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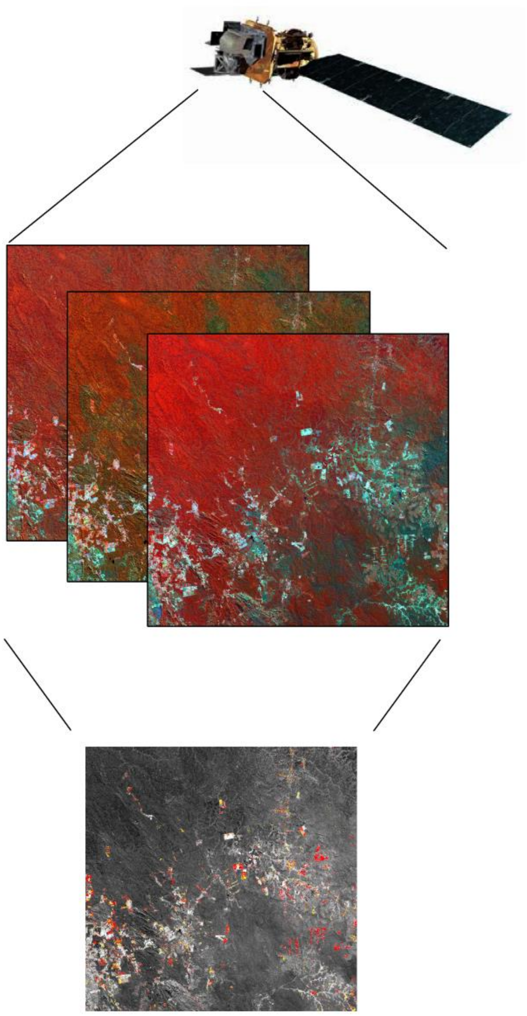
Monitoring deforestation & land cover change in the Santa Cruz region of Bolivia using Landsat satellite imagery



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Title:

MONITORING DEFORESTATION & LAND COVER CHANGE IN THE SANTA CRUZ REGION OF BOLIVIA USING LANDSAT SATELLITE IMAGERY

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PREFACE AND ACKNOWLEDGEMENTS

The final part of the course Tropical Forestry at Van Hall Larenstein University of Applied Science consist of a final thesis. During this stage of the course students need to prove their qualities which are required for graduating. This report is written as part of the final thesis and consists of the study which has been performed during four months.

Land cover change in Bolivia, together with deforestation and satellite imagery, has been chosen as the subject of this final thesis. This subject has been chosen by the collaborating organization Alterra and the student. This subject fits in with the students desire to work with satellite imagery and software programs like ArcGIS and ENVI. It also fits within the ROBIN project in which Alterra participate.

The EU FP7 project ROBIN investigates the potential of biodiversity and ecosystems for the mitigation of climate change. As such ROBIN will provide information for policy and resource the options under scenarios of socio-economic and climate change to quantify the interactions between terrestrial biodiversity, land use and climate change mitigation potential in tropical Latin America.

The study has been done within a short timeframe which made it a quite difficult time for me with ups and downs. Some difficulties were expected, like starting a study on a subject in which I did not had much knowledge. Others were unexpected, like the shutdown of the American government resulting in a denied access to necessary satellite imagery. This made it sometimes stressful. However, after four months I can show the final results which can be read in this paper. I look back at a very educational period. Therefore I want to thank all people who were involved during my stay at Alterra. Special thanks goes to Sander Mucher who had been a tremendous and supportive supervisor. Furthermore I want to thank Erika van Duijl who had been my supervisor form Van Hall Larenstein. She gave me good advice during the thesis and handed me good reviews during the thesis. I also would like to thank Gerbert Roerink and Loic Dutrieux who gave me feedback and there point of view and expertise of the subject. Finally I want to thank family and friends who supported me during the final part of the study. Support which had been necessary.

Jacob Nugteren.

ABSTRACT

Deforestation and land cover changes are still continuing processes in the Amazon, despite the increasing awareness of deforestation and its consequences. Consequences are related to increased emissions of greenhouse gases, pollution of water, and loss of biodiversity. Bolivia is a country where forest loss occurs and I tried to indicate this forest loss for a small study area together with land cover change between 1993 and 2010. Satellite images are more and more used for the monitoring of land surface processes at various scales. This study implements satellite images as source for the detection of land cover changes and deforestation.

The study area can be found near Santa Cruz and consisted of approximately 20,000 km² of which the biggest part is covered by forest (90.46% in 1993). Aim of the study was 1) to study on the methods used for the detection of land cover change and deforestation, 2) to implement a usable method for this study, 3) to indicate the major land cover changes, and 4) to indicate the deforestation rates, within the study site.

Many different methods can be used, each having its own advantages and disadvantages. The method used in this study was based on the combination between false color multi-band land cover classifications and the maximum NDVI of one year. Together they have been processed into land cover change maps including data on deforestation rates.

As expected, the most common land cover change was the one from forest to pastures. 9,414 ha was converted into pastures between 2000 and 2005 and another 26,355 ha of forest was converted to pasture between 2005 and 2010. The total land cover change between 2000 – 2005 and 2005 – 2010 differed. In the first timeframe 14,794 ha of land cover was changed whereas between 2005 – 2010 land cover change increased till 35,133 ha. This trend was also seen for the rate of deforestation. An annual deforestation rate of 0.12% was estimated between 2000 and 2005. Between 2005 and 2010 the annual deforestation rate was higher, increasing to 0.32%. From 1993 till 2000 the annual deforestation rate was estimated at 0.4%. However, these figures were below the averages of other studies.

Keywords: Land cover change, deforestation, Bolivia, satellite imagery, remote sensing.

Table of Contents

List of figures:

List of tables:

ACRONYMS AND ABBREVIATIONS

°C	= Degree Celsius
Θs	= Solar zenith angle in degrees
ρp	= Unitless planetary reflectance
ALOS	= Advanced Land Observing Satellite
Av.	= Average
AVHRR	= Advanced Very High-Resolution Radiometer
C	= Carbon
d	= Earth-Sun distance in astronomical units
DN	= Digital Number
EGS	= Ecosystem Goods and Services
ERS	= European Remote-Sensing
ESUNλ	= Mean solar exoatmospheric irradiances
EVI	= Enhanced Vegetation Index
FAO	= Food and Agriculture Organization
FSC	= Forest Stewardship Council
Ha	= Hectares
IUCN	= International Union for the Conservation of Nature
Km	= Kilometer
Km^2	= Squared kilometers
Lλ	= Spectral Radiance at the sensor's aperture in watts/(meter squared * ster * µm)
Landsat ETM+	= Landsat Enhanced Thematic Mapper Plus
Landsat MSS	= Landsat Multispectral Scanner
Landsat TM	= Landsat Thematic Mapper
LMAXλ	= the spectral that is scaled to QCALMAX in watts/(meter squared * ster * µm)
LMINλ	= the spectral radiance that is scaled to QCALMIN in watts/(meter squared * ster * µm)
M	= Million
Max	= Maximum
MERIS	= Medium Resolution Imaging Spectrometer
mm	= millimeter
MODIS	= Moderate-resolution Imaging Spectroradiometer
NASA	= National Aeronautics and Space Administration
NDVI	= Normalized Difference Vegetation Index
NIR	= Near Infrared
PALSAR	= Phased Array type L-band Synthetic Aperture Radar
QCAL	= the quantized calibrated pixel value in DN
QCALMAX	= the maximum quantized calibrated pixel value (corresponding to LMAXλ)
QCALMIN	= the minimum quantized calibrated pixel value (corresponding to LMINλ)
ROBIN	= Role Of Biodiversity In climate change mitigation
S	= South
t/ha	= Tons per hectare
TOA	= Top of Atmosphere
VIS	= Visible red
W	= West

1. INTRODUCTION

1.1 PROBLEM STATEMENT AND OBJECTIVE

Deforestation is an ongoing event with threatening consequences for the tropical forests in the world. Increasing emission of carbon dioxides, as tropical forests store high values of carbon dioxides, can result in climate change. The IUCN (2013) declared that deforestation and forest degradation consists of 17,4% of the total greenhouse emission caused by human beings. This resulted in the second largest emission group of carbon dioxide, caused by humans (Werf, et al., 2009). Average carbon stock for rainforest is around 172 tons C/ha (Hall, et al., 1985). More recent study indicates an even higher carbon stock ranging between 187 and 271 tons C/ha (Saatchi, et al., 2011). The latter study indicates that Bolivia is the number 6 country for biomass storage in tropical forests (Saatchi, et al., 2011). This indicates the importance of carbon storage within tropical forests.

Clean air is one of the ecosystem goods and services (EGS) provided by tropical forests. However, EGS are threatened by deforestation, hydrology for example. Amazon freshwater ecosystems are being impacted by increasing economic activities (Castello, et al., 2013).

Furthermore, biodiversity is threatened by deforestation. Tropical forests account for more than 50% of the world known plant species. This is a high number when you notices that tropical forests cover only 10% of the world's land surface (Mayaux, et al., 2005). Bolivia is a very diverse country reaching in the top 10 of countries with the highest species and ecosystem diversity (ARD, inc, 2008). Biodiversity will however drop when tropical forests is conversed into other land-uses (Edwards, et al., 2013) (Sodhi, et al., 2004). It is even suggested that ecological friendly agricultural practices is not as helpful for tropical conservation as thought before (Waltert, et al., 2011). Biodiversity is also threatened by forest fragmentation, which is a result of deforestation. Edge-effects can occur in these forest patches. These effects can be divided in abiotic effects, biological effects, and indirect biological effects (Murcia, 1995). Some of these effects can result in changes of the dynamics within 100 meter from the forest's edge (Laurance, et al., 1998). This means that loss of tropical forests can be a serious destruction for biodiversity and can be irreversible.

However, deforestation still continues, and the deforestation rate in South America is even accelerating. Argentina, Brazil, Bolivia, and Paraguay are the countries which are most exposed to deforestation in South America (Aide, et al., 2012). The deforestation rate for Bolivia has been increasing and was numbered as 2,900 km² per year of forest loss, in the period between 2001 and 2004 (Killeen, et al., 2007). Another resource shows an average deforestation rate of 2,700 km² between 1990 and 2005. This number was even higher between 2005 and 2010: 3,080 km² per year. This means an 8.9% loss of forest cover, in Bolivia (Mongabay, 2011). Numbers from the FAO indicate a total loss of 55,900 km² between 1990 and 2010, accounting for an average deforestation rate of 2,795 km² a year (FAO, 2010).

Though deforestation figures are not positive for the amazon, it must be said that in some cases improvement occurs. According to Aide et al (2012), there has been a reforestation rate of more than 360,000 km² in Latin America and the Caribbean. Brazil showed a decrease in deforestation rate in 2012. National Institute for Space Research calculated a decline of 27% between 2011 and 2012. Calculations indicated 4,656 km² deforestation in July 2012, compared to 6,418 km² one year earlier (Angelo, 2012).

The drivers for deforestation are mostly related to conversion of natural land for agriculture, e.g. soybean (Steininger, et al., 2001) (Aide, et al., 2012) (Grau & Aide, 2008). The biggest drivers of deforestation in the Amazon between 2000 and 2005, are cattle ranches, accounting for 60%, and small-scale farming, accounting for 33% (Ghazoul & Sheil, 2010). The main threat in Bolivia is the conversion of forest into agricultural land. This occurs around Santa Cruz (Wassenaar, et al., 2007).

The drivers are also site-specific. Therefore it is good to analyze a small study site in terms of deforestation and land cover change.

The relatively small study site (see methodology) will be studied through satellite imagery. It is possible to use remote sensing for research with the technology we have these days and it is broadly used (Veldman & Putz, 2011) (Aide, et al., 2012) (Steininger, et al., 2001) (Killeen, et al., 2007). We are far advanced with satellite imagery these days and the technology will increase fast in future, as more and more satellites are launched into space. It has been used in a lot of studies on land cover change. Unfortunately mistakes can happen during interpretation of the imagery (Mayaux, et al., 2005). Different interpretation of researchers, implementation of different techniques and use of different definitions of vegetation types are a few examples leading to different results. This makes it interesting to use satellite imagery for a research based on land cover change without fieldwork, what I will try to do with this research.

This study falls within the ROBIN project (Role Of Biodiversity In climate change mitigatioN). This is carried out by multiple institutions including Wageningen University and Alterra. Part of this project is to deliver information for understanding the role of biodiversity on climate change. This information will be provided for policy and resource uses. Remote sensing for biodiversity assessments is one of the tools to achieve the information.

As discussed before, deforestation keeps continuing. But how does this develop in the department Santa Cruz, Bolivia? And what does this mean for this area? The objective of this study is to provide valuable information on land cover change and deforestation using satellite imagery. This is done through a study on the current methods applied within remote sensing and the application of a methodology which gives an appropriate result on land cover changes and deforestation. Reforestation is also included partially within this study, as land cover change will be studied.

1.2 Research questions

The main research question is based on the land-use change in Bolivia. This has been formulated as follow:

What is the current and past development of land cover change in Santa Cruz, Bolivia?

To answer this question several sub-questions have been formulated, namely:

1. What are the current methods to detect deforestation and land cover changes?
2. Which method can be best used to detect land cover changes and deforestation within this study?
3. Which major land cover changes took place between 2000 & 2005, and 2005 & 2010, in Santa Cruz, Bolivia?
4. What are the deforestation rates in Santa Cruz, Bolivia, since 1993.

There are several terminologies used within this report which should be further defined as this could give confusion.

First of all the difference between land cover and land use should be defined as both can create confusion concerning land cover classes. Land cover can be seen as the physical cover of the land surface, which is observed (FAO, 2000). This includes forest, grasslands, swamps, etc. Land use, however, is defined by FAO as a land cover which is used for production, change, of maintenance caused by the arrangements, activities, and inputs of humans (FAO, 2000).

The definition of forest is important for this report as well, as it is related to reforestation. The definition of forest used in this report is the definition defined by the FAO. The FAO defines forest as land which have a tree crown cover of at least 10 percent. Furthermore the trees should be able to reach a height of at least five meters (FAO, 2000). Although this is hard to see based on 30 x 30 m pixels, this terminology gives an indication that forest can recover quickly based on the definition of the FAO.

2. LITERATURE REVIEW: CURRENT METHODS FOR THE DETECTION OF DEFORESTATION AND LAND COVER CHANGE

Part of the study is to investigate which methods are applied for the detection of land cover changes and deforestation. Based on the literature review an appropriate method can be selected for the study of land cover changes and deforestation within the Santa Cruz region in Bolivia.

Forest inventories based on remote sensing have been done since a long time, especially in developed countries. However, scientist started to pay more attention towards tropical forestry distribution and the change within tropical forests in a global scale since the early 1990s. But most important, the methods and techniques used still differ between programs, resulting in various outcomes (Mayaux, et al., 2005).

In this part of the report the focus lies on a small introduction on the sensors which can be applied and some examples of methods and techniques applied for the detection of deforestation and land cover change.

2.1 SATELLITE SENSORS

There are many different sensors which can be used. All of them have their own advantages and disadvantages. One of those sensors is the Advanced Very High-Resolution Radiometer (AVHRR). This sensor has been used in different studies for global land-cover and forest mapping (Mallingreau, et al., 1989) (Loveland, et al., 1999). It also had been very useful, however NGO's and aid services were not satisfied because of the spatial resolution of the AVHRR sensor (Mayaux, et al., 2005). Mayaux *et al.* (2005) indicate that there are limitations with the AVHRR dataset for land-cover mapping. This is also confirmed by Hansen *et al.* (2009) who used and compared remotely sensed data from the Moderate-Resolution Imaging Spectroradiometer (MODIS) and AVHRR sensor for changes in the rates of forest clearing in Indonesia. They noticed that data derived from the MODIS sensor had an reduced standard error compared to data from the AVHRR sensor making it a better information source. The AVHRR sensor is still used during lots of studies, however, MODIS has become more interesting for the detection of deforestation. Different studies apply both sensors but always with AVHRR for older periods and MODIS for more recent times (Hansen, et al., 2009) (Giree, et al., 2013). Indicating that MODIS is preferred to use after the launch in 1999. This has also to do with the spatial resolution[1] of both sensors, AVHRR with a spatial resolution of 1.1 km and MODIS with a spatial resolution of 250 m.

MODIS has been used widely in recent studies. Not only in global or continental studies on tropical deforestation (Aide, et al., 2012) (Mayaux, et al., 2013) (Miettinen, et al., 2011) but also on more regional studies (Caldas, et al., 2013) (Langner, et al., 2007) (Hansen, et al., 2009). Therefore, it has been proven to be a qualified tool for detecting deforestation rates. Another satellite sensor, which is comparable to MODIS, is the Medium Resolution Imaging Spectrometer (MERIS). This satellite sensor has also an moderate spatial resolution but has a slightly lower temporal resolution[2]. However, this satellite is not often used in detecting deforestation, as there are hardly any results for scientific papers related to MERIS and deforestation. However, according to Langner *et al.* (2005) MERIS have been widely used.

There are also high spatial resolution sensors which are used to indicate deforestation rates. Landsat is one example of these sensors. Two Landsat sensors are often used in studies, the Thematic Mapper (Landsat TM) and the Enhanced Thematic Mapper Plus (Landsat ETM+). Landsat

[1] Spatial resolution is the length of a single pixel (Quadri, 2012), in case of Landsat image 30 m.

[2] Temporal resolution is the revisiting time of a satellite sensor between two frames of a specific location (Satellite Imaging Corporation, 2012).

images are often used in combination with other satellite sensors. Integrating moderate/coarse spatial resolution images with high spatial resolution images is done because coarse spatial resolution data has limitations in detecting changes as these changes occur on sub-pixel level (Hansen, et al., 2009). This has been done in a wide range of studies, like Stibig et al. (2007), Achard et al. (2002), and Giree et al. (2013). Landsat has also been used as a single resource for forest classification. This has mostly be done in small scale studies (Steininger, et al., 2001) (Killeen, et al., 2007).

The disadvantage of high spatial resolution data is the interval of the satellite images. Landsat has a repeat interval of 16 days, and other high spatial resolution have an even lower repeat interval (Table 1). The narrow swath of the satellite images is also a disadvantage, besides the temporal resolution (Langner, et al., 2007).

There are several other very high spatial resolution satellite sensors which are interesting for future research. Quickbird is one example and can be used with the same method as the combination of coarse spatial and high spatial resolution. Grinand *et al.* (2013) has applied this using Landsat images with Quickbird as reference data.

Table 1, Examples of satellite sensors including spatial resolution, swath wide, repeat interval and availability.

Sensor	Spatial resolution	Swath wide	Repeat interval	Open data
SPOT VGT	1.15 km	2,250 km	1 day	No
AVHRR	1.1 km	2,500 km	12 houres	Yes
MODIS	1,000-250 m	2,330 km	1-2 days	Yes
MERIS	300 m	1,150 km	3 days	No
Landsat TM	120-30 m	185 km	16 days	Yes
Landsat ETM+	60-15 m	185 km	16 days	Yes
SPOT 6	6 – 1.5 m	60 km	1 day	No
Quickbird	2.4-0.6 m	18 km	1-3.5 days	No
PALSAR		20-350 km		No

The disadvantage of satellite imagery is the cloud cover often found in tropical forests. This problem especially occurs with high spatial resolution as they have an temporal resolution of 16 days or more. Radar systems are an solution for this. The Advanced Land Observing Satellite (ALOS) carries such a radar system named PALSAR (Phased Array type L-band Synthetic Aperture Radar). The combination of optical[3] and radar[4] data can be an improvement for classification of land use and land cover. Especially for discriminating some classes (De Oliveira Pereira, et al., 2013). Avtar *et al.* (2013) proved that there are potentials for using PALSAR for land cover classification. They implemented three different classification types resulting in high overall accuracies. However, the ALOS satellite has been declared dead after an unknown loss of communication (SPACE.com, 2011). Still there are other radar sensors which can be applied as well, like ERS and RADARSAT (Da Costa Freitas, et al., 2002).

[3] Optical data related to remote sensing makes use of the solar radiation which has been reflected from the earth surface. The reflection is recorded by sensors which detect visible, near-infrared and short-wave infrared (Centre for Remote Imaging, Sensing and Processing, 2001).

[4] Radar data is a system which can detect objects using microwave electromagnetic radiation (UC Santa Barbara, Non-dated).

2.2 METHODS FOR DETECTING LAND COVER CHANGES AND DEFORESTATION

First of all, it is good to distinguish three main methods used in global scale tropical forest monitoring which are described by Mayaux *et al.* (2005) as follow: 1) collect available information through statistics on national level, previous research papers, and expert opinions, 2) implementing fine spatial resolution satellite imagery as a source for detecting changes in forest cover, and 3) the use of coarse spatial resolution to detect forest cover change.

The first method, the collection of available information through different sources, is partly useful within this study. However, this part will not be discussed during this study as it is not for concern of this study. This study is focused to derive own results through the deployment of fine spatial resolution satellite imagery. Still it must be said that the information from other sources like the FAO are necessary for comparison of the results for this report.

The study focusses on the last two methods for deriving deforestation and land cover change maps, the implementation of fine spatial resolution and coarse spatial resolution satellite imagery. Some studies use explicitly fine spatial resolution satellite images (Avtar, et al., 2013) (Grinand, et al., 2013) (Killeen, et al., 2007) (Steininger, et al., 2001) whereas others use only coarse spatial resolution satellite images (Aide, et al., 2012). However, it is also common that both types of satellite imagery are used (Achard, et al., 2002) (Hansen, et al., 2009). This gives the advantage that the strengths of both satellite imageries can be combined and used. It must be said, however, that the methods applied within deforestation and land cover change is rather complex and they differ widely. Therefore a few examples will be given here.

Several aspects should be considered to come up with an usable method. It depends on the purpose of the study, the thematic content, scale of the study, the quality and availability of data, and the processing and analysis of algorithms (Cihlar, 2000). The purpose in this study is land cover classification and change detection. Therefore, a few studies with similar purposes will be highlighted for making the decision of a proper methodology.

Several studies try to indicate worldwide deforestation figures. One of them is Achard et al. (2002), which studied deforestation rates of the world's humid tropical forest. The method applied was based on coarse spatial resolution satellite images, used for establishing sub-continental forest distribution maps. As a second step, deforestation hot-spots areas were identified through the knowledge of local experts. This resulted in five different strata's based on the hot-spot and forest proportions. Fourthly, hundred study sites around the humid tropics were selected. This was followed by a change assessment for each of the hundred observation sites. This was done through fine spatial resolution imagery. Finally the two reference data were used to make estimations for the deforestation rates around the world, based on linearly interpolation (Mayaux, et al., 2005).

The recent study of Hansen et al. (2013) has classified worldwide forest cover change. As a first step they applied four pre-processing steps; image resampling, conversion of digital values to top of atmosphere reflectance, differentiation between cloud, shadow and water and a quality assessment, and image normalization. The second step was the collection of three different groups of data. These groups were the maximum, minimum and selected percentiles of the reflectance values. Furthermore the mean reflectance values of selected percentiles. The third group consisted of derived data on the regression between band reflectance related to the date of the image. This data, was, as a third step, converted into training data for percent tree cover, forest loss and forest gain, using different decision trees. One of those decision trees was based on the NDVI. Finally a lazy computation[5] was performed within Earth Engine resulting in the final data products (Hansen, et al., 2013).The study of Hansen et al. (2013) was based on Landsat satellite imagery, meaning a spatial resolution of 30 x 30 meter.

Langner et al. (2007) based their method on unsupervised classifications as this gave the best results. They justify their method based on the study of Chilar (2000) which indicates that this is the best method when there is little or no ground truth data. This study also used an unsupervised classification as there is no availability of field data.

Some methods have been discussed above on land cover change and deforestation, as this is the main focus of this study. However, there are many other research subjects in which remote sensing is applied for change detection. Lu et al. (2004) summarizes eight other besides land-use and land-cover change and deforestation (which also includes regeneration and selective logging). These are forest or vegetation changes, forest mortality, defoliation and damage assessment, wetland change, forest fires, landscape changes, urban change, environmental change, and other changes like road segments, glacier change and crop monitoring. Each of these research scopes can have their own technique which is most suitable for that type of study, as each technique has its own advantages and disadvantages. Lu et al. (2004) summarizes 22 techniques with their advantages and disadvantages and indicates the complexity of these techniques. Examples of techniques used for land cover classification and change detection are; image differencing, image rationing, vegetation index differencing, unsupervised change detection, and visual interpretation (Lu, et al., 2004)(table 2).

Table 2, Example of several techniques used for the detection of land cover changes from Lu et al. (2004).

Technique	Charasteristics	Advantages	Disadvantages
Image differencing	Two images of which the first image is subtracted from the second image	A simple technique and easy to interpreted	Detail of change is low because of noise, it requires a threshold to improve the results
Image rationing	The ratio of two images from different dates are calculated, band by band	The impact of sun angle, shadow and topography is reduced	Distribution of the results is often non-normal
Vegetation index differencing	Two separate vegetation indexes are produced and subtracted from each other	Impact of topographic effect is reduced together and highlights the spectral response of different features	Random noise
Unsupervised change detection	Groups of similar pixels are selected, clusters are made from different groups and detects and identifies changes	It is unsupervised and an automation of change analysis	The method has difficulties in the detection of change trajectories
Visual interpretation	On-screen digitalizing of changes by visual interpretation, the overlay of different images is used	Human knowledge is implemented. texture, shape, size and patterns are interpreted	Detailed information is not provided. Highly depends on the skills of the expert

[5] The computations of lazy computations are evaluated at the moment when results are needed and therefore are not evaluated directly (Microsoft, 2014).

3. Study area

3.1 Geographical stratification

The study area is located in the department of Santa Cruz, in the east of Bolivia. The boundaries of the site are located between 15° S 62° W (top left) and 15° S 61° W (bottom right). The size of the area is 144.27 km x 140.58 km, covering a total area of approximately 2,032,043 ha. Several urban areas are located within the study area, namely Concepción, Santa Rosa de la Roca, and a few small villages. The map below shows the exact location of the study area (figure 1).

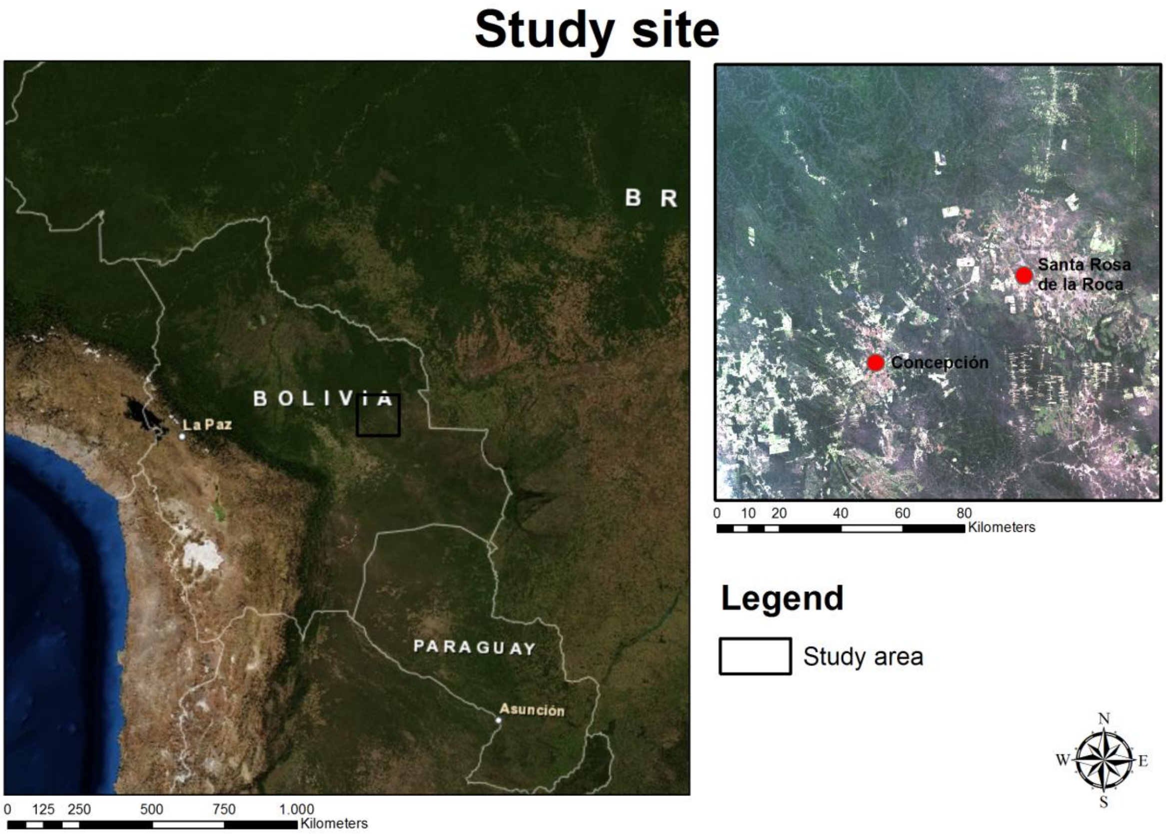

Figure 1, Location of the study area.

The area is predominantly covered by forest. The forest type for this area has been classified as tropical broadleaved evergreen forest according to a classification of the SERENA project. Tropical shrublands and croplands are indicated in this classification as well. The data from the SERENA project is derived from the MODIS satellite and is used as background information for comparison.

The Dutch wood company INPA Parket also owns forest in the study area. This company has the ownership of 30,000 hectares of forest in Bolivia. This forest has been managed in a sustainable way and the wood extraction has been certified under the FSC label (INPA Parket, 2013). INPA Parket is involved in the ROBIN project as they contribute too research related to the subject of the project.

3.2 Climate

The climate is characterized by a tropical wet and dry climate. The temperature slightly differs throughout the year and most rainfall occurs during October through April when the Northeast winds are dominating the area (Vera, 2006). The average temperature is 24.4 °C, falling towards 20.8 °C in

June and 26.6 °C during the month October (WorldClimate, 2011). A clear overview of the climate can be found in figure 2.

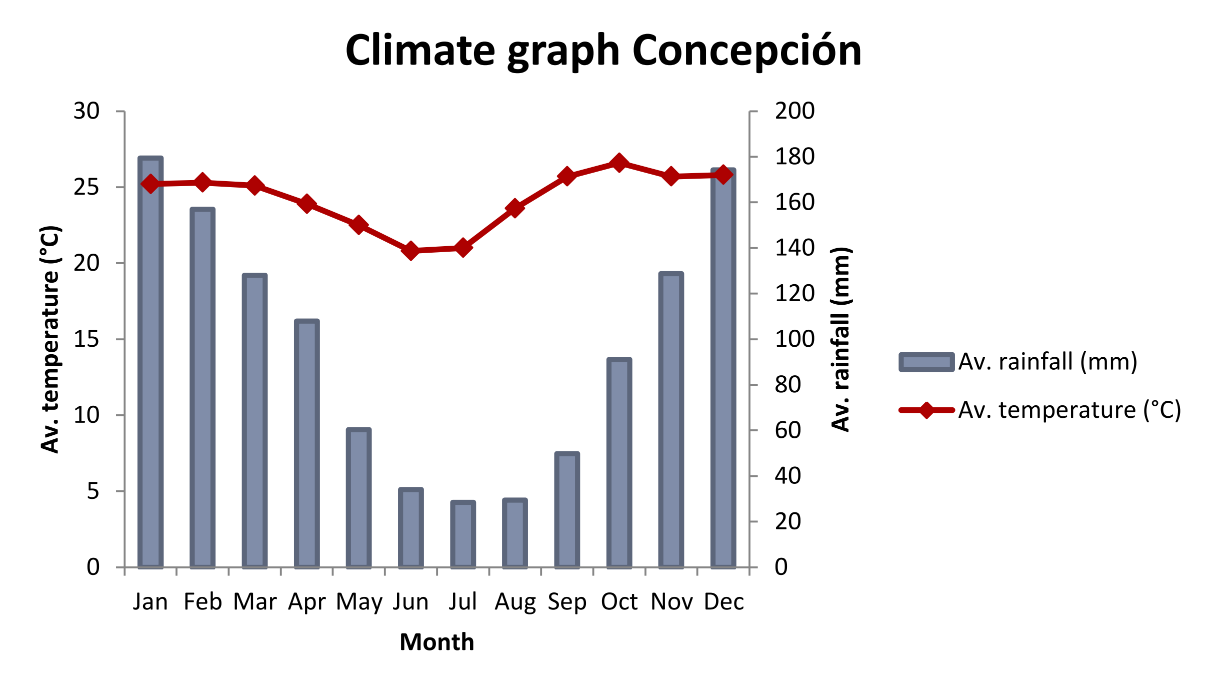

Figure 2, Temperature and rainfall in Concepción (WorldClimate, 2011)**.**

The rainfall patterns in tropical regions are quite stable and include a dry season. The region has a precipitation of around 1170 mm per year (WorldClimate, 2011). A dry season occurs from May to September, in Santa Cruz, Bolivia. During this period moisture stress is encountered which has influences on the vegetation but does not mean that trees will drop their leaves (Ghazoul & Sheil, 2010).

4. METHODS AND MATERIALS

This chapter describes the methodology of the study and the materials applied for this study. The methodology is based on the research questions of this study. The first sub-question on methods applied for the detection on land cover changes and deforestation have been discussed in the chapter 2. This chapter will answer the second sub-question as it will give the method which has been the best option for this study, related to time, knowledge, and results. It also gives an overview what had been done to answer the last two sub-questions based on land cover changes and deforestation.

4.1 SATELLITE IMAGERY

For this study satellite images from the Landsat program were used. These satellite images came from the Landsat 5 and the Landsat 7 satellites. Satellite images came from three different sensors, namely the Landsat MSS, the Landsat TM, and the Landsat ETM+. An overview of the used satellite images can be found in appendix 1.

Landsat images are multispectral images meaning that they consist of multiple bands where each band provides data reflectance and radiation (Centre for Remote Imaging, Sensing and Processing, 2001). The Landsat MSS consist of four bands, whereas the Landsat TM and the Landsat ETM+ consist of seven bands. These bands have their own wavelengths. Especially the red and the near infrared band are important for the calculation of the Normalized Difference Vegetation Index (NDVI). This index can be calculated with the reflectance of the different bands where healthy vegetation will give an higher value compared to unhealthy vegetation (figure 3 and 4).

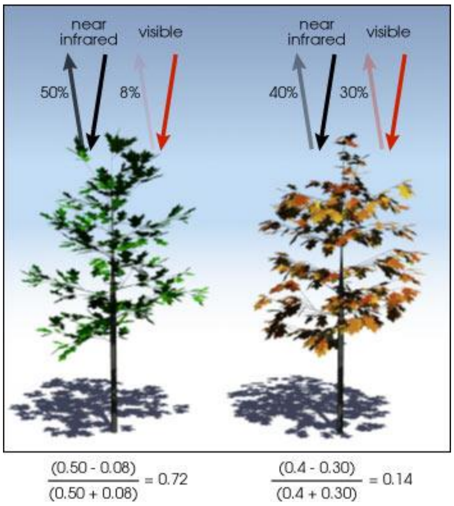

Figure 3, Reflection and NDVI (Simmon, 2013)

The satellite images had to meet several requirements to identify the major land cover changes:

- At least three images within a time frame of one year. The amount of this number of images has been chosen as there are changes in the greenness of the different land uses due to rainy and dry seasons.
- The images should be well distributed over a time frame of one year. This is related to the sun reflection. The sun changes in position throughout the year, causing shadows on steep areas. These shadows can result in different classifications.
- It is preferable to have as little cloud cover as possible in the images. Images with a high percentage of cloud cover are hardly usable as running of classifications are influenced by cloud cover. However, cloud free images are scarce in tropical forests.
- Land cover types have to be discriminated on bases of their phenology as well as it differs through time. Therefore several images should be taken over one year to see those and pay attention to those differences.

The previous mentioned requirements for satellite images are based on the images necessary for the timeframe 2000 and 2005. A total of three timeframes are studied in this study, 1993 – 2000, 2000 – 2005, and 2005 – 2010.

4.2 Preprocessing and NDVI

The first step in processing the satellite images is preprocessing of the satellite images. Several corrections had to be made before calculating the NDVI. Landsat images consist of Digital Number (DN) values which have to be converted into NDVI values. The process for calculating DN to NDVI is:

DN ---> Radiance --->TOA reflectance ---> NDVI

Satellite images are expressed in DN values and should be calibrated first as DN is a value which does not indicate a meaningful unit (Exelis, 2012). The DN value should be converted into absolute radiance. The following formula is used to calculate the radiance:

$$L\lambda = ((LMAX\lambda - LMIN\lambda) / (QCALMAX - QCALMIN)) * (QCAL - QCALMIN) + LMIN\lambda$$

Where:
- $L\lambda$ = Spectral Radiance at the sensor's aperture in watts/(meter squared * ster * μm)
- QCAL = the quantized calibrated pixel value in DN
- $LMIN\lambda$ = the spectral radiance that is scaled to QCALMIN in watts/(meter squared * ster * μm)
- $LMAX\lambda$ = the spectral radiance that is scaled to QCALMAX in watts/(meter squared * ster * μm)
- QCALMIN = the minimum quantized calibrated pixel value (corresponding to $LMIN\lambda$)
- QCALMAX = the maximum quantized calibrated pixel value (corresponding to $LMAX\lambda$) (NASA, non-dated)

The reflectance can be calculated after the radiance has been calculated. This steps makes a reduction in between scene variability. This is done through a normalization for solar irradiance (NASA, non-dated). The following formula is used to calculated the planetary reflectance:

$$\rho p = (\pi * L\lambda * d^2) / (ESUN\lambda * \cos\theta s)$$

Where:
- ρp = Unitless planetary reflectance
- $L\lambda$ = Spectral Radiance at the sensor's aperture in watts/(meter squared * ster * μm)
- d = Earth-Sun distance in astronomical units
- $ESUN\lambda$ = Mean solar exoatmospheric irradiances
- θs = Solar zenith angle in degrees (NASA, non-dated)

The NDVI can be calculated after the previous calculations has been performed. The NDVI stands for Normalized Difference Vegetation Index. This value gives a number between 0 and 1 where values close to 0 indicate water or bare soil and high values indicate forest (figure 4). The NDVI can be calculated through the following formula:

$$NDVI = (NIR - RED) / (NIR + RED)$$

Where:
- NDVI = Normalized Difference Vegetation Index
- NIR = near infrared
- RED = visible red

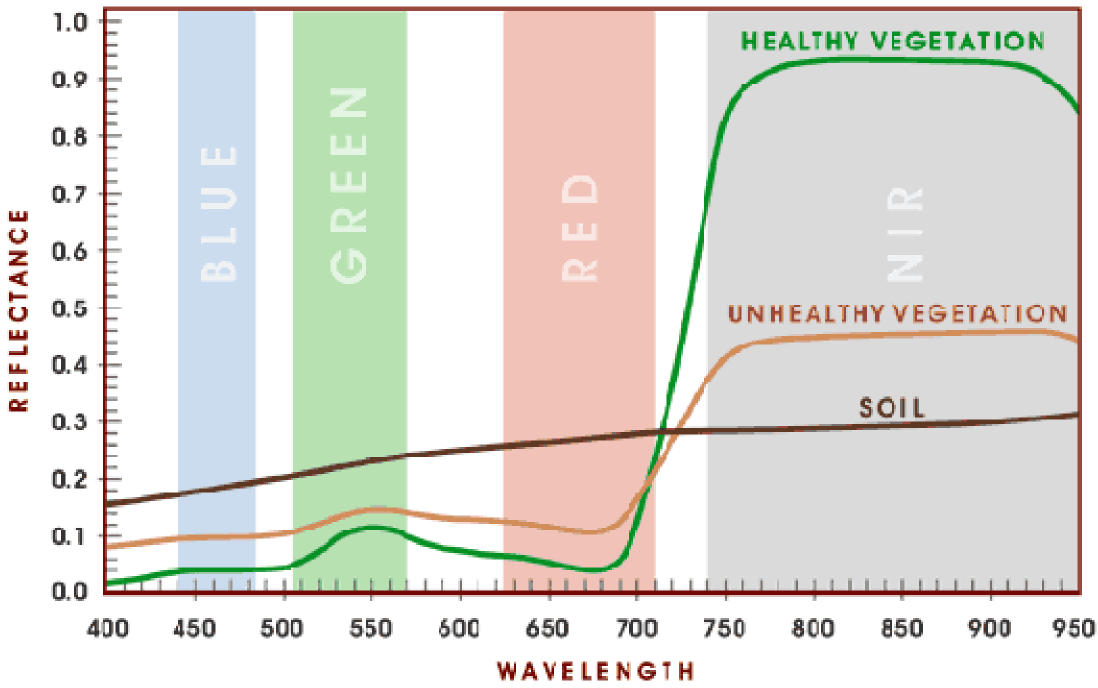

Figure 4, Reflectance of vegetation and soil.

Another type of vegetation index which can be used is the Enhanced Vegetation Index (EVI). This type of vegetation index is almost calculated in the same way as the NDVI. However, the EVI corrects atmospheric distortion from particles in the air and makes corrections for the distortions from the ground cover. Both vegetation indexes have complications related to clouds and aerosols (NASA Earth Observatory, 2013). In this case there is chosen to use the NDVI instead of the EVI. Both NDVI and EVI were calculated but it approved that the best results were obtained through the calculation of NDVI as haze created more noise on EVI images during some tests.

4.3 LAND COVER TYPES

One of the first steps to detect land cover change is to define the land cover. This has been classified through an unsupervised classification. This classification will be further explained in chapter 4.4 Change detection. Here the different classes in which the land cover has been classified and how they are identified are explained.

Knowledge of the study area is necessary for classification of the area. However, the study area has not been visited during the thesis. Therefore, Google Earth and Bing maps have been used for the assessment of the area. Pictures of the area can be extracted from Google Earth, corresponding with the area.

There are five major categories discriminated in the land cover classification of the study area. Those are:

- Tropical broadleaved evergreen forest,
- Tropical shrubland,
- Pasture,
- Water,
- Urban area.

Note that cropland is not one of the classes, while one could expect this in the study area as well. However, no land cover has been identified as cropland through verification with Google Earth and the pictures in Google Earth.

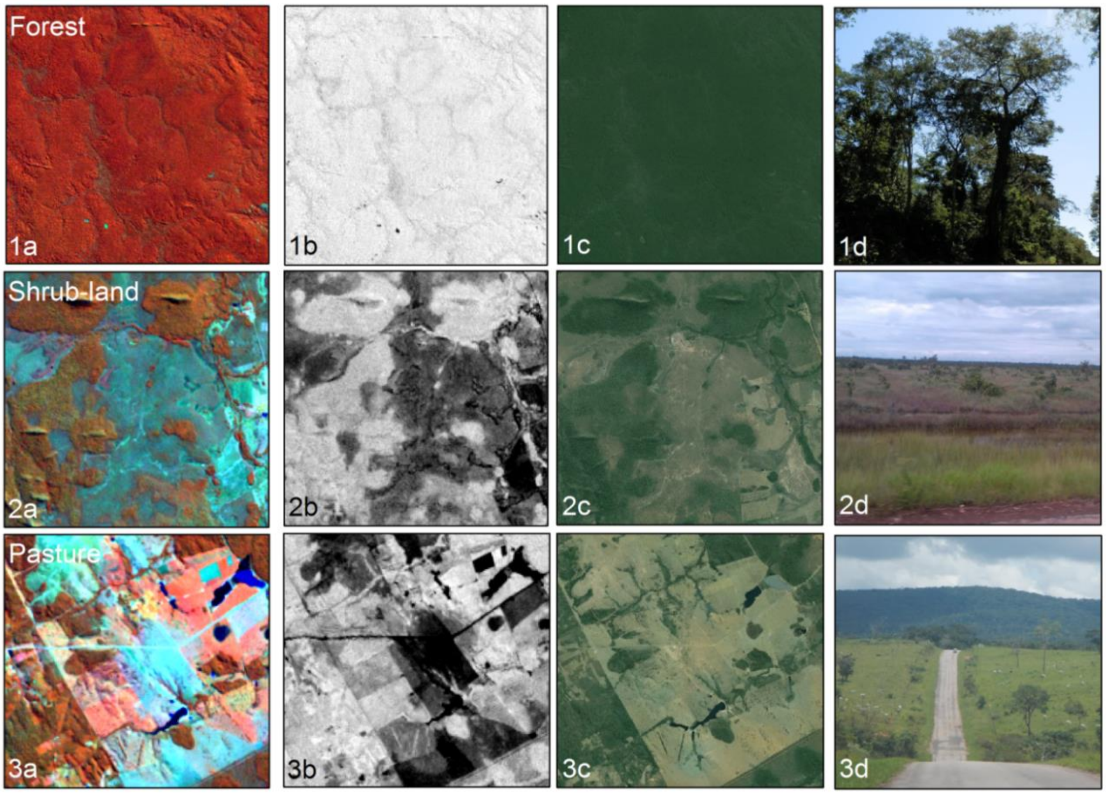

Figure 5, Four different images of 3 classes of vegetation.

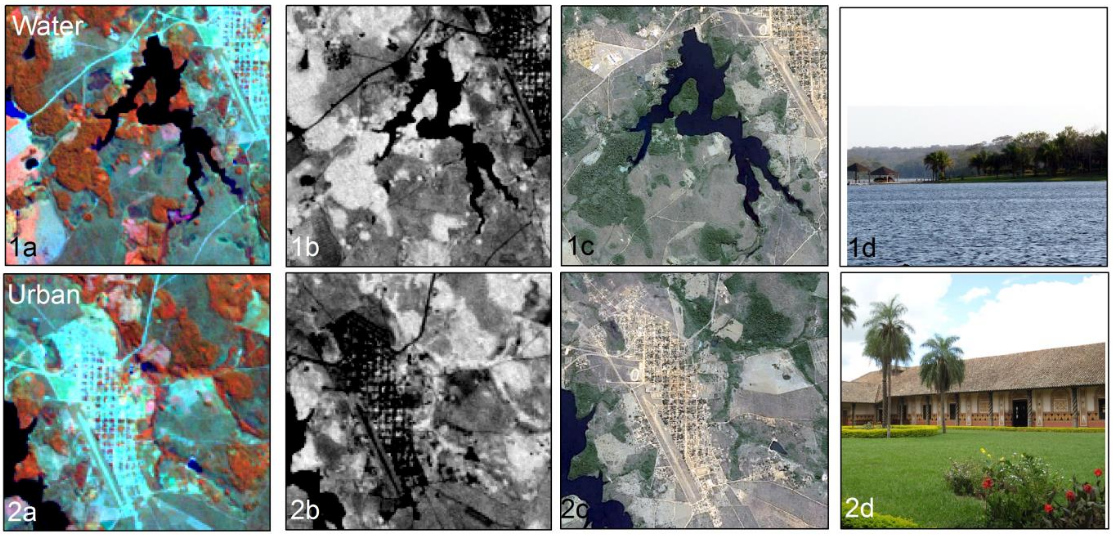

Figure 6, Illustration of the land cover classes urban and water.

4.4 CHANGE DETECTION

The model used for the detection of land cover change is a complex one and has been derived through trial and error. After testing different models, the model (figure 7) presented below appeared to be the best method for change detection within this study. In the following, the model is described through an example of land cover change between 2000 and 2005.

The first step in this method was to classify the land cover by an unsupervised classification. This was done for the timeframe 2000 and 2005, so that two classifications were carried out, one for 2000 and one for 2005. The classifications had been run on a, so called, false color composite band of the band combination 4, 5, and 3 (red, near-infrared, and green) . Three satellite images for the same year were combined to minimize mistakes in classifying land cover. After this a visual classification had been performed for the class of urban area. Urban area is hard to classify through an unsupervised classification, as it has the same characteristics, like other land cover types, due to the presence of vegetation. Therefore it is manually incorporated in the map. Both results, the 2000 classification and the 2005 classification, can be overlapped and converted into a map indicating the land cover change between the timeframe.

Some areas within the study site were classified with a high amount of incorrectness. Like the urban areas these areas have been corrected manually or through running a new classification on that part of the study area, to remove errors within the classifications.

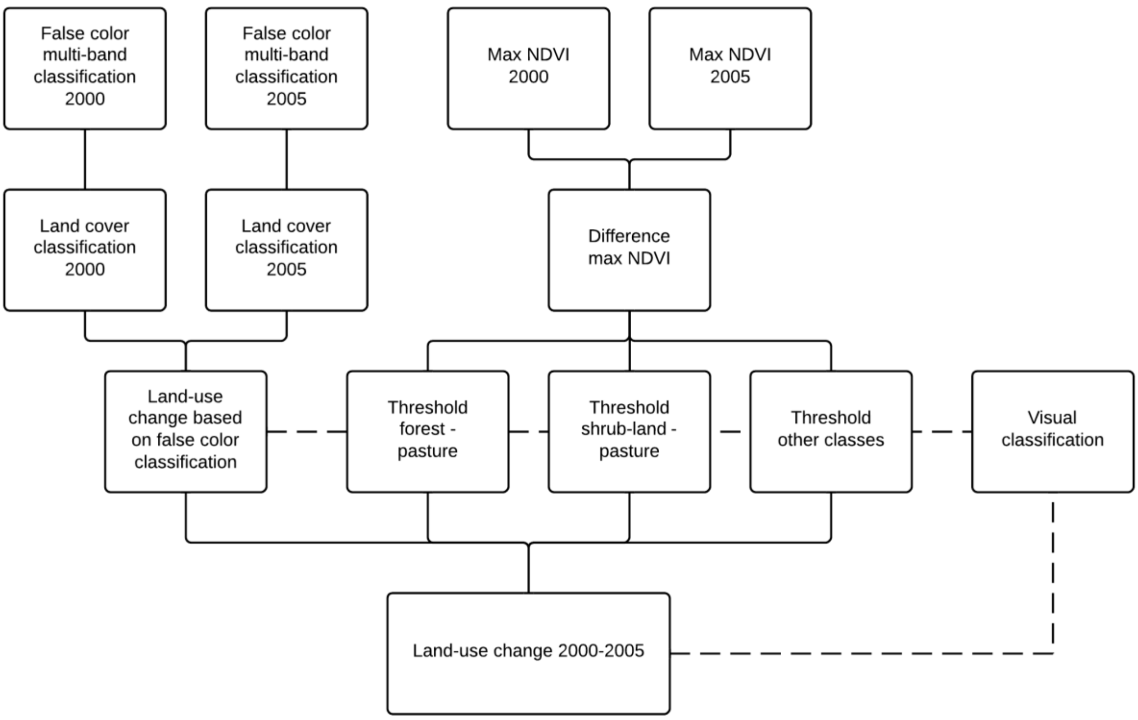

Figure 7, Model of the applied methodology.

Each class has his own spectral, spatial, and temporal characteristics as can be seen in figure 5 and 6 which indicates the characteristics of a) a false color image, b) a NDVI image, c) a Google Earth image, and d) a picture of what it looks like in the field. A detail description on each class will follow below.

- Tropical broadleaved evergreen forest: This class is characterized by the dark red areas in the false color composite bands. The patterns of water bodies can be seen as well, as well as the structure of the forest. The NDVI image indicates the forest with a high number reaching a value of 0.8. This is visualized by the white color. In Google Earth forest can be seen as the green areas where the structure of crowns can be seen.

- Tropical shrubland: This class is more difficult to be characterized. However, the color is mostly blue green on the false color image. The patterns give a clear indication that it is a natural area. The NDVI value is lower than forest, between 0.3 and 0.6. It can drop even lower when it is under influence of water. A clear difference can be seen on Google Earth. The canopy is lower than the canopy of forest.
- Pasture: Clear patterns can be seen with distinctive straight borders, bordering forest or shrubland. Colors can differ widely depending on the vegetation and the time of season. This is the same for NDVI, which can reach high numbers when grasses and trees are abundant.
- Water: Is indicated by a very low NDVI value below or close to zero and by blue and dark colors on the false color composite band. Black colors can be seen on the NDVI image but sometimes it has a more grey color due to algae's in the water. When classifying land cover, water can be confused with clouds, as they have similar spectral characteristics as water.
- Urban area: This can hardly be discriminated using unsupervised classification because of the vegetation grown in the gardens. Therefore, it can have a medium NDVI. This class is more visible using Google Earth and the square patterns of road within the cities.

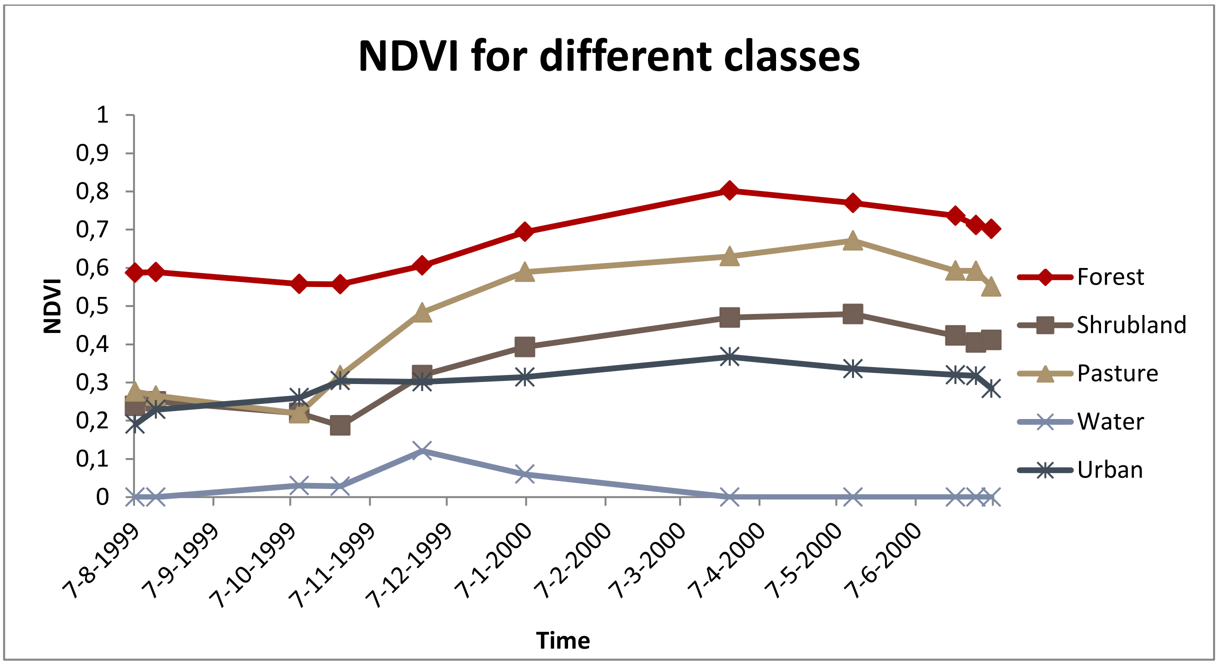

Figure 8, An example of the NDVI values for the different classes during one year.

Annual maximum NDVI composites have been calculated as well for both years. This has been done by calculating the NDVI of 10 or more satellite images for a specific year. These images are spread throughout the year as the NDVI changes substantially within a year. Hereby, an error in the maximum NDVI has been prevented. Figure 8 gives an example of the NDVI values within one year. Note that the figure gives an indication as actual values can reach higher or lower.

The images were used regardless the cloud cover as they would be filtered out by the number of satellite images used. The different NDVI images for one year were then transformed into one image with the maximum NDVI values for one year. The results for both years can then be simply subtracted from each other resulting in one image indicating the difference between the maximum NDVI for both years. A number below zero indicates a loss in NDVI and a number above zero means an increase in NDVI.

Thresholds had been set on the difference between annual NDVI images to reduce misclassification between different classes. The thresholds for the class “forest-to-pasture” and “shrubland-to-pasture” has been set separately from the other classes (see appendix 2). The other classes had a single threshold. Setting different threshold for different classes had been necessary as some classes have almost similar characteristics and are therefore hard to discriminate. The forest-to-pasture class, for example, can have almost similar NDVI values although the NDVI of forest has a more smooth NDVI throughout the year (around 0.7 to 0.8) compared to pasture. However the maximum NDVI of pasture can be close to the same NDVI of forest but can be much lower throughout the rest of the year. This makes it complicated to set a usable threshold on this class and is possible to occur with other classes as well. During this stage, a segmentation on the image has been applied on each threshold. This segmentation has been set on a minimum object size of 10 pixels. This was done to reduce the noise of small groups of pixels which could have been misclassified.

The final stage is to overlay the map indicating the difference between the false color classification and the thresholds of the different classes applied through the maximum NDVI. This had been converted into a map which only indicates the areas which have been changed in both maps. The noise of both classification had been reduced through this method.

Post classification has also been used to update the land cover maps after the land cover change has been identified. This has been done to reduce mistakes within the timeframes. So, a correction has been made on the map of 2005 and 2010 with the assumption that the classification of 2000 is correct.

4.5 SOFTWARE

Several software programs have been used during this study. The most important one was ENVI 4.8. This program have been chosen for its user-friendliness. Calibration with this program is, for example, easy. Furthermore, the comparison between different time periods can be set next to each other and linked to give a good overview of changes. ENVI 4.8 has also been used for calculating the statistics.

ArcGIS 10.1 has been used beside of ENVI. This has been used for visualizing the change and creating several maps, which is not possible in ENVI.

5. Results

After a reliable and appropriate method had been developed for using satellite images for detecting land cover change, it was possible to detect changes in land cover and analyses the process of deforestation for the Santa Cruz region.

5.1 Land cover

The total size of the study area is approximately 20,000 km². The biggest part of the area consists of forest but it is also the land cover type which is decreasing the most. There is not much change within the coverage of shrublands, which has a coverage of around 7% of the study area. Pastures increased from 2.24% coverage to 6.43% coverage, in 2010. Both water and urban show not much difference in coverage throughout time. Figure 9 gives an overview of the coverage of the different land cover types. The number of these cover types can be found in table 3.

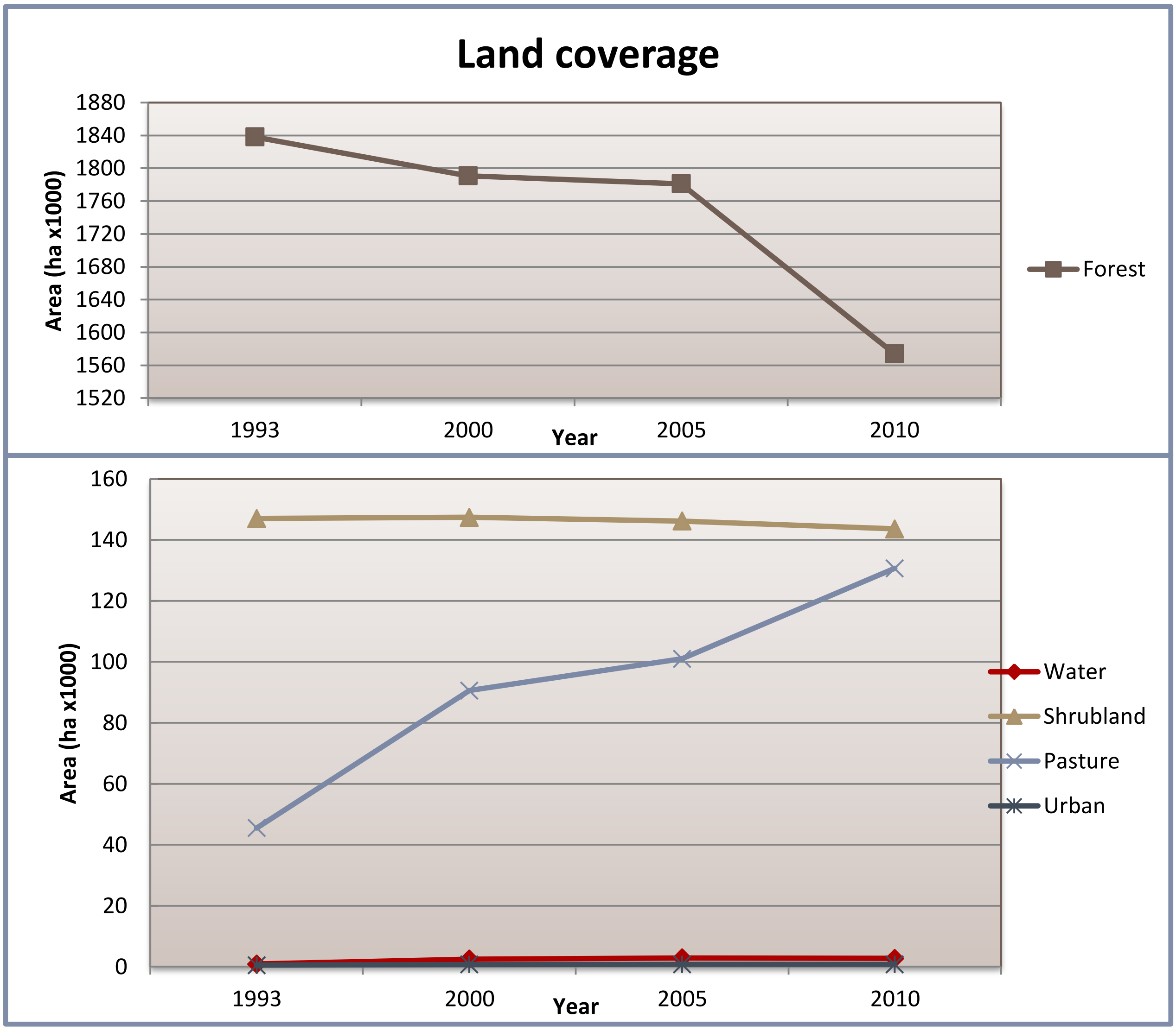

Figure 9, Coverage of the different land cover types between 1993 and 2010.

Forest cover changed the most between 1993 and 2000, with an decrease of approximately 47,000 ha. This number was lower between 2005 and 2010 when a decrease of approximately 27,000 ha occurred in the study area. The decrease of forest was the lowest between 2000 and 2005, around 10,000 ha. The coverage of shrublands has been stable. Pastures, however, show an increase of around 85,000 ha with a quite similar trend as the decrease in forest. Urban area showed a slightly increase. Notable is the increase of water, which seems to be related to dams.

Table 3, Coverage of the different land cover types between 1993 and 2010.

Land cover type	Area (ha) 1993	Area (%) 1993	Area (ha) 2000	Area (%) 2000	Area (ha) 2005	Area (%) 2005	Area (ha) 2010	Area (%) 2010
Water	898	0.04	2,508	0.12	2,892	0.14	2,732	0.13
Forest	1,838,171	90.46	1,790,858	88.13	1,781,189	87.66	1,754,293	86,33
Shrubland	146,991	7.23	147,362	7.25	146,186	7.19	143,584	7.07
Pasture	45,468	2.24	90,585	4.46	100,989	4.97	130,647	6.43
Urban	515	0.03	731	0.04	787	0.04	787	0.04
Total	2,032,034	100	2,032,034	100	2,032,034	100	2,032,034	100

5.2 LAND COVER CHANGE 2000 – 2010

A total of 14,793 ha of the study site has been undergone any form of change, in the timeframe 2000 till 2005. This is a coverage of 0.73% of the total study area. It includes all forms of land cover changes, as can been seen in table 4.

The land cover that has increased the most is pasture land: a total of 11,745 ha has been converted into pasture. This land cover was predominantly forest (9,414 ha) or shrubland (2,340 ha) in 2000, accounting for 79.2% of the total change within this timeframe (table 5).

Table 4, Land cover changes 2000 - 2005 in ha.

2000\2005	Forest (ha)	Shrubland (ha)	Pasture (ha)	Water (ha)	Urban (ha)	Total (ha)
Forest	x	814	9,414	96	2	10,326
Shrubland	376	x	2,304	280	51	3,011
Pasture	238	976	x	113	13	1,340
Water	42	43	20	x	0	105
Urban	0	4	7	0	x	11
Total	656	1,837	11,745	489	66	14,793

Table 5, Land cover changes 2000 - 2005 in %.

2000\2005	Forest (%)	Shrubland (%)	Pasture (%)	Water (%)	Urban (%)	Total (%)
Forest	x	5.50	63.63	0.65	0.02	69.80
Shrubland	2.54	x	15.57	1.89	0.35	20.35
Pasture	1.61	6.60	x	0.77	0.09	9.07
Water	0.28	0.29	0.14	x	0.00	0.71
Urban	0.00	0.02	0.05	0.00	x	0.07
Total	4.43	12.41	79.39	3.31	0.46	100

Between 2005 and 2010, the area of land converted into another land cover further increased. A total of 35,133 ha was converted into a different land cover (table 6). This is more than double compared to the five years earlier, 1.73% between 2005 and 2010 compared to 0.73% between 2000 and 2005.

Like the previous timeframe, the conversion from forest into pasture and shrubland into pasture had been the most common land cover change. This time both types of conversion account for 87.56% of the total land cover change. The land cover changes did not change very much compared between the two timeframes (table 5 and table 7).

Table 6, Land cover changes 2005 - 2010 in ha.

2005\2010	Forest (ha)	Shrubland (ha)	Pasture (ha)	Water (ha)	Urban (ha)	Total (ha)
Forest	x	1,909	26,355	67	0	28,331
Shrubland	809	x	4,406	88	0	5,303
Pasture	490	621	x	36	0	1,147
Water	137	171	44	x	0	352
Urban	0	0	0	0	x	0
Total	1,436	2,701	30,805	191	0	35,133

Table 7, Land cover changes 2005 - 2010 in %.

2005\2010	Forest (%)	Shrubland (%)	Pasture (%)	Water (%)	Urban (%)	Total (%)
Forest	x	5.43	75.02	0.19	0.00	80.64
Shrubland	2.30	x	12.54	0.25	0.00	15.09
Pasture	1.39	1.77	x	0.10	0.00	3.26
Water	0.39	0.49	0.13	x	0.00	1.01
Urban	0.00	0.00	0.00	0.00	x	0.00
Total	4.08	7.69	87.69	0.54	0.00	100

The areas which had undergone two changes during 10 years are not significant. The flowchart indicates that most changes had been within forest changed into pasture and being transferred to forest again in 2010. This type of change occurred in only 0.01% of the total study site, concerning 238 ha. Figure 10 indicates the most common changes area that have been changed 2 times during the timeframe 2000 – 2010.

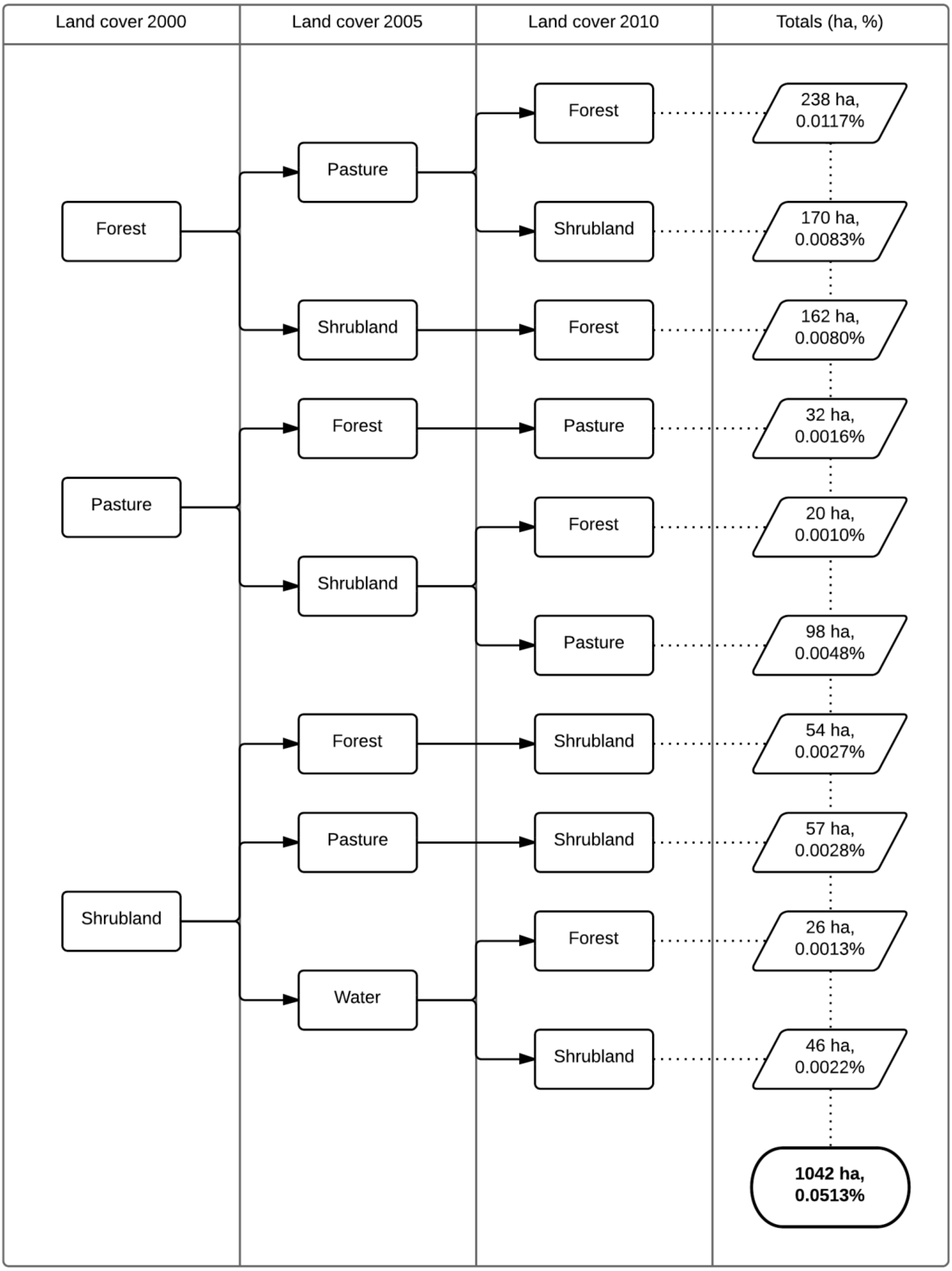

Figure 10, The ten most common land cover changes which changed twice between 2000-2010.

A major area has been unchanged, a total of 97.6% of the total study area, during the timeframe 2000 – 2010. This unchanged area consisted mostly of tropical broadleaved evergreen forest, 86.23%. Furthermore the area consisted of 6.86% unchanged shrublands and 4.36% of unchanged pastures (see table 8).

Table 8, Overview of unchanged land covers.

Land cover	Area (ha)	Area (% of total study area)
Forest	1,752,319	86.23
Shrubland	139,362	6.86
Pasture	88,581	4.36
Water	2,177	0.11
Urban	720	0.04
Total	1,983,159	97.6

5.3 Deforestation

The biggest rate of deforestation was between 1993 till 2000. During that period 51,482 ha of forest had been transformed into another land cover (table 9) during seven years, giving an annual forest loss of 7,355 ha. In 1993, 1,842,340 ha has been classified as forest, resulting in a total deforestation rate of 2.79%, over a period of seven years. The deforestation rates differ per time frame. The timeframe 2000 – 2005 indicates the lowest deforestation with 0.58% of a total of 1,790,858 ha forest, whereas 2005 – 2010 show an increase of deforestation with a deforestation rate of 1.59% over five years. Comparing the annual deforestation rates show an annual deforestation rate of 0.4% from 1993 till 2000, and decrease of deforestation between 2000 and 2005 with an annual deforestation rate of 0.12% followed by an annual deforestation rate of 0.32% between 2005 and 2010.

Deforestation is predominantly caused by the conversion of forest into pasture. This type on conversion consisted of 93.50% of the total deforestation during 1993 – 2000. The other years show a similar trend with 91.17% (2000 – 2005) and 93.03% (2005 – 2010). The expansion of urban area seems low with deforestation rates ranging between 0 and 0.04% caused by urban expansion.

Table 9, Deforestation rates for 3 different time frames.

Year	Conversion type forest to:	Area deforested (ha)	Deforestation rate (%)	Annual deforestation rate (ha)	Annual deforestation rate (%)
1993-2000	Pasture	48,134 (93.50%)			
	Shrubland	2,010 (3.90%)			
	Water	1,319 (2.56%)			
	Urban	20 (0.04%)			
	Total	**51,483**	**2.79**	**7,355**	**0.4**
2000-2005	Pasture	9,414 (91.17%)			
	Shrubland	814 (7.88%)			
	Water	96 (0.93%)			
	Urban	2 (0.02%)			
	Total	**10,326**	**0.58**	**2,065**	**0.12**
2005-2010	Pasture	26,355 (93.03%)			
	Shrubland	1,909 (6.74%)			
	Water	67 (0.24%)			
	Urban	0 (0.00%)			
	Total	**28,331**	**1.59**	**5,666**	**0.32**

6. Discussion

6.1 Methodology

There are dozens of methods which can be applied within remote sensing and the subject of land use and land cover change (Lu, et al., 2004). This has already been shown within the literature research applied during this study. The method applied within this study is not bulletproof and many obstacles have been encountered. However, it seems that this method has been the most appropriate for this study as knowledge and time were little.

Cloud cover is common within the humid tropics and block the information on satellite images, which forms a big disadvantage of using Landsat images. Therefore data influenced by clouds can be seen as no-data. The use of radar data can avoid this problem but different techniques should be applied, concerning pre-processing of satellite images and the methodology to analyse the images. I used optical data as it is more applicable for me within the short time frame of the study. The negative influence of cloud cover has been reduced by applying an appropriate method. The method was able to remove this problem by taking multiple satellite images for a one year time frame and converted those in a maximum NDVI without clouds. However, this could result in lower NDVI for small areas when areas are filled with a NDVI value of the dry season.

6.2 Classification and validation

Many studies use a type of validation to test the accuracy of the results (De Oliveira Pereira, et al., 2013) (Steininger, et al., 2001). These accuracy assessments are mostly done through data derived from fieldwork, other studies or other existing spatial data. No validation have been done for this study which makes it difficult to assess the accuracy of the classifications. The only way to test the accuracy is to use sources like Google earth and Bing maps. Both sources had been used to make sure the data is as accurate as possible. Furthermore another research (Hansen, et al., 2013) had been used as comparison for uncertainties within the classification. However this research is based on forest cover change, whereas this study includes other types of land cover change.

6.3 Deforestation rates

The total amount of deforestation for the period 1993 till 2010 has been around 90,140 ha (see table 9). This number of deforestation is for the entire study area of which 1,838,171 ha has been classified as forest in 1993. The numbers of deforestation are also available for entire Bolivia which had been derived by the FAO (FAO, 2010). It is difficult to compare these two different results as this study is for a small area which can differ depending on the remoteness of the area.

The deforestation rates do not differ much with the figures of the FAO, between 1993 – 2000. Deforestation during this timeframe was average compared to the deforestation in entire Bolivia. However the rates of the timeframe 2000 – 2005 and 2005 – 2010 are below average compared to Bolivia, meaning that there are areas which have undergone more deforestation compared to the study area of this study. An example is the area located east of the study area which had an annual deforestation rate of 4.56% during 1990 – 1998 (Steininger, et al., 2001).

Table 10, Deforestation around Santa Cruz and for Bolivia (FAO).

Year	Deforestation (ha)	Area forest (ha)	Deforestation FAO (ha)	Area forest FAO (ha)	Deforestation rate (%)	Deforestation rate FAO (%)
1993	7,355	1,838,171	270,333	61,983,331	0.40	0.44
2000	2,065	1,786,686	270,333	60,091,000	0.12	0.45
2005	5,666	1,776,361	281,283	58,734,540	0.32	0.48
2010		1,748,031		57,196,172		

The forested area has been indicated higher for this study although table 10 indicates 1,748,031 ha of forest. This is caused by the different approach of the studies. FAO only indicates the deforestation rate and table 10 is adapted to this approach. The method of this study, however, indicates land cover change and includes reforestation between 2000 and 2010. The classification of 2010 indicates a forested area of 1,754,294 ha, resulting in a difference of 6,263 ha.

Other studies show almost similar figures of deforestation compared to the data from the FAO. Mongabay (2011) indicate an average annual deforestation rate of 207,000 ha between 1990 and 2005, with an increase between 2005 and 2010 (308,000 ha). Whereas Killeen et al. (2007) indicates the annual deforestation rate is 290,000 ha between 2001 and 2004. The data from Mongabay (2011) indicate there has been 8.95% forest cover loss since 1990. This is around 7.76% forest cover loss in Bolivia since 1993. Within the study area 4.9% of forest cover has been lost due to deforestation. All those numbers indicate a higher amount of deforestation compared to the study area. The only change can be found within the annual rates between the different studies. Deforestation rates in Bolivia are increasing slowly since 1990. The study area indicates a far lower deforestation rate between 2000 -2005 and a lower rate between 2005 – 2010.

The difference within annual deforestation rates of this study and other studies does not mean that the results are incorrect. It should be realized that the study area consist of nearly 3% of the total forest area in Bolivia. However, it is remarkable that deforestation rates between 2000 and 2005 were much lower compared to other timespans. The reason here fore is unclear.

Figure 11 gives an visual overview of the areas of deforestation within the three time frames. 1993 – 2000 and 2005 -2010 are dominated by the large clearance of forest. Whereas the timeframe 2000 -2005 consisted the conversion of smaller patches of forest in to different land covers.

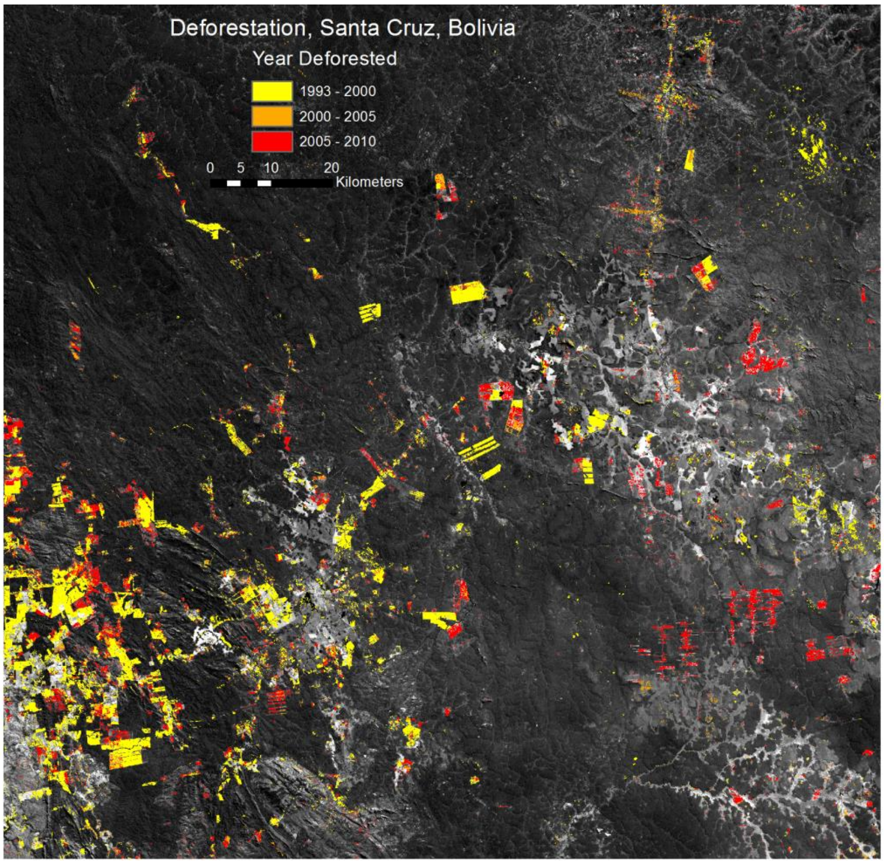

Figure 11, Overview of deforestation within the study site.

6.4 Forest recovery

This study indicates that forest can return within five years after it has been converted it to another land cover, with the exception of urban area. Results in this study show that the most common change, where the land cover has changed twice, has been from forest to pasture into forest, within ten years. This is doubtful but depending on the definition of forest is its possible. This study uses the definition for forest as defined by the FAO (FAO, 2000). Research shows that secondary forest can reach a mean height of 6.3 meters and a top height of 7.6 meters, in the Central Amazon. (Neeff & Roberto dos Santos, 2005). Other studies show a similar canopy height within five years in Mexican tropical rain forest (Van Breugel, et al., 2006). The minimum of five meter height which is necessary to define vegetation as forest, according to the FAO, can be reached in three years (Neeff & Roberto dos Santos, 2005) (Van Breugel, et al., 2006).

Figure 12 shows the forest recovery within 5 years. Validation has been discussed earlier however the false color satellite images show how small areas within the squares are classified as forest, in 2010, as they are dominated by red colors, indicating a large amount of vegetation. This is furthermore supported by a change in the maximum NDVI as used as method in this study.

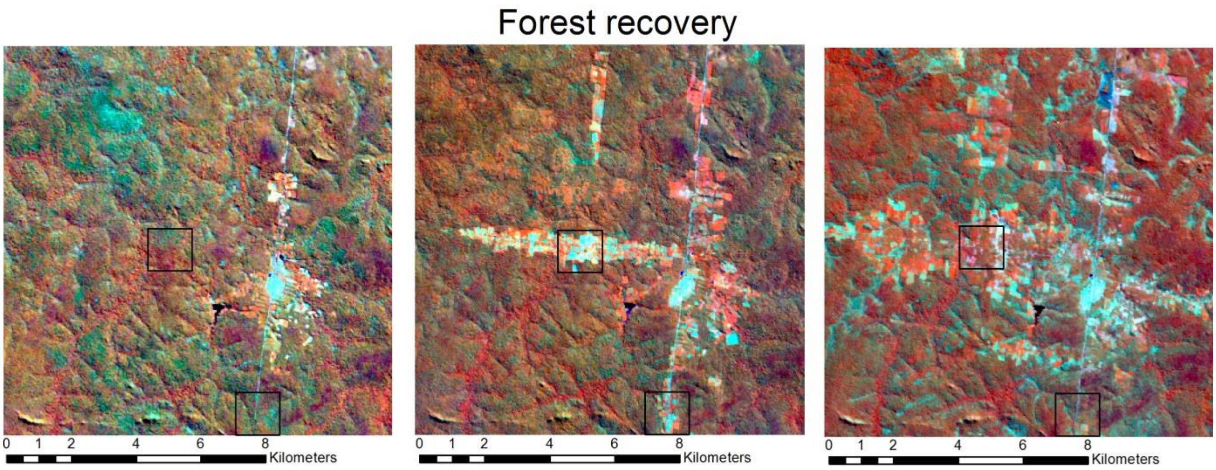

Figure 12, Example of forest recovery seen within three false color band combination images (indicating 2000, 2005, and 2010).

6.5 Classification of urban area

The urban area within the study site has been classified manually. Automatic classification using the method applied for this study was not possible for this land cover type as urban area is hard to discriminate with other land cover types. This is caused by the amount of vegetation within the cities and villages, resulting in a relative high NDVI. Manual classification can however result in misclassified urban areas. Those areas are rather small and therefore do not have much influence on the final results.

7. CONCLUSION

Deforestation is still an ongoing process within the humid tropics and that can be seen in Bolivia as well. The study site shows a decrease in forest around 4.13% since 1993. This number includes also reforestation. Therefore, the number of deforestation is even higher with 4.9% of forest loss, covering 90,140 ha. This land cover is mostly replaced by pastures as pastures have been increased from 2.24% coverage, in 1993, to 6.43 in 2010.

The results from the land cover change support the conclusion of forest changed in pasture as land cover change between forest and pasture consisted of 63.6%, between 2000 and 2005, and 75%, between 2005 and 2010. This is despite the low amount of pasture converted into forest again, which reached between 1 and 2% during both timeframes.

There is a strong fluctuation within the deforestation rates in the Santa Cruz region. Between 1993 and 2000 the deforestation rate has been 0.4% per year. This number did decrease till 0.12% per year between 2000 and 2005, and did increase to an annual deforestation rate of 0.32% between 2005 and 2010.

Deforestation rates of the study area differ from the average within Bolivia. The timeframe from 1993 until 2000 is with a 0.4% deforestation rate slightly below other figures (FAO, 2010) (Mongabay, 2011). However, this number has been decreased to 0.12% between 2000 and 2005. The timeframe 2005 – 2010 show a higher pressure on the forest in the study area. With 0.32% it is still lower than the average of Bolivia, but it does show that the pressure on the forest is increasing again. This is not strange as the area in the west of the study area is highly deforested (Steininger, et al., 2001) and therefore deforestation will move eastwards. Therefore deforestation is still a threat, despite the large amount of forest which has remained forest between 2000 and 2010 (86.23%).

8. Recommendations

During the thesis many ideas came up and have been discussed which are interesting for further study. It is good to mention those findings and ideas here as there has not been time enough to implement them within this study but can be valuable for further study.

8.1 Selective logging

In chapter 2 it has been discussed that a Dutch wood company, named INPA Parket, can be found within the study site. Selective logging could be seen within the forest of this wood company (figure 13). This has been seen in the images of the maximum NDVI for that year. Still, there are complications towards detecting this activity as the NDVI recovers within a couple of months. Furthermore, the time of logging activities influences the detectability of selective logging as the rainy season will give a high NDVI which makes the decrease of NDVI values within forest more notable.

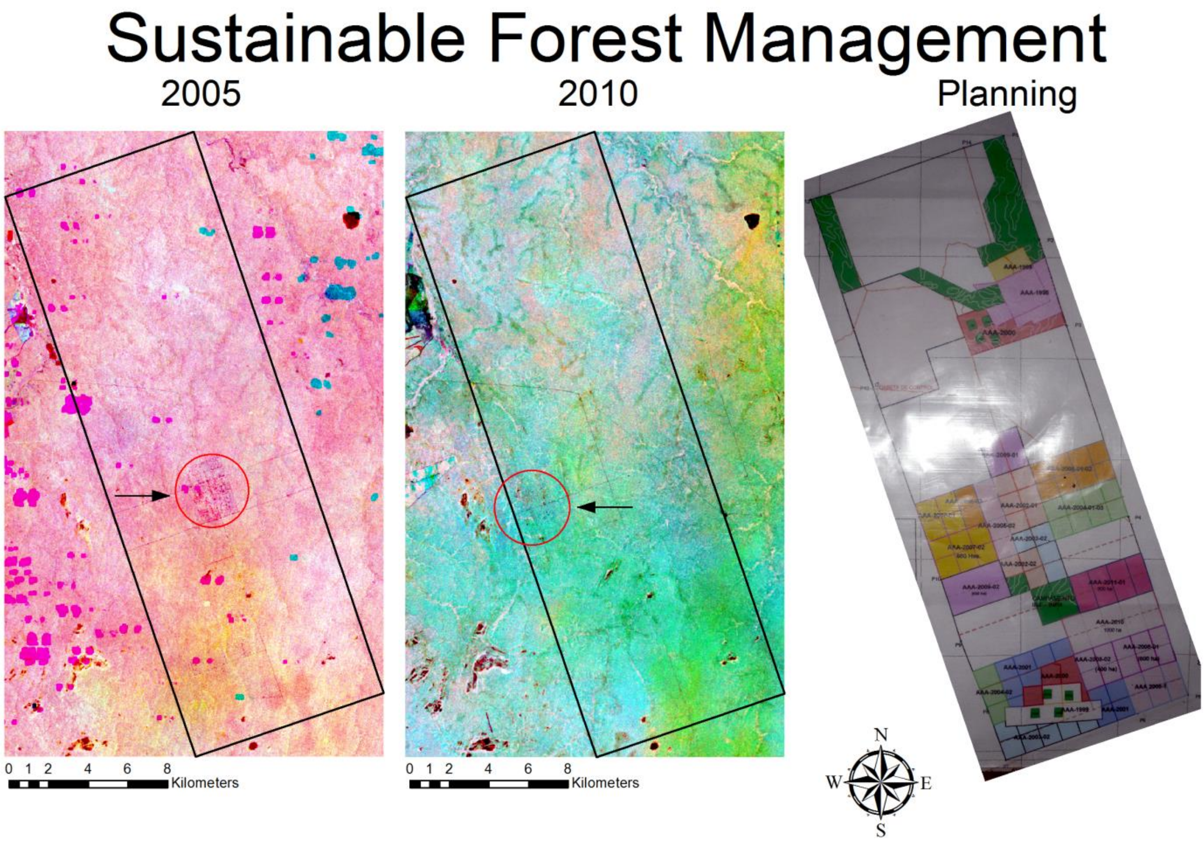

Figure 13, Selective logging within the INPA forest.

The model used in this study was able to detect this selective logging but it highly depended on the amount of cloud free satellite images used. Selective logging cannot be observed with satellite images covered by clouds and haze during the rainy season. A low number of satellite images during the rainy season results in a lower detectability of selective logging, as can be seen in 2010. Both, availability and the time of selective logging, are imported factors to detect selective logging and therefore a study on an applicable method would be interesting as it can be used for monitoring logging. Especially when it concerns logging under a sustainable logging certificate as monitoring is one of the important criteria for sustainable forest management (FSC, 1996).

8.2 FOREST FIRES

Forest fires are also an interesting subject for research. The study site for this research indicates some severe forest fires in 2005. During this year a large amount of forest had been affected by forest fires. Like selective logging, this was clearly visible in the maximum NDVI images (figure 14). A usable model for this would be interesting to see how much of this forest is influenced by fires, how fast the forest recovers, and what this means for biodiversity. The last question could be related to deforestation and forest fragmentation as animals could have trouble finding forest to escape, due to forest fire, in highly deforested or fragmented areas.

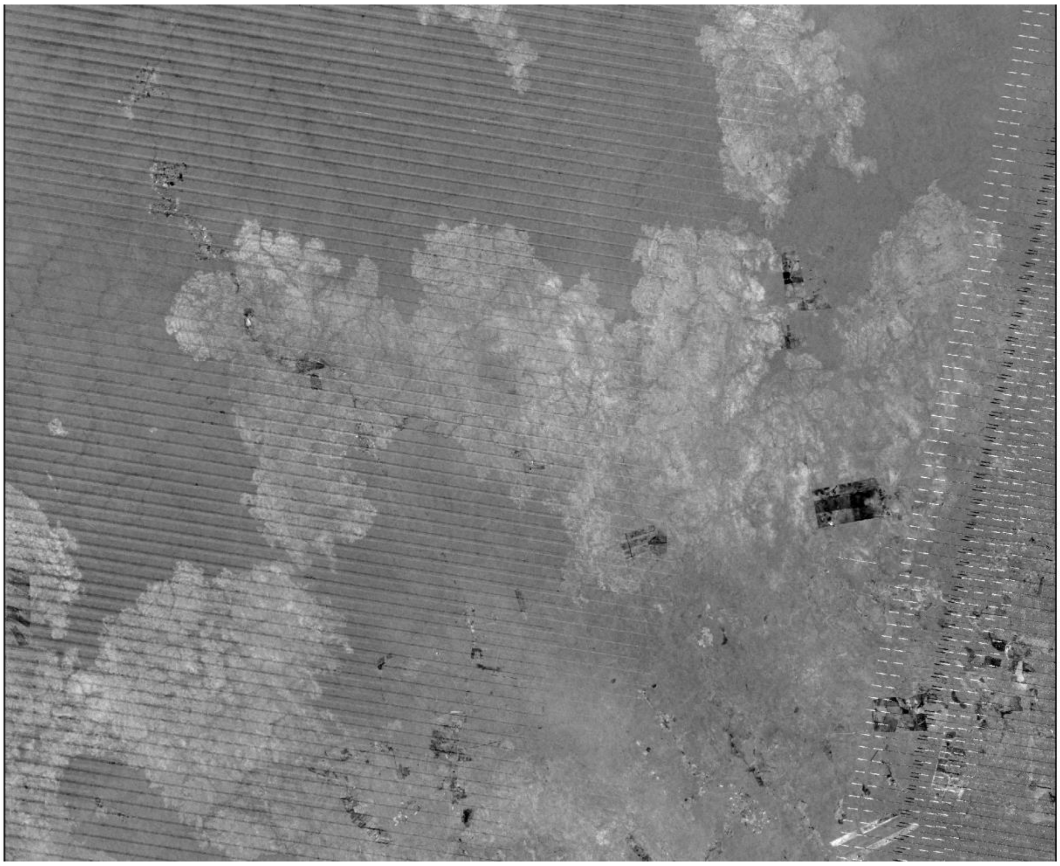

Figure 14, Forest fires seen on a NDVI image between the difference maximum NDVI of the years 2005 and 2010.

8.3 ROAD EXPANSION

Finally road expansion is an important factor related to deforestation. Forests near roads are more likely to be deforested (Rosa, et al., 2013). Furthermore, roads should not be underestimated is they can have a substantial effect on biodiversity. The roads may be a small proportion but have a considerably large effect on biodiversity caused by forest fragmentation and edge effects.

It is therefore interesting to study this as it can predict future deforestation and is of importance for biodiversity conservation. There was not enough time to include this in this study, but it is for sure that road networks are expanding and deforestation will continue within this area, as can be seen in figure. However, the proportion of road expansion in this area stays unclear.

Figure 15 gives in indication of road expansions within the Santa Cruz Region. In both cases you can see that roads are built and later on agricultural lands will be formed next to the roads.

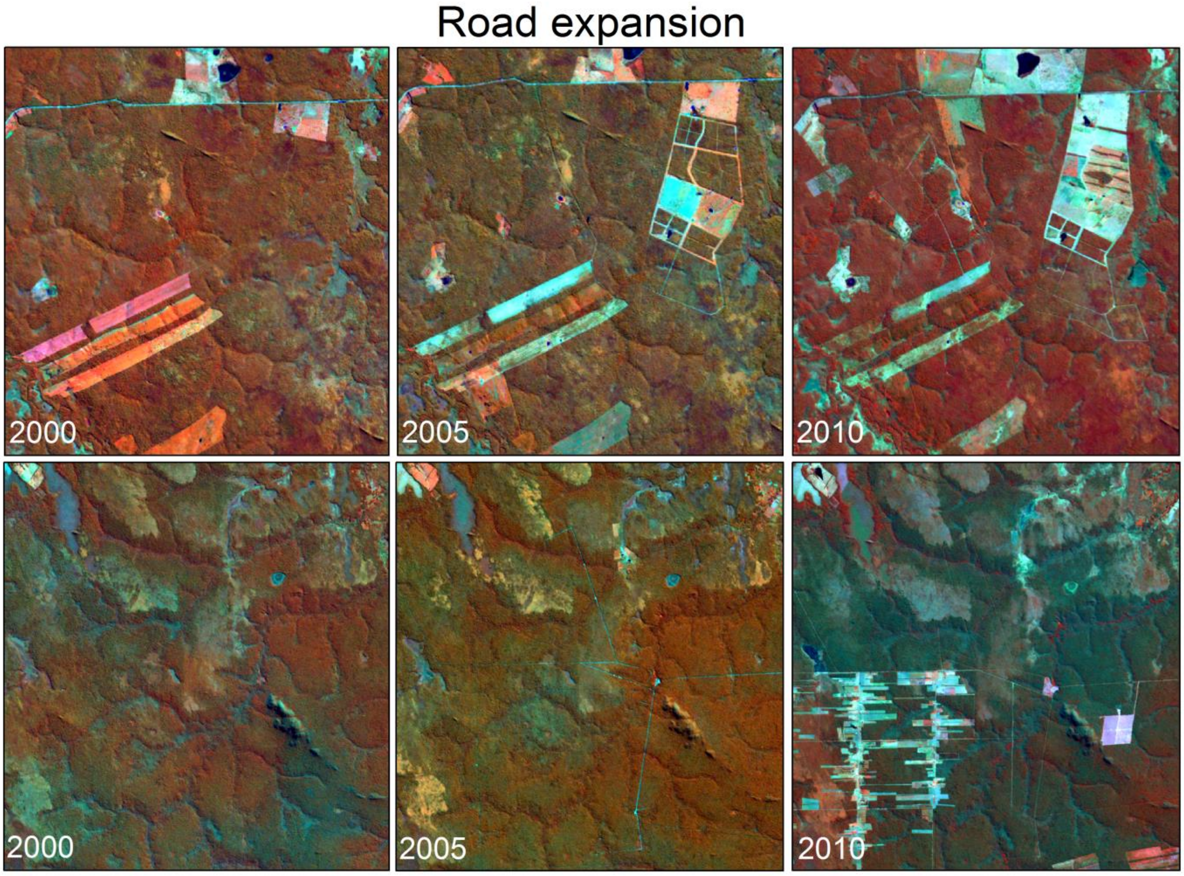

Figure 15, Two examples of road expansions.

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APPENDIX 1, SATELLITE IMAGES USED

Year	Date	Landsat sensor	Used for
1992 - 1993	03-08-1992	Landsat TM	Max NDVI
	20-09-1992	Landsat TM	False color multi-band classification Max NDVI
	22-10-1992	Landsat TM	Max NDVI
	07-11-1992	Landsat TM	Max NDVI
	10-01-1993	Landsat TM	Max NDVI
	27-02-1993	Landsat TM	Max NDVI
	15-03-1993	Landsat TM	Max NDVI
	03-06-1993	Landsat TM	Max NDVI
	19-06-1993	Landsat TM	False color multi-band classification Max NDVI
	21-07-1993	Landsat TM	False color multi-band classification Max NDVI
1999 - 2000	07-08-1999	Landsat TM	Max NDVI
	15-08-1999	Landsat ETM+	Max NDVI
	10-10-1999	Landsat TM	False color multi-band classification Max NDVI
	26-10-1999	Landsat TM	Max NDVI
	27-11-1999	Landsat TM	Max NDVI
	06-01-2000	Landsat ETM+	Max NDVI
	26-03-2000	Landsat ETM+	False color multi-band classification Max NDVI
	13-05-2000	Landsat ETM+	Max NDVI
	22-06-2000	Landsat TM	False color multi-band classification Max NDVI
	30-06-2000	Landsat ETM+	Max NDVI
	06-07-2000	Landsat TM	Max NDVI
2004 - 2005	04-08-2004	Landsat TM	False color multi-band classification Max NDVI
	20-08-2004	Landsat TM	Max NDVI
	05-09-2004	Landsat TM	Max NDVI
	21-09-2004	Landsat TM	Max NDVI
	07-10-2004	Landsat TM	Max NDVI
	08-11-2004	Landsat TM	False color multi-band classification Max NDVI
	19-01-2005	Landsat ETM+	Max NDVI
	16-03-2005	Landsat TM	Max NDVI
	17-04-2005	Landsat TM	Max NDVI
	11-05-2005	Landsat ETM+	Max NDVI
	04-06-2005	Landsat TM	False color multi-band classification Max NDVI
	22-07-2005	Landsat TM	Max NDVI
2009 - 2010	18-08-2009	Landsat TM	Max NDVI
	26-08-2009	Landsat ETM+	Max NDVI
	11-09-2009	Landsat ETM+	Max NDVI
	27-09-2009	Landsat ETM+	Max NDVI
	05-10-2009	Landsat TM	False color multi-band classification Max NDVI
	06-03-2010	Landsat ETM+	Max NDVI
	07-04-2010	Landsat ETM+	Max NDVI
	01-05-2010	Landsat TM	False color multi-band classification

			Max NDVI
	10-06-2010	Landsat ETM+	Max NDVI
	18-06-2010	Landsat TM	Max NDVI
	04-07-2010	Landsat TM	Max NDVI
	20-07-2010	Landsat TM	False color multi-band classification Max NDVI

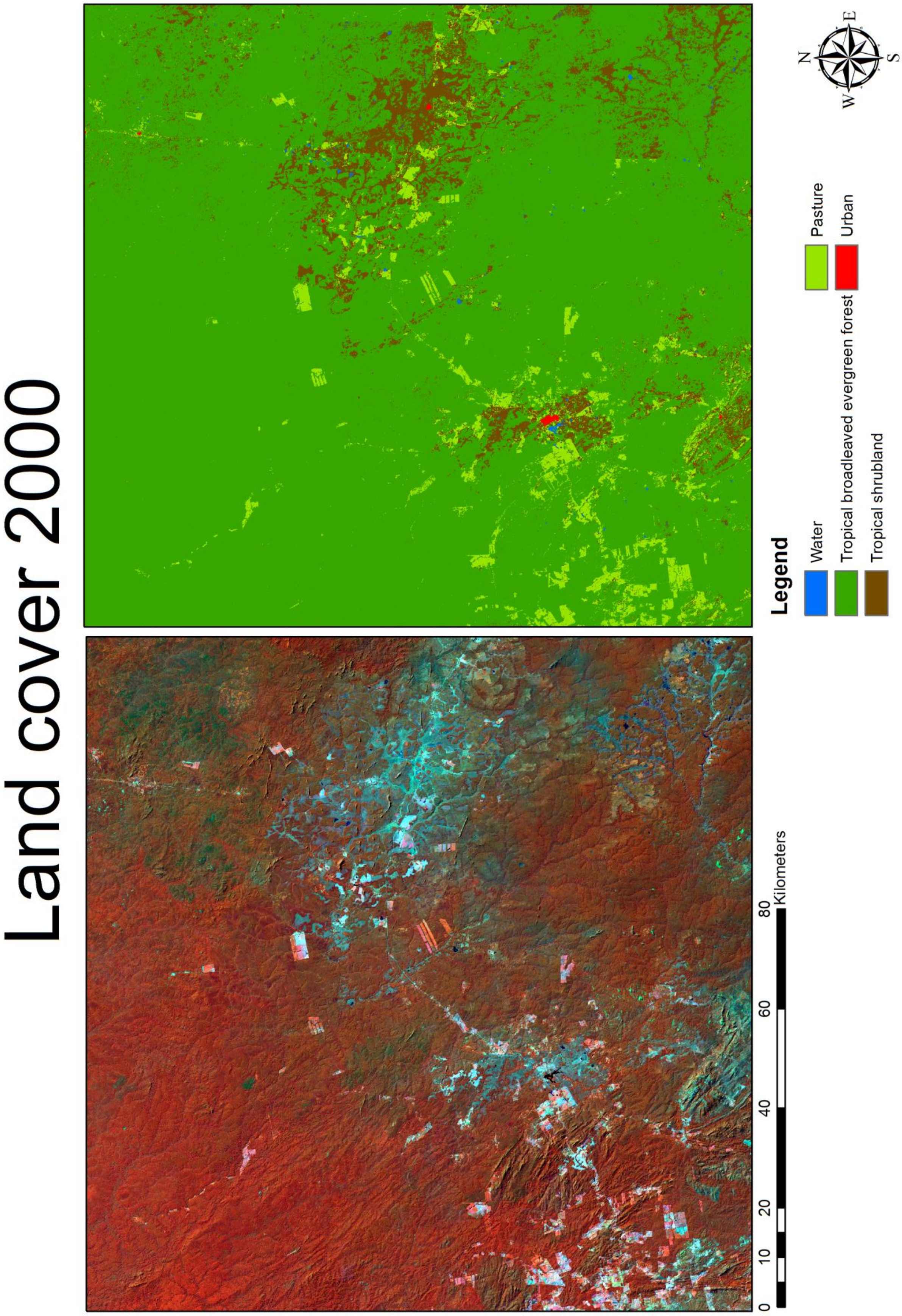
APPENDIX 2, THRESHOLDS NDVI IMAGES

Timeframe	From land cover type	To land cover type	Threshold
1993 - 2000	Forest	Pasture	No threshold, manual correction
	Forest	Shrubland	≤ -0.09 and ≥ 0.09
	Forest	Water	No threshold, manual correction
	Forest	Urban	No threshold, manual correction
2000 - 2005	Forest	Pasture	≤ -0.024 or ≥ 0.024
	Shrubland	Pasture	≤ -0.05
	Other combinations*	Other combinations*	≤ -0.09 or ≥ 0.09
2005 – 2010	Forest	Pasture	≤ -0.015 or ≥ 0.02
	Forest	Shrubland	≤ -0.11
	Shrubland	Pasture	≤ -0.07
	Water	All other classes®	≤ -0.1 or ≥ 0.1
	All other classes®	Water	≤ -0.1 or ≥ 0.1
	Other combinations*	Other combinations*	≤ -0.1 or ≥ 0.1

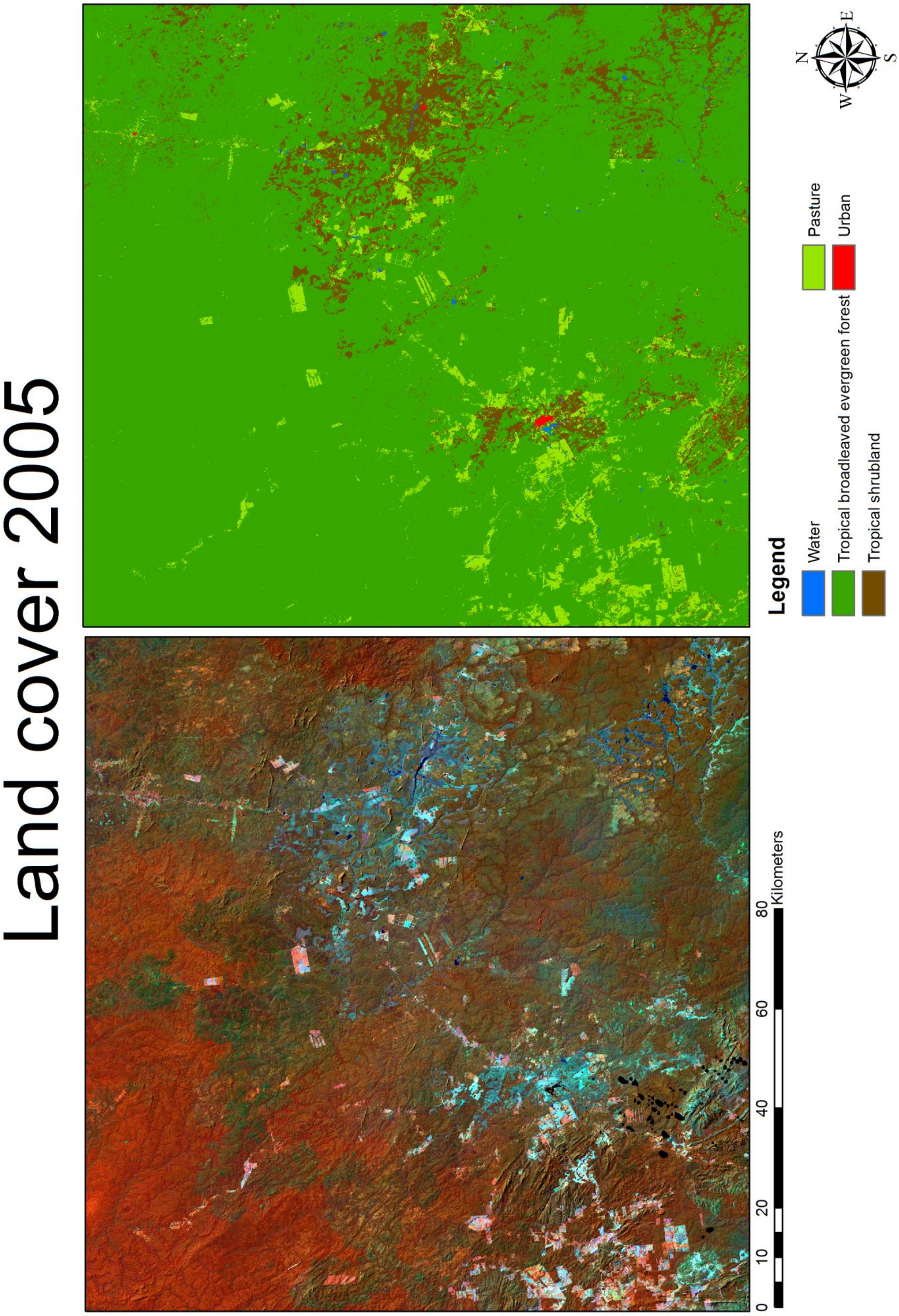
* Other combinations are all possible combinations of land cover changes which had not been mentioned within the timeframe.

® All other classes are the land cover classes which are not water. These includes forest, shrubland, pasture, and urban area.

APPENDIX 3, LAND COVER MAP 2000



APPENDIX 4, LAND COVER MAP 2005



APPENDIX 5, LAND COVER MAP 2010