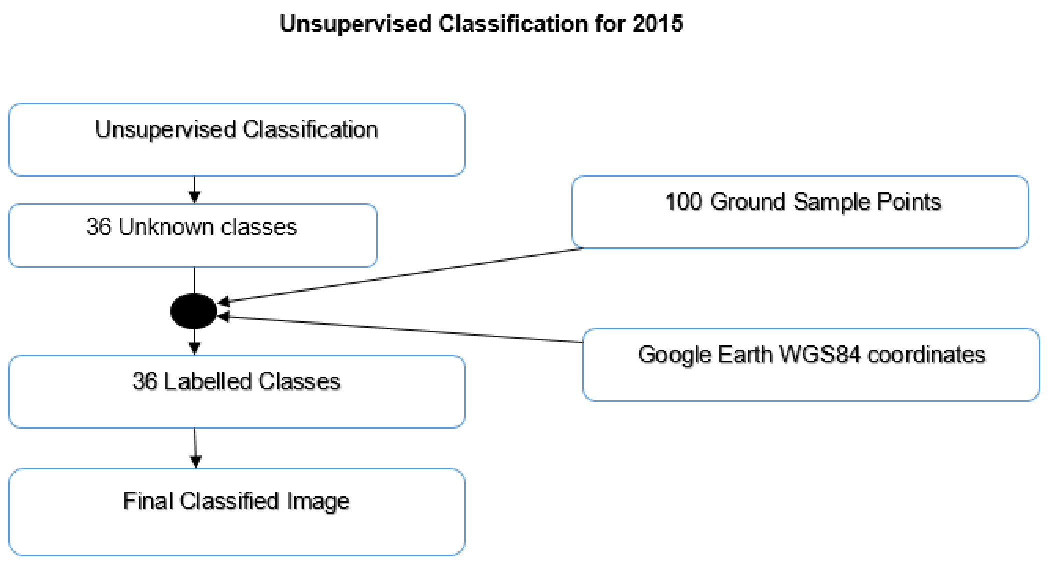

Figure 3.2-1 The flow diagram for the unsupervised classification for 2015 image

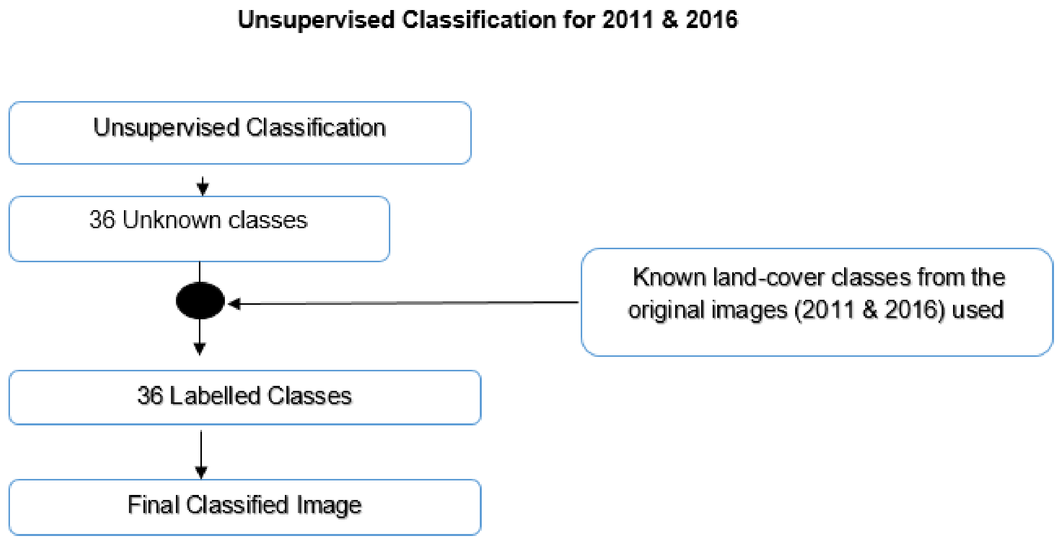

Figure 3.2-2 The flow diagram for the unsupervised classification for 2011& 2016 images

3.2.2 K-means and ISODATA

In unsupervised classification, K-means is a technique in which a predetermined number of clusters is chosen for the pixels to be classified into classes. In this research project, the classification algorithm chosen was the Iterative Self-Organising Data Analysis Technique (ISODATA) was used. K-means and ISODATA are part of the Unsupervised Classification tool in ERDAS Imagine and both were used in this study.

Given a predetermined number of iterations (in this project this was set at 10), ISODATA splits and merges clusters of pixels based on the mean distance to the centre of each clusters of pixels vector until the maximum number of iterations or a percentage of the pixels of a specific cluster is reached (Jensen, 1996). It uses the minimum distance formula to determine which cluster a pixel is placed. Other thresholds set when using ISODATA in this research were a convergence threshold of 0.95 and a skip factor of 1. The convergence threshold was set at 95%, meaning only a maximum of 5% of pixels can be changed at any iteration

ISODATA clustering improves on K-means by carrying out a number of checks on the pixels at the end of each iteration, i.e., after they have been assigned to a class (Richards, 2012), it calculates the mean of each cluster that is distributed in n-dimensional data space, where n is the number of bands input into the algorithm. It then recalculates new means and re-classifies each pixel according to the new means. In this way, it assigns each pixel to a possible class according to its relationship to the means of all the clusters, by recalculating means at each iteration new clusters can be created. For example, it can split as clusters of ‘forest’ pixels and bring out new clusters of ‘forest’ pixels based on reflectance thresholds calculated at an iteration, which are based on forest canopy properties. Recalculating means and re-clustering is important in areas where there are many potential land-use classes with overlapping spectral properties, e.g., in Chapare, an example would be overgrown citrus plantations and medium-height secondary forest, which would not be possible by forcing training classes defined by land-use observations in a supervised classification. This argument is supported by Finkl (2016), who discriminated mangrove forests from other forest vegetation using ISODATA, and (Garrison, 2010) who also used ISODATA to map forest environments from Quickbird data in Mesoamerica for later ground surveys.

3.2.3 Re-coding Clusters into Classes

Analysis of the clusters generated in an unsupervised classification is required to determine the relationships between different clusters and land uses and land covers occurring in an area being researched. In this project the cluster outputs of the ISODATA algorithm were re-coded with reference to the ground survey of land use conducted along eight transects (Appendix 3.1) in Chapare in August and September 2015. The major land cover classes identified in the field survey were:

forest (both lowland and mountain forest, high regrowth, medium regrowth, low regrowth, citrus, palmetto, banana, pasture, bare soil, water, and cultivation (small agricultural plots combined together).

Re-coding was done for the 2015 imagery. The land use verification points recorded by GPS were re-projected to a UTM projection. This process has a number of steps that are illustrated in Figure 3.2-3. These steps are:

1. Locations with unambiguous land-use and land-cover classes were selected from the field sheets (Appendix 3.2).
2. GPS coordinates for the locations selected in [1] were converted to latitude and longitude coordinates in the correct WGS84 datum, because ERDAS Imagine uses the WGS84 coordinate system.
3. These locations were studied in Google Earth along with the field sketch maps and field photos, and land parcels that could be used as reference data for re-coding were selected.
4. Latitude and longitude coordinates of the land parcels identified in [3] were recorded.
5. Each of the pixels identified in [3] were examined on the classified image and a land-use or land-cover class identification made (Appendix 3.3). This was repeated for other pixels.
6. Once a land-use or land-cover class had been identified by reference to a number of known field locations, the pixels in that cluster were re-coded to form named land-use or land-cover class. This is done by using the recode tool from Raster GIS Toolkit in ERDAS Imagine.
7. Once all the clusters had been named by reference to the field data, as outlined in Step 6. Classes were merged into forest and non- forest classes,

as well as a water and unclassified pixels classes to create a forest/non-forest raster image.

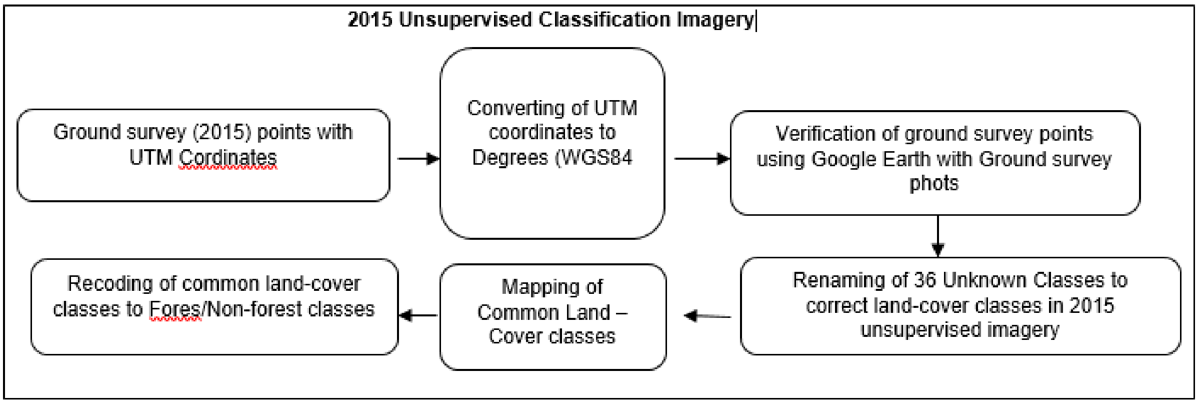

Figure 3.2-3 Flow chart of the re-coding of clusters from ISODATA classification to forest and non-forest classes.

Re-coding for 2011 and 2016 imagery was by reference to land-use and land-cover that were unlikely to have changed between 2011 and 2016. These included the Universidad Mayor San Simon Forest Reserve in eastern Chapare, montane forests in the Serrania des Mosotenes, and forest areas that were mapped in TIPNIS in 2016 as these are still primary forest areas. Key non-forest areas that are known not to have changed were selected by reference to the 2003, 2007 and 2015 ground surveys, these included large pastures in eastern Chapare, pastures between Ivirgarzama and Vueltadero, and banana plantations north of Chimoré and in eastern Chapare. A flow chart illustrating this is provided in Figure 3.2-4.

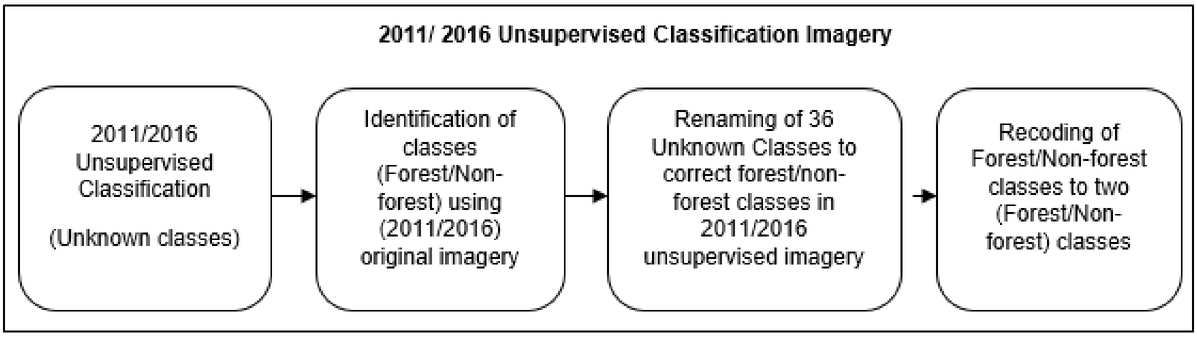

Figure 3.2-4; Flow chart of the re-coding process applied to the 2011 and 2016 unsupervised classifications.

3.3 Forest and non-forest mapping

Forest and non-forest mapping was carried out using ArcGIS after the re-coding of classes in ERDAS Imagine. This was done because for a proper mapping product basic information such as the projection coordinate system, direction and symbology needs to be shown for the users' convenience. Skaloš and Engstová (2010) show how important this information is in mapping forest and stress that this information itself can portray a lot of information.

The steps in creating the 2011, 2015 and 2016 forest and non-forest maps are as follows:

1. The clusters are combined to create forest and non-forest raster data layers as described above.
2. The raster images were projected to the correct WGS datum, as indicated above.
3. After the raster images were projected, gridlines, co-ordinates, direction arrows, scale bars and legends were added.
4. The maps from step [3] were saved and exported in pdf format and are presented in Chapter 4.

However, for the forest/non-forest maps for community-level analyses, additional tasks were undertaken prior to mapping.

1. The forest/non-forest maps created in the steps above were overlaid with shape files of land-tenure grids for Communities I to III. These grids were made available to the researcher, as they are part of the archive of Chapare data currently held at Flinders University. A new grid was made for Community IV by drawing lines backwards from cleared areas, so that each farm comprised 20 ha, the standard for non-grazing land holdings in Chapare.
2. The forest and non-forest classes for each community were clipped using the Extract by Mask tool in Spatial Analyst extension for ArcGIS.
3. The shape files of the land parcel boundaries for each community were overlaid on the forest /non-forest maps.
4. Steps [2] and [3] from the steps outlined above were repeated for the community-level maps.
5. The maps were saved and exported as pdf files.

These steps were repeated for each community starting from step 2.

3.4 Determining the accuracy of classified images

3.4.1 Use of field sample points for 2015 imagery

Accuracy assessment was undertaken for the 2015 classified image using a selection of land-use survey points from those collected by Andrew Millington in 2015, the details of which are provided in Appendix 3.4. The points selected for accuracy analysis were chosen by reference to the following criteria:

1. They had at least one unambiguous land use class on the field sketch map that could be confirmed by reference to the accompanying field photographs and/or Google Earth imagery from 2015.
2. That there was a spread of points across Chapare, points were taken from all eight transects (Appendix 3.1) from IS transect in the north west to A6 transect in the south east (Figures 3.4-1 to 3.4-4)

Once a point that met the first criteria had been identified, the following procedure was followed:

1. The map, field photographs and Google Earth imagery were consulted and as many areas of unambiguous land use were identified as possible close to that point.
2. For each of the unambiguous areas of land use, the UTM coordinates were obtained from Google Earth.
3. The UTM coordinates were converted to the WGS 84 datum and a point shape file created using ArcMap 10.4.
4. The image of land-cover classes derived from the classified 2015 imagery were imported in ArcMap 10.4
5. The Extract Multiple Values to Points in the Extraction tool in ArcMap 10.4 was used to generate a new column in the attribute table of the points shape file, which contains the id values of land cover at the selected point.
6. Another new column is added to the attribute table of the point shape file in preparation for the names of the land use or land cover classes after step 7.
7. The two attribute tables were joined together using the id values in the classified imagery to the newly generated column when extracting points to values.

8. The land use or land cover class names were generated using the Field Calculator to convert id values to class names.
9. The attribute table from Step 8 was exported to dBase file to build the confusion matrix for accuracy assessment.

The sample points are illustrated in the following figures. Note that when examining these figures that the sample points may have more than one unambiguous land-use class associated with it.

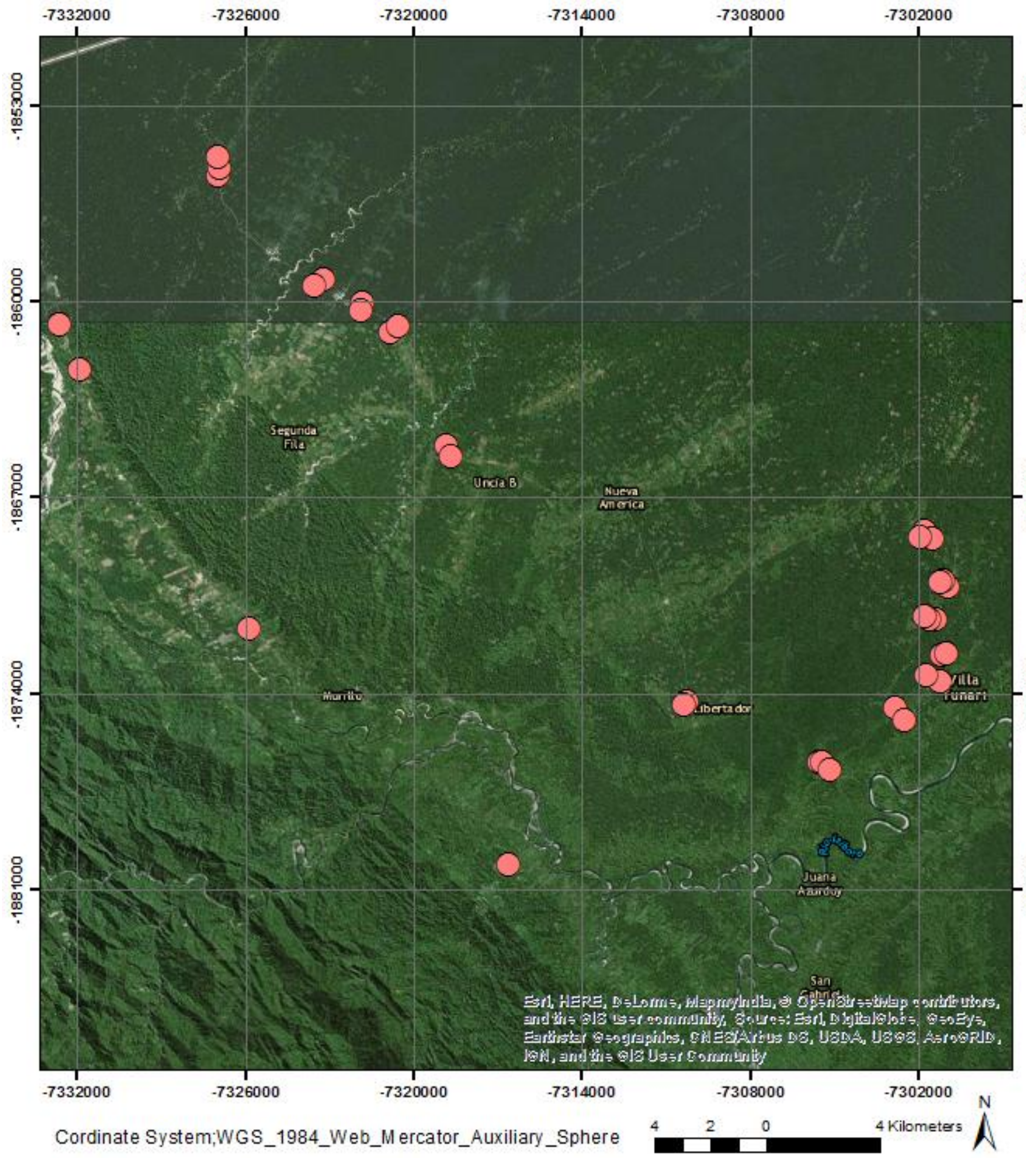

Figure 3.4-1; Sample points used in accuracy assessment in North West Chapare, in Territorio Indigena y Parque Nacional Isiboro Securé along the three IS transect

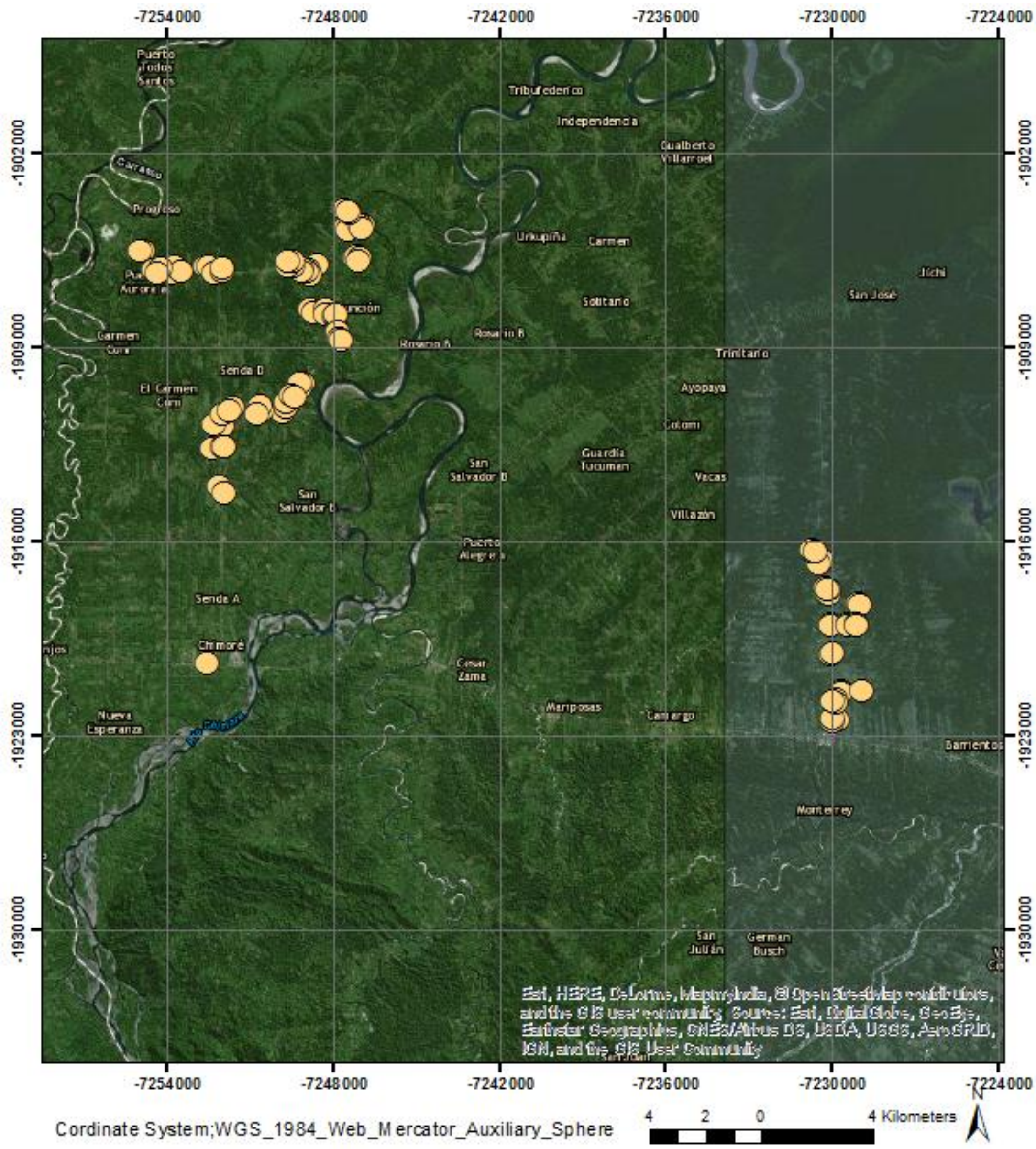

Figure 3.4-2; Sample points used in accuracy assessment in central Chapare, north of Chimoré between Río Chimoré and Río Coni along A1 transect (upper west of image) and along Senda 6, part of the A2 transect (east of image)

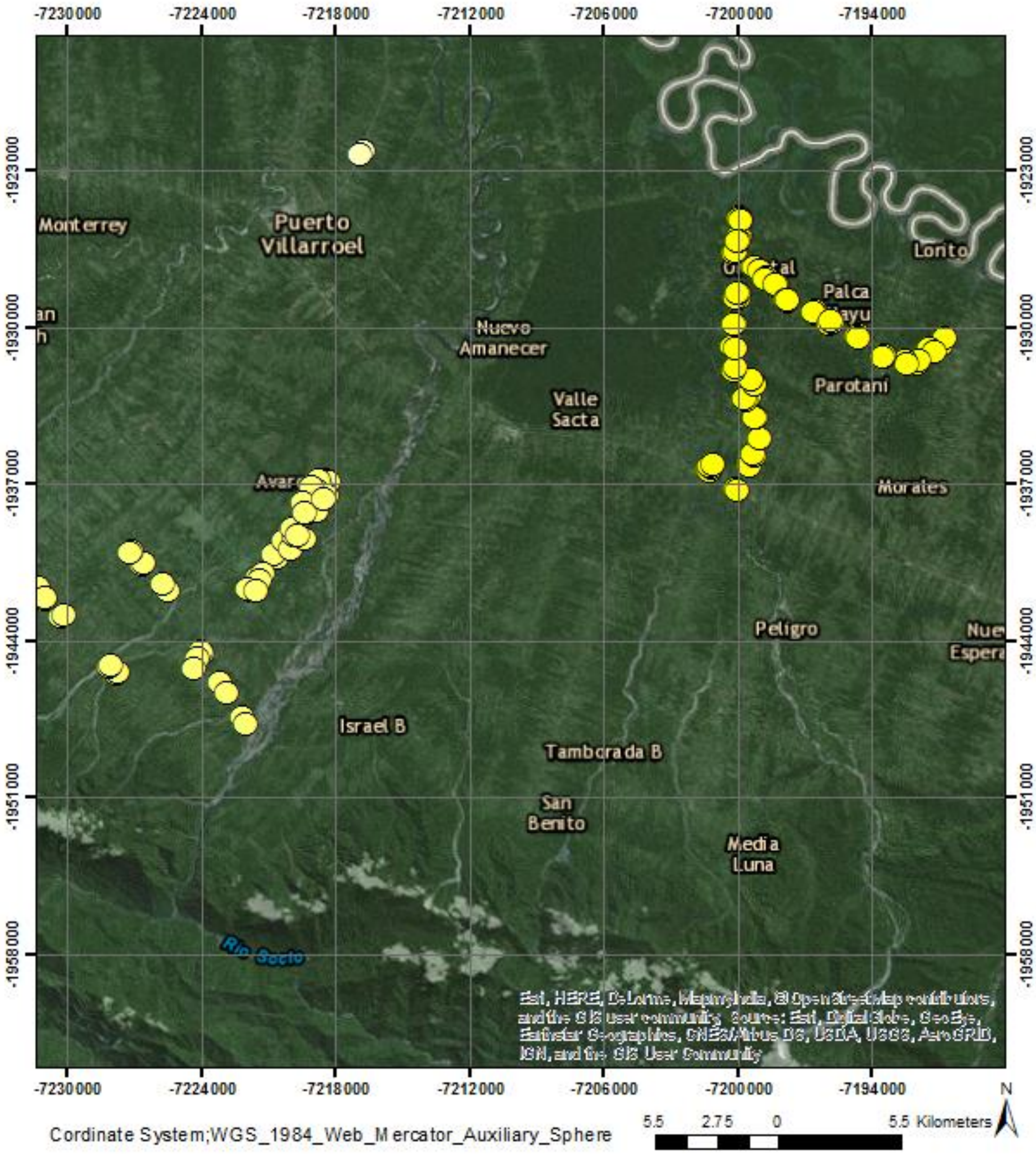

Figure 3.4-3; Sample points used in accuracy assessment in east central Chapare, along the Ivigarzama-Puerto Villaroel road (A4 transect), the Ivigarzama sector (A3 transect) and north of Ruta Nacional 4, between Río Sajta and Entre Rios (A5 transect)

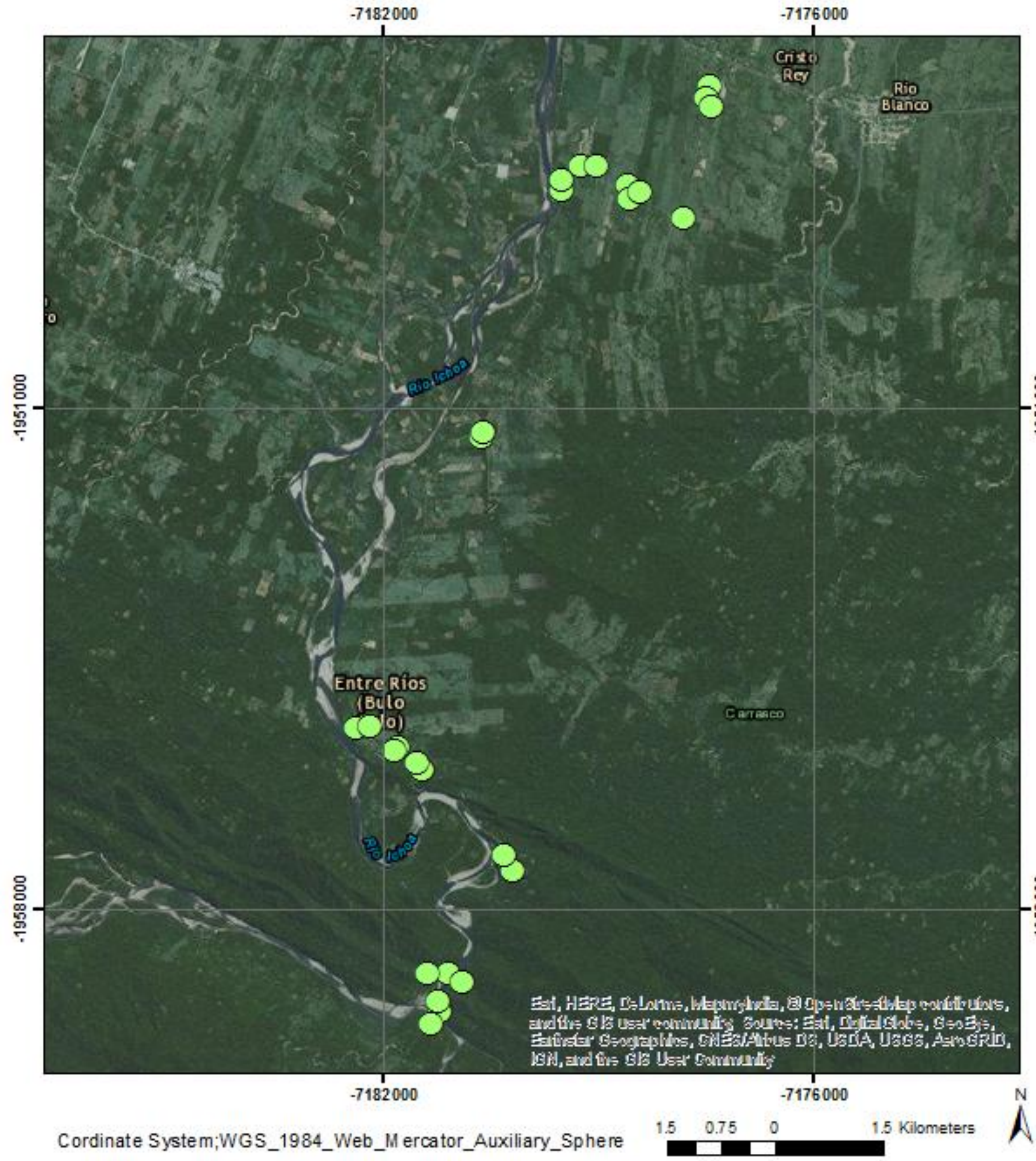

Figure 3.4-4; Sample points used in accuracy assessment along the A6 transect east of Río Ichoa, in eastern Chapare

3.4.2 Accuracy Assessment

Accuracy assessment is a key element in proving the results from any form of classification (Agyemang *et al.*, 2011) to the degree of which the results is correct. This is because accuracy assessment quantitatively verifies agreement between the remote sensing outputs and reference data (either ground verification, which is sometimes erroneously called ground truth), which nowadays often includes Google Earth imagery. The remote sensing output is the land-use and land-cover classification. Stehman and Czaplewski (1998) state that, "*accuracy assessment using statistically rigorous methods must be done before scientific decisions and polices are made*" based on the remotely sensed data that has been analysed.

The statistical techniques used for accuracy assessment depend on the nature and the type of study undertaken. Habitat modelling, for example, routinely uses Receiver Operator Characteristics (ROC) and Generalized Cross Validation (GCV) both are statistic model curves to measure the degree of correctness. Moreover, land cover classification employs techniques such as Pearson (R^2) correlation coefficients, Kappa coefficients and Base Error matrices, which are also known as confusion matrices for accuracy assessments. The latter analyse the level of agreement between land class data derived from remote sensing analyses and reference data from ground observations or other imagery. The accuracy of individual classes, commission and omission errors, and overall accuracy are calculated. Accuracy of the 2015 unsupervised classified image was assessed using a Kappa co-efficient and a confusion matrix. Accuracy assessment for the 2011 and 2016 classified image used the same method. However, as there was no simultaneous ground verification data, the original (downloaded) image was used.

This image was used to create random points for each of the major land-use and land-cover classes. These points were then compared to the classified image using ArcGIS to create a matrix table for their accuracy assessment similar to the steps employed for 2015 image.

3.4.3 Computing statistics for accuracy assessments

The statistics listed above were calculated from the confusion matrix for the 2015 image to assess the accuracy of the predicted land-use and land-cover classes. The overall accuracy of the land-use classes in the AOI and for the forest and non-forest classes was calculated using Equation 3.4-1:

Overall accuracy = correct prediction/ overall prediction (Equation 3.4-1)

The Kappa coefficient (*K*) was calculated using Equation 3.4-2:

$$\kappa = \frac{p_o - p_e}{1 - p_e}$$ (Equation 3.4-1)

Where, *Po* = observed agreement from the ground truth data, and *Pe* = expected agreement from the classification. After the Kappa co-efficient has been calculated a qualitative assessment of how good the classification is can be made by reference to the values in Table 3.4-1 (Alagu Raja *et al*., 2009). These statistics can be made more robust by checking the occurrence of any variable used with a predicted variable rather than using simple overall percentage agreement (Resler *et al*., 2014) in the study.

Table 3.4-1; Kappa values and characteristics (Source; Anand *et al*, 2009)

Value	Characteristics
<0	No agreement
0-0.2	Slight Agreement
0.21-0.4	Fair Agreement
0.41-0.6	Moderate Agreement
0.61-0.8	Strong Agreement
0.81-1	Perfect Agreement

3.5 Community-level forest change analysis

Testing Bradley and Millington's (Bradley and Millington, 2008b) hypothesis requires forest and non-forest maps to be created for each farm or land parcel in communities and forest and non-forest area statistics for that year, and forest clearance rates between years to be calculated.

Bradley and Millington (2008b) constructed shape files for three communities, which comprise 255 land parcels in total, from the original land parcel plans constructed by field surveyors as each community was established. The shape files from their study were made available for this research project.

The three communities studied previously were in central and eastern Chapare, and it was decided to add a fourth community in this research in western Chapare where forest dynamics are different. The four communities names are not revealed because of the sensitivity of coca as illicit drug and agreement with parcel owners when data was collected (Bradley, 2005). However, according to Andrew Millington the original survey plans are no longer available under the MAS government. The fourth community is selected along the Isiboro transect to give evenly distributed results over the study area for a better summary of the changing deforestation rate over the study region. A shape file for the new community was added using the editor tool in ArcMap, and it was created as follows:

1. A new polygon file was created using ArcMap 10.4.1
2. A base map (imagery with labels) was added as a new layer.
3. The boundaries of each land parcel in the community was drawn in the correct projection for western Chapare (WGS 84 Zone 19S) using the Editor tool.
4. These land parcels were saved and overlain on the community and the fit checked,
5. The community was clipped from the forest/non-forest map for Chapare.

The shape file was adjusted to fit the land use patterns using common points in the spatial adjustment tool. The shape file was then overlayed on the classified image as discussed in Section 3.3 when mapping forest and non-forest areas. The shape file and the multispectral image were geo-referenced in ArcMap. This was done for the four communities.

3.5.1 Community-level statistics

The formula below (Equation 3.5-1) was used to calculate rate of forest cover change for the four communities investigated in this study. The standardised method known as the Compound Interest Law, is applied in this study to calculate annual rates of deforestation (Puyravaud, 2003)

$$\boldsymbol{R} = \frac{\boldsymbol{A_1} - \boldsymbol{A_2}}{\boldsymbol{T_2} - \boldsymbol{T_1}} \qquad \text{Equation 3.5-1}$$

Where, A_1 is forest area at time 1 (T_1) and A_2 is forest area at time 2 (T_2)

CHAPTER 4

4 : RESULTS

This chapter provides the results from the methods outlined in Chapter 3 applied to the image data for Chapare. The pre-processing section mainly looks at the results of mosaicking and pan sharpening. This chapter shows the enhanced image after classification. The following two sections shows the maps land use and land cover classification (LULCC), and forest and non-forest areas. Those are then followed by the results of the accuracy assessment. The final section presents the community level forest, non-forest and forest clearance statistics and compares these to prior data (Bradley and Millington 2008, and unpublished data).

4.1 Image Pre-Processing

The images acquired in 2015 that were used in mosaicking are illustrated in Figure 4.1-1. All the results in this section are illustrated with 2015 image data. The four scenes in this image are Landsat 8 images. That on the left is path 233, row 071 in the Landsat worldwide reference system (WRS), the middle top scene is path 232, row 71, the middle bottom scene is path 232, row 72 and the image on the right is from is on path 231, row 72. Figure 4.1-1 shows subsets of imagery (see table 3.1-2 in Section 3.1.1) from each image rather than the entire images. Mosaicking (Section 3.1.4) was also done for the 2011 and 2016 images using the imagery for the same WRS paths and rows. The subsets cut from each scene were stitched together to form a single raster image (Figure 4.1-2). The 2011 and 2016 scenes were treated in the same way including colour corrections within the mosaicking procedure to give a good colour contrast for classification.

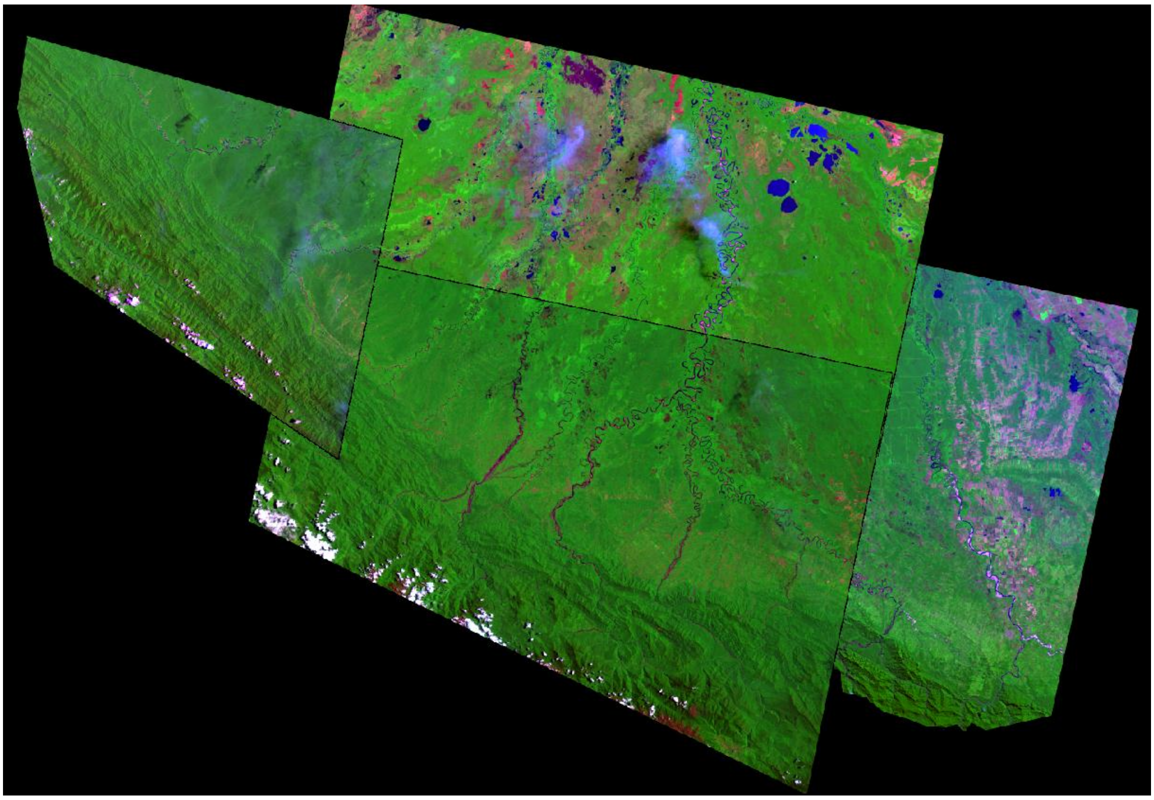

Figure 4.1-1; 2015 images after sub-setting and before mosaicking. These images have been geo-rectified and radiometrically corrected.

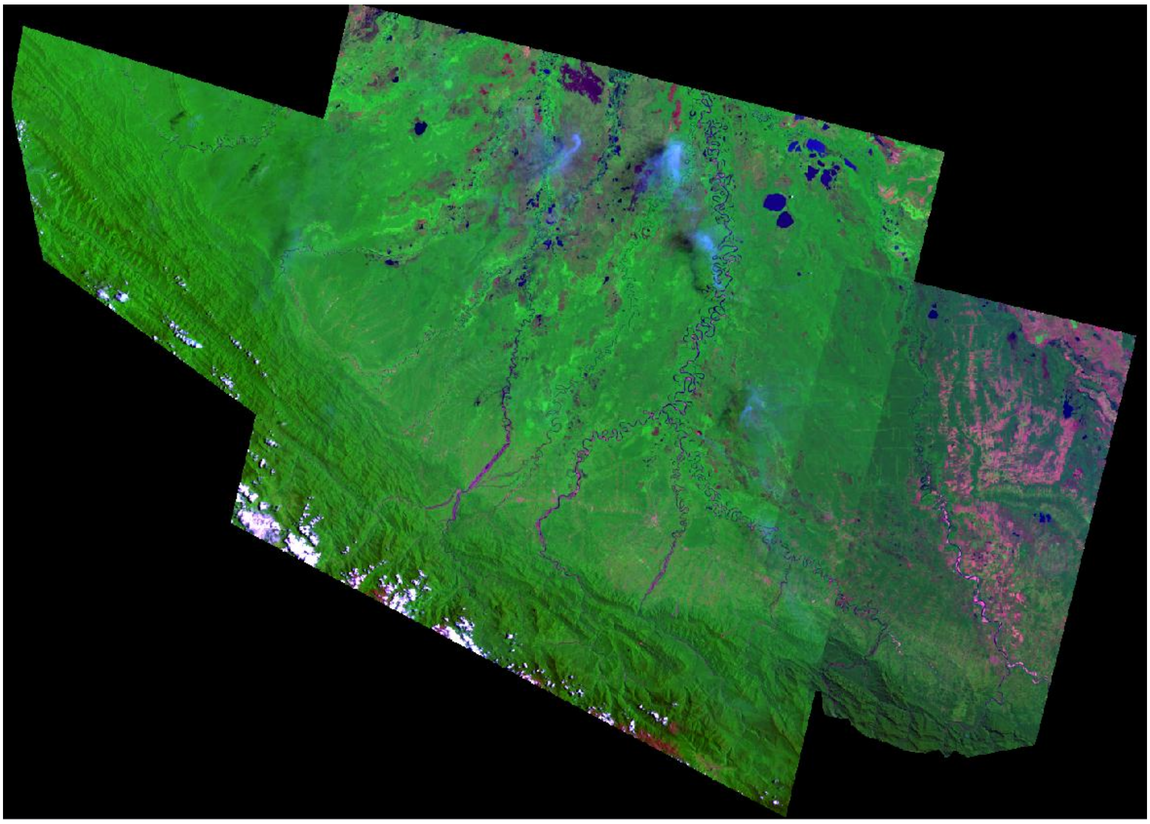

Figure 4.1-2; Histogram-matched 2015 image mosaic in which the radiance values have been corrected across the four scenes.

4.1.1 Normal and pan sharpened images

The 2015 and 2016 images (Table 3.1-1 Landsat bands) have panchromatic bands that was used in pan sharpening the mosaicked images to increase image contrast. Figure 4.1-3 shows the normal and pan-sharpened image for a subset that includes Chimoré airport, features such as roads, urban areas and the airport's runway are more distinct in the pan-sharpened image (Figure 4.1-3b) compared to the false colour composite (FCC) image that has not been pan sharpened (Figure 4.1-3a). For the FCC, band 2 was given the blue colour gun, band 5 was given the green and band 7 was given the red colour gun.

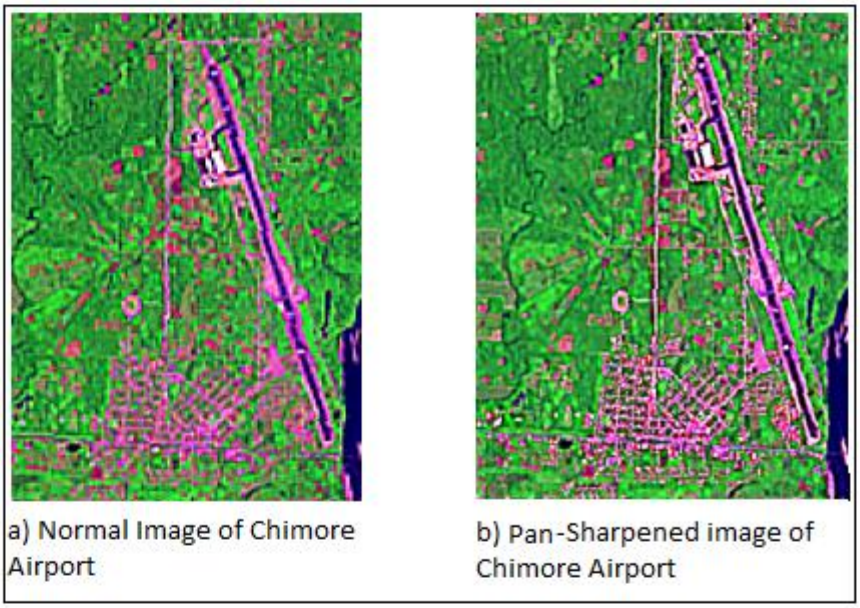

Figure 4.1-3 ; a) False Colour Composite - FCC (Band 257) of Chimoré Airport, b) Pan-sharpened image with FCC (band 257). The image is approximately 3 x 4 km.

4.2 Land use and land cover classification

Unsupervised classification (k-means and ISODATA, Section 3.2.2) were applied to the image mosaics to derive land use and land cover classes for the study area. This land use and land cover map for the study area for the 2015 are illustrated in Figure

4.2.1. The images for 2011 and 2016 focused on deriving the forest and non-forest classification areas rather than full LULCC classification. The 2015 image was utilised to derive full major LULCC because of the availability of field survey points before proceeding to obtain the forest and non-forest class. Most classes on this map are the main LULC (land use and land cover) classes recorded in the field from the August-September 2015 field survey (Appendix 3.2), which are based on the classes recorded in the 2003 and 2007 field surveys. However, during the unsupervised classification processes, thirty-six classes were identified during the unsupervised classification because of the variance of the colour shading over the entire image. The classes that were found after classification that were not recorded in the field survey were ‘mixed classes’, i.e. where two or more of the main LULC classes occur in the classified image under one ‘mixed class’. The classes in the legend are therefore a combination of main and ‘mixed’ LULC classes. Whereas most of the forest classes are unambiguously assigned to one forest class or another, the grassland and cropping areas are not. This occurs because of the difficulties of separating the main LULC classes on the basis of their spectral properties alone. The main reasons this occurs in the classified image map are as follows:

a) Some land uses have very similar spectral signatures in the parts of the electromagnetic spectrum sensed by Landsat ETM and OLI, e.g. i) the low shrubby regrowth have similar spectral signatures as pineapples and ii) medium growth have similar spectral signature as citrus;
b) The small-scale mixed nature of farming often means many crops occurring over a small area and mixed pixels are frequent throughout the image.

c) Weeds and lianas infesting tree crop plantations and as these are only cleared once a year that can occur in different stages of growth and, therefore, with slightly different spectral properties. For example, the farmers do not attend to citrus plantations when the harvesting season is over allowing for weeds and regrowth. It can be classified as shrubs from a spatial perspective when the regrowth was recent or can be classified as forest regrowth when it's bushy.

The above reasons listed are further discussed in section 5.1.1 and section 5.1.2 in chapter 5 but not in full detailed, as this is not the focus of this study. The map shows that tropical mountain forest dominates the bottom part of the image from southeast to the north west of along the mountain ranges from Isiboro Sécure National Park to Carrasco National Park and further towards Amboro National Park. The mosaic of seasonally flooded forest and grassland are mapped in varying light blue colours in the middle part of the image, with forests and grasslands that are flooded for much of the year occurring in the north of the image. Most of the agricultural area and bare soil (varying orange shading in figure 4.2-1) can be identified in the eastern part of the image. The forest classes are in varying green colour, while pasture and wetland areas including agricultural classes are in blue and purple.

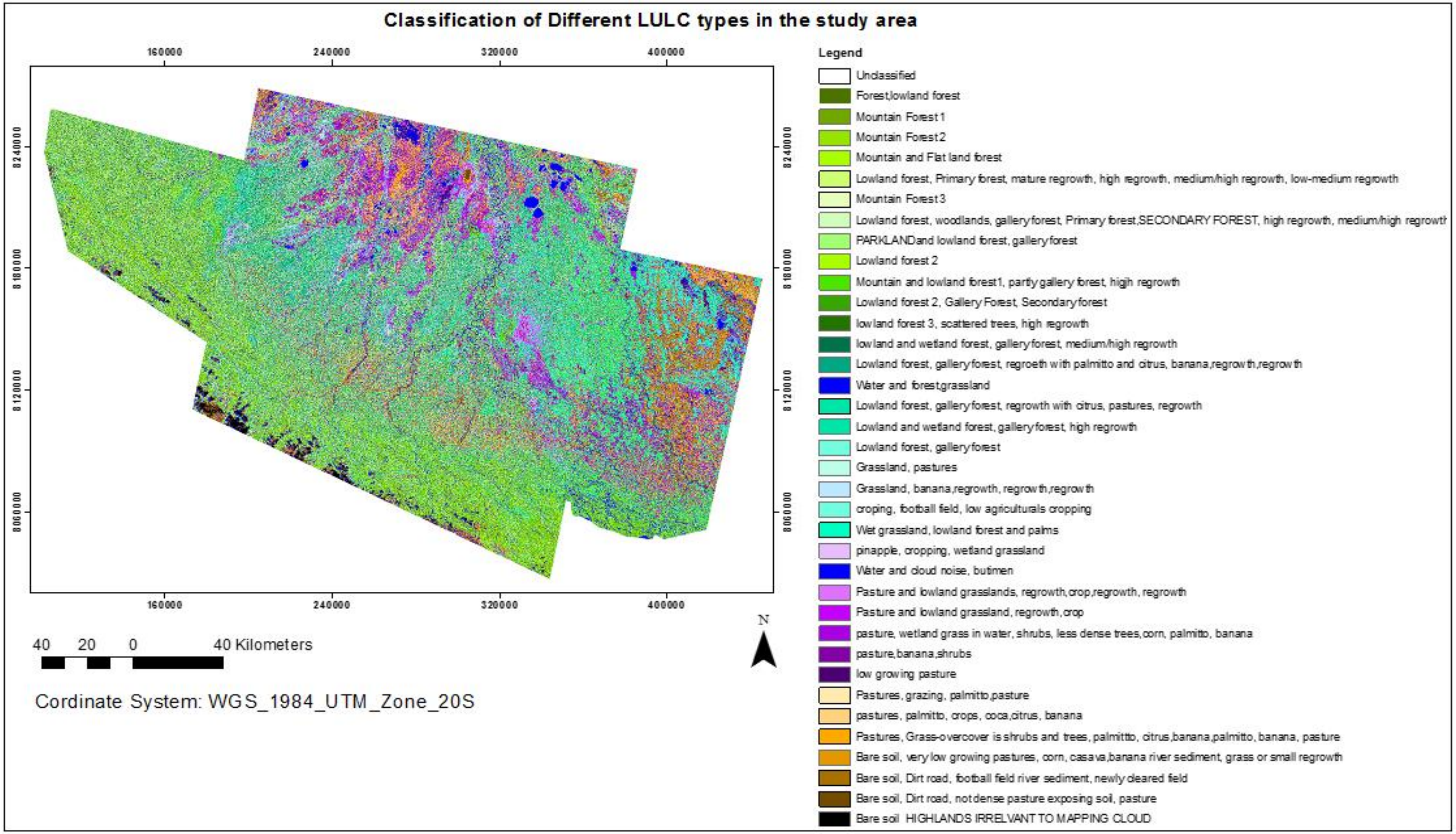

Figure 4.2-1; Classification of the different LULCC in the study area using the 2015 unsupervised classification method for the study area in Bolivia.

4.3 Forest and Non-Forest Maps

Forest and non-forest mapping was carried out using ArcGIS after the re-coding of classes for 2011, 2015 and 2016 mosaicked images. The steps in creating those forest and non-forest maps were given in Section 3.3. The forest and non-forest maps for each of the three years is presented below.

In the 2011 forest and non-forest map (Figure 4.3-1), forest cover (green pixels) dominate the mountain ranges in the southern part of the study area, as it does in 2015 and 2016 (Figures 4.3-2 and 4.3-3). An exception to this is in the lowlands along the Espiritu Santo and San Mateo valleys to the south west of Villa-Tunari, which are old areas of settlement that have recently witnessed a surge in people moving into the area to cultivate coca (Millington, in press) (Appendix 4.2 *Note that this image is not included in the thesis because of confidentiality surrounding the village names as per social science normal practice*). These old and new areas of settlement were clearly indicated as non-forest (yellow pixels). The main non-forest areas (yellow pixels) are located in belt that runs from the southeast to the northwest of the map, this corresponds to the Chapare colonization zone (Chapter 2) to the west of UTM easting 340000 and the Yapacani colonization zone in Santa Cruz Department to the east of that coordinate (Millington, in press). Furthermore, in describing the images, there are also areas of non-forest pixels outside the area of settlement in the north of the image map interspersed with forest, some of which are quite large. These are areas of flooded grassland and floating vegetation around lakes, and seasonally flooded grasslands. The forests adjacent to and between them are seasonally flooded forests and woodlands. Blackwater lakes, i.e. lakes with low sediment loads, and rivers are mapped in blue in these images. The blue class also includes areas of deep shadow in the mountains ranges in the south of the image.

This occurs because both water bodies that have little sediment and forested areas in deep shade have similar spectral signatures dominated by high absorption in the visible and near-to-middle infrared parts of the electromagnetic spectrum.

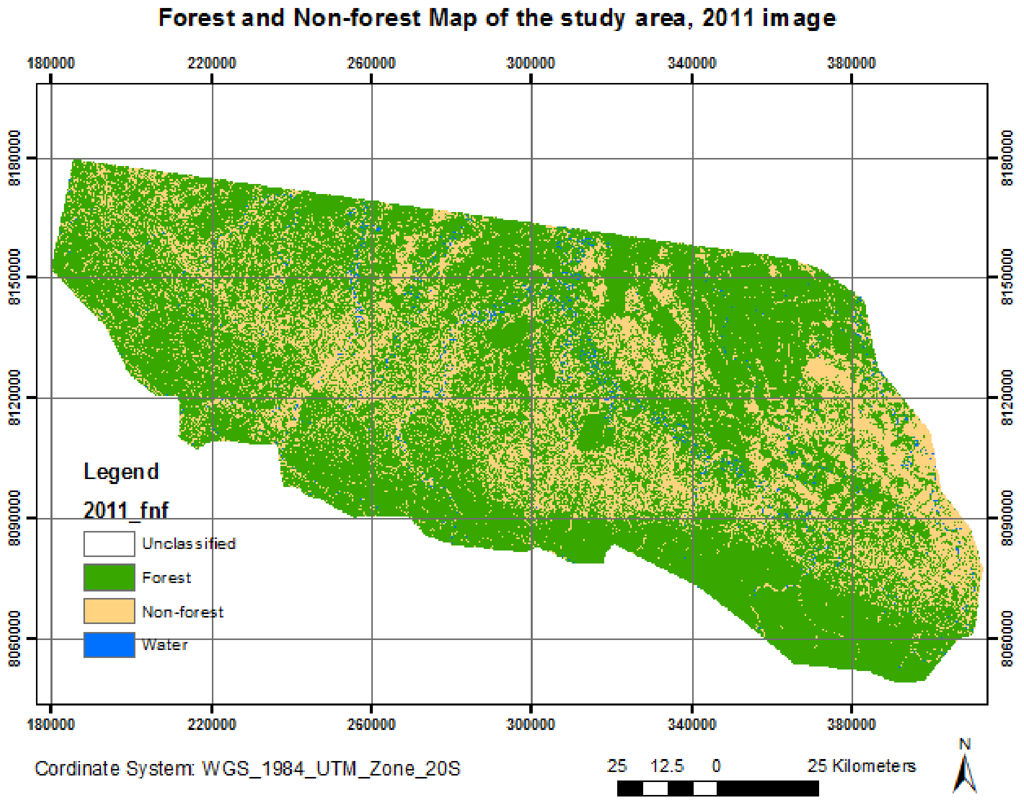

Figure 4.3-1; Central Bolivia: Forest and non-forest map 2011

The general pattern of forest and non-forest vegetation in 2011 is similar to that in the 2015 and 2016 forest and non-forest maps (Figures 4.3-2 and 4.3-3). The 2015 map covers a larger area (cf. Section 4.1) and the equivalent area is in the lower part of the image map indicated. The forest and non-forests areas in the north of the 2015 image map are extensions of the seasonally flooded land cover identified in Figures 4.2-1 and 4.3-2 and are not discussed further. The maximum cloud cover is 15% covering areas in the mountain ranges and further east of the study image (Table 3.1-2). The water features in this image map mapped in blue, are more extensive, and better defined than those in the 2011 map. In the 2016 map (Figure 4.3-3) is again similar to the 2011 and 2015 forest and non-forest maps.

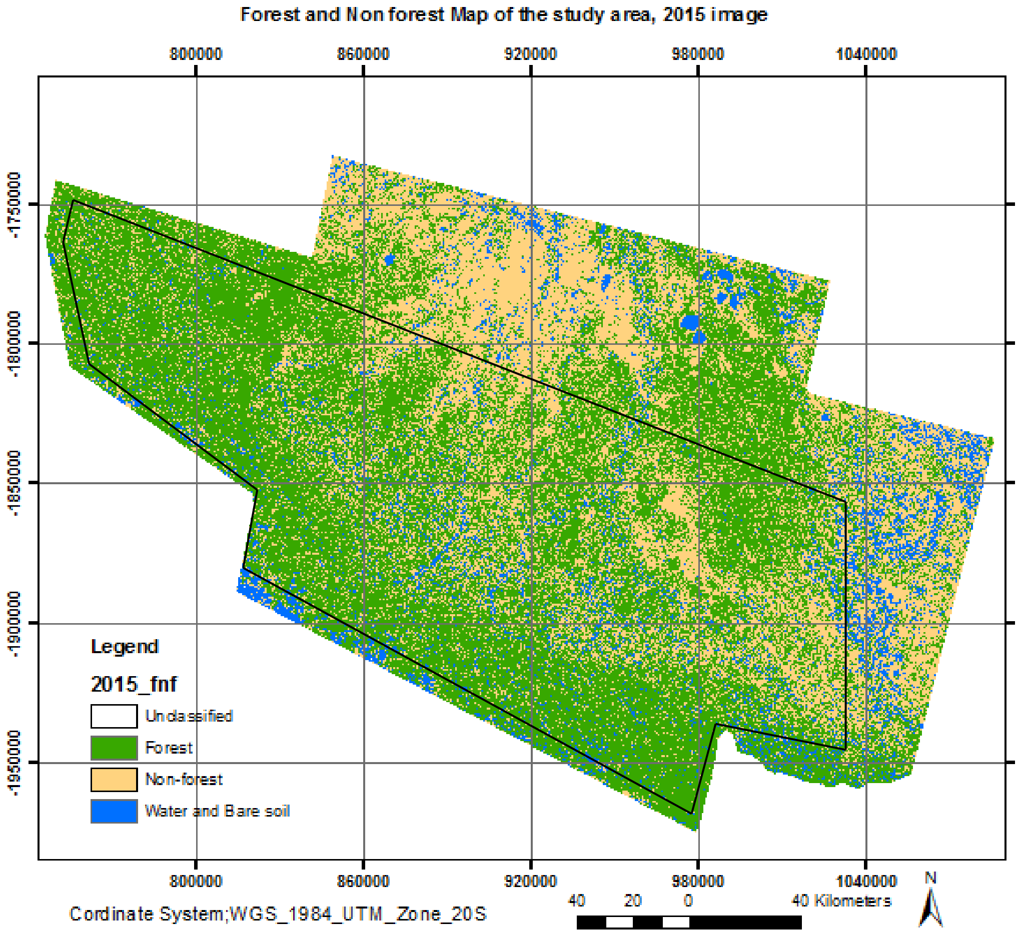

Figure 4.3-2; Central Bolivia: Forest and non-forest map 2015 with the area of interest indicated with black line boundary.

The consistency in overall patterns of forested and non-forested areas over the six-year period in which they were acquired is anticipated, and provides confidence in the classification and mapping procedures. Levels of confidence are augmented by the fact that these maps are similar to maps from the early 21st Century produced by Bradley (2005) and unpublished maps produced by Mlenge Mgendi in the archive of Chapare data I was given access too.

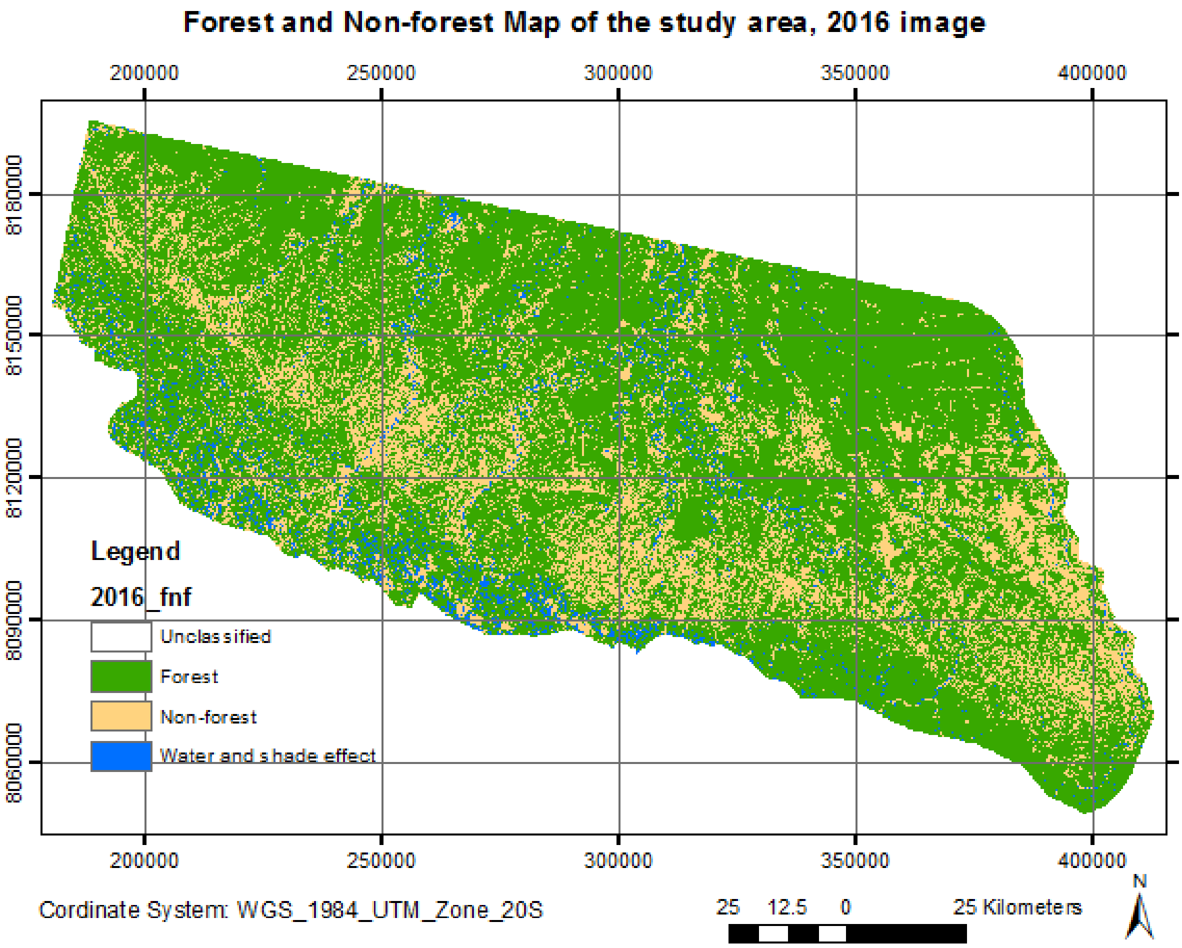

Figure 4.3-3; Central Bolivia: Forest and non-forest map 2016

4.4 Accuracy Assessment

4.4.1 LULC class accuracy (2015 classified image)

The accuracy assessment of the 2015 LULCC class map (Figure 4.2-1) was undertaken by comparison with the land uses identified and mapped during the 2015 field survey (Appendices 3.2 and 3.4), This is illustrated below using a confusion matrix (Table 4.4-1) in which the field observations (columns) are referenced to the mapped classes (rows). Eleven individual classes were used in the analysis (Section 3.2.3) and the data for each of these is provided. The classes were broadly grouped into forest (forest, high regrowth and medium regrowth classes), non-forest (low regrowth, citrus, palmetto, banana, other cultivation, pasture and bare soil) and water, which are shaded in green, orange and blue respectively. The pink classes show groups of misclassified pixels for forest classes classified as non-forest classes and vice-versa. Mainly it is the pasture and citrus, which is classified as forest, and medium regrowth as pasture. The reason for that is explained in section 5.1.

Table 4.4-1; Confusion matrix table for 2015 image

		Observed land use in field survey (Ground verification data)											
		Forest	High regrowth	Medium Regrowth	Low regrowth	Citrus	Palmetto	Banana	Cultivation	Pasture	Bare Soil	Water	**Total**
Predicted land-use and land cover from 2015 classification	Forest	70	10	36	1	7		2		6			**132**
	High regrowth	1	12	1		1							**15**
	Medium Regrowth	1		18	2	1							**22**
	Low regrowth			2	1	2		1		2			**8**
	Citrus					1				1			**2**
	Palmitto						2						**2**
	Banana					1		3			0		**4**
	Cultivation				1			2		4			**7**
	Pasture	4	2	10	3	3	3	15	1	47	1		**89**
	Bare Soil			2						6	17		**25**
	Water											5	5
	Total	**76**	**24**	**69**	**8**	**16**	**5**	**23**	**1**	**66**	**18**	**5**	**311**

All five water classes that were predicted from the classification matched field observations, and no field observations of water were misclassified.

The accuracies of the predicted classes and the overall map for 2015 are given in Table 4.4-2 below. The overall accuracy of the map is low at 56.6%. This is in line with previous analysis of accuracy assessments for Chapare when individual land cover classes are mapped and compared to known land use and land cover on the ground. The reason this low accuracy is achieved is that the wide range of accuracy levels of individual classes, which range from 0 and 6.25% for the other cultivation and citrus classes to 92.1% for forest. Forest classes generally have higher accuracies than the non-forest classes, though these decrease with decreasing forest height and biomass (Table 4.4-2), which may in part reflect variations in field observations.

Table 4.4-2; Accuracy Assessment for the 2015 land-use and land-cover classification 2015

			Ground verification data
	Forest Accuracy	0.921053	92.10%
	High Regrowth Accuracy	0.5	50%
Prediction	Medium Regrowth Accuracy	0.26087	26.10%
	Low Regrowth Accuracy	0.125	12.50%
	Citrus Accuracy	0.0625	6.25%
	Palmetto Accuracy	0.4	40%
	Banana Accuracy	0.130435	13.04%
	Cultivation Accuracy	0	0%
	Pasture Accuracy	0.712121	71.21%
	Bare Soil Accuracy	0.944444	94.44%
	Water Accuracy	1	100%
	Overall Accuracy	0.565916	56.60%
	Observed agreement	0.57	0.57
	Expected agreement	0.21	0.21
	Kappa-Coefficient	0.45	0.45

The non-forest classes generally have lower accuracies than forest classes, though pasture (71.21%) and palmetto (40.0%) are exceptions to this general rule-of-thumb. These lower accuracies are due to the issues outlined in Section 4.2. While these accuracies are unconvincing for detailed land-use and land-cover mapping, they do provide the basis for the more robust and more accurate forest and non-forest cover mapping which has been extensively applied in studies of forest dynamics (Shimada *et al*., 2014, Pekkarinen *et al*., 2009, Hansen *et al.*, 2008) and is discussed in the next section.

4.4.1 Forest and non-forest map accuracies

Accuracy assessment was carried out on the forest and non-forest classifications for 2011, 2015 and 2016 is as shown in Table 4.4-3 using the confusion matrices for the respective years. In total 142 ground verification points were extracted (Section 3.4.2) and used for the accuracy analysis of the 2011 map (Table 4.4-3). The overall accuracy was 84.5%; with the forest class having 98% accuracy, water 95.4% and the non-forest class at 70%. The kappa co-efficient of 0.75 indicates a strong agreement.

Table 4.4-3Accuracy assessment for the 2011 forest and non-forest map.

		Verification points			
		Forest	**Non-Forest**	**Water**	**Verification data**
Prediction	**Forest**	49	20	1	70
	Non-Forest	1	50	0	51
	Water	0	0	21	21
	Total	50	70	22	142
	%	98	71.4285714	95.4545455	
	Forest Accuracy		0.98	98.00%	
	Non-Forest		0.7143	71.43%	
	Water		0.9545	95.50%	
	Overall accuracy		0.84507042	84.5%	
	Observed agreement		0.84507042		
	Expected agreement		0.373537		
	Kappa-Coefficient		0.75269158		

Table 4.4-4 summarises the accuracy assessment calculations for the 2015 forest and non-forest and reveals an overall accuracy of 87.84%, which is slightly higher than the 2011 map's accuracy assessment. The number of ground verification data extracted totalled 329. The water class recorded 100% accuracy followed by forest at 88.2% and the non-forest class at 87.1%. The verification data in this analysis were collected along the eight transects along the study area in 2015 (Appendix 3.4).

The kappa co-efficient of 0.76 again shows strong agreement between predicted and observed land covers.

Table 4.4-4; Accuracy assessment for forest and non-forest maps for 2015

		Verification points			
		Forest	**Non-Forest**	**Water**	**Verification data**
	Forest	149	20	0	169
Prediction	**Non-Forest**	20	135	0	155
	Water	0	0	5	5
	Total	169	155	5	329
	%	88.16568	87.09677419	100	
	Forest Accuracy		0.88165	88.20%	
	Non-Forest		0.87096	87.10%	
	Water		1	100.00%	
	Overall accuracy		0.878419453	87.84%	
	Observed agreement		0.878419453		
	Expected agreement		0.486054268		
	Kappa-Coefficient		0.763436994		

The 2016 forest and non-forest map has an overall accuracy assessment of 98.42%. This is a more accurate and a better performing classification than for the 2011 and 2015 forest and non-forest classifications. In total 191 ground verification data points were extracted in ArcGIS from the original image. This is another set of verification points to test the accuracy while the other points were used to label classes after the unsupervised classification. Once again, the water class had 100% accuracy; both forest (98.67%) and non-forest class (97.44%) had very high accuracies. Not surprisingly, the kappa coefficient of 0.97 indicates perfect agreement (Table 4.4-5).

Table 4.4-5; Accuracy assessment for 2016 forest and non-forest map.

		Verification points			
		Forest	Non-Forest	Water	Verification data
Prediction	Forest	74	2	0	76
	Non-Forest	1	76	0	77
	Water	0	0	38	38
	Total	75	78	38	191
	%	98.6666667	97.43589744	100	
	Forest Accuracy		0.9867	98.67%	
	Non-Forest		0.9744	97.44%	
	Water		1	100.00%	
	Overall accuracy		0.984293194	98.42%	
	Observed agreement		0.984293194		
	Expected agreement		0.36046161		
	Kappa-Coefficient		0.975440401		

4.5 Community-level matrices

Forest and non-forest maps from 2011, 2015 and 2016 for the three communities (I, II and III) examined in detail by Bradley (2005) and Bradley and Millington (2008) are presented below along with statistical summaries. A new community—Community IV–in TIPNIS is included in this thesis.

4.5.1 Community I

The forest and non-forest maps for Community I (Figures 4.5-1 to 4.5-3) are interesting as they show the western part of the community has high levels of forest cover while there is more clearance on the east. The distribution of forest and non-forest areas indicates that the area has been extensively farmed and that it is likely that much regrowth had occurred. This theme will be returned too in the next chapter. Imagery from 1966, taken acquired only three years after the community was founded, will be shown and the history of this community discussed. None of the other communities mapped has such a long history of settlement and cultivation. Like Community II and Community III, the land parcel owners have cleared forest backwards along their land parcels from a central access road. In 2015 (Figure 4.5-2) and 2016 (Figure 4.5-3), there appears to be much forest regrowth compared to 2011(Figure 4.5-1). Again, 2015 classification is not consistent because of reasons discussed in section 5.3. Summary statistics for Community I can be found in Table 4.5-1. The average land parcel size is 19 ha with the standard deviation of 3 ha, which is close to that anticipated from a cultivation-based settlement with 20 ha land titles even accounting for variations such as those introduced for Community III. In this case, part of the explanation is that land parcels designated for houses and other buildings along the north-south road that passes through the community at approximately between UTM easting 271500 are much smaller.

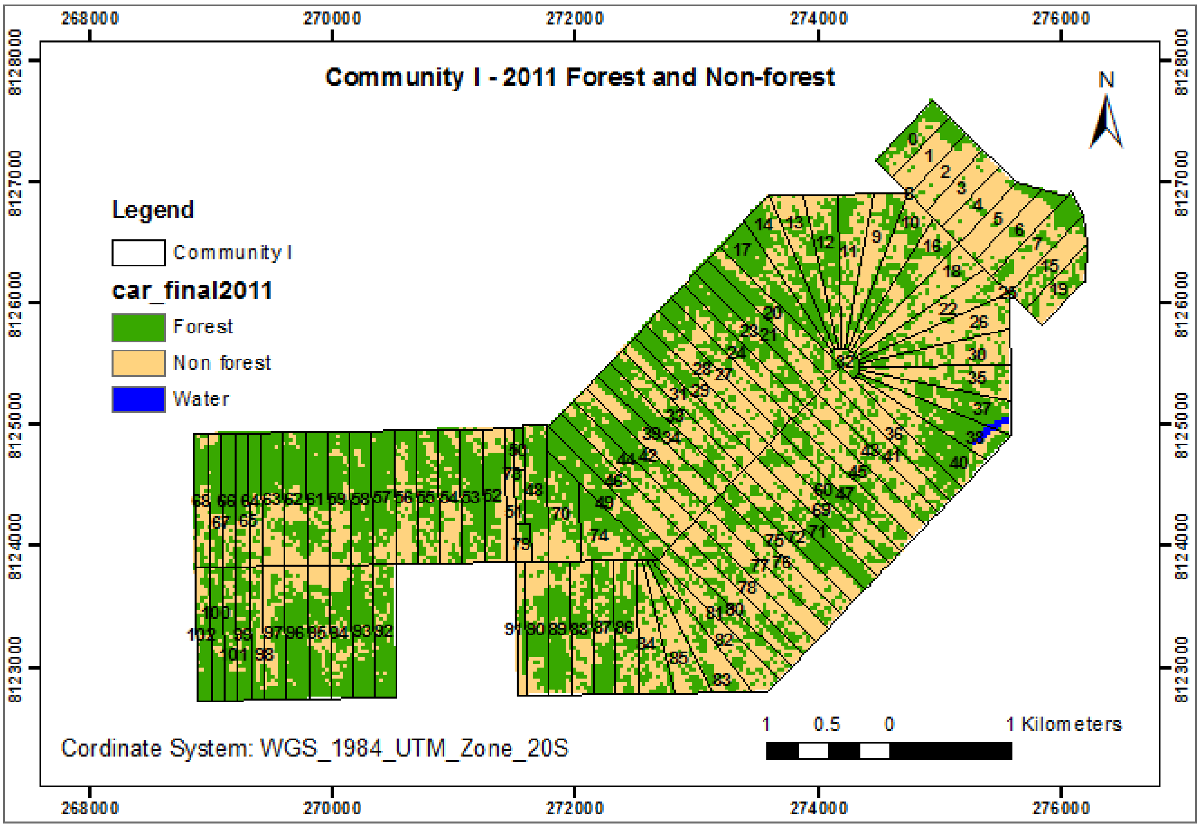

Figure 4.5-1; Community I forest and non-forest map for 2011

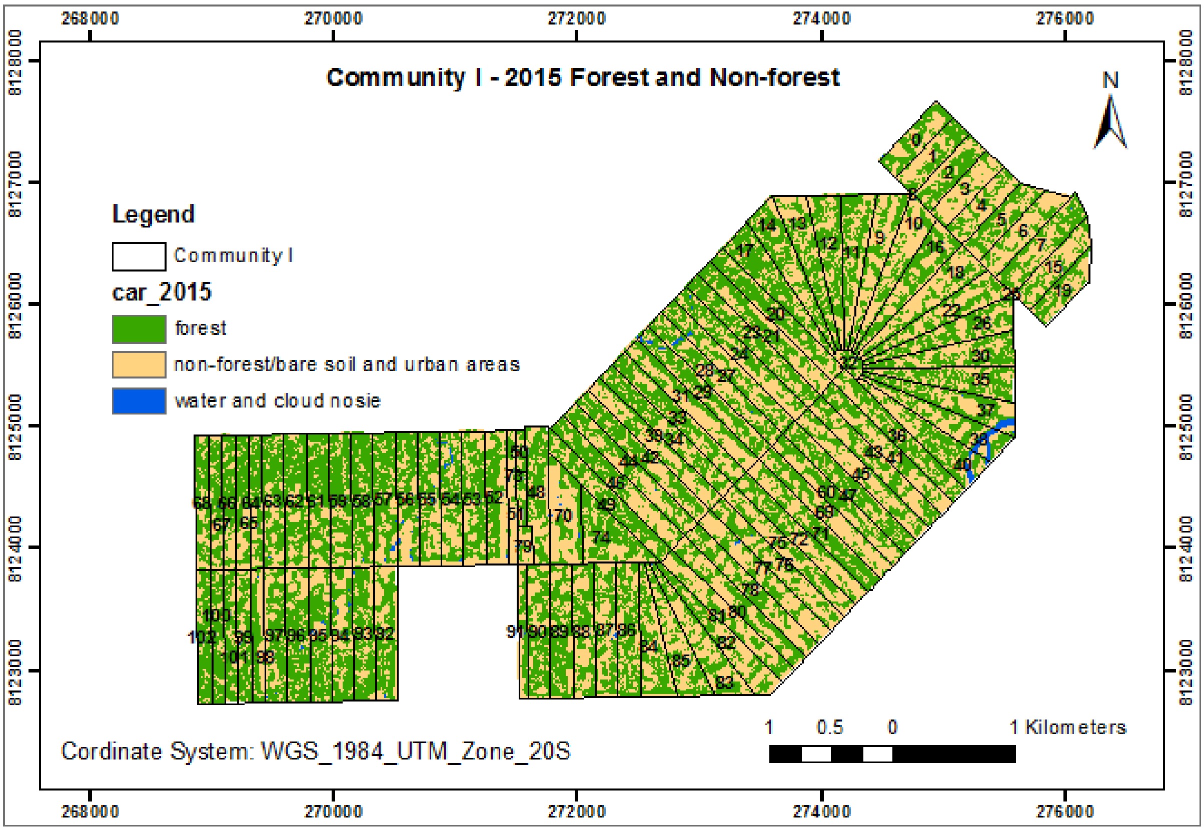

Figure 4.5-2; Community I forest and non-forest map for 2015

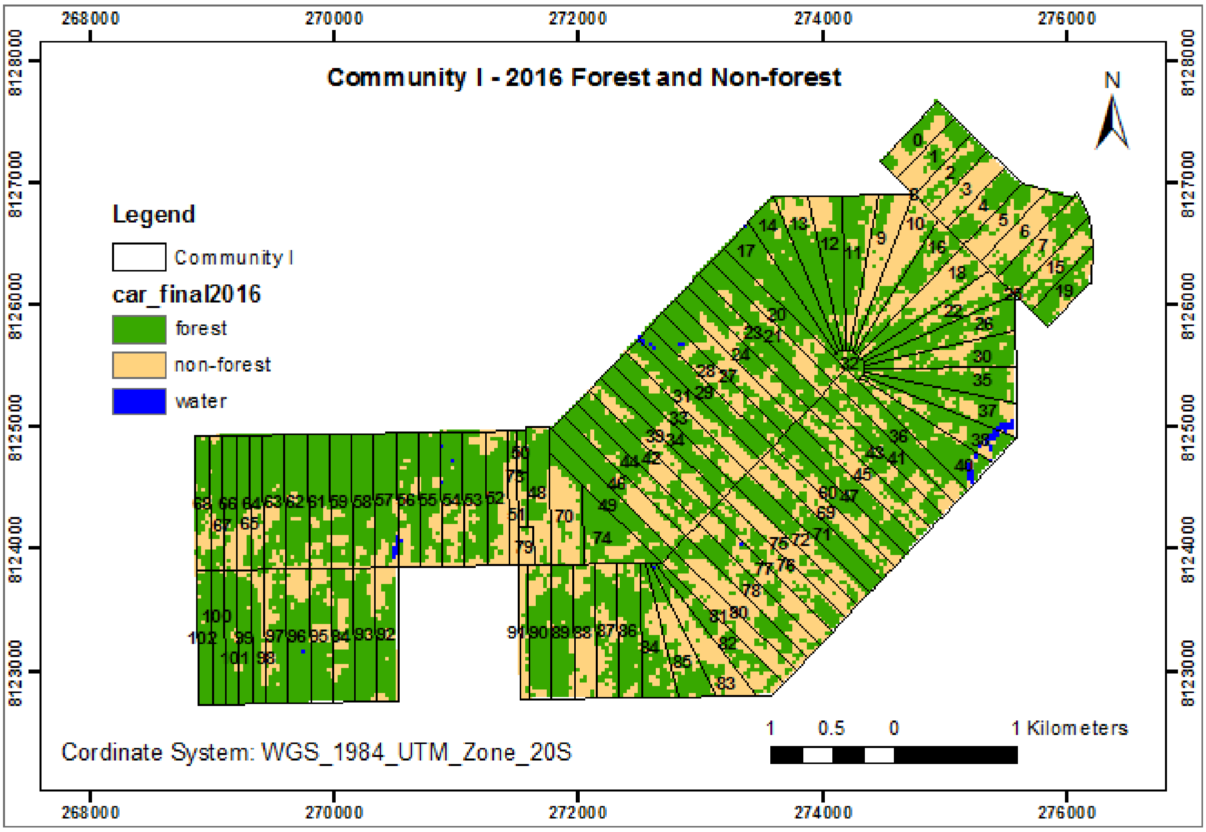

Figure 4.5-3; Community I forest and non-forest map for 2016

These are the thin land parcels in the maps above and were not included in the statistics which are land parcels 32, 50, 51, 73, 79 and 91. These land parcels are not farmland, but rather roads and the village settlement. The list of the feature class ID (FID[4]) is given in Appendix 4.1 with full forest and non-forest statistics for individual land parcels. In addition, land parcels of different sizes were added to this community in an area known to community residents as the XXX[5] after the original plan was surveyed. Thus, the land parcels with the lowest area is 12 ha (land parcel 101) located to the west similar to the ones located to the east with approximately 13 hectares each.

Table 4.5-3 shows that there is some regrowth in 2015 and much more regrowth in 2016. The forest cover increased from 946.8 ha in 2011 to 1176.12 ha in 2016. The clearance rate for those year were -90.03 ha/year, -6.15 ha/year and -204.73 ha/year respectively as given in Table 4.5-1. The combined statistics for the deforestation rate calculated from period when data was collected is given Appendix 6.1.

[4] FID- is the name used for shape files in ArcGIS indicating the feature classes quite similar to object id (OID)

[5] XXX- residential areas added recently to the community at the on the northeast section of the community map. The name is labelled as XXX because of confidentiality of the area due to coca trade.

Table 4.5-1; Forest and non-forest statistics for Community I

	Total area (ha)	1816			
	Number of Farms (lease) including the villages	102			
	Average (ha)	19			
	Min (ha)	12			
	Max (ha)	21			
	Std dev	3			
Year	**Forest Cover (ha)**	**Non-Forest cover(ha)**	**Forest cover (%)**	**Non-Forest cover (%)**	**Clearance rate (ha/annum)**
2011	946.80	868.95	52.14	47.86	-90.03
2015	971.39	848.45	53.38	46.62	-6.15
2016	1176.12	639.63	64.77	35.23	-204.73

4.5.2 Community II

The 2011 forest and non-forest map in Community I (Figure 4.5-4) shows that the forest areas are mainly restricted to the end of the parcel boundaries at relatively long distances from the central road where clearance started (Bradley, 2005). Most farmers live along the access road through the middle of the community and extend their cleared areas towards the end of their land parcels. Therefore, most of the non-forest areas, which in this case are pasture, are in the middle of the community. There are a few patches of forest interspersed in the non-forest areas. A similar pattern of land cover can be seen in Figures 4.5-5 and 4.5-6 for 2015 and 2016 respectively. However, in 2015, there is less forest than in 2011 and 2016. There is a lot of forest signifying more regrowth from those three years compared from previous data further discussed in Section 5.4. Moreover, 2015 image shows few water bodies which can be caused by noise and its acquisition during the dry season.

Table 4.5-2 shows the forest and non-forest class statistics for Community II in 2011, 2015 and 2016. The average size of each individual land parcels in Community II is larger than others are as this was originally designated pasture (50 ha land titles) rather than cultivation (20 ha), thus with some smaller farms in Community II brings the average is around 34 ha. This also evident with a standard deviation of 15 ha with the minimum land parcel at 11 ha and maximum at 54 ha.

The result shows much regrowth in 2011 and much more in 2016, when it was -786.36 ha/year. That is to say, between 2015 and 2016, there has been additional 786.36 ha of forest regrowth. There is evident in the 2015 maps of a clearance rate of 147.4 ha/ year, which increased the non-forest areas by two (2149.13 ha) compared to the other two years analysed (2011 and 2016).

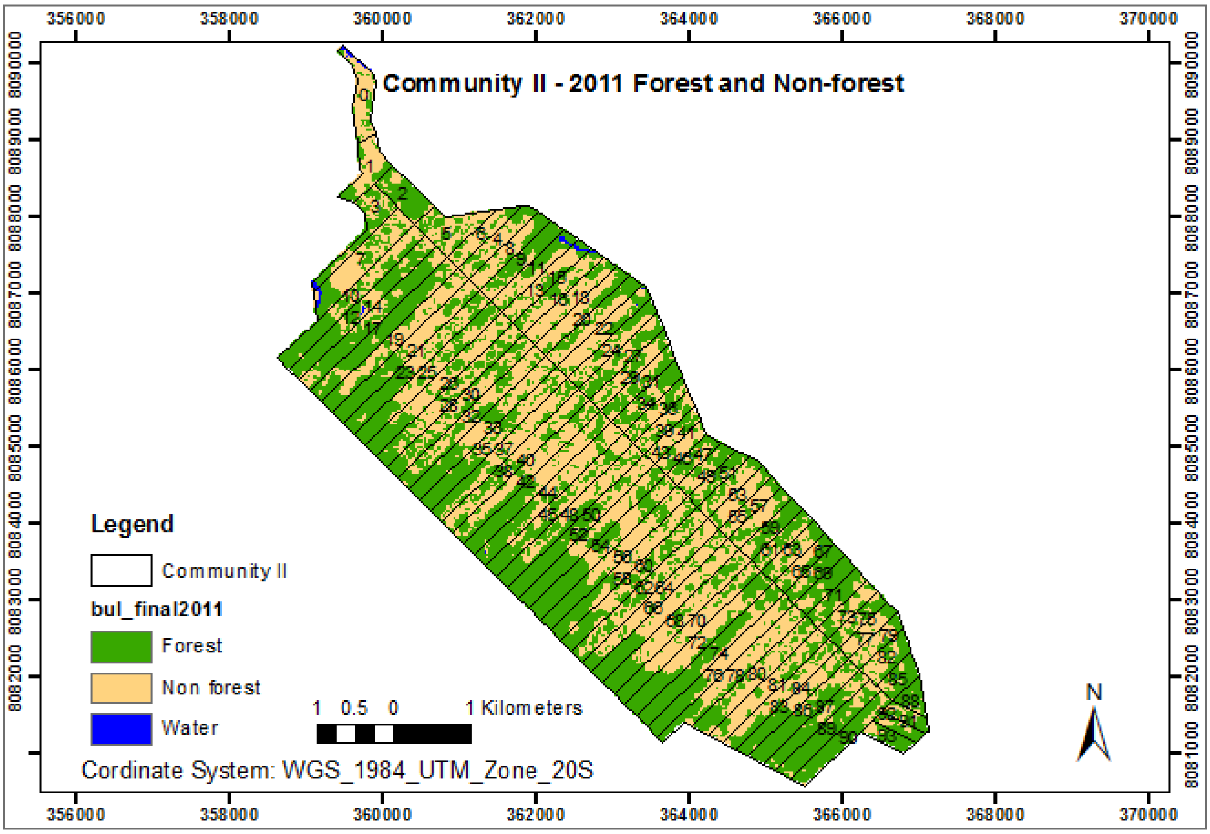

Figure 4.5-4; Community II forest and non-forest map for 2011

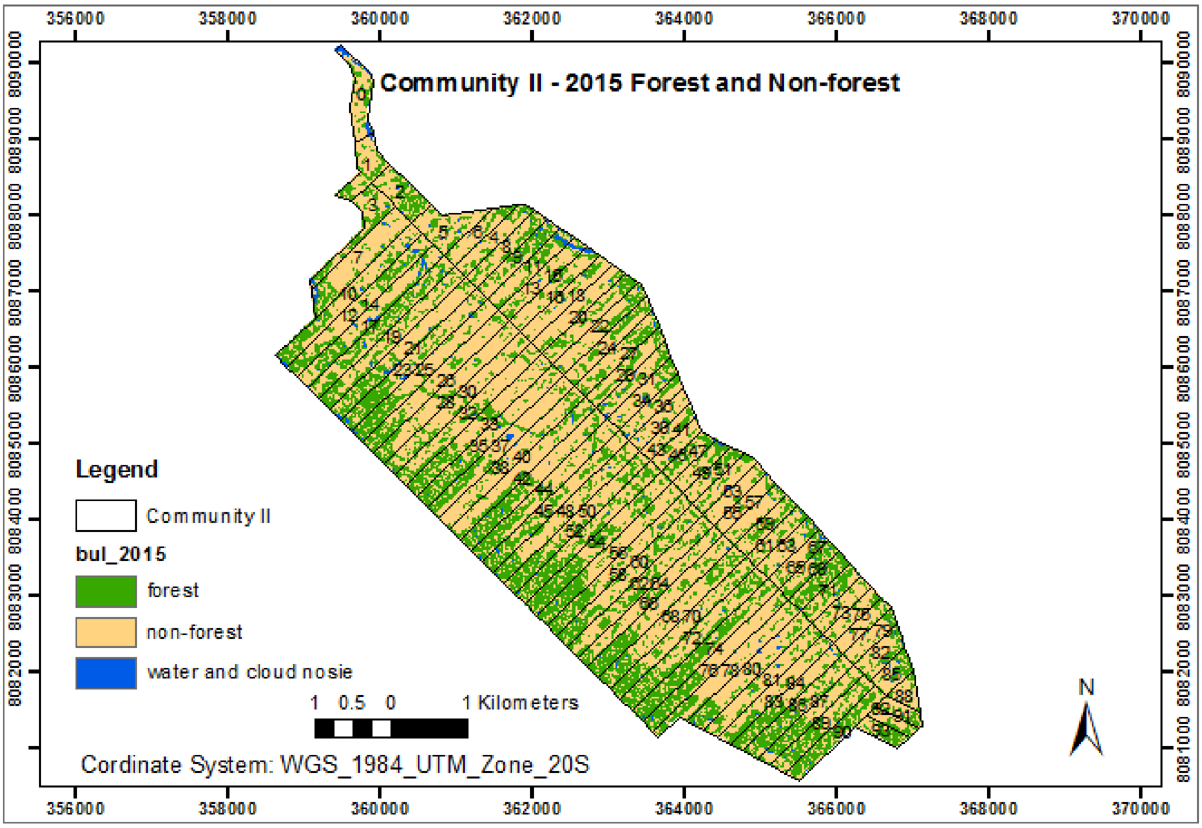

Figure 4.5-5; Community II forest and non-forest map for 2015

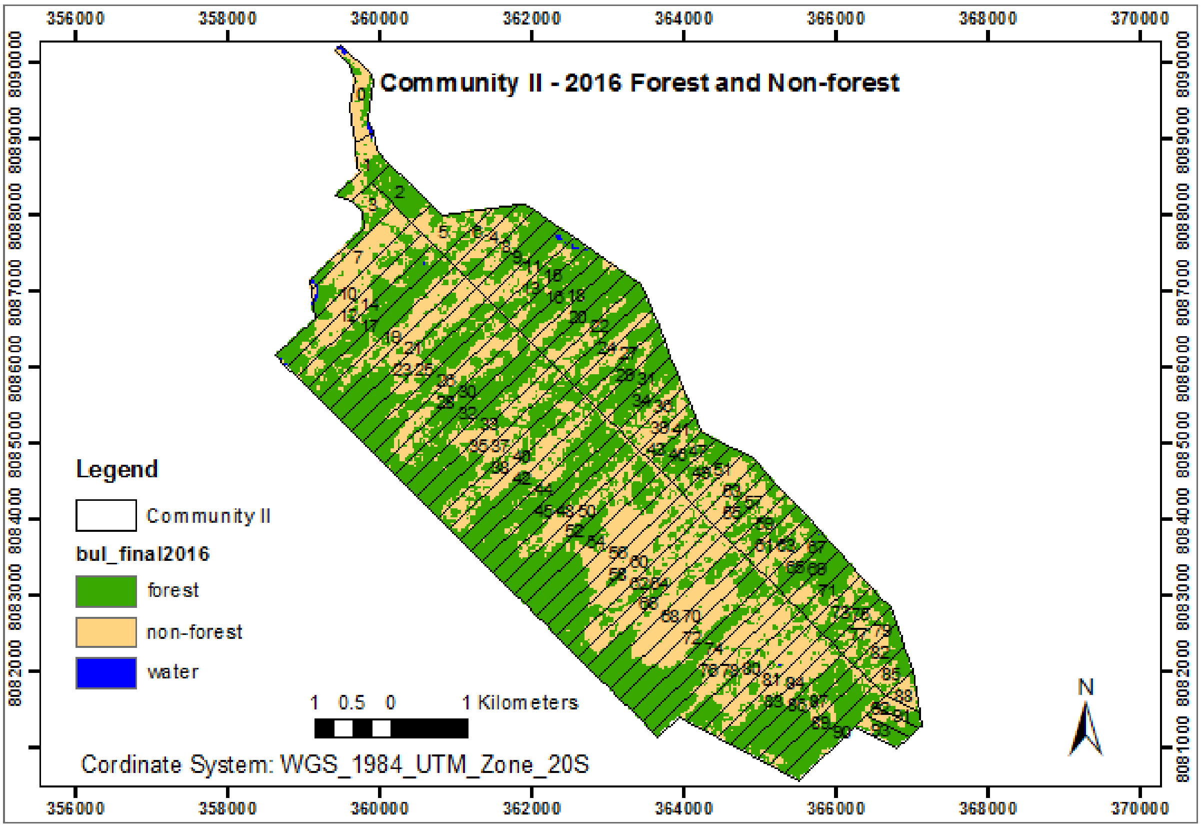

Figure 4.5-6; Community II forest and non-forest map for 2016

Overall, the 2015 classification does not correspond well with the 2011 and 2016 classification which is explored in the discussion section (Section 5.3) as it is impossible to have that much regrowth rate of -786.36 ha/year between 2015 and 2016. However, comparing the overall trend, there is an increase in forest cover at the end of the study period.

Table 4.5-2; Forest and non-forest statistics for Community II

Total area (ha)	3199
Number of Farms (lease)	93
Average (ha)	34
Min (ha)	11
Max (ha)	54
Std dev	15

Year	Forest Cover (ha)	Non-Forest cover(ha)	Forest cover (%)	Non-Forest cover (%)	Clearance rate (ha/annum)
2011	1658.07	1540.71	51.83	48.17	-26.46
2015	1068.46	2149.13	33.21	66.79	147.40
2016	1854.81	1343.97	57.98	42.02	-786.35

4.5.3 Community III

The forest and non-forest map in Community III shows the forest areas in the middle of the parcel boundaries and more forest cover on the northeast part of the community. The forest and non-forest areas shows that the area has been extensively farmed from both ends of the land parcels (Figure 4.5-7). Like Communities I and II, the land parcel owners or the farmers live along the access road through the middle and farm their land towards the end of their land parcels. That can also be seen in Figures 4.5-8 and 4.5-9 for 2015 and 2016 forest and non-forest respectively. However, in 2015, the image is quite different from 2011 and 2016 as previously identified in Community I. The 2015 image shows few water bodies which can be caused by noise and precipitation during the time the image was taken, as was the case in Communities I and II

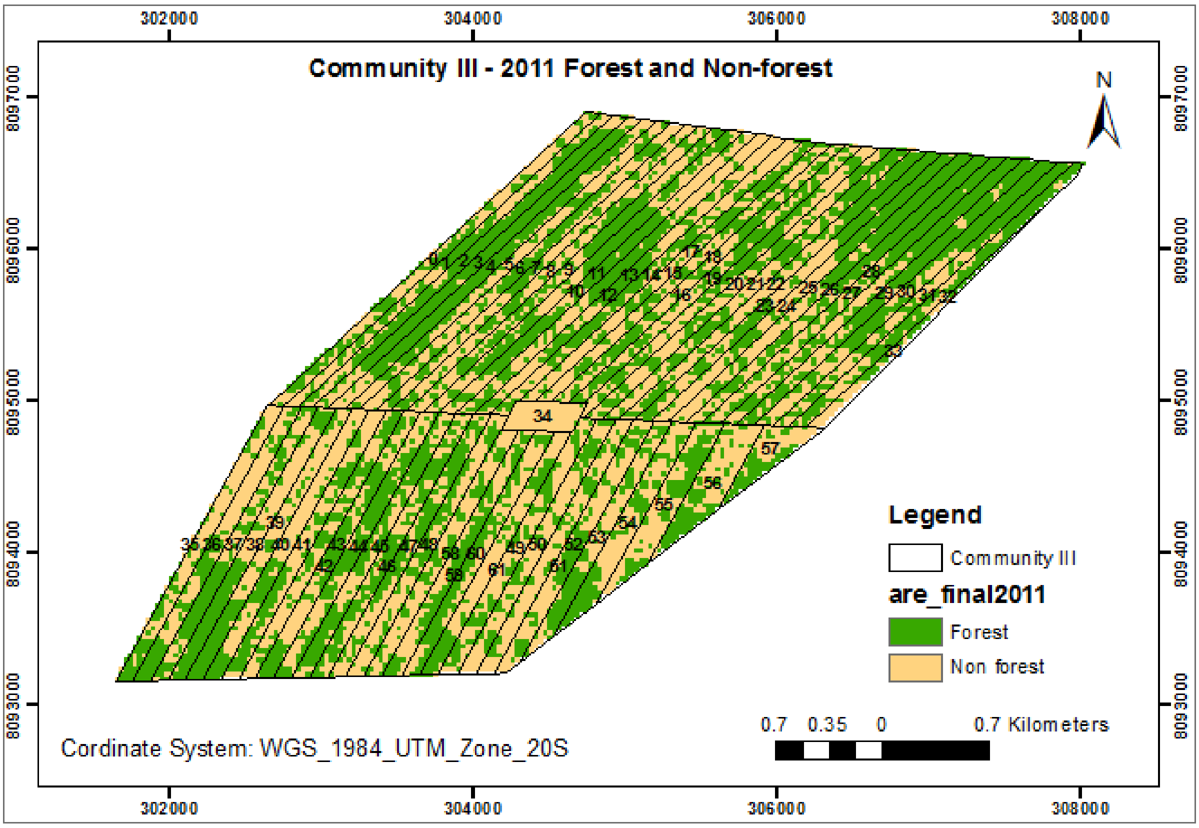

Figure 4.5-7; Community III forest and non-forest map for 2011

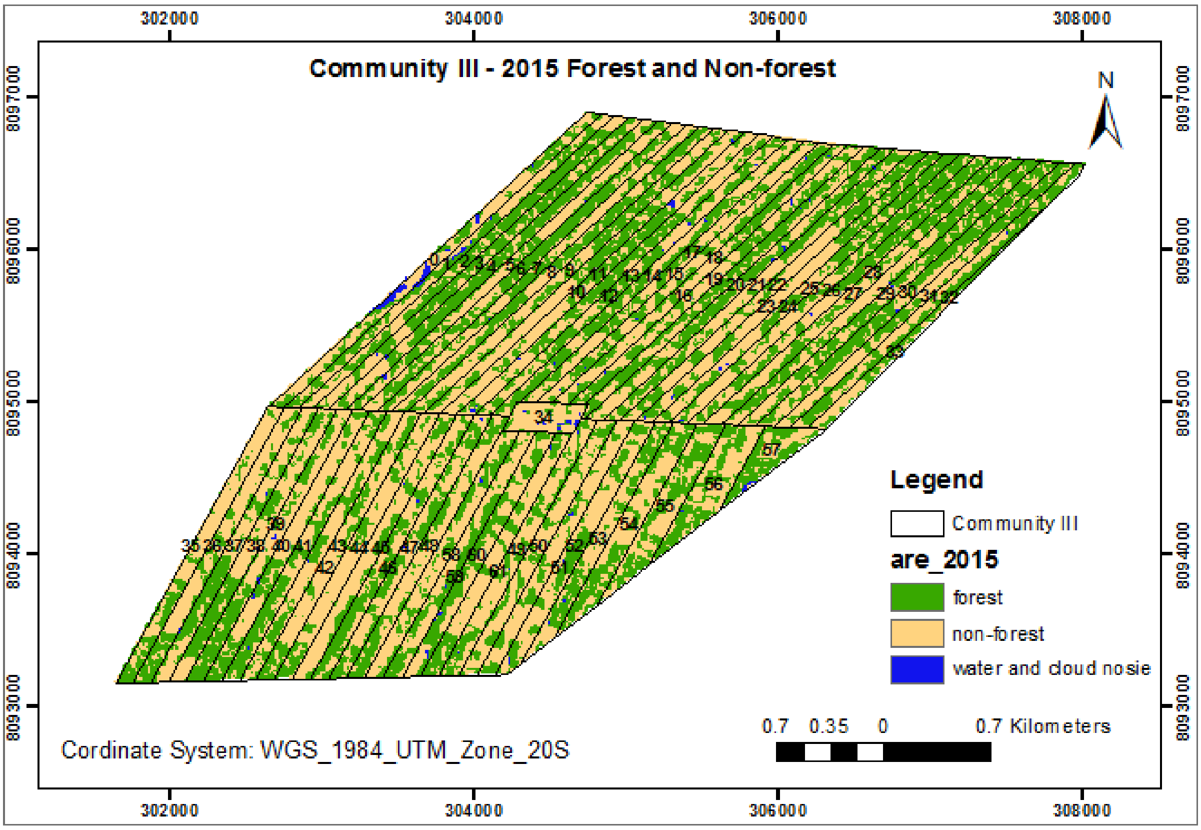

Figure 4.5-8; Community III forest and non-forest map for 2015

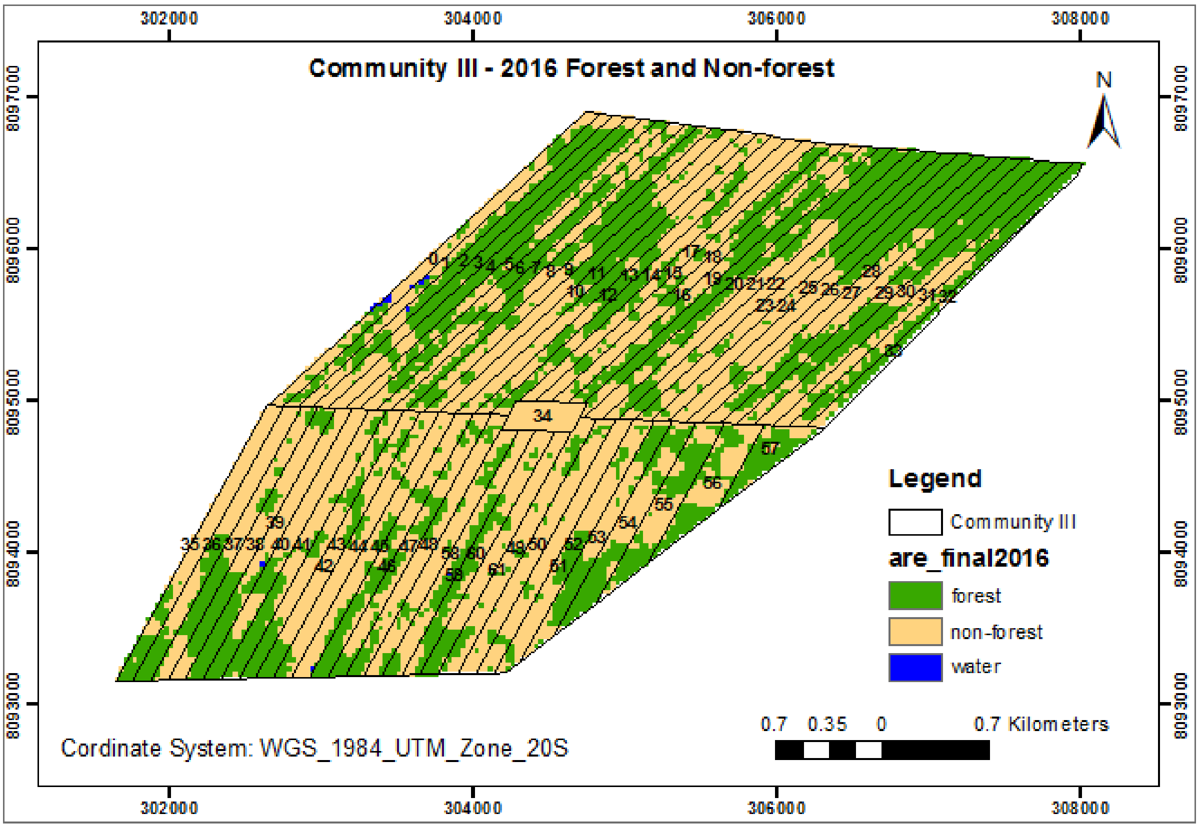

Figure 4.5-9; Community III forest and non-forest map for 2016

The forest and non-forest statistical summary for Community III is provided in Table 1.5-3. The average farm size is calculated as 20 ha. This supports the accuracy of the land tenure grid for this community because the INC land titles for Community III were 20 ha as it was planned as a cultivation-based farming settlement. Small variation arises because as farmers cut forest along their land parcels that were not able to accurately follow the INC survey lines and thus, the standard deviation is 2 ha. The village centre is also mapped as a land parcel in the map (land parcel 34) but was omitted when calculating the average and standard deviation as it is not a farm land.

The results in the Table 4.5-3 revealed regrowth in 2011 and clearance in 2015 and 2016 with the clearance rate of 20.3 ha/year and 25.18 ha/year respectively. That is evident in their maps presented in 2011 having a forest cover of 631.17 ha which decrease to 549.968 ha in 2015 and further decrease to 524.79 ha in 2016. Thus, a clearance of approximately 26 ha in one year is a notable drop in forest cover in the community. However, the forest and non-forest covers are more in line for all three years, but the 2015 map is quite different from 2011 and 2015. Again, the reason for that will be discussed in Section 5.3.

Table 4.5-3 Forest and non-forest statistics for Community III

	Total area (ha)	1219
	Number of Farms (lease)	60
	Average (ha)	20
	Min (ha)	9
	Max (ha)	22
	Std dev	2

Year	Forest Cover (ha)	Non-Forest cover(ha)	Forest cover (%)	Non-Forest cover (%)	Clearance rate (ha/annum)
2011	631.17	587.43	51.79	48.21	-45.71
2015	549.97	675.32	44.88	55.12	20.30
2016	524.79	693.81	43.06	56.94	25.18

4.5.4 Community IV

The forest and non-forest map for Community IV shows most of the forested areas at the end of the two ‘rows’ of land parcels. An investigation of Google Earth imagery for this indicates that this is probably two communities, and that houses at the eastern end of these two ‘rows’ of land parcels. The settlement in TIPNIS, where Community IV is located, probably dates back to the 1980s and at this time would have probably have been illegal *sensu stricto*. The fact that is still exists along with other communities in this area suggests its status in probably now *de facto* legal, but not *de jure* legal. This makes detailed field investigation of this site awkward, though Professor Millington told me he has conducted ground surveys in TIPNIS twice.

Community land tenure maps may not have existed for the community when it was first settled, as was the case with Communities I to III. In any case, as noted earlier in the thesis, these maps are now highly restricted under the Morales administration because of disputes over land tenure.

The pattern of the land clearance is from the east towards the west in both ‘rows’ of land parcels as can be seen on all three maps (Figures 4.5-10 to 4.5 -12). The three images reveal deforestation in the area. There was clearance from 2011 to 2016 unlike the other three communities.

Statistics for the forest and non-forest classes for Community IV are presented in Table 4.5-4. It is interesting to note that the mean land parcel size is slightly over 30 ha. This may reflect the fact that these communities were probably settled illegally, as they do not fit the 20ha and 50ha cultivation and grazing-community guidelines that existed elsewhere is Chapare.

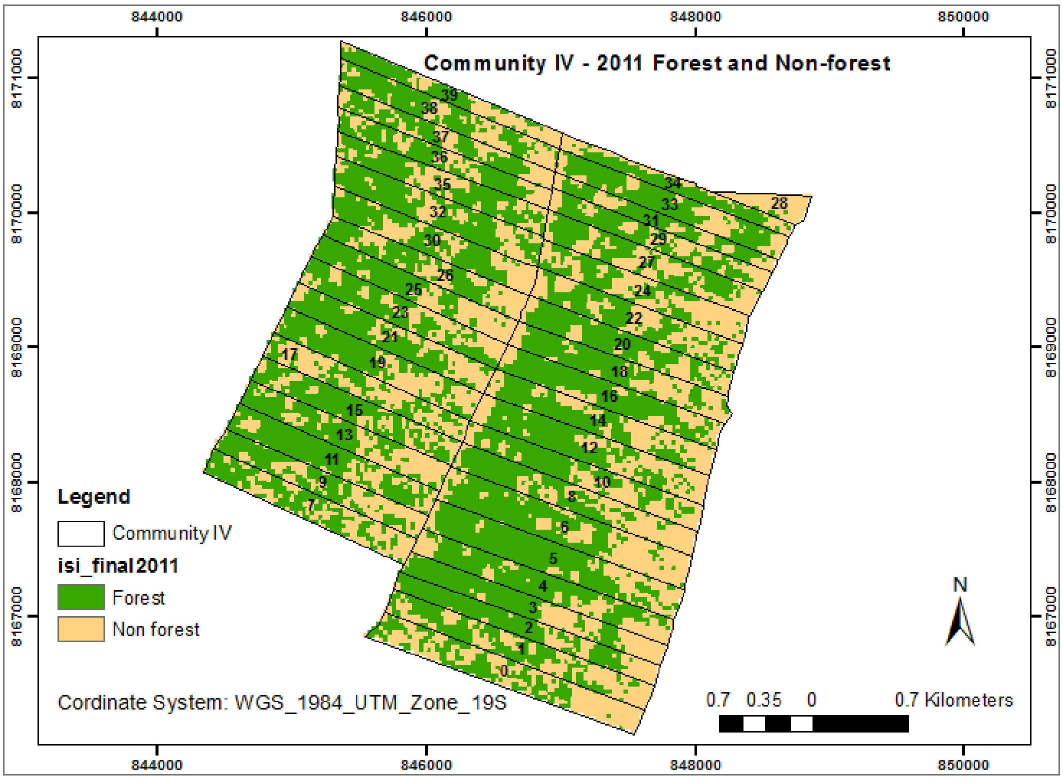

Figure 4.5-10; Community IV: forest and non-forest map for 2011

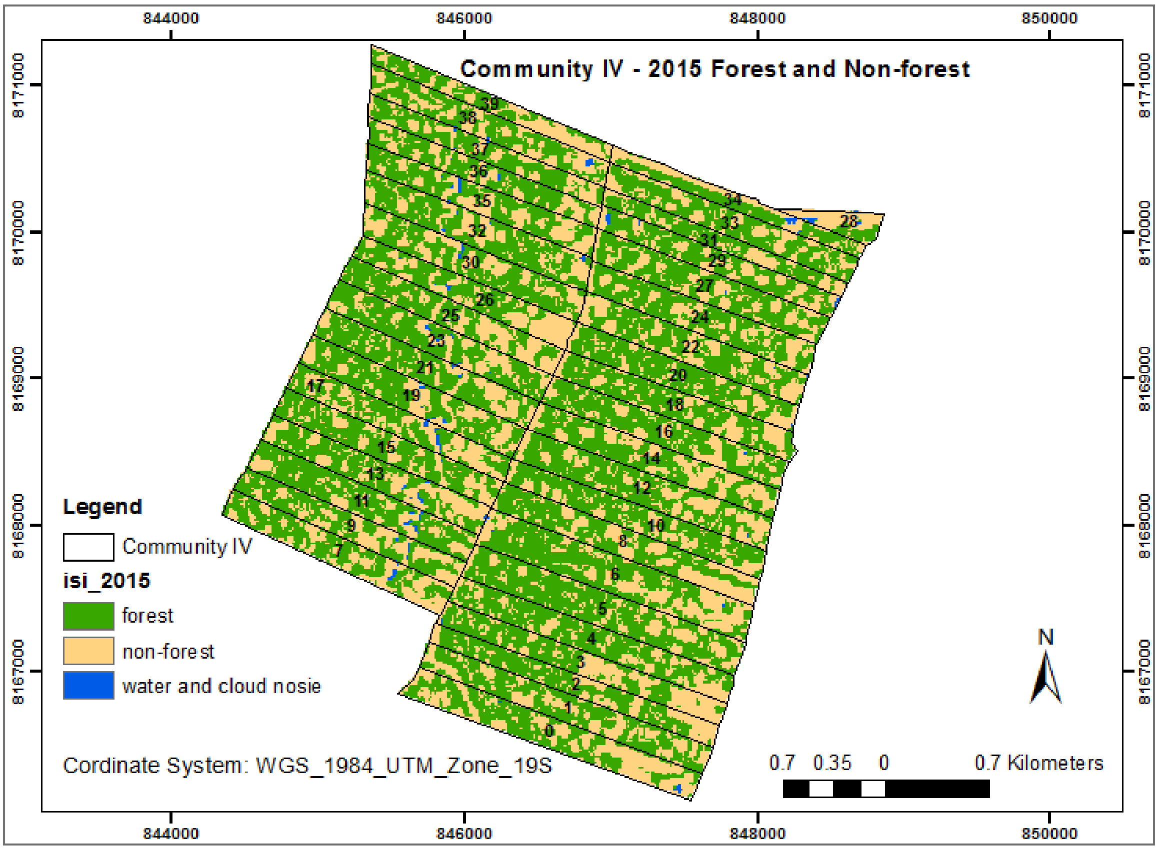

Figure 4.5-11; Community IV: forest and non-forest map for 2015

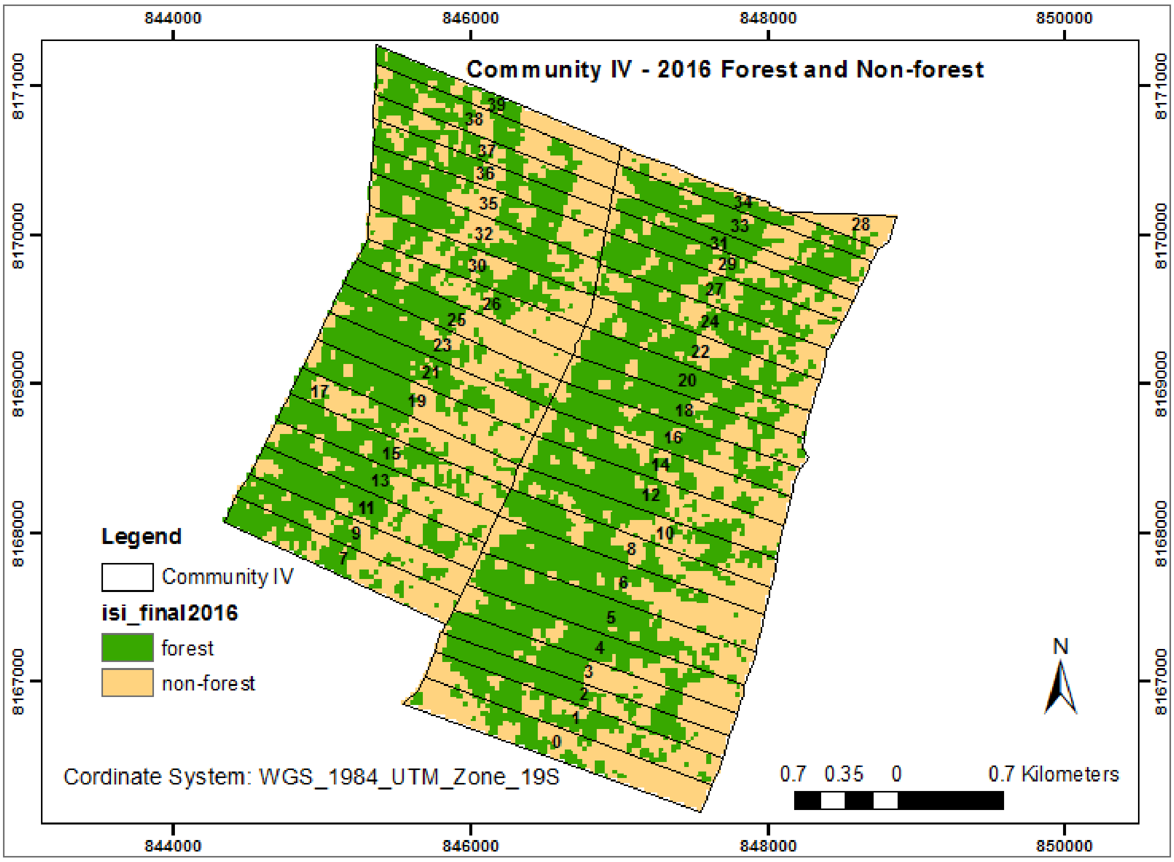

Figure 4.5-12; Community IV: forest and non-forest map for 2016

The land parcels vary between 19 and 50 ha (Appendix 4.1). In TIPNIS, grazing was and is common, but there is also much cultivation. The average parcel size of 33 ha possibly also confirms that there are two ‘rows’ of farms in this ‘community’. The parcel owners in the row to the east live in the middle while the parcel owners in the west rows lives along the western border. That is evident in the pattern of clearance from west to east as stated previously.

The results in Table 4.5-4 also shows regrowth in 2015 and deforestation in 2016. The clearance rate for 2011 is not available because this community was mapped out in this study for the first time and cannot be referenced to past statistics. The forest cover decreased from 763.11 ha in 2011 to 717.84 ha in 2016. Thus, the clearance rate between 2015 and 2016 is 79.56 ha/year.

Table 4.5-4; Forest and non-forest statistics for Community IV

Total area (ha)	1295.82
Number of Farms (lease)	40
Average (ha)	33.0558231
Min (ha)	19.2771
Max (ha)	50.6714
Std dev	6.28702723

Year	Forest Cover (ha)	Non-Forest cover(ha)	Forest cover (%)	Non-Forest cover (%)	Clearance rate (ha/annum)
2011	763.11	532.71	58.89	41.11	N/A
2015	797.4	500.3555	61.44	38.56	-8.5725
2016	717.84	577.98	55.40	44.60	79.56

CHAPTER 5

5 : IMAGE AND CLASSIFICATION ANALYSIS

This chapter discusses the issues that are related to the remote sensing, image processing and geospatial analysis elements of this thesis in the context of the integrity and plausibility of the results.

5.1 Unsupervised classification over large areas

When large study areas are considered, the application of classification methods to map land-use and land-cover classes can generate many errors from ground sampling to the methods employed in classification. Therefore, is it necessary to discuss the application of unsupervised classification in this research even though the kappa coefficients for the overall accuracy of the forest and non-forest rate maps rate the agreement between verification data sets and predicted data sets as strong to perfect (Table 5.1-1).

Table 5.1-1; Summary of accuracy statistics for the 2011, 2015 and 2016 forest and non-forest maps

Accuracy	Years		
	2011	**2015**	**2016**
Forest Accuracy	98.00%	88.20%	98.67%
Non-Forest	71.43%	87.10%	97.44%
Water	95.50%	100.00%	100.00%
Overall accuracy	84.50%	87.84%	98.42%
Observed agreement	0.85	0.88	0.98
Expected agreement	0.37	0.49	0.36
Kappa coefficient	0.75	0.76	0.98
Agreement ranking	Strong	Strong	Perfect

The forest class accuracies for 2011 and 2016 turned out to be close to 100% correct. While the results appear to be very good, they are higher than the accuracy for 2015. This is because both years lack true ground points compared to 2015.

Nonetheless, all three years have very high levels of accuracy for forest mapping. In addition, the forest, non- forest and water are easily distinguished in the unsupervised classifications presented in the previous chapter. This is particularly important for the forest and non-forest classes.

The results for the non-forest class accuracies are slightly more confusing than at first sight: increasing from a low 71.43% in 2011 to an impressive 97.44% in 2016. To a certain extent, the ground data collected at the end of the 2015 dry Austral winter and spring is almost as representative of 2016 as it is of 2015 given the slow nature of land-use change that Chapare now experiences; and because fields for the 2016 wetter summer growing season were being prepared by September 2015. Nevertheless, this does not explain the lower non-forest accuracy in the 2015 map. Three of the individual LULC classes—forest, bare soils and urban, and pasture–had accuracy levels >70% in the 2015 classified image. Other forest and agricultural classes fell below 50% correct. The reason for this is explained in terms of pixel misclassification later in this Chapter.

Returning to the application of classification over large areas, a non-parametric statistical approach in unsupervised classification is required in the absence of ground reference points. The process of using spectral signatures to statistically match pixels in a single image to form a land cover class is the basis of this approach and has been used extensively (Richards, 2012). However, the risk of introducing inaccuracies in classification, increases when applying the n-dimensional quantitative envelope for spectral signatures obtained from one image to another image and this has been proven when classifying landscapes in Canada (Olthof *et al.*, 2005). This problem persuaded Knorn *et al*. (2009) to adopt support machine vectors in what they termed chain processing to classify land use and land cover

over large areas. Other techniques to address these issues had been investigated by Chilar *et al*.(1998), Chilar (2000) and Pax-Lenney *et al*. (2001). In addition, over large areas it is unrealistic to expect all land-use and land-cover types to be found in all images that comprise the landscape. Therefore, if spectral signatures are only collected from one image, classes in other images may not be represented and classification errors will arise. Sometimes signatures collected in training sites in supervised classification, either in the field or from an image, may not be as accurate as the trainer expects because the context of the geographical location is also important, e.g., background soil conditions. The technique used by Chilar (2000) to overcome large area issues was adopted in this study.

5.2 Misclassification of Pixels for specific class types

Pixel misclassification is a well-known issue in classification that occurs because of a variety of reasons. The first of these is that different images are captured at slightly different times of the day between 1400 hrs and 1430 hrs local time and, more importantly, different dates even though they are from the same sensor. This can be particularly problematic in classification of multi-image mosaics as noted above. That is the reason why the colour correction and histogram matching is used when mosaicking the images for classification. Thus, land cover types with statistically similar reflectance values should be classified as the same land-cover class over the full extent of all the images in a mosaic: but that does not occur because techniques like colour correction and histogram matching cannot overcome large differences in pixel reflectance caused due to phenological (seasonal growing cycle) differences in land cover. That is why according to the confusion matrix some pixel known to be citrus from the ground verification date were classified as forest, and palmetto and banana pixels can be classified as pasture (Figure 5.2-1).

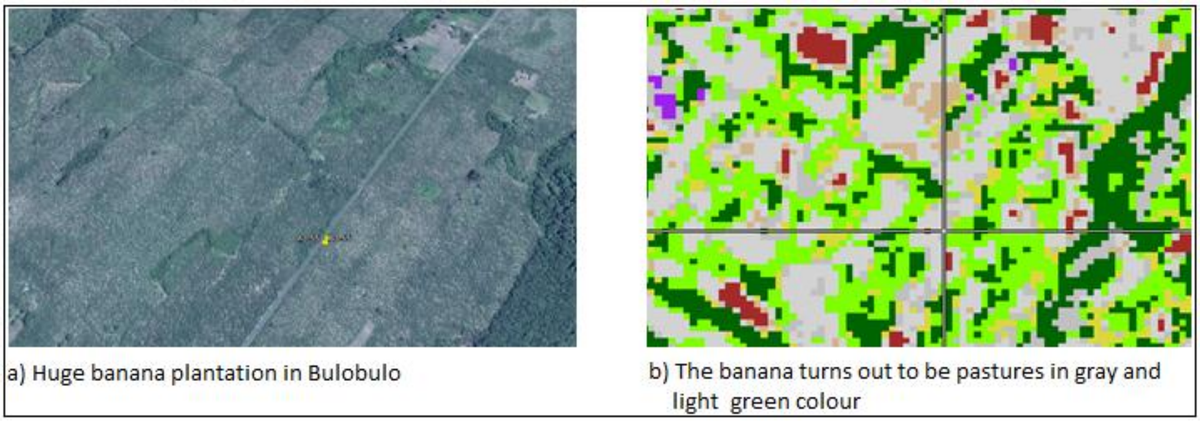

Figure 5.2-1 a) Google Earth image of a banana plantation near Bulo Bulo, which from a spatial view looks like pasture. b) The classified image of the same banana plantation which turns out as the pasture class given in both light green and grey colour. Bare soil areas also turn out in that image.

The various forms of image classification are the preferred digital image analysis techniques for mapping land use and land cover types in that they all cluster pixels with statistically similar reflectance values. Focusing on the unsupervised classification used in this study, many of the land-use and land-cover classes were misclassified in the more detailed mapping carried out on the 2015 imagery: though this was not the case for the forest and non-forest classification maps. Misclassification in the case of the detailed mapping occurred because of the limitations of the classification method employed, particularly because of the iterative nature of the process and the fact that the algorithm is based on a polarimetry classifier (Xu *et al.*, 2014). The spectral reflectance recorded by the sensor are polarized signals and classifiers involving those signals in unsupervised classification such as i) Maximum Likelihood, and ii) Parallelepiped are referred to as 'polarimetry classifiers'.

The other factors at play would have been noise in the imagery and the environment condition, i.e. wind, precipitation and dust particles as indicated by Al-Fares (2013). Image noise, which can be a function of illumination angle and azimuth, and atmospheric conditions, is known to affect image classification in agricultural areas (Blaschke, 2005): the non-forest areas in this study are probably affected by image noise. For example, there is much cloud cover in the lower south part of the study area in 2015. Though it is restricted to the mountains to the south, water vapor levels in the atmosphere over the lowlands are likely to be high and may not have been totally accounted for by the image correction algorithms applied by NASA (Section 3.1) This accounts for the speckling all over the image that seems apparent in the community maps in the results. In the LULC cover image for 2015, this has probably led to water bodies with high sediment loads being classified as concrete (Figure 4.1-3) right after the wet season between January and June (Figure 5.2-2). I have used monthly rainfall data from the Climate Change Knowledge Portal (2017) which have data up to 2015 at the time of thesis writing to compared rainfall in 2011 and 2015.

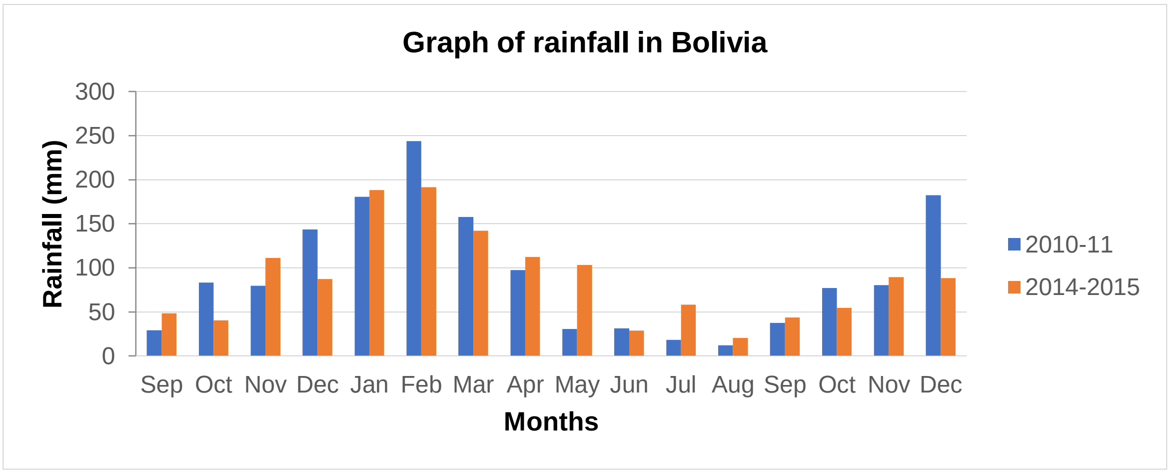

Figure 5.2-2 Rainfall data in Bolivia between 2010-2011 and 2014-2015. (Source: Climate Change Knowledge Portal, 2017)

The classification of the agricultural areas is another area of concern for detailed land-use and land-cover mapping because of the size, shape and pattern of cropped areas in comparison to primary vegetation and secondary bush and tree growth. Even in semi-arid environments, with less vegetation cover, the spectral overlap between land cover types and the small areas of some cultivated fields compared to pixel size makes imagery susceptible to error in image classification. Susceptibility to this type of error is much greater in humid tropical environments with high LAI and fast rates of vegetative growth and the similar reflectance responses in the imagery for many land cover types results in misclassification (Todd and Hoffer, 1998, Huete *et al*., 1985). That can be restated as the heterogeneity in the vegetation and soil exposure. The low organic presence of cultivated topsoil in this region means that exposed soil reflectance is very similar to reflectance from the various fabrics of urban areas.

Soil background reflectance influences pixel values when there is <100% ground cover and has much of the influence on, for example, NDVI (Pau *et al*., 2012). This applies to the imagery from Chapare as it was taken in the dry season, when vegetation is dormant, crops have been harvested and there is partial vegetation cover in areas under pineapple, *maracuya* (passion fruit), young trees crops, and pasture. Citrus orchards are an interesting case as they can be classified as a forest or bare soil. Citrus orchards are cleared of regrowth occasionally, in some cases once a year and in other cases not every year. Therefore occurrence of weeds, shrubby regrowth and lianas can easily produce 100% cover (with an LAI>1.0): such pixels will be easily confused with forest. Newly planted or recently cleaned citrus farm will reveal >70% soil depending if the trees are young or mature and how long it has been since clearance of regrowth: they are likely to classified as soil. Soil moisture may also influence pixel spectral properties when there is only partial vegetation cover (Wang *et al*., 2007).

Another factor that can affect pixel classification is the difference in the seasons in which imagery was acquired. This is because the season of the year may have a strong influence in the reflectance values, e.g. in the dry season when permanent vegetation is under stress even though it retains a high LAI. This also affects permanent pastures, which range from LAIs of approximately 1.0 during the growing season (assuming they are not overgrazed and it is not a growing season with relatively low rainfall totals) to almost bare soil in the dry season. Image resolution has a role as well because if the field sizes are less than the spatial resolution of the imagery mixed pixels can be created from stressed and low LAI elements in conjunction with high LAI elements (Al- Fares, 2013).

A further factor that coincides with the illumination giving high reflectance or reduced reflectance is the topography of the area. The Chapare lowlands are, for the most part relatively flat; although there are small minor mountain ranges in the southeast and northwest extremes of the study area where over-illumination and shadow affects occur. These are mainly still forest. However, where tall primary or secondary forest occurs directly north and northeast of cleared areas or a low canopy of crops or early regrowth deep shadow areas exist, a problem also found in Bradley (2005), which does lead to misclassification of pixels, this occurs north of Bulo Bulo for example where primary forest is adjacent to pasture.

Noise and errors can never be underestimated in classification as reiterated by Guerschman *et al.*, (2009). Imagery acquired in the wet seasons always has cloud noise that influences results. Noise influences pixels values leading to land cover classes being misclassified. Moreover, noise and errors can affect land cover classes whose pixel values are close together. Common examples are dry grass and grazing having similar pixel values. Again, the primary reason is the strong soil reflectance because of excessive grazing and dry grass reflectance with the noise, both class will be classified as a single land cover type.

5.2.1 Misclassification of Pixels for Forest and Non-forest

Pixel misclassification is low in the three forest and non-forest maps. The few pixels that are misclassified due most likely due to the noise, shadow and edge effects discussed above. Classification of areas known to have cloud cover pose a real challenge in image processing (Salberg, 2011). In some robust classification exercises carried out on a small area with cloud noise and missing pixels, statistical algorithms can be applied to predict their classes. It was not felt necessary to do that in this thesis. Nonetheless, there is some cloud noise in the mountains to the south of the images: but it does not affect the lowlands which were the focus of the research.

Heterogeneity in the vegetation as discussed above affects the radiometry values. This is because the spatial resolution of Landsat TM image data (30m x30m) may lead to mixed pixels of different vegetation types and different spectral properties

The shade effect also contributes to pixel misclassification. This can be due to differences is slope angle and aspect, but also can be due to shadows cast by tall vegetation as noted in the above section. This leads to the anisotropic reflectance (Colby and Keating, 1998), and would have been a significant issue if forests in the mountains to the south had been mapped in detail. There is not much of an edge effect in the forest and non-forest mapping. Thus, in the classification of forest areas, all forest types (i.e., mountain forest, lowland forest, wetland forest and gallery forest with high illumination or shaded) were relatively simple to merge into one class. However, edge effects are noticeable is areas where there are roads and clearance adjacent to mature forest.

5.3 Error Analysis

From pre-processing to classification and mapping, steps were taken and check for, and avoid generating errors. The fact that the overall accuracy of the three forest and non-forest image maps is >80% accuracy is testament to the effectiveness of this. Nonetheless, error analysis can be undertaken to rank the accuracy of an assessment and examine where the errors were generated.

The first step undertaken was to examine the GPS coordinates of the ground verification data (Appendices 3.2 and 3.4) in Google Earth to verify the locations were correct. This was done by comparing the Google Earth images to the sketch maps on the LULC recording sheets and looking of the ground photos. Thus, errors in the location of ground verification points were eliminated. Errors are also generated in pre-processing, but as these processes were done by the image provider, they cannot be checked and eliminated by the user.

The application of the algorithms used to cluster pixels together into their respective land cover types also generates errors. These errors can be considered misclassification errors, and their causes have been dealt with in detail in the previous section. These factors were considered when distinguishing classes across the entire classification before recoding all classes in forest and non-forest classes in the 2015 image map. One of the simple techniques used as a preliminary guide to verify the classification of forest and non-forest was to generate a NDVI image of the same area and then use the swipe tool in ERDAS Imagine too identify misclassified pixels. Normalized Difference Vegetation Index (NDVI) is a spectral index model that is used very widely in vegetation studies and can be applied to change detection. It is derived from the following formula given in Equation 5.3-1.

$R_{NIR} - R_{VISRed} / R_{NIR} + R_{VISRed}$ (Equation 5.3-1)

Where R – reflectance and near infrared $_{(NIR)}$ and visible red $_{(VISRed)}$ wavelengths.

NDVI values ranges from -1 to +1. NDVI values for healthy vegetation have NDVI values of values >0.2, while other vegetation types are >0. Negative values are usually <0. Thus, any ambiguous pixel can be picked out easily when swiping carefully through the two images. Ambiguous pixels found were correctly reclassified again.

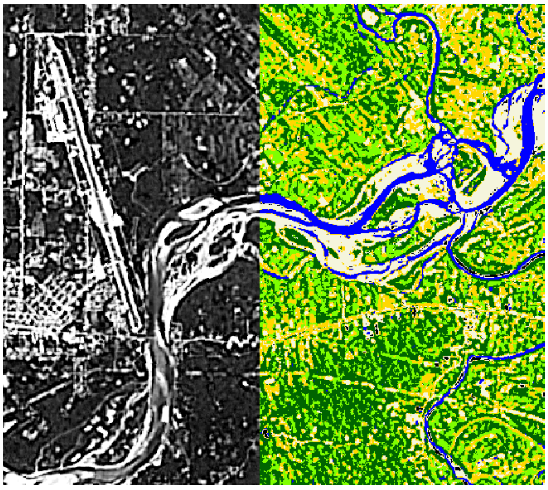

Figure 5.3-1NDVI image for the Chimoré Airport subset in black and white (left) with the classified image (Green = Forest areas, orange=non-forest & Blue = water. The swipe tool in ERDAS Imagine has been used to set the division between the NDVI and classified parts of the image. The darker areas in the NDVI image are forest areas.

5.4 Comparison of the classified forest and non-forest 2015 image with 2011 and 2016 images.

The 2015 forest and non-forest maps are different from those derived for 2011 and 2016. The differences can be tied down to one major factor, which are the differences of the spatial resolution of the images used in the supervised classification that preceded forest and non-forest mapping. The base spatial resolution for the three sets of images was 30m (Table 3.1-1). However, pan sharpening was carried out on the 2015 image (Sections 3.1). During the process of image enhancement by pan sharpening, the resolution of the 2015 imagery was converted from 30m to 15m, because the pan-sharpening algorithm uses a panchromatic 15m spatial resolution band to enhance the images. Tarolli *et al.* (2014) show that pan sharpening leads to improved definition of the pixel edges whether it be remote sensing, medical imaging or forensic science. Therefore, the new enhanced image has a spatial resolution of 15x15 m with more clearly defined edges for forest and non-forest classes. Therefore, pan-sharpening in the 2015 images discriminate and gives details of forest and non-forest class than 2011 and 2016 forest and non-forest classes as further elaborated in Section 5.4-1. A recent study by Dorji and Fearns (2017) in investigating the impact of the spatial resolution of satellite remote sensing showed that class discrimination increased as spatial resolution decreased (i.e., pixel size became smaller). It is can be argued to as introduction of noise, however it outlines the shadow, roads, small streams, understory vegetation and reveal features that may not be a land cover class.

5.4.1 Pixel resolution and LULCC discrimination

The primary reason why the 2015 classification imagery looks so different to the 2011 and 2016 classified images is due the spatial resolution. This is a common error, as stated above in the discrimination of classes, which pushes for classifications to include more spatial resolution data. This make sense because for a tree with a canopy size of 200 m^2 in 900 m^2 area of water will appear water in a

30x30 m pixel size but the tree would be revealed at 15 meter resolution. This was reiterated by Ming *et al*., (2011) in selecting appropriate spatial resolution for remote sensing applications. It was known that in any spatial analysis, the need for choosing the scale and resolution is a necessary (Ming *et al*., 2011, Curran and Atkinson, 2002, Lázaro *et al.*, 2013), to discriminate various classes more precisely (Dorji and Fearns, 2017). Higher spatial resolution imagery discriminates classes more accurately compared to coarser resolution imagery (Lázaro *et al*., 2013). This is supported by Singh *et al*. (2012) who showed that the higher the spatial resolution the better the accuracy for all classes. This was also revealed with this study where the Community IV land parcels for 2015 (Figure 5.3-1). Comparing it to the classified image, a fine spatial resolution FCC (R= Band 7, G = Band 5 and B = Band 2) correctly classified the forest and non-forest classes. The water class was also clearly discriminated and appears on the forest and non-forest map shown in Figure 5.4-1.

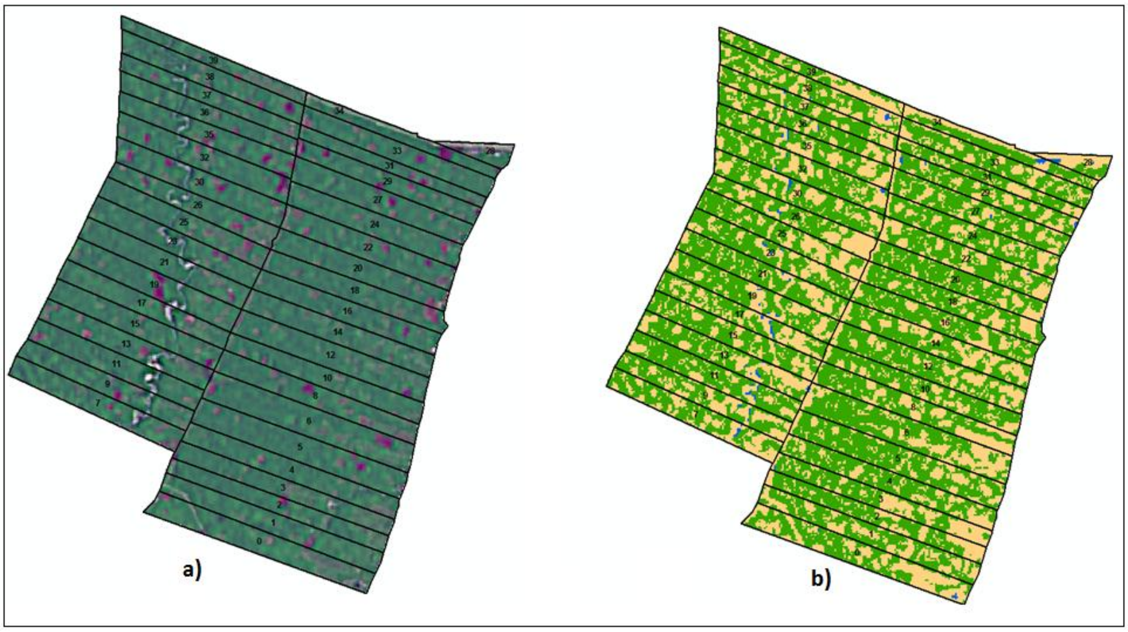

Figure 5.4-1; The land parcels for Community IV a) Reflectance image given in false colour (band 2-blue, band 5-green & band 7-red) b) The unsupervised forest and non-forest classification (forest in green and non-forest in orange while blue indicates water class)

In this study, 2015 images were classified for different land uses in the study area because of the availability of the ground verification data while the 2011 and 2016 images were classified for forest and non-forest areas only. Therefore using a 15m by 15m resolution clearly defines the different land use because a small field size of coca plot or a cassava plot on average is around the same size as the pixel size. Thus, (Curran and Atkinson, 2002) reiterated that scale and pixel size for any classification is important and stating that "…the length of a phenomena depends on the spatial resolution of our measurement". Therefore, when using the higher resolution of the 2015 image, every class feature turned out well for we can see small clearance areas in forest areas clearly. This approach picked out degraded forest and newly cultivated areas rather than identifying each agricultural crop types. Unlike in the 2011 and 2016 images, just because 60% of the cover type is forest in a pixel size, the pixel was classified as a forest neglecting the 40% non-forest. These reveals and proved that heterogeneity in an image does affect the radiometry values with respect to the spatial resolution of the image as argued by Wang *et al.* (2007). Moreover, high spatial resolution data from a multispectral sensor can be used for digitising a base map (Unger *et al.*, 2013) that also shows that it discriminate classes very well. From the 2011 and 2016 classified images in the respective communities, forest areas turned out to be homogenous which is mostly unlike areas of settlements. However, comparing the three images, they all have the same pattern of cultivation and regrowth, which shows the accuracy of the classification. Because of the above reason, 2015 images shows small areas in between forest areas that are non-forest. In addition, the water feature that shows up in 2015 image for the Community IV was not seen in the same community in 2011 and 2016 images. However, the accuracy assessments show that all images were classified better with better preference to 2011 and 2016 classification.

CHAPTER 6

6 : DEFORESTATION RATES AND POLICY SHIFTS IN CHAPARE

The aim of this chapter is to evaluate the deforestation in the communities studied in detail in relationship to the narcotics policies that have been implemented under different presidential regimes for this study period. Specifically in this chapter the hypothesis put forward by Bradley and Millington (2008b) that deforestation rates are lower under pro-coca (or lax enforcement of anti-narcotics policies) is tested. To do this, the maps of Communities I, II and III that were created by Andrew Bradley (2005) and Mlenge Mgendi (Texas A&M University) for 2008, which are not published yet, are used along the maps I have produced for 2011, 2015 and 2016.

Those data combine were analysed to answer the key research questions presented in chapter one. That includes the deforestation rates and the policy drivers in the study region.

6.1 Extending the statistical analysis of community metrics

The fragmentation patterns of forests were analysed for four communities (I-IV); for I to III the analysis includes the data 1966, 1986, 1993, 1996, 2000 and 2008 (Sections 6.1.1 to 6.1.4).

These communities contain 11 to 54 ha land parcels which are generally long and narrow. The Instituto Nacional de Colonización that was founded in 1963 assigned each parcel to a colonist farmer. The communities were accessed by a dirt road through the centre (Communities I-III) or to one side (Community IV) of the community. In Communities II, III and IV colonists cleared land backwards from the access road, first clearing forest to grow their first year's crop and to get timber to build a house. In Community I and III houses were located along central roads and patches were cleared backwards from an east-west access road. In subsequent years, farmers cut further into the forest in their plots. Forest clearance patterns and rates reflected different land use and land management practices (Bradley, 2005, Bradley and Millington, 2008a). The communities were founded at different times: Community I was founded in the 1960s, Communities II and III in the 1980s (Bradley and Millington, 2008a) and Community IV was likely founded recently in the 1990s; even though colonisation parts of Chapare dates back to the start of the 20th Century (Millington, in press). The results of the analysis in the three communities is from 1986 to 2016. The time span for Community IV only covers 2011 to 2016 at the present time.

The communities comprise different numbers of farms with different sizes (Community I - 102 farms, Community II – 93, Community III – 60, and Community IV – 40). Communities I and III have a central location for a shop, market, school, and a football field. These facilities are elsewhere for Communities II and IV. The mean farm size for each community is different (Table 6.1-1).

Table 6.1-1 Mean farm size for the communities sampled

Community	**Farm size**	
	Mean (ha)	**Standard deviation (ha)**
Community I	19	3
Community II	34	15
Community III	20	2
Community IV	33	6

6.1.1 Community I Deforestation matrices

The sections on deforestation metrics for Communities I, II and III have the same format. First, the deforestation metrics outlined by Bradley (2005) and Bradley and Millington (2008a) are summarised; then the metrics for 2000-2016 are presented and discussed.

Community I had seen much forest clearance by 1986. The community was founded in 1963, meaning 23 years of clearance had taken place before the 1986 image was acquired. A Corona KH-4A acquired three years after the community was founded can be seen in Figure 6.1-1. Details of the Corona missions can be found in the book by Ruffner (1995).

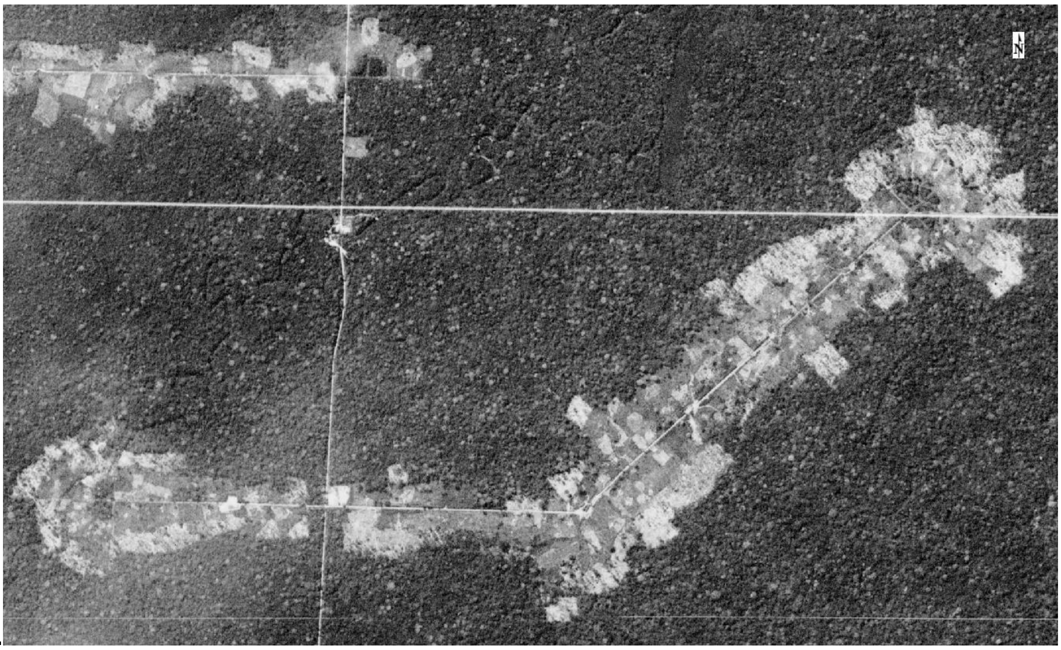

Figure 6.1-1 Corona KH-4A image acquired in 1986 in Community I (Source; Bradley and Millington, 2008)

By 1986, 1198.35 ha of forest had been cleared leaving 617.36 ha. The net forest cover remained more-or-less same from 1986 to 1996 and there was some regrowth between 1996 and 2000. By 2000, the forest cover in Community I was 44%. It can be argued that this was because much of the area was under citrus (Bradley 2005) a reasonably stable tree cover of mature citrus *and* remnant forest existed after 23 years of settlement and farming.

Between 2000 and 2016, there has been almost no further forest clearance, which has allowed secondary forest regrowth. The 2016 estimate of forest cover is 1176.52 ha (Figure 6.1-2) which equates to a proportional forest cover of 64.77%. There is a slight increase (approximately 1%) in the forest cover from 2011 to 2015. That is the period of uncertainty for drug enforcement, demand reduction and alternative farming in line with the European drugs policy 2013-2020 (EU, 2014) putting pressure on Bolivian government on illicit drug cultivation. It was also stated that there was a 9 % decrease in coca cultivation in 2013 indicated by US Department of State (2015) in their 2015 report and that shows the slight decline in forest between 2011 and 2015. Between 2014 and 2015, there is further increase (30%) in coca production in the area as reported by US State Department (2016) in 2016. Therefore, I argue that in Community I forest cover increased in 2016 because of this increase in coca cultivation. Thus, the entire period is within the period of influence of the Movement towards Socialism, which was codified when President Evo Morales Presidential Administration was elected in 2006: this is considered a pro-coca era in modern Bolivia politics (Table 2.4-1).

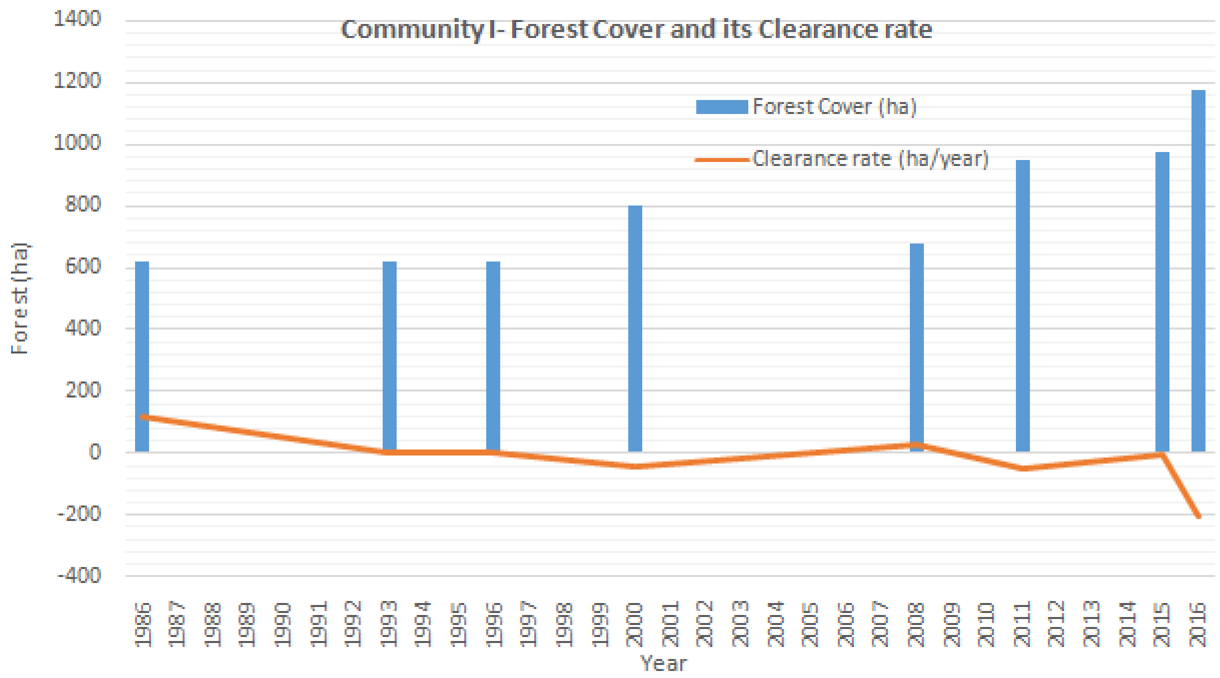

Figure 6.1-2 The graph of Community I showing the forest cover and clearance rate.

The clearance rate was 119.83 ha/year from the start of settlement to 1986 and declined from 1986 to 2000. Between 1996 and 2000, forest loss was negative. In the period considered in this thesis, the deforestation rate from 2000-2008 was higher than 1996-2000, 30.56 ha/year, and since 2008 it has been negative allowing for much regrowth (Figure 6.1-2).

The discussion of these trends is restricted to the period from 2000-2016, when there has generally been an increase in forest cover (from 44 % in 2000 to 64.77 % in 2016) which has been accompanied by a general decrease in forest clearance rate, to the extent that this is negative for a number of the inter-image periods under consideration. The clearance rates have varied from 30.56 ha/yr (0.31 ha/yr for individual farms) between 2000 and 2008 to -204.7 ha/yr (-2ha/yr for individual farms) between 2015 and 2016. While it is straightforward to ascribe the low deforestation rates and forest regeneration to the farmers in Community I being able to grow coca and therefore not needing to clear new forest areas for other crops, three other factors need to be taken into account when considering the actual values for Community I:

a) Citrus is a dominant crop in this community and mature citrus has a spectral signature which overlaps with forest (Section 4.5) which inflates forest cover percentages;
b) The 2008 forest and non-forest map was derived from CBERS-2 imagery and the forest and non-forest classes may vary slightly to those derived from TM imagery; and
c) A number of farms that existed in the southwest of the community in 2000 no longer exist (cf. maps of Community I in Section 4.5.1). This is because of major infrastructure construction in that location. That section was removed in 2011 imagery to be consistent with 2015 and 2016 maps.

6.1.2 Community II deforestation Matrices

In Community II the area of forest cleared by 1986 amounted to 506.88 ha and by 1992 it doubled to 1157 ha (Bradley, 2005). Despite the extensive clearance, it was estimated that only about a third of the forest in that community cleared had been cleared by this time because this was designated a cattle-rearing community with most of the land parcels being set at 50 ha, rather than 20 ha in cultivation communities like I and III. By 1996, an additional 447 ha of forest had been cleared which pushed the cleared area up to 49.86%. (Figure 6.1-2). Between 2000 and 2016, there has been little clearance and the 2016 estimate for forest cover is 1854.81 ha (figure 6.1-1) which equates to a proportional forest cover of 57.98 %.

There is drop in forest cover in 2015 relating to European Union applying pressure on Bolivian government as discussed in Section 6.1.2

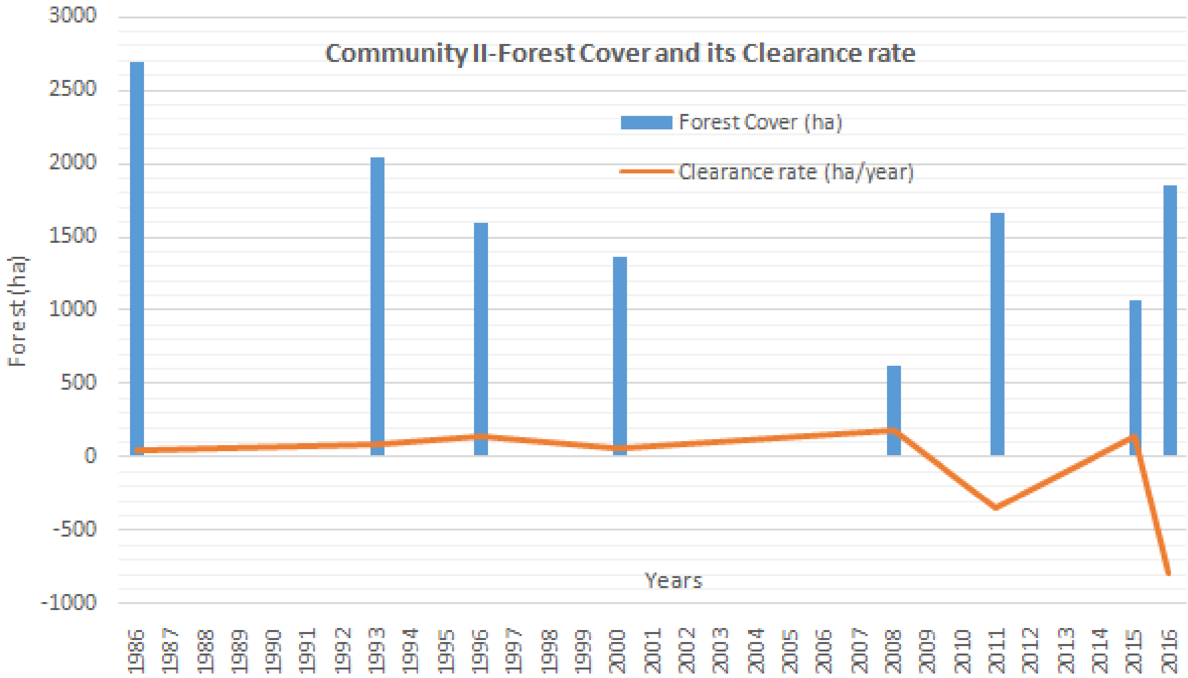

Figure 6.1-3The graph of Community II showing the forest cover and clearance rate.

The discussion of these trends in clearance rates is again mainly restricted to the period from 2000-2016. However, it is notable that the forest clearance rates increase slightly between 2000 and 2008 but decreased between 2008 and 2016. Thus, given a steady increase in clearance rate between 1986 and 1996 as pastures expanded resulting in a decrease in forest cover. In 1986 the clearance rate was 50.69 ha/year and had increased to around 57 ha/year by 2000. The continued growth in forest clearance rates up to 2000 is in contrast to Communities I and III and is likely due to the fact that alternative crops were not introduced here as part of anti-coca policies (as was the case in Communities I and III), which is related to the fact that this area is climatically-marginal for coca cultivation (Millington, in press). There has been an overall increase in forest cover (from 42.74 % in 2000 to 57.98%

in 2016) which has been accompanied by a general decrease in forest clearance rate, to the extent that this was negative for a number of the inter-image periods under consideration. The clearance rates have varied from 184.78 ha/yr (1.8 ha/yr for individual farms) between 2000 and 2008 to -786.35 ha/yr (-8 ha/yr for individual farms) between 2015 and 2016. As noted in the discussion of clearance rates in Community I, this entire period is within the pro-coca period of influence of the Movement towards Socialism: but again, other factors need to be taken into account when considering Community II:

a) Pasture is the dominant form of non-forest land in this community. Deforestation rates are higher under pastoral communities than those reliant on crop cultivation (Kass and Somarriba, 1999, Armenteras *et al*., 2013);
b) Coca is not an important crop in this community, and the influence of anti- and pro-coca policies on forest cover and clearance rates has probably been low; and
c) The 2008 forest and non-forest map was derived from CBERS-2 imagery and the forest and non-forest classes may vary slightly to those derived from TM imagery.

6.1.3 Community III deforestation matrices

Bradley (2005) estimated that the forest cover in Community III had decreased by almost 60% between 1986 and 1993. That result can be considered valid because Community III was allocated to crop farming with land parcels of 20 ha. The forest cover further decreased between 1993 and 2000, when the cover was 19.08 % (Figure 6.1-4.). There has been significant regrowth since 2000 and there is now about 524.8 ha (43.06 %) of forest in the community.

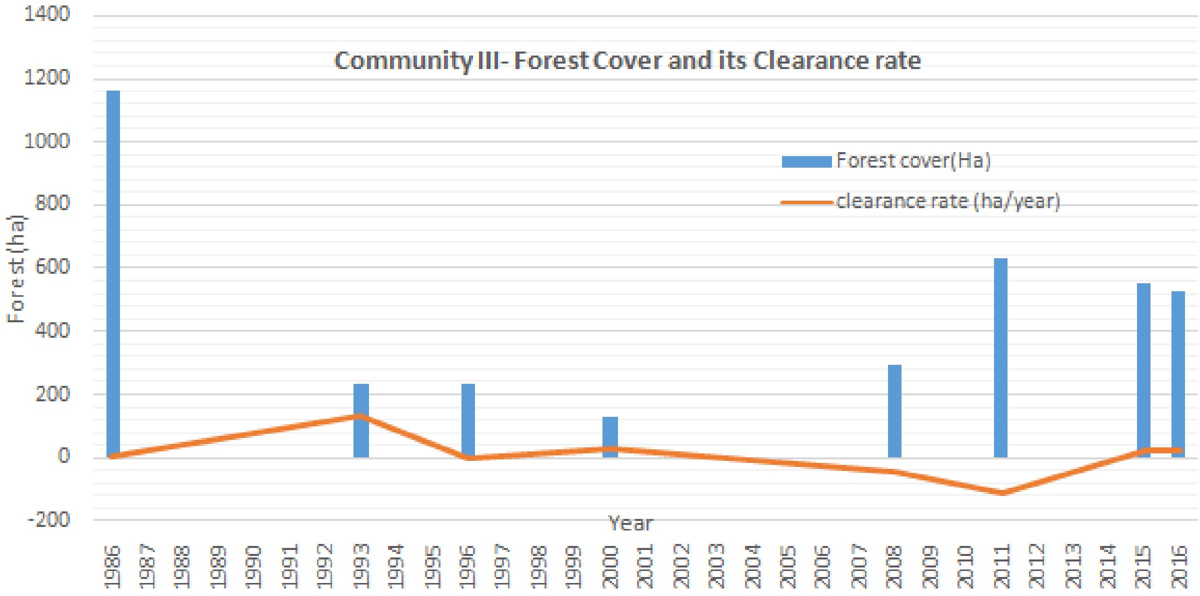

Figure 6.1-4 The graph of Community III showing the forest cover and clearance rate.

The discussion of these trends in clearance rates is again mainly restricted to the period from 2000-2016. There was a rapid decrease in the forest area from 1986 (just three years after the community was founded) to 2000 (Figure 6.1-4). The clearance rate between 1983 and 1986, when the community was filling with settlers migrating to Chapare, was very high as forest was being cleared for timber to build houses and to sell as hardwood (which has a high market price (Crabtree and Chaplin, 2013)); and the first land cleared was planted to rain-fed rice as a subsistence staple food and a crop that had high demand in Bolivia. This was also a period of when eradication of coca were enforced. However, because it is close up in the foothills of the Andes, there is high probability of coca being grown there. Forest clearance rates increased markedly between 1986 and 1993 with 1161.09 ha of forest cover to 128.34 ha. That is a clearance rate of 133.36 ha/yr. In between 2000 and 2011 there has been increase in forest regrowth in this community. That ties in with very low clearance rate, which is less than zero from 2000-2011; though since then there has been a slight decrease in the forest cover and correspondingly slight increase in clearance rates.

This was a community in which coca has been grown as part of the crop mix and is therefore likely to be influenced by shifts in, and levels of enforcement of, anti- and pro-coca policies like Community I and in contrast to Community II. Nonetheless, other factors need to be taken into account, the most pertinent of which is that CBERS imagery was used to create the 2008 forest and non-forest map.

6.1.4 Community IV Deforestation Matrices

The trends in forest cover and deforestation rates in Community IV were relatively steady between 2011 and 2016. The forest cover is above 50% although it may be starting to decrease in the 2016: 79 ha of forest were cleared between 2015 and 2016 equating to a mean clearance rate per farm of 1.99 ha/year. This is low compared to the other three communities (Figure 6.1-5). This is one of the remotest communities in Chapare at the present time and in an area where successive UNODC coca monitoring reports have indicated high coca cultivation densities. Whilst research protocols do not allow the name of this community to be disclosed, I have been informed by my supervisor that it is impossible to reach this community from the centre of Chapare and return in the same day by road. Moreover, there are only a handful of communities that are less accessible that this one in the region. Coca is grown liberally in this and surrounding communities and Google Earth imagery shows many small clearing in adjacent forests throughout the community where it is highly probably that coca is being grown (UNODC, 2005, Dávalos and Bejarano, 2008, Dávalos *et al.*, 2011, UNODC, 2016b)

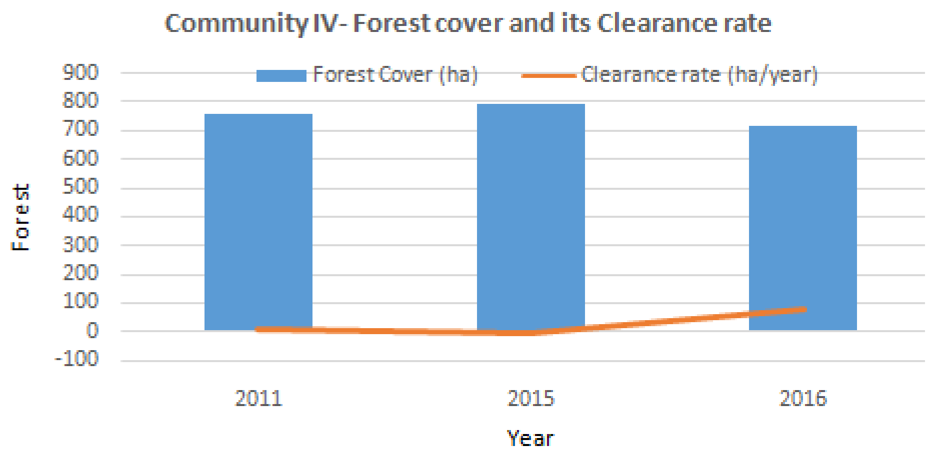

Figure 6.1-5 Community IV showing the trend of deforestation rate and forest cover in Isiboro.

6.2 The Driving factors of Deforestation in Bolivia

Overall, it is clear from Section 6.1 that deforestation rates in the four communities studied in detail have been very low since 2000, and that they have declined compared to rates in the 1980s and 1990s in Communities I-III (details are provided in Appendix 6.1).

Many factors are in play when considering deforestation, not just narcotics policies (Section 2.4). For example, market demand and prices stimulate farmers to cultivate certain types of agricultural crops, and even the farmers' choices are not constant over entire region (Armenteras *et al.*, 2013). This was also supported by recent research on tobacco as a dominant agricultural activity during the years under consideration in this study in Santa Cruz valleys to the south of Chapare that lies in between Isiboro and Carrasco National Parks (Noriega *et al*., 2013). In Chapare, it has been estimated that about two hectares of land can generate an annual average profit of US$800 if coca is grown (UNODC, 2016a). Thus, because of the persistent poverty in rural Bolivia, it is unlikely that farmers would move away from coca unless forced too. Bradley (2005) arrived at the same conclusion when considering the profit margins for coca and palmetto.

The use of improved techniques in agriculture is not a major factor in this area, coca is a hand planted and harvested crop, and the high amounts of regrowth are reasonably evident that, mechanization is not a major component of most farming systems in Chapare. However, agrochemicals are integral to coca cultivation, though they are only applied by hand (fertilisers) or backpack sprayers (pesticides).

There has been an improvement in food security and food productivity in Bolivia in the recent years (Salazar *et al.*, 2016), who mention that people have some form of access to portable water and health services improving their livelihoods. This has put less stress on farmers to use the forest (or cleared forest) to meet their dietary needs, and is a compounding factor in the decline in rate of deforestation compared to those outlined by Bradley and Millington (2008a). The others factors identified to be causing the deforestation in the study area would be population growth, demographic expansion, new settlements and infrastructure development (Armenteras *et al*., 2013). The issue of new settlements would explain why there was a sudden increase of deforestation in Community IV. That trend is not going to change and is common in other developing tropical countries around the globe.

This leaves the following question. As there has been a decrease in deforestation rates since c. 2000 compared to the 1980s and 1990s, how far can that be explained in terms the policies and legislation around coca cultivation that were discussed in Chapter 2? The policy element could well be part of the explanation of the recent clearance in Community IV because it is in a park and indigenous areas (Devere *et al*., 2017). More overtly related to coca, because Chapare is known to be a coca source region. As a result, there are lots of policies and development programs relating to coca cultivation (Bradley and Millington, 2008a, Bradley and Millington, 2008b, Elsner, 2016, Farthing and Ledebur, 2014, Marcy, 2010, Xie, 2011, Sorrell, 2010). A number of authors (Sturm and Smith, 1993, Bradley and Millington, 2008a, Elsner, 2016, Ofstehage, 2012) have considered the alternative farming policies, which are part of the programs to reduce or eliminate the cultivation of coca. During the tenure of the MAS government led by the current president, Eva Morales, policies and regulatory systems have been changed allow increased legal coca cultivation for the first time since the 1950s-1970s when legislation was first mooted and approved. This has given farmers the confidence to grow more coca, to grow it openly and obviated the need to focus on alternative farming systems (Ofstehage, 2012). Therefore, in terms of policies and the rate of deforestation this points towards a relationship existing between the deforestation rate and anti-narcotics polices that supports that hypothesised by Bradley and Millington (2008b) This is explored in the next section.

6.3 Linking Deforestation rates and anti-narcotics policy.

The 2011, 2015 and 2016 deforestation dynamics in the study area shows that there has been a slight increase in deforestation in one remote community (Table 6.3-1) and much regrowth in the other three communities.

Table 6.3-1 Average clearance rates of the four communities in this study.

Community	Average Clearance rate (ha/annum) per farm
Community I	-2.2
Community II	-8.37
Community III	0.39
Community IV	1.99

Bradley and Millington (2008a) showed that under weakly enforced or no anti-narcotics policies deforestation rates on farms in Communities I-III varied from negative values to 0.4 ha/year compared to higher rates (0.9-1.1 ha/year) when coca eradication programs were enforced effectively. When the rates in Table 6.3-1 are compared to these values, it can be seen that contemporary and post-2000 deforestation rates in these communities are in the range predicted for weakly enforced or no anti-narcotics policies deforestation rates.

This confirms what would be predicted based on pro-coca policies on the back of the "*Coca si, Cocaine non*" mantra Evo Morales introduced when he became president in 2006. Under these policies farmers are allowed to grow coca on a limited scale and its production is monitored so only the demand for chewing is met (Farthing and Ledebur, 2014, Dangl, 2010) Another major boost came in 2009 when coca leaf consumption was recognised as part of the Bolivian culture or national heritage. That meant that people could grow coca leaves for domestic use more easily and market them legally, thereby putting less stress on the forest to clear new fields for less profitable crops. These and other coca-related policies were one of the main reasons for voting in Evo Morales (who is also president of the coca grower's federation) as president of Bolivia and was into direct contrast with the Banzer's strong anti-narcotics policies of the late 1990s.

This included Law 18265 of 1986 that had the aim of compensating land parcel owners for forfeiting their coca plots (Bradley and Millington, 2008b). The policies of the governments during the 1980s and 1990s were "neoliberal capitalist reforms" with support from US that binds up with the US imposed-War on Drugs. The Bolivian Government offered compensation of US$2500, which was unfavourable in economic terms. The president, himself a union leader, coca farmer and trumpet player from before he rose to power in 2006, focussed his campaign on the “ War on Drugs” (Xie, 2011) as a threat and invasion to the Andean culture (Farthing and Ledebur, 2014, Dangl, 2010).

Thus, within the period up to 2011 from the time his government took power, was a time of much change in terms of changing crops, planting coca and allowing forest to regenerate. Significant regrowth can occur in humid tropical forests in five years, the period between Morales being elected and the acquisition of the of 2011 imagery (let alone the period from 2000 when Morales influence first began to be experienced in national politics. With that trend in policy and politics, the reduced rate of deforestation would clearly be evident by 2011 and will have continued subsequently as government (Section 2.4) has passed more pro-coca policies. Therefore, a direct correlation between the type and status of coca policies and deforestation rates. That is what the results of this research have shown and they correspond with research from Colombia that shows that illicit drug cultivation is not related to land clearance but rather to forest regrowth (Armenteras *et al.*, 2013).

CHAPTER 7

7 : CONCLUSION

This chapter briefly concludes by returning to the two research objectives addressed in Section 1.3., and then proceeds by reviewing other important research findings and, finally, making recommendations as to how this research might be continued in the future. The emphasis is on geospatial aspects given that this research was done for a Masters in Geospatial Information Science.

7.1 Research Aims

It is important to reflect on the research objectives and see if this study covers what it is intended to cover. The aims of this study were two-fold (Section 1.3) and are restated here:

c) To map forest and other non-forest land covers for 2011, 2015 and 2016 for the study area.

d) To test the hypothesis (Bradley and Millington, 2008a) that deforestation rates are significantly less under conditions where coca is encouraged than under well-enforced anti-coca policies.

Therefore, it is satisfying to point out that the two objectives of this research have been achieved. Chapters 4 and 5 illustrate and discuss forest and non-forest maps. In terms of the second aim, community-level statistics were derived from 2011, 2015 and 2016 forest and non-forest maps (Chapter 4) and examined in the context of statistics that had been derived by others for 1986, 1993, 1996, 2000 and 2008 image data. The results are clear, the rates of deforestation have generally decreased since 2000 and there has been forest regrowth in the communities as farmers stop clearing land as they are encouraged to grow coca through a raft of policies that the government had put in place since 2006. Though there are some issues, e.g. citrus orchards maturing and their tree cover being confused with forest regrowth, the evidence for low deforestation rates is strong. The additional analysis for a fourth community, which was newly chosen in this research, in a peripheral part of Chapare where coca cultivation is commonplace, confirmed low deforestation rates in circumstances where coca can be grown with impunity. The evidence is incontrovertible, even accounting for errors, Bradley & Millington's hypothesis holds true: deforestation rates are significantly under weak enforcement or encouragement of coca cultivation compared to the rates under well-enforced anti-coca policies.

7.2 Other important research findings

Other important findings from this research are briefly identified below.

7.2.1 Deforestation rate and forest cover

It is can be noted from the graphs of deforestation rates for the different communities from 1986 to 2016 (Section 6,1), that the curves of deforestation rates and forest cover mirror each other quite well despite the differences between Communities I, II and III. When there is a decrease in clearance rates, there is an increase in the forest cover. This indicates that the polices that influence forest clearance probably work is tandem in these three communities, and no doubt many of the other 600 or so rural communities in Chapare. It will be interesting to test this for Community IV, something I hope to be able to do in a publication once this thesis is completed.

7.2.2 Driving forces of deforestation in Chapare

Considering the findings of this research, it is hard not to conclude that shifts in anti-narcotics policies are the major drivers in deforestation in Chapare in Bolivia, and have been since anti-narcotics policies were introduced in the 1980s. This major policy driver can either encourage or discourage deforestation in the region. It is an underlying cause in Geist and Lambin's framework and works to drive the rates of two proximate causes—agricultural expansion and infrastructure development, specifically extension of the feeder road network though it mainly works in tandem with proximate causes. Of course, the ability to make a good living as a coca farmer had probably encouraged more migration to this colonisation zone that others in Bolivia, so population growth cannot be dismissed as a driver. Nonetheless, it can be argued that the Bolivian government's attitude to coca cultivation before and after 2000, and its ability and willingness to enforce anti-coca policies during the 1980s and 1990s, have been the main underlying cause of changes in deforestation rates in Chapare.

7.2.3 Deforestation and coca trade

The comparison to previous studies in Section 5.6, and the introduction of the "*Coca si, Cocaine non*" mantra accompanied by pro-coca policies and legislative measure has seen a lot of new cultivation in the area. Since 2004, when it is has been monitored by the United Nations, there is a clear pattern of expansion into new, peripheral parts of Chapare where cultivation densities are high, e.g. compare coca cultivation density maps for Chapare between 2004 and 2015. Farmers have tended to farm more coca in more remote regions. Is the amount of coca leaf being produced in Chapare in excess of the national demand for chewing? According to internal regulation of coca cultivation within Chapare it is, but it is difficult to square that with what must be an obvious increase in production and rather low population growth rate in Bolivia. Quantification and discussion of this is beyond this thesis, but copious press reports from Latin America, North America and Europe would suggest that a lot of cocaine paste is being sourced from Bolivia, and much of that is from Chapare.

7.2.4 Pixel resolution and accuracy

This study revealed that when using a pan-sharpened image with finer spatial resolution, land cover classes could be discriminated more accurately. Other researchers have made the same observation in the land science arena (Ming *et al.*, 2011, Lázaro *et al.*, 2013, Masek *et al.*, 2006, Feng *et al.*, 2013). This is a key geospatial finding in the context of this study and though it does not negate the analysis of 30-m resolution forest and non-forest maps it does suggest that there more accurate maps can be made on a routine basis. This is further elaborated in the section below.

7.3 Recommendations and future research

Using different approaches or methods to an issue or validate a hypothesis is an important aspect of collective interpretation of an idea. A different method can be seen as an alternative way to tackle a problem. Therefore, while this study may seem accurate; however, a level of uncertainty still exists because the research has relied on geospatial analysis applied to land-use and land-cover data. An important issue for future study is the extent to which the EKC[6] effect actually reverses as opposed to simply slows down the rate of deforestation and related environmental degradation (Ehrhardt-Martinez *et al*., 2002).

Much more could be done in terms of this by looking at the situation again in the future, e.g., when another 20 years of land cover data is available. That is a long-term study plan in which new data can be added to the data already collected, i.e.

[6] EKC effect is the relationship between the pollution and income per household with respect to clean air.

Bradley (2005), Bradley and Millington (2008a) and this thesis and any publications that emerge from it. It is timely to say that future work should be done at finer spatial resolution satellite data, which is increasingly becoming available in global data set. As the analysis of the 2015 data showed in this research, this will help improve land-use and forest regrowth classes to be identified. It would also allow other dimensions of the wider problem, like soil degradation, to be tied to this coca and cocaine production in this region (Dávalos *et al*., 2011).

It is recommended that future iterations of this “study” move from 30 m resolution data with a period in which both 30 m and finer spatial resolution data are used so the 1986-2016 data set can be calibrated with a new finer resolution time series of data starting in 2015. That would lead to consistency with past data, while allow more accurate discrimination of land-use classes in the future (Ming *et al*., 2011, Lázaro *et al*., 2013, Masek *et al*., 2006, Feng *et al*., 2013).

Furthermore, the use of fine spatial resolution to study the impacts of coca cultivation in the area is very important because of wider links between the cocaine trade’s effects on economy and environment require attention (Crabtree and Chaplin, 2013, Elsner, 2016, Dávalos *et al*., 2011). One satellite that would provide a very good spatial resolution is Quickbird (see figure 7.4-1, for basic information) because it’s very fine spatial resolution provides the possibility of identifying items such a tree crowns that are important in determining regrowth.

Sensor

Satellite	Sensor	Band#s	Spectral Range	Scene Size	Pixel Res
QuickBird-2	Multi-spectral	1=Blue	450 - 520 µm	16.5 km X 16.5 km	2.44 - 2.88 meter
		2=Green	520 - 600 µm		
		3=Red	630 - 690 µm		
		4=NIR	760 - 900 µm		
	Panchromatic	Pan	760 - 850 µm		61 - 72 cm

Figure 7.3-1; Table showing the sensor on-board Quickbird with its high-pixel resolution of 2.44-2.88 meter which is seen ideal for LULCC classification in mapping out coca plots.

It is already used with other fine spatial resolution images and photographs that are mosaicked together by the coca monitoring teams to map coca areas (UNODC, 2016): the focus is on the relationship between the characteristics of the real environmental conditions and the information using remote sensing (Schloderer *et al*., 2011). There are of course, alternatives to Quickbird and as these are becoming increasingly available and the costs of fine spatial resolution image data are falling, such data will be feasible for extending time series of forest cover data in the near future.

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Appendix 2.1 Photos of banana Infrstructure in Bolivia

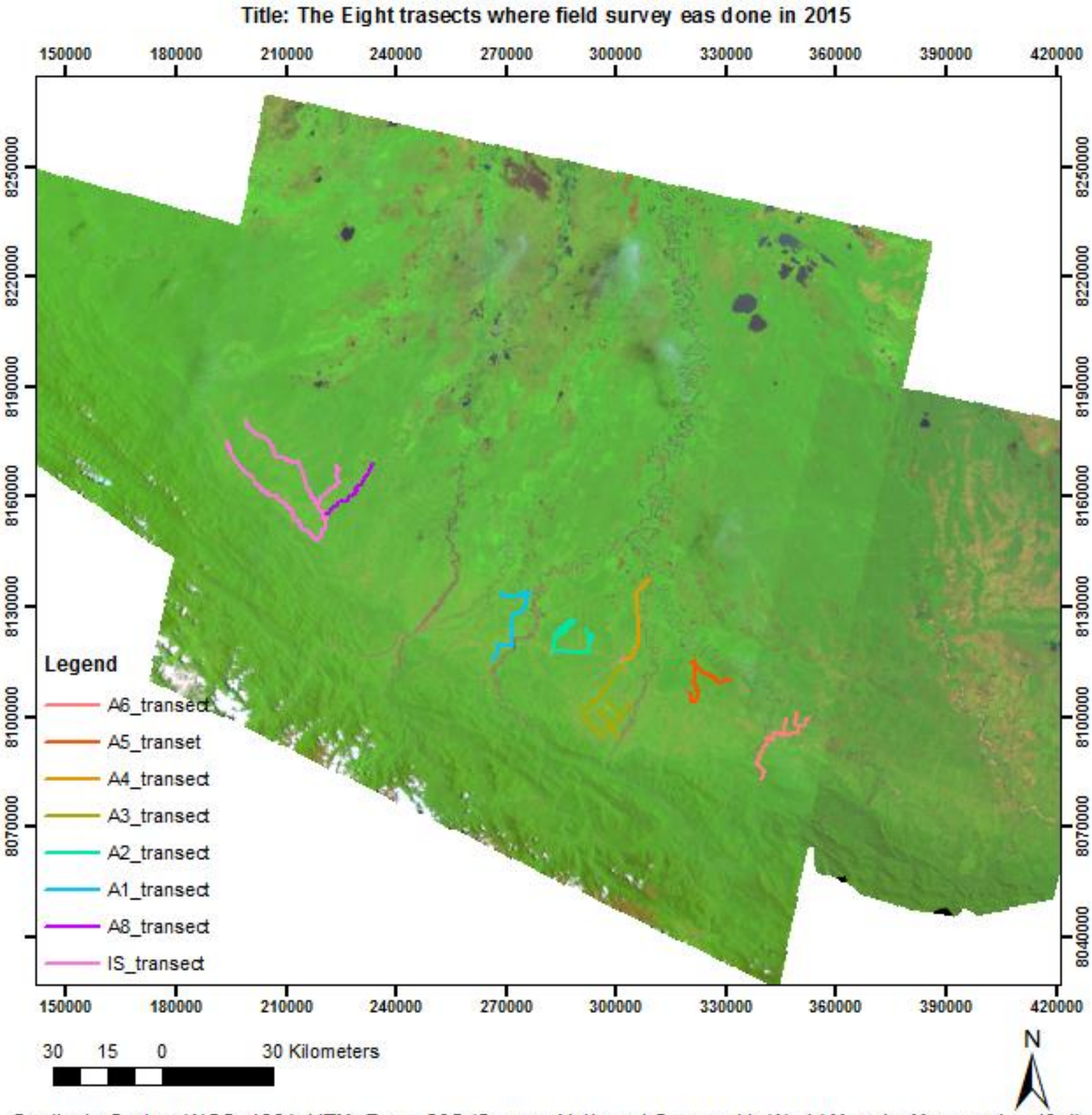
a) The image showing the pullies to winch banana from the garden to decrease labour time and labour intensity

b) The image showing the pullies to winch banana from the garden to decrease labour time and labour intensity

b) Banana arrives straight to the packing and storage facilities

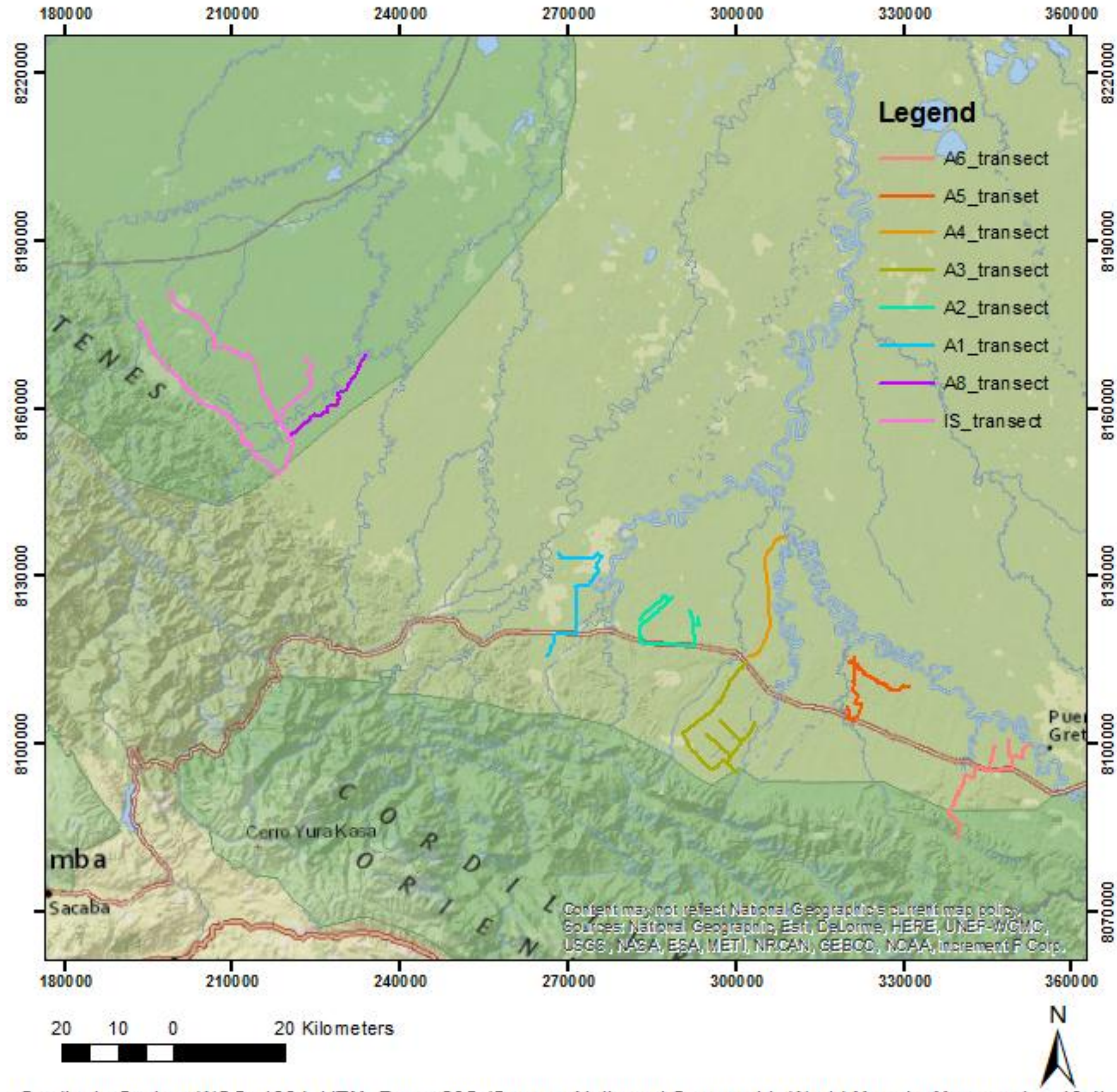
(Source of the image a,b&c; http://www.freshplaza.com/article/172706/Bolivian-banana-producers-meet-requirements-to-export-to-Russia)

Appendix 3.1 The Transects Eight Transects where the field survey was done in 2015



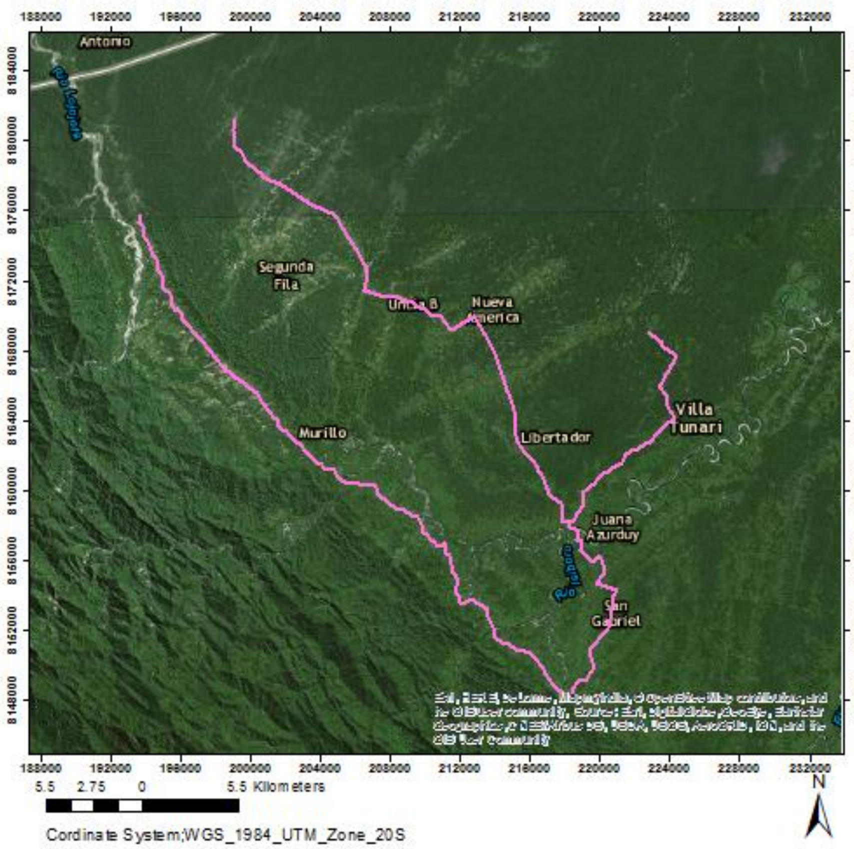
Cordinate System;WGS_1984_UTM_Zone_20S (Source: Natiaonal Geographic World Map-ArcMap version 10.4)

Title: The Eight trasects where field survey eas done in 2015

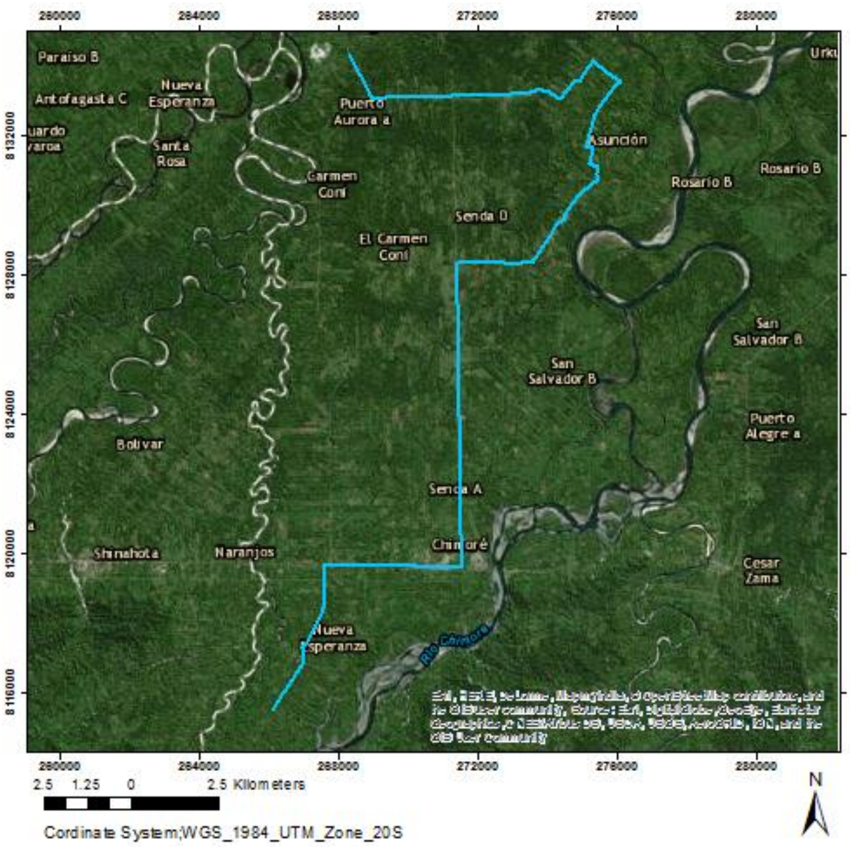


Cordinate System;WGS_1984_UTM_Zone_20S (Source: Natiaonal Geographic World Map-ArcMap version 10.4)

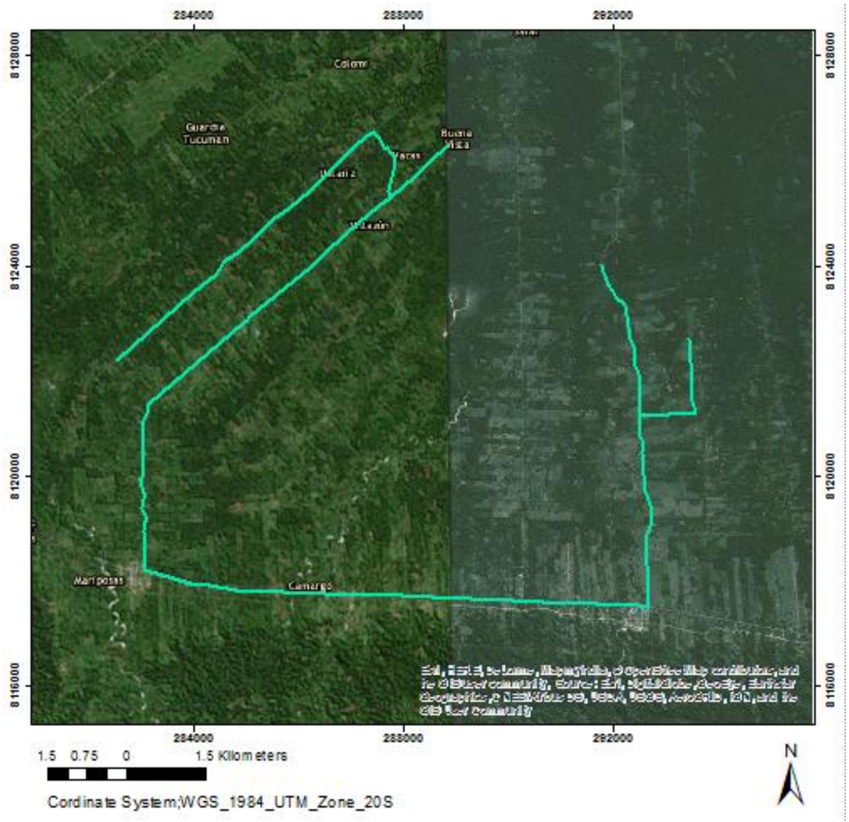
Transect IS



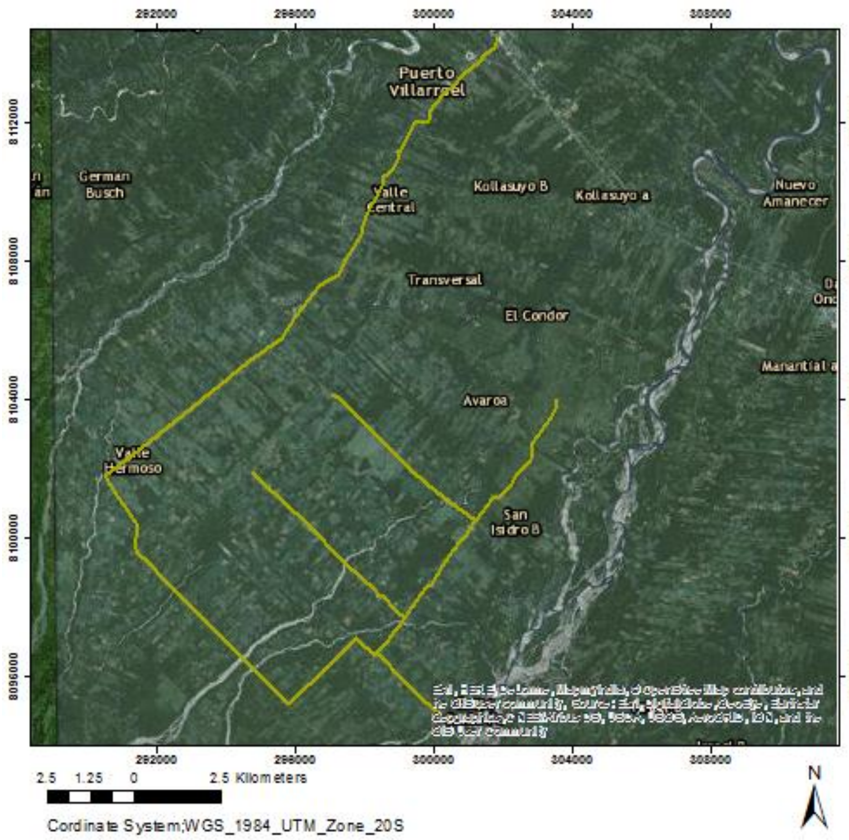
Transect A1



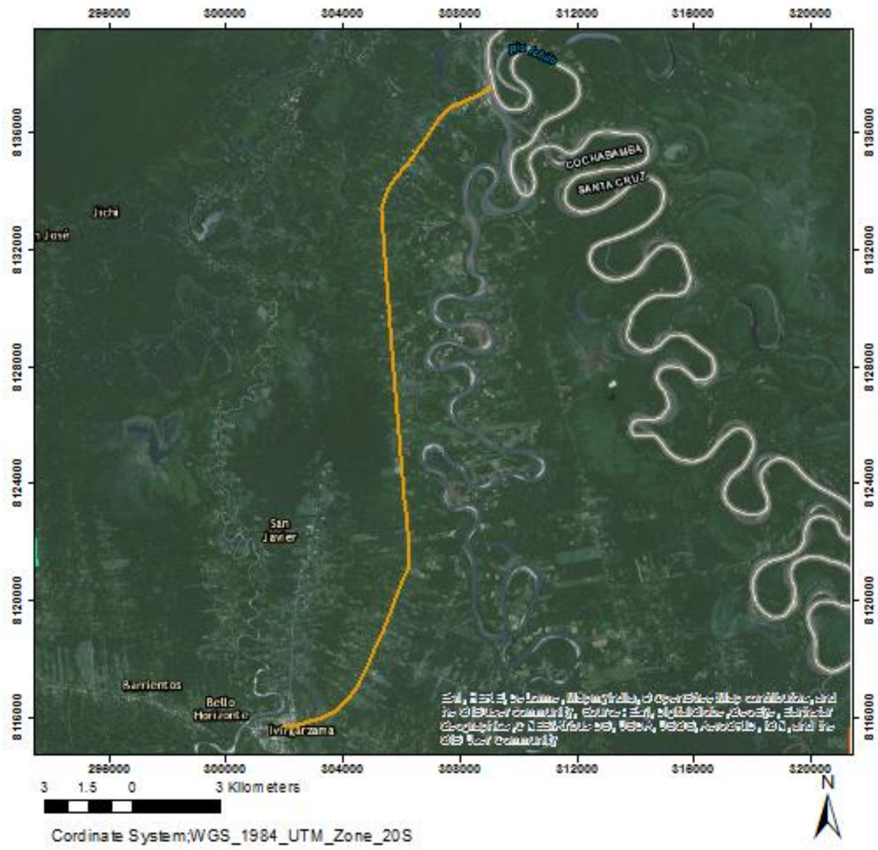
Transect A2



Transect A3

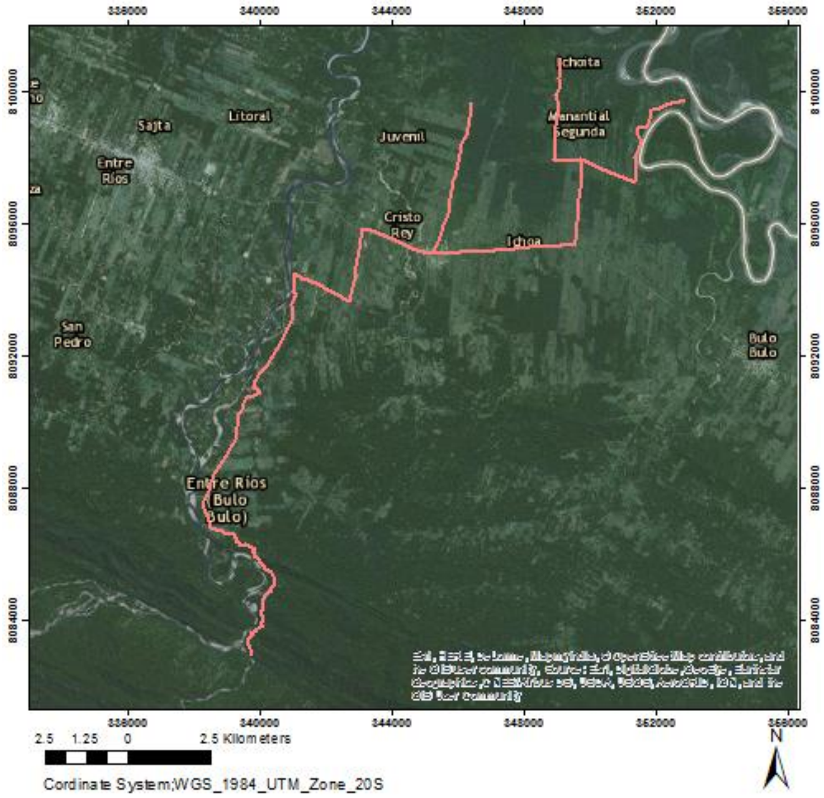


Transect A4

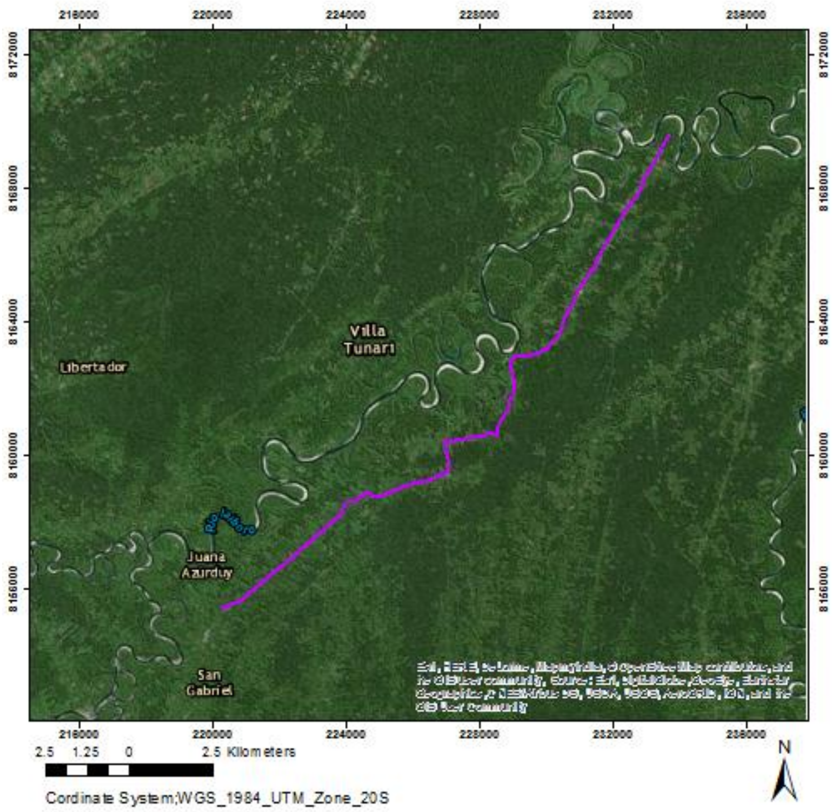


Transect A5

Transect A6



Transect A8



Appendix 3.2: Survey Point used for re-coding and renaming of land-cover classes in 2015 Classification

Data Collected in 2015 between August and September of 2015 with all coordinates given in UTM coordinates.

Code = My code for field site
Lat = latitude
Long = longitude
LULC = land use/land cover

Unambiguous LULC classes on the ground are mainly: primary forest, mature secondary forest, pasture from low grass bare to deep grass (includes village football fields), bananas, pineapples, bare soil, sometimes palmetto (4 m high feathery palms planted as a plantation crop)

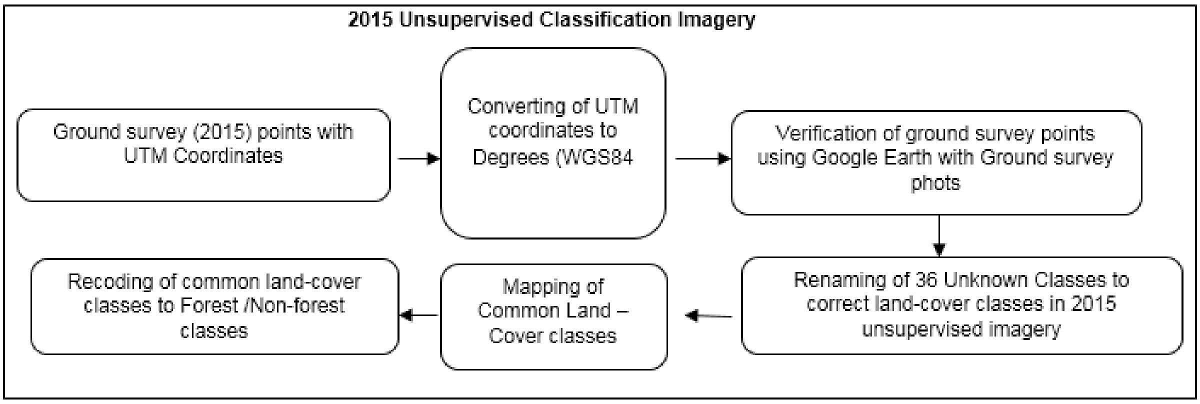
Code	Date	Lat	Long	LULC	Test Points /Classifications
	IS Southern Road (IS-50-60)				
IS-55	26 Au	0193532	8176144	Pasture	Test point
IS-56	26 Au	0193630	8175349	Medium regrowth, slope pasture	Test point
IS-57	26 Au	0193751	8175160	Pasture	Used for land cover selection
IS-58	26 Au	0194251	8173830	Pasture / Regrowth	Test point
IS-53	26 Au	0194962	8171749	Pasture/ regrowth/ forest	Used for land cover selection
IS-52	26 Au	0195392	8171146	Pasture	Used for land cover selection
IS-51	26 Au	0199036	8165141	Pasture	Test point
IS-61	26 Au	0211207	8156279	Pasture	Test point
IS-62	26 Au	0212691	8153609	School, pasture, baresoil, village	Used for land cover selection
IS-50	26 Au	0200899	8164612	Pasture	Used for land cover selection
IS central road (IS-100 to 121)					
IS-102	27 Au	0216347	8161246	Primary forest	Test point
IS-103	27 Au	0215237	8162798	Primary forest	Used for land cover selection
IS-104	27 Au	0214647	8165725	Primary forest	Used for land cover selection
IS-105	27 Au	0213842	8167959	Primary forest	Test point
IS-121	27 Au	0213775	8168105	Primary forest	Used for land cover selection
IS-107	27 Au	0209021	8170786	Pasture	Used for land cover selection
IS-108	27 Au	0206875	8171235	Regrowth forest	Test point
IS-118	27 Au	0206599	8172134	Primary forest	Used for land cover selection
IS-110	27 Au	0204650	8175739	Primary forest	Used for land cover selection
IS-111	27 Au	0202582	8176883	Primary forest	Used for land cover selection
IS-114	27 Au	0199025	8180148	Primary forest	Used for land cover selection
					Used for land cover selection
IS-113	27 Au	0199032	8180584	pasture	Test point
IS-112	27 Au	0199048	8180767	Pasture	Test point
IS-116	27 Au	0203985	8176089	Primary forest	Test point
IS-117	27 Au	0205013	8175307	Regrowth	Test point
IS-100	27 Au	0217999	8158066	Grass (football field)	Used for land cover selection
IS East Road (IS-27 to 44)					
IS-27	28 Au	0222968	8168942	Primary forest	Used for land cover selection
IS-28	28 Au	0223238	8168682	Primary forest	Test point
IS-29	28 Au	0223818	8168062	High secondary forest	Used for land cover selection
IS-30	28 Au			High secondary forest	Test point
IS-31	28 Au	0224240	8167329	Grass (football field)	Used for land cover selection
IS-32	28 Au	0223969	8166846	Secondary regrowth forest	Test point
IS-33	28 Au	0223622	8166202	Regrowth forest	Used for land cover selection
IS-34	28 Au	0223405	8165802	Regrowth	Test point
IS-35	28 Au	0223883	8165201	High secondary forest (or Primary)	Used for land cover selection

IS-36	28 Au	0224009	8164520	Regrowth / Forest	Test point
IS-38	28 Au	0223614	8163608	Regrowth	Used for land cover selection
IS-40	28 Au	0222998	8162901	Regrowth	Test point
IS-40	28 Au	0222478	8162538	Forest and regrowth	Used for land cover selection
IS-41	28 Au	0219916	8160665	Forest	Used for land cover selection
IS-43	28 Au	0219916	8160665	Regrowth	Test point
A1-Senda 3 and Chimore (A1-1 to 39)					
A1-1	24 Sep	0266724	8116478	Citrus	Used for land cover selection
A1-2	24 Sep	0266940	8116749	Medium regrowth	Used for land cover selection
A1-3	24 Sep	0267306	8117940	Medium regrowth	Used for land cover selection
A1-4	24 Sep	0267495	8118323	Rubber plantation/Med regrowth	Used for land cover selection
A1-5	24 Sep	0267580	8118811	Forest/regrowth/grazing	Used for land cover selection
A1-6	24 Sep	0267276	8119004	Rubber/dense undergrowth of citrus	Used for land cover selection
A1-7	24 Sep	0267578	8119483	Medium regrowth	Used for land cover selection
A1-8	24 Sep	0267778	8119716	urban	Used for land cover selection
A1-9	24 Sep	0267726	8119804	Urban/ football field	Used for land cover selection
A1-10	24 Sep	0267772	8120097	Banana	Used for land cover selection
A1-11	24 Sep	0267761	8120703	Citrus/pamitto/grazed	Used for land cover selection
A1-12	24 Sep	0267754	8121123	banana	Used for land cover selection
A1-13	24 Sep	0267749	8121631	banana	Used for land cover selection
A1-14	24 Sep	0267730	8122496	Pamitto/high regrowth	Used for land cover selection
A1-15	24 Sep	0267732	8122732	Medium regrowth	Used for land cover selection
A1-16	24 Sep	0267727	8123846	pasture	Used for land cover selection
A1-16A	24 Sep	0267735	8124452	Medium to high regrowth	Used for land cover selection
A1-17	24 Sep	0268105	8125041	High regrowth / pasture	Used for land cover selection
A1-18	24 Sep				
A1-19	24 Sep				
A1-20	24 Sep	0269666	8125977	High / medium regrowth	Used for land cover selection
A1-20A	24 Sep	0268804	8125926	pasture	Used for land cover selection
A1-21	24 Sep	0267380	8126778	Medium regrowth	Used for land cover selection
A1-22	24 Sep	0267409	8127755	Pasture	Used for land cover selection
A1-23	24 Sep	0267429	8128145	Pasture/regrowth	Used for land cover selection
A1-24	24 Sep	0267830	8128195	Pasture/medium regrowth	Used for land cover selection
A1-25	24 Sep	0268453	8128199	Medium regrowth	Used for land cover selection
A1-26	24 Sep	0266978	8128231	Pasture/ medium to high regrowth	Used for land cover selection
A1-27	24 Sep	0266717	8127643	Pasture/ medium to high regrowth	Used for land cover selection
A1-28	24 Sep	0266825	8127951	Medium regrowth	Used for land cover selection
A1-29	24 Sep	0267372	8128397	High to medium regrowth	Used for land cover selection
A1-30	24 Sep	0267418	8128773	Citrus/ pasture	Used for land cover selection
A1-31	24 Sep	0267493	8131275	Citrus/ shrubby regrowth	Used for land cover selection
A1-32	24 Sep	0267526	8130562	Citrus	Used for land cover selection
A1-33	24 Sep	0267912	8132219	Medium regrowth/citrus	Used for land cover selection
A1-34	24 Sep	0267722	8133090	New banana plantation	Used for land cover selection
A1-35	24 Sep	0267997	8134004	Medium to tall regrowth	Used for land cover selection
A1-36	24 Sep	0268112	8134856	Citrus/medium regrowth	Used for land cover selection
A1-37	24 Sep	0269284	8135072	Mixed farming and regrowth	Used for land cover selection
A1-38	24 Sep	0267444	8135717	Banana/ forest	Used for land cover selection
A1-39	24Sep	0266757	8136021	Urban/ villages	Used for land cover selection
Mariposa (A2-1 to 15)					
A2-1	23 Se	0283076	8119262	Clearance for future housing.	Used for land cover selection
A2-1	23 Se	0283076	8119262	Pineapple	Used for land cover selection
A2-3	23 Se	0284616	8122606	Pasture	Test point
A2-4	23 Se	0286916	8124585	Medium regrowth/High regrowth	Used for land cover selection
A2-5	23 Se	0287343	8124957	Low to medium regrowth	Used for land cover selection
A2-6	23 Se	0287523	8126369	Tall forest regrowth/Mature secondary forest	Used for land cover selection

A2-7	23 Se	0288898	8126316	Newly cleared field. Bare Soil	Used for land cover selection
A2-7A	23 Se	0287802	8125948	Tall forest regrowth or forest	Test point
A2-8	23 Se	0286914	8126080	Low to high regrowth	Used for land cover selection
A2-9	23 Se	0286342	8126097	Low to high regrowth	Used for land cover selection
A2-10	23 Se	0284791	8124185	Forest,cropping	Used for land cover selection
A2-11	23Se	0284111	8123596	Regrowth Cropping	Used for land cover selection
A2-12	23Se	0283544	8123111	Regrowth	Used for land cover selection
A2-14	23Se	0282964	8122558	Medium regrowth	Used for land cover selection
A2-15	23Se	0282941	8121601	Medium to high regrowth	Used for land cover selection
A3-1	2 Se	0300061	8112562	Pasture	Used for land cover selection
A3-2	2 Se	0299729	8111993	Pasture	Used for land cover selection
A3-3	2 Se	0298514	8110188	Pasture	Used for land cover selection
A3-4	2 Se	0298206	8109210	Pasture	Used for land cover selection
A3-4	2 Se	0298206	8109210	Bare soil? = recently burnt pasture	Used for land cover selection
A3-5	2 Se	0297673	8108394	Palmitto	Used for land cover selection
A3-11	2 Se	0297107	8104325	Palmitto	Used for land cover selection
A3-15	2 Se	0298931	8102407	Pasture	Used for land cover selection
A3-17	2 Se	0299886	8101411	Pasture	Used for land cover selection
A3-18	3 Se	0300522	8100838	Pasture	Used for land cover selection
A3-20		0300942	8100126	Pasture	Used for land cover selection
A3-21		0300566	8099618	Bananas	Used for land cover selection
A3-21	3 Se	0300566	8099618	Pasture	Used for land cover selection
A3-24	1 Se	0298594	8096983	Palmitto	Used for land cover selection
A3-24	1 Se	0298594	8096983	Bare field = recently burnt	Used for land cover selection
A3-25	1 Se	0298445	8096530	Citrus	Used for land cover selection
A3-26	1 Se	0298339	8096634	Citrus	Used for land cover selection
A3-26	1 Se	0298339	8096634	Palmitto	Used for land cover selection
A3-27	1 Se	0299168	0299168	Cassava = Yuca	Used for land cover selection
A3-27	1 Se	0299168	0299168	Citrus	Used for land cover selection
A3-27	1 Se	0299168	0299168	Palmitto	Used for land cover selection
A3-28	1 Se	0299668	8095341	Palmitto	Used for land cover selection
A3-29	1 Se	0300446	8094355	Palmitto	Used for land cover selection
A3-49	1 Se	0307191	8101501	Bananas	Used for land cover selection
A3-50	1 Se	0302522	8101941	Bananas	Used for land cover selection
A3-50	1 Se	0302522	8101941	Pasture	Used for land cover selection
A3-55	1 Se	0303703	8104306	Bananas	Used for land cover selection
A3-53	1 Se	0303014	8102981	Bananas	Used for land cover selection
A3-53	1 Se	0303014	8102981	CitrusA3-53	Used for land cover selection
A6-19	28 Au	0348018	8095217	Pasture	Used for land cover selection
A6-20	28 Au	0348444	8095295	Pasture	Test point
A6-21	28 Au	0349210	8095349	Pasture	Used for land cover selection
A6-23	28 Au	0349639	8096668	Pasture	Used for land cover selection
A6-24	28 Au	0349720	8097557	Pasture	Test point
A6-26	28 Au	0351598	8098636	Mature gallery forest	Used for land cover selection
A6-28	28 Au	0352774	8099704	Cropped and bare fields (cassava and corn)	Used for land cover selection
A6-29	28 Au	0349125	8097912	Pasture	Used for land cover selection
A6-30	28 Au	0348899	8098058	Pasture	Used for land cover selection
A6-32	28 Au	0349075	8100548	Forest	Test point
A6-32	28 Au	0349075	8100548	Cropped and bare field (corn and coca)	Used for land cover selection
A6-22	29 Au	0349543	8095652	Pasture	Used for land cover selection
South of Bulobulo					
A6-34	29 Au	0351892	8093830	Urban	Used for land cover selection
A6-35	29 Au	0351849	8093341	Pasture	Used for land cover selection

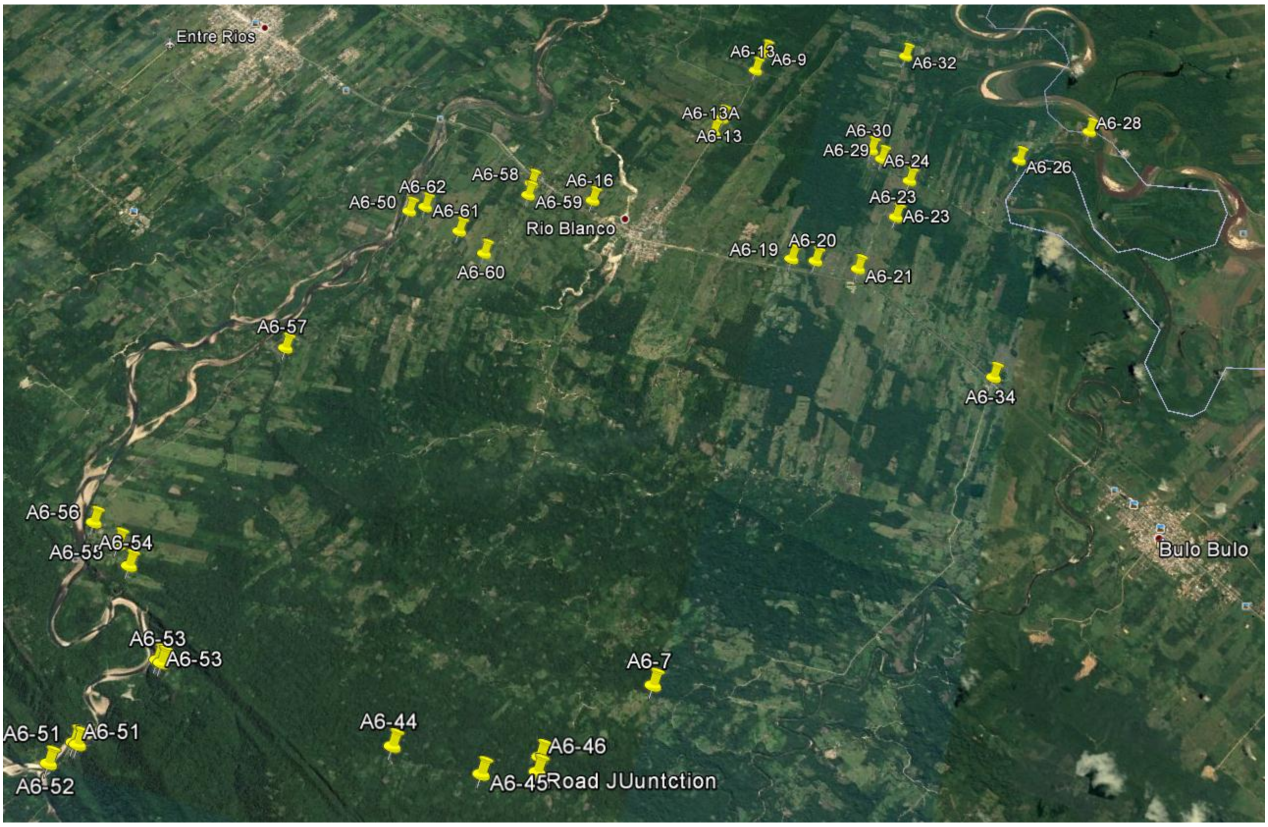
A6-37	29 Au	0351566	8090066	Forest	Used for land cover selection
A6-38	29 Au	0350758	8088709	Pasture	Used for land cover selection
A6-40A	29 Au	0348685	8087375	Forest	Used for land cover selection
A6-1	29 Au	0348323	8087154	Forest	Used for land cover selection
A6-5	29 Au	0349668	8086744	Forest	Used for land cover selection
A6-6	29 Au	0349030	8086439	Forest	Used for land cover selection
A6-6	29 Au	0349030	8086439	Pasture	Used for land cover selection
A6-3	29 Au	0348605	8086504	Pasture	Used for land cover selection
A6-2	29 Au	0348179	8086852	Pasture	Used for land cover selection
A6-7	29 Au	0347783	8086919	Pasture	Used for land cover selection
West of Rio blanco					
A6-16	31 Au	0344217	8095416	Pasture	Test point
A6-13	31 Au	0346013	8097994	Pasture	Used for land cover selection
A6-10	31 Au	0346339	8099350	Cleared field, new pineapple	Used for land cover selection
A6-9	31 Au	0346412	8099843	Pasture	Test point
A6-13A	31 Au	0345958	8097612	Pasture	Used for land cover selection
A6-50	31 Au	0341059	8094104	Pasture	Used for land cover selection
Vueltadero A3 and linking roads (A7-6 to 14					
A7-6	02 Sep	0300908	8113477	Grass/ low regrowth	Used for land cover selection
A7-7	02 Sep	0299108	8111324	Citrus/grass/pasture/mix shrubs	Used for land cover selection
A7-8	02 Sep	0298461	8110083	Grass bare soil, pasture	Used for land cover selection
A7-9	02 Sep				
A7-10	02 Sep	0299983	8107312	Palmetto/ pasture	Used for land cover selection
A7-11	02 Sep	0300874	8106882	Palmitto / forest	Used for land cover selection
A7-12	02 Sep	0297703	8108458	Mix cropping/ palm	Used for land cover selection
A7-13	02 Sep	0299009	8107442	pasture	Used for land cover selection
A7-14	02 Sep	0297900	8107753	Pasture	Used for land cover selection
A7-15	02 Sep	0295245	8105485	Pasture	Used for land cover selection
A7-16	02 Sep	0293606	8104191	Pasture	Used for land cover selection
A7-18	02 Sep	0290030	8098272	Palmitto	Used for land cover selection
A7-19	02 Sep	0289249	8095529	Regrowth/ palmetto	Used for land cover selection
A8 Monte Sanai roads and A5 (A5-1 to A517 are in all electronic copy.					

Appendix 3.3: Flow chart of the unsupervised classification in detail.



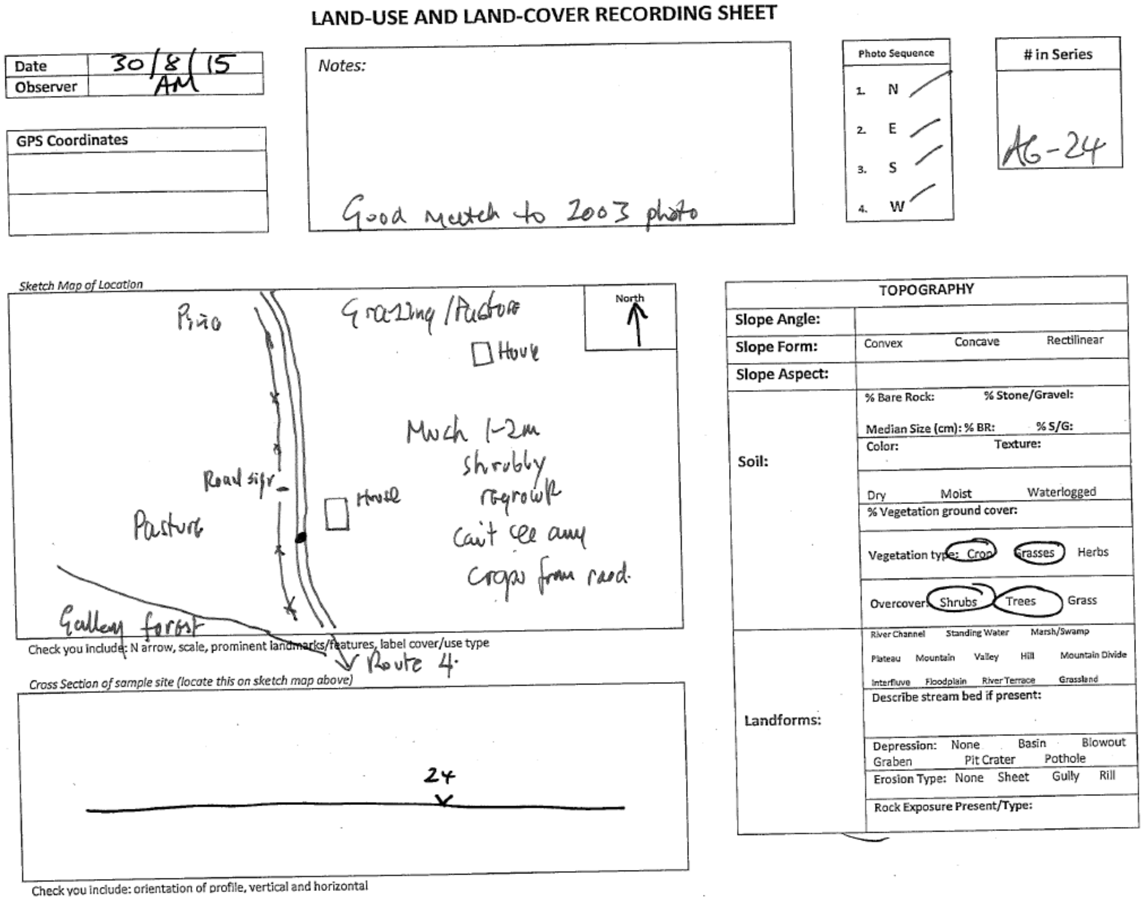
From the above flow chart as given in the report, the images below is illustrative of how it was done in 2011 image.

- By running the unsupervised classification of pre-processed image, 36 unknown classes were obtained.
- The ground control survey points were given in Appendix 3.2. An example of a ground sample points would be A6-24 seen below for the points selected in Bulobulo.



- Those points were cross-referenced with its ground survey photo (looking East, West, and North & South) and survey sheet as show below.

Point A6-24



LAND-USE AND LAND-COVER RECORDING SHEET

Date	30/8/15
Observer	AM

GPS Coordinates

Notes:
Good match to 2003 photo

Photo Sequence
1. N
2. E
3. S
4. W

in Series
A6-24

Sketch Map of Location

Check you include: N arrow, scale, prominent landmarks/features, label cover/use type

Cross Section of sample site (locate this on sketch map above)

Check you include: orientation of profile, vertical and horizontal

TOPOGRAPHY

Slope Angle:
Slope Form: Convex Concave Rectilinear
Slope Aspect:

Soil:
% Bare Rock: % Stone/Gravel:
Median Size (cm): % BR: % S/G:
Color: Texture:
Dry Moist Waterlogged
% Vegetation ground cover:
Vegetation type: Crop Grasses Herbs
Overcover: Shrubs Trees Grass

Landforms:
River Channel Standing Water Marsh/Swamp
Plateau Mountain Valley Hill Mountain Divide
Interfluve Floodplain River Terrace Grassland
Describe stream bed if present:
Depression: None Basin Blowout Graben Pit Crater Pothole
Erosion Type: None Sheet Gully Rill
Rock Exposure Present/Type:

Photo looking east

Photo looking west

Photo looking north

Photo looking south

- After verification, the renaming of classes according to its location and later the recoding is was done. That was done on every points given in appendix 3.2

Appendix 3.4: Land-cover points used for the accuracy assessment in the 2015 classified image.

Landcover points used for accuracy assessments

IS Transect

		Survey point cordinates			Landcover cordinates	
Names	**Date**	**X**	**Y**	**Lancd over type**	**X**	**Y**
IS-56	26 Au	193593	8175339	Medium regrowth, slope pasture	193593	8175339
IS-58	26 Au	194251	8173830	Pasture / Regrowth	194300	8173849
IS-51	26 Au	199036	8165141	Pasture	200202	8165119
IS-61	26 Au	211207	8156279	Pasture	209201	8157167
IS-103	27 Au	215237	8162798	pasture	215208.33	8162798.48
IS-103	27 Au	215237	8162798	Primary forest	215097	8162729
IS-108	27 Au	206875	8171235	high regrowth	206882.74	8171393.56
IS-108	27 Au	206875	8171235	Regrowth forest	207022.86	8171050.26
IS-111	27 Au	202582	8176883	forest	202611.67	8177034.64
IS-111	27 Au	202582	8176883	Primary forest	202293.84	8176772.98
IS-113	27 Au	199032	8180584	pasture	198934.78	8180514.48
IS-112	27 Au	199048	8180767	Pasture	198964.35	8180786.12
IS-112	27 Au	199048	8180767	Football field	198923.35	8181115.23
IS-116	27 Au	203985	8176089	Primary forest	203928.04	8176227.75
IS-116	27 Au	203985	8176089	Primary forest	203877.18	8175980.16
IS-117	27 Au	205013	8175307	Regrowth	204901.9	8175268.15
IS-117	27 Au	205013	8175307	Medium regrowth	205139.7	8175464.43
IS-28	28 Au	223238	8168682	Primary Forest	223261.87	8168714.94
IS-28	28 Au	223238	8168682	Primary Forest	223518.31	8168478.42
IS-28	28 Au	223238	8168682	Primary forest	223113.4	8168525.36
IS-32	28 Au	223969	8166846	Regrowth	224097.15	8166841.69
IS-32	28 Au	223969	8166846	Regrowth	223950.64	8167054.49
IS-32	28 Au	223969	8166846	Secondary regrowth forest	223827.57	8167015.73
IS-34	28 Au	223405	8165802	forest	223660.06	8165739.81
IS-34	28 Au	223405	8165802	forest	223483.62	8165698.03
IS-34	28 Au	223405	8165802	Regrowth	223289.57	8165835.16
IS-36	28 Au	224009	8164520	Forest	223909.74	8164519.39
IS-36	28 Au	224009	8164520	Regrowth / Forest	224091.37	8164575.93
IS-38	28 Au	223614	8163608	Regrowth	223853	8163626.89
IS-38	28 Au	223614	8163608	Regrowth	223388.46	8163797.14
IS-40	28 Au	222998	8162901	forest	222658.57	8162285.98
IS-40	28 Au	222998	8162901	Regrowth	222358.26	8162706.56
IS-43	28 Au	219916	8160665	Regrowth	219741.69	8160800.09
IS-43	28 Au	219916	8160665	Forest	219868.89	8160834.2
IS-43	28 Au	219916	8160665	high regrowth	220110.6	8160556.49

A1 Transect

A1-40	24-Sep	268576	8133736	Medium regrowth	268646.22	8133717.71
A1-40	24-Sep	268576	8133736	Medium regrowth	268519.78	8133691.28
A1-41	24-Sep	269860	8133044	pasture	269816.18	8132994.59
A1-41	24-Sep	269860	8133044	Medium regrowth	269621.64	8132980.23
A1-41	24-Sep	269860	8133044	High Regrowth	269714.02	8133186.76
A1-41	24-Sep	269860	8133044	low-high regrowth	269952.57	8132994.65
A1-42	24-Sep	269047	8133025	regrowth	269030.93	8133072.29
A1-42	24-Sep	269047	8133025	mix regrowth	269231.69	8133125.13
A1-42	24-Sep	269047	8133025	low-medium regrowth	269164.68	8132949.05
A1-43	24-Sep	270595	8133062	Pasture	270788.43	8133197.66
A1-43	24-Sep	270595	8133062	Medium regrowth	270930.34	8133207.35
A1-43	24-Sep	270595	8133062	fish pond	271066.41	8132986.96
A1-45	24-Sep	275714	8134612	Citrus(overgrown)	275651.33	8134639.25
A1-45	24-Sep	275714	8134612	Banana and regrowth	275823.83	8134621.73
A1-45	24-Sep	275714	8134612	citrus and regrowth	275712.48	8134505.58
A1-45A	25-Sep	276188	8134578	Grassland	276221.51	8134696.65
A1-45A	25-Sep	276188	8134578	Grassland	276119.82	8134671.06
A1-45A	25-Sep	276188	8134578	Citrus	276147.01	8134545.77
A1-46	25-Sep	275647	8135155	High Regrowth	275589.51	8135194.8
A1-46	25-Sep	275647	8135155	low-medium regrowth	275736.31	8135108.35
A1-46	25-Sep	275647	8135155	regrowth	275719.68	8135128.79
A1-48	25-Sep	276032	8133536	Banana	275955.57	8133534.13
A1-48	25-Sep	276032	8133536	Medium regrowth	276052.1	8133459.46
A1-48	25-Sep	276032	8133536	citrus	276023.56	8133626.27
A1-48	25-Sep	276032	8133536	citrus & banana	276109.3	8133544.21
A1-49	25-Sep	274626	8133358	Banana	274658.31	8133302.29
A1-50	25-Sep	274438	8133118	Pasture	274345.37	8133123.24
A1-50	25-Sep	274438	8133118	Medium regrowth	274293.55	8133068.93
A1-50	25-Sep	274438	8133118	Medium regrowth	274440.77	8132951.22
A1-51	25-Sep	274203	8133064	Medium regrowth	274290.58	8133065.67
A1-51	25-Sep	274203	8133064	Pasture	274090.01	8133197.6
A1-51	25-Sep	274203	8133064	Medium regrowth	274091.99	8133089.57
A1-52	25-Sep	273675	8133315	gallery forest	273805.38	8133229.91
A1-52	25-Sep	273675	8133315	Pasture	273628.89	8133264.97
A1-52	25-Sep	273675	8133315	pasture	273832.76	8133390.55
A1-52	25-Sep	273675	8133315	forest	273652.49	8133388.05
A1-54	25-Sep	271377	8133076	regrowth	271381.42	8133015.18
A1-54	25-Sep	271377	8133076	low-medium regrowth	271388.44	8133168.4
A1-59	25-Sep	274480	8131739	gallery forest	274407.14	8131771.11
A1-59	25-Sep	274480	8131739	gallery forest	274544.39	8131681.3
A1-60	25-Sep	275050	8131685	Banana	274963.11	8131763.23
A1-60	25-Sep	275050	8131685	Banana	275007.7	8131613.67
A1-60	25-Sep	275050	8131685	High Regrowth	274942.66	8131601.65
A1-61	25-Sep	275232	8131399	Regrowth	275235.04	8131540.84
A1-61	25-Sep	275232	8131399	Banana and regrowth	275313.33	8131519.79
A1-61	25-Sep	275232	8131399	pasture	275327.06	8131627.34

A1-62	25-Sep	275398	8131000	Medium Regrowth	275365.36	8131017.32
A1-62A	25-Sep	275475	8030756	Banana and regrowth	275439.43	8130772.76
A1-62A	25-Sep	275475	8030756	Banana	275478	8130699.68
A1-62B	25-Sep	274183	8129279	Pasture	274190.86	8129260.59
A1-62B	25-Sep	274183	8129279	pasture	274128.28	8129072.38
A1-62B	25-Sep	274183	8129279	medium regrowth	274080.04	8129264.57
A1-63	25-Sep	271380	8127805	Football field	271441.01	8127738.54
A1-63	25-Sep	271380	8127805	pasture	271125.92	8127778.78
A1-63	25-Sep	271380	8127805	Urban bare soil	271416.21	8128170.98
A1-64	25-Sep	273494	8128343	Pasture	273511.75	8128229.65
A1-64	25-Sep	273494	8128343	Medium regrowth	273650.23	8128398.5
A1-64	25-Sep	273494	8128343	forest	273639.94	8128577.79
A1-66	25-Sep	271401	8127031	pasture	271127.8	8126993.67
A1-66	25-Sep	271401	8127031	pasture	271459.92	8127022.67
A1-66	25-Sep	271401	8127031	Regrowth	271496.36	8127014.22
A1-67	25-Sep	273876	8128827	Citrus	273828.4	8128845.87
A1-67	25-Sep	273876	8128827	citrus and regrowth	273936.3	8128788.31
A1-69	25-Sep	271428	8125625	Pasture	271329.33	8125656.6
A1-69	25-Sep	271428	8125625	pasture	271513.38	8125448.1
A1-70	25-Sep	271004	8119632	Urban	271004	8119632
A1-73	25-Sep	271877	8128314	Medium regrowth	271816.14	8128407.23
A1-73	25-Sep	271877	8128314	Medium regrowth	271700.73	8128260.73
A1-75	25-Sep	272816	8128305	Medium regrowth	272804.06	8128267.58
A1-75	25-Sep	272816	8128305	pasture	272767.27	8128459.39
A1-75	25-Sep	272816	8128305	pasture	272616.74	8128181.16
A2 Transect						
A2-16	25-Sep	292648	8117920	pasture	292743.87	8117886.98
A2-16	25-Sep	292648	8117920	football field	292598.11	8117804.72
A2-16	25-Sep	292648	8117920	pasture	292576.11	8117938.89
A2-17	25-Sep	292665	8118615	pasture	292665	8118615
A2-17	25-Sep	292665	8118615	pasture	292672.19	8118480.5
A2-17	25-Sep	292665	8118615	pasture	292561.89	8118562.97
A2-18	25-Sep	292592	8120166	Low regrowth	292508.41	8120148.64
A2-18	25-Sep	292592	8120166	Low regrowth	292570.97	8120180.74
A2-20	25-Sep	292390	8122159	Old pamitto and low regrowth	292361.93	8122161.81
A2-20	25-Sep	292390	8122159	Old pamitto and low regrowth	292434.37	8122158.7
A2-21	25-Sep	292372	8122364	Medium regrowth	292402.34	8122372.45
A2-21	25-Sep	292372	8122364	pasture	292327.23	8122402.7
A2-21	25-Sep	292372	8122364	Medium regrowth	292344.99	8122336.67
A2-22	25-Sep	292114	8123299	Medium regrowth	292151.32	8123330.96
A2-22	25-Sep	292114	8123299	Medium -High regrowth	292081.06	8123263.76
A2-23	25-Sep	291868	8123638	Water logged grassland	291824.27	8123624.63
A2-23	25-Sep	291868	8123638	medium regrowth	291792.98	8123706.19
A2-23	25-Sep	291868	8123638	medium regrowth	291935.43	8123625.29
A2-24	25-Sep	292498	8121126	Citrus	292517.31	8121139.63

A2-24	25-Sep	292498	8121126	Pasture	292468.53	8121189.48
A2-24	25-Sep	292498	8121126	Medium regrowth	292474.08	8121095.92
A2-25	25-Sep	293068	8121148	Medium regrowth	293065.03	8121194.02
A2-25	25-Sep	293068	8121148	High regrowth	293064.92	8121102.98
A2-26	25-Sep	293478	8121894	Medium regrowth	293446.63	8121896.33
A2-26	25-Sep	293478	8121894	Medium regrowth	293502.19	8121855.52
A2-27	25-Sep	293372	8121170	Medium regrowth	293372.42	8121200.64
A2-27	25-Sep	293372	8121170	Medium regrowth	293375.75	8121144.54
A2-28	25-Sep	292861	8118840	Pasture	292860.17	8118876.57
A2-28	25-Sep	292861	8118840	Pasture	292894.22	8118806.89
A2-29	25-Sep	293559	8118853	pasture	293553.56	8118883.13
A3- Transect						
A3-48	1-Sep	301730	8101091	med-high regrowth	301695.32	8101018.63
A3-48	1-Sep	301730	8101091	med-high regrowth	301544.36	8101142.46
A3-49	1-Sep	302191	8101501	banana	301958	8101765
A3-49	1-Sep	302191	8101501	banana	302260.76	8101403.96
A3-50	1-Sep	302522	8101941	pasture	302472	8101983
A3-50	1-Sep	302522	8101941	banana	302370.98	8102249.26
A3-50	1-Sep	302522	8101941	banana	302859.46	8101861.91
A3-50	1-Sep	302522	8101941	Banana	302593.3	8101984.31
A3-55	1-Sep	303703	8104306	Banana	303741.53	8104332.73
A3-55	1-Sep	303703	8104306	banana	303861.3	8104279.23
A3-55	1-Sep	303703	8104306	banana	303529.21	8104118.51
A3-55	1-Sep	303703	8104306	banana	303448.64	8104312.89
A3-53	1-Sep	303014	8102981	Banana	303017.37	8102930.75
A3-53	1-Sep	303014	8102981	banana	303362.99	8103026.53
A3-53	1-Sep	303014	8102981	banana	302815.22	8103367.47
A3-53	1-Sep	303014	8102981	Citrus and forest	302864.25	8102941.76
A3-54	1-Sep	303509	8103766	banana	303371.79	8103871.1
A3-54	1-Sep	303509	8103766	banana	303817.15	8103705.52
A3-54	1-Sep	303509	8103766	banana	303132.19	8104071.05
A3-54	1-Sep	303509	8103766	banana	303651.89	8103567.5
A3-20	1-Sep	300942	8100126	Pasture	300891.78	8100162.66
A3-20	1-Sep	300942	8100126	Urban	301100.59	8100311.14
A3-20	1-Sep	300942	8100126	Football field/baresoil	300948.21	8100052.71
A3-21	1-Sep	300566	8099618	Pasture	300612.3	8099568.36
A3-21	1-Sep	300566	8099618	forest	300482.65	8099655.45
A3-21	1-Sep	300566	8099618	pasture	300837.01	8099602.61
A3-24	1-Sep	298591	8096918	Palmitto	298591	8096918
A3-24	1-Sep	298591	8096918	med-high regrowth	298509.21	8096985.73
A3-25	1-Sep	298310	8096594	Citrus	298310	8096593.94
A3-25	1-Sep	298310	8096594	forest	298315.22	8096742.55
A3-25	1-Sep	298310	8096594	pasture	298223.36	8096309.38
A3-27	1-Sep	299168	8095826	palmitto	299336.33	8095696.1
A3-28	1-Sep	299651	8095271	Palmitto	299651	8095271

A3-29	1-Sep	300446	8094355	Palmitto	300287.31	8094216.92
A3-29	1-Sep	300446	8094355	Forest	300430.28	8093950.31
A3-32	1-Sep	297046	8099555	Citrus	297045.65	8099554.8
A3-33	1-Sep	296963	8099729	Citrus	296862.92	8099865.76
A3-35	1-Sep	296013	8100643	regrowth	295920.74	8100676.47
A3-35	1-Sep	296013	8100643	low regrowth	296024.34	8100719.99
A3-36	1-Sep	295440	8101187	citrus	295457.7	8101210
A3-36	1-Sep	295440	8101187	shrubs	295413.06	8101158.33
A3-39	1-Sep	291396	8099954	regrowth	291295.3	8099754.03
A3-40	1-Sep	291496	8099486	pasture	291506.33	8099630.77
A3-41	1-Sep	291849	8099114	pasture	291814.17	8099122.68
A3-41	1-Sep	291849	8099114	shrubs and trees	291846.72	8099232.03
A3-43	1-Sep	294881	8096089	regrowth	294888.59	8096029.89
A3-43	1-Sep	294881	8096089	forest regrowth	294953.05	8096084.67
A3-44	1-Sep	294674	8096301	forest	294584.38	8096337.82
A3-44	1-Sep	294674	8096301	forest	294677.54	8096374.48
A3-47	1-Sep	292488	8098463	forest	292499.34	8098402.84
A3-47	1-Sep	292488	8098463	Forest	292609.15	8098466.77
A4 Transect						
A4-9	2-Sep	305036	8118246	Forest/Regrowth	305234.32	8118348.24
A4-9	2-Sep	305036	8118246	Young citrus	305116.62	8118209.65
A4-8	2-Sep	305791.79	8126998.08	med-high regrowth	305355.62	8126976.26
A4-8	2-Sep	305791.79	8126998.08	Forest/Regrowth	305720.13	8126870.26
A4-5	2-Sep	306273	8135007	Pasture	306450.22	8134873.35
A4-5	2-Sep	306273	8135007	Forest/Regrowth	305904.4	8135231.14
A4-2	2-Sep	308941	8137378	football field	308731.71	8137350.21
A4-2	2-Sep	308941	8137378	Urban	308941	8137378
A4-1	2-Sep	309035	8137425	sand	309035	8137425
A4-1	2-Sep	309035	8137425	river	309099.86	8137427.03
A4-1	2-Sep	309035	8137425	Forest	309440.37	8137288.89
A5 Transect						
A5-18	30-Aug	330099	8110343	pasture	330061.63	8110313.18
A5-18	30-Aug	330099	8110343	forest	330169.1	8110584.14
A5-19	30-Aug	329643	8110099	forest	329529.83	8110121.65
A5-19	30-Aug	329643	8110099	forest	329766.6	8109998.38
A5-20	30-Aug	329058	8109527	forest	328992.8	8109494.3
A5-20	30-Aug	329058	8109527	forest	329073.96	8109611.31
A5-21	30-Aug	328533.45	8109520.95	Forest	328512.52	8109601.02
A5-21	30-Aug	328533.45	8109520.95	Forest	328562.44	8109470.96
A5-27	30-Aug	320187	8104914	Citrus	320125.59	8104905.33
A5-27	30-Aug	320187	8104914	maize	320182.41	8104849.72
A5-27	30-Aug	320187	8104914	medium regrowth	320242.65	8104991.52
A5-28	30-Aug	321262.57	8104110.65	Urban	321275.9	8104140.14

A5-28	30-Aug	321262.57	8104110.65	baresoil	321320.91	8104067.76
A5-29	30-Aug	320199	8105140	citrus	320191.9	8105114.77
A5-29	30-Aug	320199	8105140	medium regrowth	320273.37	8105130.22
A5-31	30-Aug	321830	8105142	medium regrowth	321894.39	8105217.04
A5-31	30-Aug	321830	8105142	medium regrowth	321827.87	8105248.86
A5-31	30-Aug	321830	8105142	medium regrowth	321861.32	8105099.13
A5-32	30-Aug	322013	8105547	medium regrowth	322055.28	8105543.15
A5-32	30-Aug	322013	8105547	medium regrowth(abandon pasture)	321991.9	8105578.65
A5-33	30-Aug	322335	8106273	medium to high regrowth	322296.43	8106298.29
A5-55	30-Aug	322100	8107147	medium regrowth	322136.82	8107172.99
A5-55	30-Aug	322100	8107147	pasture	322037.39	8107137.65
A5-36	30-Aug	321761	8108076	forest	321820.21	8108057.86
A5-36	30-Aug	321761	8108076	forest	321720	8107916.92
A5-36	30-Aug	321761	8108076	forest	321628.01	8107936.09
A5-37	30-Aug	322051	8108583	medium regrowth	322049.87	8108653.38
A5-37	30-Aug	322051	8108583	forest	322078.83	8108559.36
A5-58	30-Aug	321892	8108781	regrowth	321916.36	8108805.81
A5-58	30-Aug	321892	8108781	pasture	321891.31	8108763.26
A5-59	30-Aug	321208	8109286	forest	321187.29	8109130.83
A5-59	30-Aug	321208	8109286	pasture	321225.41	8109313.98
A5-60	30-Aug	321175	8110165	pasture	321108.54	8110177.62
A5-60	30-Aug	321175	8110165	pasture	321236.33	8110112.52
A5-60A	30-Aug	321190	8111120	medium regrowth	321216.17	8111100.13
A5-60A	30-Aug	321190	8111120	pasture	321131.52	8111081.67
A5-62	30-Aug	321262.62	8112184.38	medium to high regrowth	321262.62	8112184.38
A5-62	30-Aug	321262.62	8112184.38	medium to high regrowth	321330.42	8112192.54
A5-61	30-Aug	321291.26	8112282.89	forest	321219.93	8112250.93
A5-63	30-Aug	321293.66	8112431.5	forest	321332.44	8112434.88
A5-63	30-Aug	321293.66	8112431.5	forest	321268.73	8112417.13
A5-64	30-Aug	321178	8114159	Medium regrowth	321139.12	8114193.51
A5-64	30-Aug	321178	8114159	low regrowth	321132.13	8114125.78
A5-64	30-Aug	321178	8114159	medium regrowth	321221.87	8114170.76
A5-65	30-Aug	321361	8114864	low to medium regrowth	321382.66	8114861.2
A5-65	30-Aug	321361	8114864	low to medium regrowth	321328.73	8114859.08
A5-66	30-Aug	321353	8115605	forest	321399.87	8115599.79
A5-66	30-Aug	321353	8115605	forest	321324.28	8115648.96
A5-66	30-Aug	321353	8115605	forest	321319.49	8115577.39
A5-66	30-Aug	321353	8115605	citrus	321387.97	8115507.86
A5-67	30-Aug	321330	8114645	medium regrowth	321370.31	8114637.1
A5-67	30-Aug	321330	8114645	medium regrowth	321279.68	8114637.47
A5-68	30-Aug	321983	8113521	medium to high regrowth	321944.31	8113525.79
A5-68	30-Aug	321983	8113521	medium regrowth	322026.86	8113555.7
A5-69	30-Aug	322195	8113320	baresoil	322256.63	8113369.97
A5-70	30-Aug	322479	8113085	forest	322501.98	8113119.8
A5-70	30-Aug	322479	8113085	forest	322451.06	8113073.68
A5-71	30-Aug	322825	8112832	gallery forest	322988.82	8112791

A5-71	30-Aug	322825	8112832	gallery forest	322896.58	8112732.72
A5-71	30-Aug	322825	8112832	grass	322885.55	8112796.81
A5-72	30-Aug	323404	8112139	medium to high regrowth	323350.79	8112165.71
A5-72	30-Aug	323404	8112139	medium to high regrowth	323407.16	8112084.27
A5-72	30-Aug	323404	8112139	forest	323465.48	8112161.11
A5-73	30-Aug	324510	8111685	gallery forest	324651.65	8111678.25
A5-73	30-Aug	324510	8111685	school	324593.38	8111709.86
A5-73	30-Aug	324510	8111685	forest	324642.36	8111578.79
A5-73	30-Aug	324510	8111685	forest	324512.41	8111645.36
A5-75	30-Aug	326406	8110666	forest	326443.34	8110702.04
A5-75	30-Aug	326406	8110666	forest	326371.01	8110676.27
A5-75	30-Aug	326406	8110666	forest	326442.44	8110609.61
A5-76	30-Aug	325345	8111130	forest	325229.63	8111175.5
A5-76	30-Aug	325345	8111130	bare soil	325392.1	8111218.89
A5-76	30-Aug	325345	8111130	bare soil	325315.52	8111268.51
A5-77	30-Aug	327565	8109712	helipad/baresoil	327586.85	8109776.34
A5-77	30-Aug	327565	8109712	forest	327592.1	8109831.14
A5-77	30-Aug	327565	8109712	forest	327500.71	8109765.82

A6 Transect

A6-55	31-Aug	33892	8086652	Pasture	338932.7	8086673.7
A6-55	31-Aug	33892	8086652	forest	338903.1	8086623.21
A6-54	31-Aug	339297	8086380	Medium regrowth	339281	8086374
A6-54	31-Aug	339297	8086380	Forest	339195.42	8086458.41
A6-57	31-Aug	339928	8090867	Medium regrowth	340015.68	8090790.81
A6-57	31-Aug	339928	8090867	low regrowth/grassland	340045.29	8090856.01
A6-56	31-Aug	338437	8086980	Pasture	338376.41	8086910.04
A6-56	31-Aug	338437	8086980	Pasture	338579.51	8086936.99
A6-62	31-Aug	341342	8094331	Palmitto	341318.26	8094388.49
A6-62	31-Aug	341342	8094331	Pasture	341536.4	8094391.91
A6-53	31-Aug	340401	8085087	Forest	340490.62	8085057.16
A6-53	31-Aug	340401	8085087	Forest	340363.14	8085250.69
A6-50	31-Aug	341055.09	8094071.63	Pasture	341055.09	8094071.63
A6-50	31-Aug	341070.65	8094214.92	palmitto	341070.65	8094214.92
A6-51	31-Aug	339752	8083570	water	339636.57	8083681.07
A6-51	31-Aug	339752	8083570	Forest	339820.16	8083557.17
A6-52	31-Aug	339520	8083180	Sand	339520	8083181
A6-52	31-Aug	339520	8083180	water	339493.1	8083306.74
A6-52	31-Aug	339520	8083180	forest	339357.03	8083679.54
A6-52	31-Aug	339520	8083180	forest	339419.46	8083017.3
A6-58	31-Aug	343063	8095572	pasture	343016.75	8095473.09
A6-59	31-Aug	342996	8095207	Pasture	342992.33	8095292
A6-59	31-Aug	342996	8095207	woodland/forest	343044.22	8095193.77
A6-60	31-Aug	342714	8093677	Pasture	342698.17	8093713.23
A6-61	31-Aug	341880	8094082	pasture	341948	8094130.98
A6-61	31-Aug	341880	8094082	citrus	341963.59	8093968.56

A6-61	31-Aug	341880	8094082	Forest	342105.75	8094045.01
A8 Transect						
A8-2	28-Aug	228300	8160584	med-high regrowth	228273.5	8160757.52
A8-2	28-Aug	228300	8160584	med-high regrowth	228298.36	8160327.85
A8-4	28-Aug	229033	8162087	medium regrowth	229406.53	8161924.78
A8-4	28-Aug	229033	8162087	medium regrowth	228650.82	8161408.72
A8-5	28-Aug	229780	8163092	forest	229703.83	8163300.15
A8-5	28-Aug	229780	8163092	forest	229870.93	8162874.15
A8-6	28-Aug	232237	8167117	medium regrowth	232047.51	8167192.8
A8-6	28-Aug	232237	8167117	medium regrowth	232468.06	8166996.21
A8-7	28-Aug	233356	8169029	forest	233686.52	8169313.74
A8-7	28-Aug	233356	8169029	medium regrowth	233068.53	8169060.03
A8-7	28-Aug	233356	8169029	pasture	233365.58	8168662.41

Appendix 4. 1: Forest and Non-forest cover for individual land parcels in the respective Communities in the study corresponding to their forest and non-forest maps.

Community I- Land Parcels with forest and non-forest cover including its FID

	2011			2015			2016			
FID_	Forest (ha)	Non-forest (ha)	Water (ha)	Forest (ha)	Non-forest (ha)	Water (ha)	Forest (ha)	Non-forest (ha)	Water (ha)	Total area (ha)
0	8.28	4.77	0	7.245	5.67	0	7.29	5.76	0	13.1503
1	3.24	9.72	0	6.3225	6.6375	0	5.49	7.47	0	13.1006
2	1.44	11.7	0	7.56	5.6925	0	6.84	6.3	0	13.3121
3	1.17	11.97	0	3.105	10.26	0	1.62	11.52	0	13.1651
4	1.62	11.16	0	4.8825	7.6725	0	8.55	4.23	0	12.9502
5	2.25	12.24	0	7.8075	6.7725	0	4.86	9.63	0	14.3139
6	4.23	12.33	0	4.7475	11.4975	0	4.77	11.79	0	16.4821
7	7.92	9.72	0	9.405	8.055	0.0225	10.98	6.66	0	17.712
9	6.39	13.59	0	7.9875	12.195	0	4.5	15.48	0	20.3817
10	10.17	10.26	0	6.885	13.545	0	4.68	15.75	0	20.3486
11	8.19	12.24	0	11.25	9.045	0	15.57	4.86	0	20.175
12	11.88	8.01	0	12.105	8.2125	0	14.67	5.22	0	20.3415
13	9.81	10.17	0	10.8675	9.1575	0	14.67	5.31	0	20.1152
14	12.96	7.38	0	11.655	8.6625	0	18.99	1.35	0	20.2447
15	4.95	10.89	0	5.625	9.855	0	6.93	8.91	0	15.8143
16	8.91	11.52	0	12.0825	8.2575	0	13.32	7.11	0	20.5338
17	16.2	3.15	0	13.725	6.48	0.045	18.45	0.81	0.09	20.197
18	4.68	15.57	0	6.1875	14.58	0	6.84	13.41	0	20.4115
19	5.22	7.29	0	6.345	5.5125	0	10.26	2.25	0	12.1104
20	12.24	9.18	0	13.14	8.19	0	17.01	4.41	0	21.248
21	14.58	6.03	0	10.3275	10.2375	0	13.05	7.56	0	20.4621
22	5.58	14.31	0	9.7875	10.395	0	11.88	8.01	0	20.1593
23	15.03	5.94	0	12.915	7.6725	0	18.27	2.7	0	20.4814
24	12.06	8.73	0	10.6425	9.945	0.09	11.97	8.82	0	20.5559
26	5.76	14.67	0	11.475	8.505	0	16.2	4.23	0	20.2171
27	9.81	10.98	0	9.495	10.89	0.1125	13.14	7.65	0	20.4714
28	6.93	13.5	0	9.6525	10.485	0.27	12.87	7.38	0.18	20.4384
29	10.17	9.81	0	11.295	8.775	0.3825	18.54	0.9	0.54	20.4845
30	6.93	14.04	0	10.8675	9.3375	0	14.76	6.21	0	20.324
31	9.36	10.8	0	8.7525	11.655	0	10.71	9.45	0	20.4508
33	9.63	10.53	0	11.8575	8.7525	0	13.14	7.02	0	20.5348
34	14.31	6.48	0	11.9025	8.595	0	18.27	2.52	0	20.4036
35	7.2	12.78	0	10.9575	9.27	0	16.83	3.15	0	20.3869
36	8.64	12.33	0	12.0375	8.7075	0	15.03	5.94	0	20.7955
37	12.24	6.66	0.99	10.2375	8.7075	0.9675	14.04	4.86	0.99	20.1295
38	12.78	6.3	0.99	9.5175	8.7975	1.7325	12.51	6.3	1.26	20.1479
39	7.38	13.41	0	7.92	12.6675	0	10.08	10.71	0	20.4876
40	13.14	7.29	0	9.7875	9.3375	0.945	16.29	3.24	0.9	20.183
41	7.2	13.59	0	9.4275	10.935	0	14.13	6.66	0	20.461

42	13.59	7.2	0	11.745	8.8875	0	15.3	5.49	0	20.5055
43	7.65	12.51	0	9.7425	10.71	0	12.6	7.56	0	20.5099
44	10.08	10.8	0	10.3725	10.26	0.0225	14.94	5.94	0	20.5826
45	5.67	14.31	0	7.74	12.7575	0	7.29	12.69	0	20.5408
46	12.69	8.01	0	10.665	10.035	0	12.24	8.46	0	20.6216
47	11.25	8.64	0	12.7125	7.74	0	17.28	2.61	0	20.4594
48	14.13	6.21	0	10.44	8.505	0.0225	12.33	8.01	0	19.0909
49	14.4	4.59	0	12.8925	6.93	0	17.73	1.26	0	19.7637
52	12.51	8.01	0	10.4625	9.4275	0.045	12.51	8.01	0	20.0753
53	15.03	5.22	0	12.285	8.19	0.0675	15.39	4.86	0	20.1916
54	10.98	9	0	10.3275	9.3375	0.5175	13.68	6.03	0.27	20.0126
55	12.96	6.48	0	11.4975	8.1225	0.36	15.57	3.87	0	20.1317
56	9.18	10.26	0	10.8225	8.685	0.405	13.41	5.49	0.54	20.0697
57	16.11	3.33	0	13.4325	6.3225	0.2475	16.92	2.25	0.27	20.1532
58	16.83	3.15	0	15.0075	4.995	0.045	18.09	1.89	0	20.0055
59	11.52	8.46	0	14.0175	6.3675	0	16.92	3.06	0	20.0443
60	10.71	9.81	0	10.62	9.8775	0.0225	13.86	6.66	0	20.4515
61	15.57	4.86	0	14.58	5.6025	0	16.92	3.51	0	20.0801
62	13.86	6.57	0	13.8825	5.985	0	18.27	2.16	0	20.0182
63	12.6	7.74	0	12.7575	7.065	0.045	16.2	4.14	0	19.9963
64	7.2	4.86	0	7.8075	4.1175	0	8.55	3.51	0	12.0809
65	10.44	2.88	0	8.0775	4.0725	0	9.45	3.87	0	12.0366
66	8.82	2.43	0	7.7625	4.4775	0	8.91	2.34	0	12.2232
67	7.65	4.23	0	7.695	4.2975	0.0225	8.46	3.42	0	12.0339
68	8.01	4.95	0	8.2125	4.3425	0	9.36	3.6	0	12.2013
69	7.83	13.23	0	7.5375	13.0725	0	7.29	13.77	0	20.4848
70	11.7	9.36	0	7.155	14.0625	0.2025	5.58	15.48	0	21.353
71	12.33	8.46	0	12.015	8.55	0	15.12	5.67	0	20.4539
72	9.81	10.98	0	9.5625	11.0925	0	12.69	8.1	0	20.5225
74	13.77	7.02	0	12.8925	8.4375	0	16.56	4.23	0	21.1884
75	7.56	12.87	0	8.4375	11.925	0	4.14	16.29	0	20.4074
76	7.56	12.24	0	8.55	11.88	0.0225	11.34	8.46	0	20.4738
77	4.32	15.93	0	6.9975	13.32	0.135	5.76	14.4	0.09	20.4956
78	7.11	13.32	0	9.5625	11.0025	0.0225	9.54	10.89	0	20.6255
80	8.19	12.42	0	10.62	9.8325	0	8.64	11.97	0	20.5702
81	8.55	12.24	0	8.1225	12.2625	0	5.04	15.75	0	20.406
82	6.3	13.23	0	9.09	10.53	0	12.33	7.2	0	19.6522
83	8.64	12.6	0	9.3375	10.8675	0.045	6.12	15.03	0.09	20.3282
84	7.38	12.15	0	10.125	9.405	0	13.95	5.58	0	19.3109
85	5.58	13.95	0	9.225	10.7325	0	11.16	8.37	0	19.8971
86	11.79	8.73	0	11.52	8.3925	0	16.2	4.32	0	20.0808
87	14.13	6.57	0	10.0125	10.0125	0.1125	11.43	9.27	0	20.2219
88	9.72	10.08	0	10.485	9.6075	0	7.56	12.24	0	19.9973
89	15.39	4.05	0	13.095	7.3125	0	16.83	2.61	0	20.1543
90	9.99	9.54	0	12.105	8.0775	0	15.03	4.5	0	20.0546
92	16.65	4.05	0	11.1825	8.0325	0.0675	13.95	6.75	0	20.136

93	16.56	3.15	0	13.3875	6.5025	0.0675	17.37	2.34	0	19.9469
94	11.88	7.83	0	11.61	8.055	0.225	14.4	5.31	0	20.0021
95	12.06	7.38	0	13.1175	6.795	0.2025	14.31	5.13	0	20.0824
96	16.38	3.6	0	13.8825	6.1875	0.09	15.75	4.14	0.09	20.0154
97	9.99	9.99	0	11.925	8.145	0.045	13.5	6.48	0	19.9543
98	6.57	5.67	0	6.39	5.67	0.045	8.1	4.14	0	12.0457
99	8.82	2.25	0	7.9875	4.095	0.0225	10.26	0.81	0	12.1114
100	10.44	2.88	0	8.3925	3.5775	0	12.42	0.9	0	12.1343
101	10.62	1.62	0	9.18	2.9475	0	12.15	0.09	0	12.0513
102	8.01	3.24	0	9.495	2.61	0	10.62	0.63	0	12.1657

Average(ha)	**18.79**
Min (ha)	**12.03**
Max (ha)	**21.35**
Std Dev	**3.02**

Community II- Land Parcels with forest and non-forest cover including its FID

	2011			**2015**			**2016**			
FID_	**Forest (ha)**	**Non-forest (ha)**	**Water (ha)**	**Forest (ha)**	**Non-forest (ha)**	**Water (ha)**	**Forest (ha)**	**Non-forest (ha)**	**Water (ha)**	**Total area (ha)**
0	5.04	19.35	1.71	6.075	16.9875	3.195	7.02	17.55	1.53	26.0953
1	8.55	16.47	0	7.7625	16.5825	0.6075	11.07	13.5	0.45	24.7171
2	21.33	4.59	0	11.88	14.6925	0.4275	24.57	1.35	0	26.8728
3	18.99	10.26	0.36	11.88	16.2225	0.7875	17.64	11.88	0.09	28.7193
4	10.26	14.76	0	7.0875	17.775	0.2025	10.08	14.94	0	24.9471
5	12.33	18.81	0	8.1	23.7375	0.4725	13.32	17.82	0	32.0975
6	6.03	14.58	0	5.4	15.3	0.045	10.62	9.99	0	20.676
7	18.99	30.69	1.35	10.5525	38.8125	1.6425	13.05	36.9	1.08	50.7597
8	8.55	16.92	0	8.4825	17.3925	0.1575	15.75	9.72	0	25.8429
9	20.16	6.57	0	11.2275	14.8275	0.585	20.7	6.03	0	26.5517
10	30.51	20.34	0	17.55	32.5125	0.945	23.13	27.54	0.18	50.7136
11	14.13	12.15	0.72	10.1475	16.2675	1.1475	14.67	11.88	0.45	27.372
12	37.26	12.24	0.54	18.8775	30.915	0.5175	19.98	29.97	0.09	49.9901
13	9	18.45	0.9	6.4575	20.4975	1.2375	19.08	8.91	0.36	28.0671
14	36.54	13.95	0	15.9525	32.4	1.935	40.23	10.17	0.09	50.0447
15	12.42	15.57	0.45	6.7275	21.5775	0.7425	23.31	5.04	0.09	28.8214
16	6.66	22.86	0	5.5125	23.805	0.3375	25.29	4.23	0	29.5499
17	42.75	7.47	0	26.0775	23.85	1.035	42.75	7.47	0	50.6191
18	9.09	21.15	0	4.2975	26.235	0.09	22.32	7.92	0	30.3968
19	18.18	32.85	0	17.505	33.345	0.2025	20.97	30.06	0	50.7858
20	15.93	15.03	0	10.4175	20.8575	0.045	25.11	5.85	0	31.1
21	29.07	21.69	0	16.875	32.895	1.1475	25.56	25.2	0	50.6204
22	9.9	21.06	0.18	8.2575	22.8375	0.27	18.81	12.33	0	31.2298
23	30.42	20.07	0	19.62	29.8125	1.485	28.35	22.14	0	50.599
24	14.13	15.39	0	10.44	19.1025	0.27	19.62	9.9	0	29.643

25	29.25	21.78	0	16.245	33.795	0.9	37.98	13.05	0	50.6347
26	21.33	28.8	0	14.0175	36.585	0.2475	36.9	13.23	0	50.5911
27	15.57	12.24	0	9.8775	17.73	0.405	15.57	12.24	0	27.8653
28	24.12	27.18	0	10.575	40.1175	0.1125	23.85	27.45	0	50.5629
29	10.89	15.03	0	9.315	17.01	0.09	18.72	7.2	0	26.253
30	26.64	23.13	0	11.115	39.555	0.1125	34.74	15.03	0	50.4607
31	14.22	10.53	0	7.695	16.4925	0.495	22.23	2.52	0	24.5431
32	22.68	28.8	0	13.275	37.485	0.09	45.72	5.76	0	50.6157
33	26.82	23.04	0	17.5725	33.0525	0.225	36.72	13.14	0	50.5695
34	15.57	7.11	0	6.9525	15.7275	0.5175	19.8	2.88	0	23.0519
35	30.69	20.52	0	18.0675	32.13	0.6075	29.07	22.14	0	50.4398
36	10.26	10.44	0	5.625	14.7375	0.2025	11.61	9.09	0	20.4449
37	21.96	28.08	0	14.265	35.64	0.945	31.32	18.72	0	50.5952
38	18.99	32.04	0	9.4725	41.0175	0.315	26.1	24.93	0	50.4557
39	7.56	11.43	0	2.1375	16.9425	0.36	5.13	13.86	0	19.3346
40	20.52	29.97	0	12.33	38.475	0.2025	22.14	28.35	0	50.7581
41	6.75	9.45	0	3.8025	11.97	0.135	5.58	10.62	0	15.7782
42	28.98	21.96	0	20.5425	29.7675	0.7425	34.29	16.65	0	50.772
43	5.04	10.35	0	2.8575	12.6	0.2025	9.27	6.12	0	15.6528
44	25.83	25.83	0.09	19.0575	32.0625	0.4275	43.02	8.73	0	51.3379
45	25.02	24.03	0	18.945	30.1275	0.5625	45.27	3.78	0	49.334
46	9.63	7.02	0	6.7725	9.315	0.2475	12.69	3.96	0	16.2296
47	8.64	7.47	0	5.3325	11.0475	0.5175	10.35	5.67	0.09	16.7548
48	25.65	25.29	0	15.39	35.325	0.36	30.06	20.88	0	50.7649
49	11.07	6.12	0	6.7275	10.8675	0.18	9	8.19	0	17.6805
50	32.49	12.6	0	17.415	28.035	0.09	23.49	21.6	0	45.3128
51	8.37	10.53	0	4.77	13.7925	0.27	3.6	15.3	0	18.7313
52	29.52	20.16	0	24.3	25.38	0.18	38.88	10.8	0	49.5116
53	5.22	14.22	0	2.88	16.3575	0.0675	7.38	12.06	0	19.1998
54	34.38	17.19	0	26.55	25.5375	0.0675	31.77	19.8	0	51.8716
55	5.13	12.42	0	2.475	15.255	0.27	6.21	11.34	0	17.8674
56	25.11	24.84	0	18.45	30.915	0.2475	22.14	27.81	0	49.3717
57	7.92	11.88	0	3.4875	15.57	0.2925	10.8	9	0	19.2876
58	23.67	25.11	0	18.0225	30.6	0.18	18.63	30.15	0	48.4992
59	14.76	4.86	0	7.1775	12.735	0.0675	12.51	7.11	0	19.8362
60	26.46	21.96	0	17.6175	30.7575	0.18	19.08	29.34	0	48.3002
61	11.7	7.02	0	4.59	14.0625	0.0675	9.81	8.91	0	18.6125
62	19.98	28.8	0	17.01	32.31	0.0675	18.9	29.88	0	49.0959
63	9.18	10.62	0	4.4775	15.345	0.405	8.73	11.07	0	20.1226
64	12.51	34.02	0	11.25	34.9875	0.0225	11.16	35.37	0	46.0307
65	8.82	9.27	0	5.13	12.96	0.36	10.71	7.29	0.09	18.3336
66	20.25	29.34	0	19.1475	31.2525	0.1575	23.13	26.46	0	50.2163
67	13.41	3.87	0	8.325	9.09	0.09	15.93	1.35	0	17.4219
68	24.03	28.35	0	17.775	34.155	0.3375	19.98	32.4	0	52.0182
69	15.66	3.51	0	12.2625	7.0425	0.0225	13.5	5.67	0	19.1491
70	17.01	32.13	0	17.01	32.4675	0.135	14.76	34.38	0	49.3259

71	16.65	4.32	0	9.675	10.71	0.2925	15.48	5.49	0	20.6251
72	28.53	25.56	0	24.03	29.8575	0.2025	29.34	24.75	0	53.7568
73	7.11	10.17	0	4.0725	13.6575	0.0675	7.38	9.9	0	17.6766
74	41.13	8.82	0	29.925	19.5525	0.225	41.13	8.73	0.09	49.4392
75	9.81	7.02	0	3.42	13.4775	0.045	13.32	3.51	0	16.8149
76	21.51	26.01	0	16.7625	30.51	0.405	24.12	23.4	0	47.4126
77	5.13	11.34	0	3.1275	13.3875	0.135	8.37	8.1	0	16.594
78	14.76	33.03	0	9.8775	37.98	0.5625	14.94	32.85	0	48.1189
79	6.12	10.62	0	3.33	12.96	0.135	7.65	9.09	0	16.2914
80	21.33	25.56	0.09	12.3525	33.9075	0.9	20.88	25.92	0.18	46.8509
81	11.7	27.27	0	9.495	29.6325	0.315	10.71	28.17	0.09	39.2209
82	11.7	10.08	0	6.5025	14.9625	0.3375	12.42	9.36	0	21.6919
83	12.42	24.12	0	8.9775	27.4275	0.3375	12.15	24.39	0	36.5713
84	19.8	15.48	0	13.8375	21.3075	0.2925	21.06	14.22	0	35.2114
85	12.78	3.06	0	6.1875	9.6525	0.4275	9	6.84	0	16.1946
86	25.83	9.63	0	16.56	18.4725	0.7425	29.97	5.49	0	35.6007
87	24.21	7.83	0	13.2525	18.7425	0.2025	24.93	7.11	0	31.9521
88	10.8	0.99	0	2.385	9.18	0.0225	2.52	9.27	0	11.5324
89	28.08	6.3	0	16.8975	17.55	0.2025	28.44	5.94	0	34.4702
90	29.52	3.69	0	21.3525	11.7	0.27	29.7	3.51	0	33.1228
91	7.02	4.23	0	4.5	6.93	0.0225	5.58	5.67	0	11.3384
92	7.56	3.24	0	4.185	6.48	0	6.21	4.59	0	10.614
93	9.09	2.34	0	6.5025	5.1975	0.0225	8.28	3.15	0	11.6689

Average (ha)	34.03
Min (ha)	10.61
Max (ha)	53.76
Std Dev	14.70

Community III- Land Parcels with forest and non-forest cover including its FID

FID_	2011 Forest (ha)	2011 Non-forest (ha)	2015 Forest (ha)	2015 Non-forest (ha)	2015 Water (ha)	2016 Forest (ha)	2016 Non-forest (ha)	2016 Water (ha)	Total area (ha)
0	9	10.8	5.7375	13.005	1.3725	4.05	15.21	0.54	20.0059
1	9.18	11.16	8.7525	10.8225	0.6075	9.63	10.44	0.27	20.1396
2	15.3	4.41	12.285	7.515	0	14.22	5.4	0.09	19.726
3	17.01	2.43	12.2175	7.245	0.045	14.31	5.13	0	19.4174
4	17.01	4.05	14.3775	6.7725	0.0675	14.04	7.02	0	21.1222
5	7.65	12.6	7.3575	12.6225	0.18	8.01	12.24	0	20.1217
6	10.08	9.54	12.69	7.335	0.0225	13.14	6.48	0	19.9032
7	7.47	12.6	8.0775	11.9925	0.0225	9.18	10.89	0	20.0742
8	8.46	12.15	12.5325	8.1675	0	13.59	7.02	0	20.5857
9	11.7	8.37	8.28	11.8125	0	7.92	12.15	0	19.9459
10	12.33	8.19	9.135	11.3625	0.0225	7.38	13.14	0	20.4975

11	12.42	8.28	7.7175	12.8475	0.135	6.12	14.58	0	20.6715
12	9.45	10.8	9.5175	10.71	0.1125	7.11	13.14	0	20.2473
13	9.27	10.98	9.8775	10.53	0.09	8.64	11.61	0	20.4378
14	9.9	9.63	10.2825	9.54	0.09	9.72	9.81	0	19.7725
15	8.46	10.44	7.9875	10.98	0	3.51	15.39	0	18.9337
16	8.1	10.8	7.92	10.9125	0.1125	6.84	12.06	0	18.8449
17	9.72	9.36	8.6175	10.08	0.045	6.93	12.15	0	18.6828
18	10.35	8.37	7.8525	10.98	0.09	9.18	9.54	0	18.8622
19	10.62	9.45	12.9825	7.065	0.09	16.02	4.05	0	20.0726
20	8.73	11.16	11.1375	8.955	0.1125	12.24	7.65	0	20.0839
21	11.79	9.54	10.1025	11.205	0.0225	9.99	11.34	0	21.2815
22	10.44	9.54	7.92	12.0825	0	7.65	12.33	0	19.9031
23	12.51	7.29	8.2575	11.3625	0.09	9.27	10.53	0	19.6576
24	10.53	9.18	9.54	10.17	0.09	8.46	11.25	0	19.7039
25	11.43	9.09	10.0575	10.3725	0.0675	9.63	10.89	0	20.4689
26	15.03	5.58	11.7	9.135	0.045	10.98	9.63	0	20.7467
27	13.77	6.93	10.2375	10.7325	0	9.9	10.8	0	20.8496
28	13.32	6.75	9.9675	10.035	0	11.97	8.1	0	19.9824
29	15.84	5.4	12.33	8.91	0.045	15.93	5.31	0	21.1596
30	15.39	6.3	15.03	6.6375	0	15.3	6.39	0	21.654
31	12.06	8.55	9.1575	11.4525	0.0225	9.27	11.34	0	20.4633
32	14.04	5.76	11.0025	9.0225	0.045	13.95	5.85	0	20.0239
33	3.42	3.96	5.22	4.3425	0	5.94	1.44	0	9.46057
35	7.2	13.41	6.21	14.265	0	5.13	15.48	0	20.3829
36	8.37	11.97	6.2775	14.3325	0	5.94	14.4	0	20.4797
37	12.06	8.73	9.3375	11.43	0.1125	8.46	12.33	0	20.8259
38	11.25	9.54	9.6525	11.115	0	8.91	11.88	0	20.6678
39	9.36	10.89	9.6075	10.53	0.0675	7.92	12.24	0.09	20.1559
40	6.66	14.04	6.345	13.9725	0.135	6.39	14.31	0	20.3946
41	9.99	10.44	10.215	10.1925	0.0225	8.37	12.06	0	20.43
42	7.92	11.79	7.38	12.5325	0.045	8.01	11.7	0	19.9174
43	11.97	8.82	6.885	14.1525	0	6.39	14.4	0	20.9979
44	11.97	8.55	5.6025	15.1425	0	3.87	16.65	0	20.7616
45	13.41	7.2	4.9725	15.7725	0.0225	3.24	17.28	0.09	20.5477
46	12.06	8.1	10.26	9.945	0.0225	10.08	10.08	0	20.1212
47	11.7	8.46	9	11.205	0.1125	8.28	11.88	0	20.1489
48	8.28	11.97	8.28	11.9025	0	5.58	14.67	0	20.1283
49	8.28	12.69	7.2	13.6575	0.1125	4.5	16.47	0	20.9437
50	7.2	13.14	6.39	14.175	0	2.43	17.91	0	20.5045
51	5.94	14.31	5.4675	14.7375	0.09	1.26	18.99	0	20.31
52	8.01	13.14	7.875	13.455	0.135	5.67	15.48	0	21.424
53	9.09	9.9	7.9425	11.115	0.0675	8.55	10.44	0	19.0467
54	9.81	11.07	9.9	11.025	0	11.16	9.72	0	20.856
55	9.18	11.88	10.4625	10.5075	0	11.07	9.99	0	20.8868
56	8.82	10.89	9.1575	10.62	0.045	9.9	9.81	0	19.7674
57	5.22	5.85	7.3125	3.6225	0.2025	8.28	2.79	0	11.1087

58	7.38	12.6	6.4575	13.545	0.0675	4.32	15.66	0	19.9276
59	9.9	9.27	8.3025	10.755	0.045	6.93	12.15	0.09	19.0402
60	11.34	8.37	9.945	9.405	0.225	9.27	10.44	0	19.501
61	6.75	12.24	6.3225	12.465	0.0675	4.68	14.31	0	18.8051

Average (ha)	19.86
Min (ha)	9.46
Max (ha)	21.65
Std Dev	1.89

Community IV- Land Parcels with forest and non-forest cover including its FID

	2011		2015			2016		
FID_	**Forest (ha)**	**Non-forest (ha)**	**Forest (ha)**	**Non-forest (ha)**	**Water (ha)**	**Forest (ha)**	**Non-forest (ha)**	**Total area (ha)**
0	17.1	26.01	22.2075	21.15	0.225	10.8	32.31	43.6173
1	19.89	20.07	23.6025	15.9075	0	18.9	21.06	39.4917
2	21.69	8.37	19.26	11.16	0	20.07	9.99	30.4798
3	19.53	12.87	17.775	15.1875	0.0675	17.19	15.21	32.995
4	24.93	13.41	25.83	12.465	0	22.77	15.57	38.3215
5	34.47	12.69	33.525	13.545	0.0225	33.3	13.86	47.0614
6	28.98	22.41	31.095	19.4625	0.135	28.35	23.04	50.6714
7	17.64	14.85	18.405	13.86	0.2475	15.48	17.01	32.5318
8	19.35	17.46	20.9025	16.245	0	17.91	18.9	37.1748
9	16.65	13.68	17.145	12.96	0.2025	14.4	15.93	30.2907
10	18.99	14.4	22.7475	10.575	0	18.81	14.58	33.3814
11	25.38	8.19	23.9625	9.36	0.36	21.33	12.24	33.6499
12	24.21	16.47	26.01	14.805	0.045	24.21	16.47	40.7639
13	17.64	14.13	18.2475	13.2075	0.315	16.11	15.66	31.8047
14	19.98	16.56	20.565	15.5475	0	18.27	18.27	36.2053
15	22.14	10.08	21.8475	10.5525	0.0225	20.79	11.43	32.3616
16	25.11	8.46	23.175	10.7325	0.0225	22.77	10.8	33.8728
17	11.7	17.01	15.12	13.0725	0.3825	10.44	18.27	28.5495
18	19.62	13.59	21.4875	11.745	0	22.23	10.98	33.266
19	21.87	13.41	22.3875	12.7125	0.2475	17.46	17.82	35.335
20	21.42	10.89	22.8375	9.4725	0.0225	23.76	8.55	32.3129
21	21.96	11.43	22.6575	10.755	0.135	21.51	11.88	33.5248
22	16.83	18	20.7225	14.265	0.045	19.44	15.39	34.9533
24	19.35	12.33	20.9925	10.5075	0.2475	19.8	11.88	31.7645
25	13.59	20.7	22.05	11.8575	0	19.62	14.67	33.9924
26	18.54	12.42	17.955	12.8475	0	15.39	15.57	30.7836
27	15.48	13.05	15.435	13.1625	0.1575	11.25	17.28	28.5663
28	19.71	16.11	23.4	12.7575	0.045	24.12	11.7	36.232
30	16.02	12.24	17.145	10.485	0.36	16.29	11.97	28.017
31	20.88	13.77	20.835	13.4325	0.225	17.46	17.19	34.6797

32	12.15	6.93	12.3075	6.975	0.0225	13.05	6.03	19.2771
33	24.93	11.34	23.535	12.33	0.3375	22.77	13.5	36.1576
34	21.87	10.53	20.4975	11.97	0	21.96	10.44	32.5129
35	12.06	8.19	10.755	9.2025	0.405	9.27	10.98	20.297
36	20.07	10.89	18.405	12.69	0.27	17.01	13.95	31.3272
37	16.74	9.9	16.7175	9.675	0.09	15.3	11.34	26.5554
38	13.5	10.8	15.0975	9.225	0.09	12.33	11.97	24.4056
39	19.26	12.69	18.405	13.1175	0.3375	15.48	16.47	32.0024
40	11.34	8.55	9.9675	9.945	0	9.81	10.08	19.9899

Average (ha)	33.06
Min (ha)	19.28
Max (ha)	50.67
Std Dev	6.29

APPENDIX 6.1: COMBINE STATISTICS FOR DEFORESTION IN THE THREE COMMUNITIES IN THE STUDY

Evaluation of lanscape metrics in the three communities including Andrew Bradley's statistics

Community I

Total area (ha)	1816	**Min (ha)**	12	
Number of Farms (lease)	102	**Max (ha)**	21	
Average lease (ha)	19	**Std dev**	3	

Year	Forest Cover (ha)	Non-Forest cover(ha)	Forest cover (%)	Non-Forest cover (%)	Clearance rate (ha/annum)
1986	617.355	1198.395	34	66	
1993	617.355	1198.395	34	66	0
1996	617.355	1198.395	34	66	0
2000	798.93	1016.82	44	56	-45.39375
2008	676.7	1241	37	68	30.5575
2011	946.8	868.95	52.14	47.86	-90.03
2015	971.393	848.453	53.38	46.62	-6.14825
2016	1176.12	639.63	64.77	35.23	-204.727

Community II

Total area (ha)	3199	**Min (ha)**	11	
Number of Farms (lease)	93	**Max (ha)**	54	
Average lease (ha)	34	**Std dev**	15	

Year	Forest Cover (ha)	Non-Forest cover(ha)	Forest cover (%)	Non-Forest cover (%)	Clearance rate (ha/annum)
1986	2691.9	506.88	84.15	15.85	
1993	2041.78	1157	63.83	36.17	92.87
1996	1594.78	1604	49.86	50.14	149.00
2000	1367	1831.78	42.74	57.26	56.95
2008	627.89	2565	19.63	80.37	184.78
2011	1658.07	1540.71	51.83	48.17	-343.39
2015	1068.46	2149.13	33.21	66.79	147.40
2016	1854.81	1343.97	57.98	42.02	-786.35

Community III

Total area (ha)	1219	**Min (ha)**	9	
Number of Farms (lease)	60	**Max (ha)**	22	
Average lease (ha)	20	**Std dev**	2	

Year	Forest Cover (ha)	Non-Forest cover(ha)	Forest cover (%)	Non-Forest cover (%)	Clearance rate (ha/annum)
1986	1161.09	57.51	95.28	4.72	

1993	232.47	986.13	19.08	80.92	132.66
1996	232.47	986.13	19.08	80.92	0.00
2000	128.34	1090.26	10.53	89.47	26.03
2008	297	886.5	24.37	75.63	-42.17
2011	631.17	587.43	51.79	48.21	-111.39
2015	549.968	675.316	44.88	55.12	20.30
2016	524.79	693.81	43.06	56.94	25.18

Community Four: Isiboro

Total area (ha)	1295.82
Number of Farms (lease)	40
Average lease (ha)	31.6571

Year	Forest Cover (ha)	Non-Forest cover(ha)	Forest cover (%)	Non-Forest cover (%)	Clearance rate (ha/annum)
2011	763.11	532.71	58.89	41.11	
2015	797.4	500.3555	61.44	38.56	-8.5725
2016	717.84	577.98	55.40	44.60	79.56