

**Deforestation in the Kayabi Indigenous Territory:
Simulating and Predicting Land Use and Land
Cover Change in the Brazilian Amazon**

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Abstract

The Amazon basin sustains more than half of the world's remaining tropical rain-forest and plays a vital role in maintaining biodiversity, climate and terrestrial carbon storage. The Amazon has the world's highest absolute rates of deforestation. Land use/cover change (LUCC) practices in the Brazilian Amazon, such as cattle ranching, logging, agriculture, mining, and urbanization are the major contributors to deforestation and have major impacts on ecosystems and environmental processes at local, regional and global scales. Such impacts include land fragmentation and degradation, biodiversity loss, alteration in atmospheric composition and climate change.

Understanding the determinants of LUCC is vital for developing sustainable environmental management policies and forest protection. Modelling provides insights on land use dynamics and the driving factors of change and allows to quantitatively predicting where future change might occur.

A simulation of future landscape in 2020 in the Kayabi Indigenous Territory in the Brazilian Amazon was carried out using Geographic Information Systems (GIS), Remote Sensing and the IDRISI's Land Change Modeler following five sequential steps: (1) Creation of forest land cover maps from 2000, 2006 and 2009 derived from CLASlite's fractional cover image; (2) Land-change cover analysis by cross-tabulating forest land cover maps; (3) Calculation of transition potentials from forest to anthropogenic disturbance using a MLP neural network methodology. Afterwards, a prediction of future landscape was simulated using a Markovian process; (4) Assessment of the model performance by predicting a 2009 land cover and comparing it with an actual 2009 land cover map and (5) Predicting a 2020 land cover map.

The model was able to successfully simulate deforestation expansion in the region and identify the main landscape attributes driving anthropogenic disturbance expansion in the

studied area. Distance from roads and distance from existing disturbance were found as the key factors driving deforestation in the Kayabi area.

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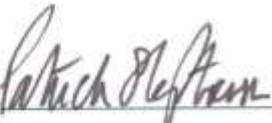
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Declarations

I have read and understood the section of the handbook that explains plagiarism, including that related to group work. I testify that, unless otherwise acknowledged, the work submitted herein is entirely my own. This dissertation is my own unaided work and has not been submitted for a further degree at any other Higher Education Institution. It does not exceed the word limit of 10,000 words.

Signed:  (12/09/2011)
Hugo de Alba

This dissertation uses data, research and other resources that have been made available to the author within the following institution: The Arrow Rainforest Foundation & Bow Charity. However, the undersigned testifies that the dissertation is an individual and self-motivated study undertaken by the author alone for the sole purpose of achieving a Master's degree and not as part of existing or future obligatory research commitments for this institution.

Signed:  (12/09/2011)
Patrick Stephenson (Chairman).

List of Acronyms

ARF – The Arrow Rainforest Foundation and Bow Charity

B – Bare substrate

DEM – Digital Elevation Model

FUNAI - National Indian Foundation

GIS – Geographic Information System

IBAMA - Brazilian Institute of Environment and Natural Resources

INDECO – Integration, Development and Colonization, Ltd.

INTERMAT - Mato Grosso State Land Agency

ISA - Instituto Socioambiental

LCM – Land Change Modeler

LUCC – Land use and land cover change

MAUP – Modifiable Areal Unit Problem

MLP – Multi-Layer Perceptron

NIR – Near Infrared

NPV – Non-photosynthetic vegetation

PV – Photosynthetic vegetation

ROC - Receiver Operating Characteristic

SPI - Service for Indian Protection

SWIR – Shortwave Infrared

TIR – Thermal Infrared

1. Introduction

The Amazon basin sustains about 60% of the world's remaining tropical rain-forest and plays a vital role in maintaining biodiversity, regional hydrology and climate, and terrestrial carbon storage. This region also has the world's highest absolute rates of deforestation and fragmentation (Laurance, et al., 2002). According to the Instituto Socioambiental (2010) in Brazil, 20% of the Amazon has been cleared, and nearly half of its forest (approximately 350,000 km²) was torn down in the past 20 years.

During 2007, over 80% of both current clearing and cumulative clearing has been concentrated in a band along the eastern and southern edges of the forest, this band is called the 'arc of deforestation' (Fearnside, 2007) - see Figure 1. However, in addition to the overall deforestation expansion, smaller clearings that are located far from existing frontier play a more importance role in the process than their area would suggest. These new areas serve as seeds for a more intense clearing activity in the future.



Figure 1. 'Arc of deforestation' in Legal Amazon

The process of Land use/cover change (LUCC) is bringing a fast deforestation processes; the most common LUCC practices in the Brazilian Amazon include cattle ranching, logging, agriculture, mining, and urbanization. (Asner, Keller, Pereira, Zweede, & Silva, 2004) LUCC practices have significant impacts that affect ecosystems and environmental processes at local, regional and global scales. Such effects include land fragmentation and degradation, biodiversity loss, alteration in atmospheric composition and climate change. (Vitousek, Mooney, Lubchenco, & Melillo, 1997)

Indigenous lands and different categories of parks and reserves located at the edge of the 'arc of deforestation' serve as a primary defence against deforestation. In many places in the arc of deforestation the only forest that remains standing is what is in indigenous areas (Fearnside, 2007). This is the case of the Kayabi Indigenous Territory located in the states of Mato Grosso and Para, in the Brazilian Amazon. However, since 2000 anthropogenic processes have critically speeded deforestation in the Kayabi Territory. According to the Brazilian Institute of Environment and Natural Resources (IBAMA), between 2000 and 2005 more than 30,000 hectares of forest were lost to anthropogenic disturbance in the area (IBAMA, 2006).

In order to develop sustainable environmental management policies and adequate land use planning in the Kayabi Territory, it is vital to understand the determinants of LUCC. In this context, modelling provides insight into the land use change dynamics and its driving factors (Ademola & Takashi, 2007). In addition, models not only help to improve the understanding of these changes, but also allow us to quantitatively predict where future change might happen. For these reasons models are a very important tool to monitor and ultimately protect the forest from further deforestation.

This dissertation aims to investigate the deforestation process through modelling and predicting future land change for the Kayabi Indigenous Territory.

The situation in the Kayabi Territory is very complex and there are many factors that play roles as deforestation driving forces. The assessment of these factors is very important in order to understand and therefore, predict future deforestation. Thus, in a first stage, this dissertation evaluates these factors at local level by analysing information about the demarcation process of the Kayabi Territory as indigenous land; available information about land ownership and land titles was revised in order to understand the underlying causes of the high deforestation rates observed in the area. In addition, close analysis was made in order to assess unofficial logging in the area. In this dissertation, anthropogenic disturbance and deforestation are equally defined as the clear-cutting of forest for pasture, agricultural, urban, cattle ranching, logging and other uses.

In a second stage, a model of LUCC for the Kayabi Territory was developed and simulation of future landscape in 2020 was carried out using Geographic Information Systems (GIS), Remote Sensing and the IDRISI's Land change Modeler software. Land cover maps from 2000, 2006 and 2009 were derived from CLASlite's fractional cover images and used as model input. LUCC was analysed by cross-tabulating forest land cover maps. Subsequently, transition potentials from forest to anthropogenic disturbance using a MLP neural network methodology were calculated. It is important to mention that in this dissertation, anthropogenic disturbance and deforestation are equally defined as the clear-cutting of forest for pasture, agricultural, urban, cattle ranching, logging and other uses. Finally, the future landscape was simulated using a Markovian process.

2. The Kayabi Indigenous Territory

Considering that Indigenous lands are cultural spaces which sustain livelihoods that are adapted to the diversity of tropical forests and that therefore are compatible with and beneficial to the maintenance of the forests and the equilibrium of ecosystems which provide environmental services. Therefore, it is important to develop conditions for indigenous people to implement their own territorial management projects according to their customs and their forms of seeing and understanding the world (ISA, 2011).

The Kayabi (also spelled Kaiabi, Kajabi, Kayaby, Caiabi, Cajabi) are indigenous people inhabiting the northern Brazilian state of Mato Grosso, and the Xingu Indigenous Park and the Indian Territory of Apiaká-Kayabi south of Pará. (Wikipedia, Kaiabi, 2011).

The Kayabi people have resisted the constant invasion of their territory by rubber companies since the end of the 19th Century. In the 1950s, the region of Teles Pires, Peixes and Arinos was divided up into glebes that became ranches and the Kayabi were divided into three groups and forced to move north to the river Teles Pires and to the Xingu Indian Park (ISA, 2011). Moreover, the forest of the Kayabi Territory is under huge pressure from illegal loggers, land grabbers and the expansion of the agricultural frontier. (The Arrow Rainforest Foundation, 2009).

The Kayabi have been attempting to get their land regularized for over 20 years but it currently remains unprotected. During this time, more and more of the forest on their southern border has been invaded and degraded.

Under process number 1776/82 on 31.05.1982 the Service for Indian Protection (SPI), forerunner to the National Indian Foundation (FUNAI), started the demarcation process for an area of 117.247 hectares close to Currizinhio in the state of Para. On the 15.09.1994 the initial Kayabi area was delimited and identified under order 1.137/93da (ARF, 2010).

According to ARF (2010), as part of a colonization project in 1984, INTERMAT (Mato Grosso state land agency) took the administrative measures to legalize the division of land of the Mato Grosso part of Kayabi, by a judicial process known as ‘Acao Discriminatoria’. It declared large area of land (glebas) as unoccupied and as nobody’s land’ and through INDECO (Integration, Development and Colonization Ltd) the ‘empty land’ was subdivided into divided into 4 main glebas (approximately 150,000 hectares each); Sao Tome 1,2,3,4; Raposa Tavares e Estancia Bom Jardim and Gelba Ximari. (ARF, 2010). See Figure 2. Appendix 1 shows a map by INTERMAP with the land titles in Nothern Mato Grosso.

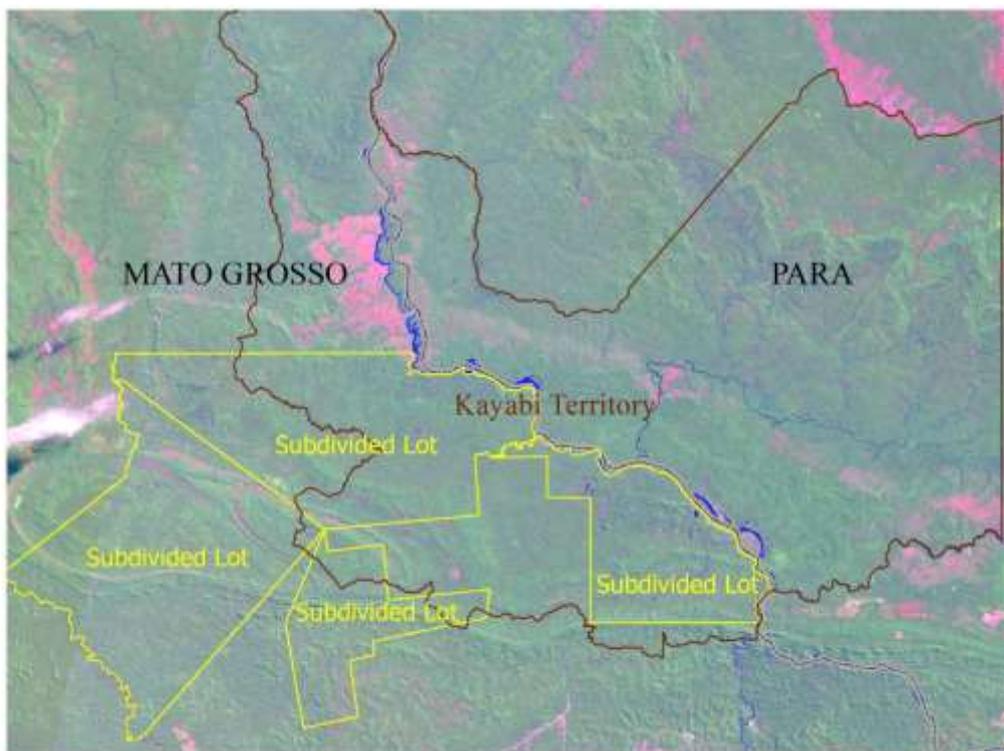


Figure 2. Original Land Divisions (1984) superimposed on a 1993 Landsat 5

INDECO was responsible for much of colonization and development of Northern Mato Grosso, bringing families from Parana to provide them a new life in the Amazon. INDECO started this private colonization process supported by the Brazilian government in the early 1970’s with the development of lands in Aripuana and subsequently developed the towns of

Alta Floresta, Paranita and Apiacas. (INDECO, 2011). In the Kayabi Area INDECO built the main roads that demarcated the principal land areas (glebas). These glebas were then subdivided into mainly 3000 hectare lots and sold to different companies with interests in the area and farmers. Many of these smaller land lots were then subsequently sold and transferred to one large Brazilian conglomerate and one multinational company (ARF, 2010).

On the 08.01.1996 under decree number 1755/96 , FUNAI started the process of identification and delimitation of much larger Kayabi area, which included a large area of Mato Grosso and an additional area of land between Munduruku and Sao Benedito . The size of the original area proposed was 1,408,000 hectares (ARF, 2010).

On October 2nd, 2002, the Ministry of Justice, through decree 1,149, declared the possession of an area the possession of an area of approximate 1.5 million hectares to the Indians Kayabi, Munduruku and Apiaká present in the southern city of Jacareacanga in Pará and northern Apiacás Paranaíta and in Mato Grosso (IBAMA, 2006).

As shown in Figure 3, the demarcated Kayabi Territory is located in the south west border of Para state with Mato Grosso state, the river *São Manuel ou Teles Pires* flows in the middle of the territory dividing the terror from south east to north west. The Kayabi area is in a strategic position and would complete the Mosaic of protected areas created to stop the ‘Arc of deforestation’. (The Arrow Rainforest Foundation, 2009).

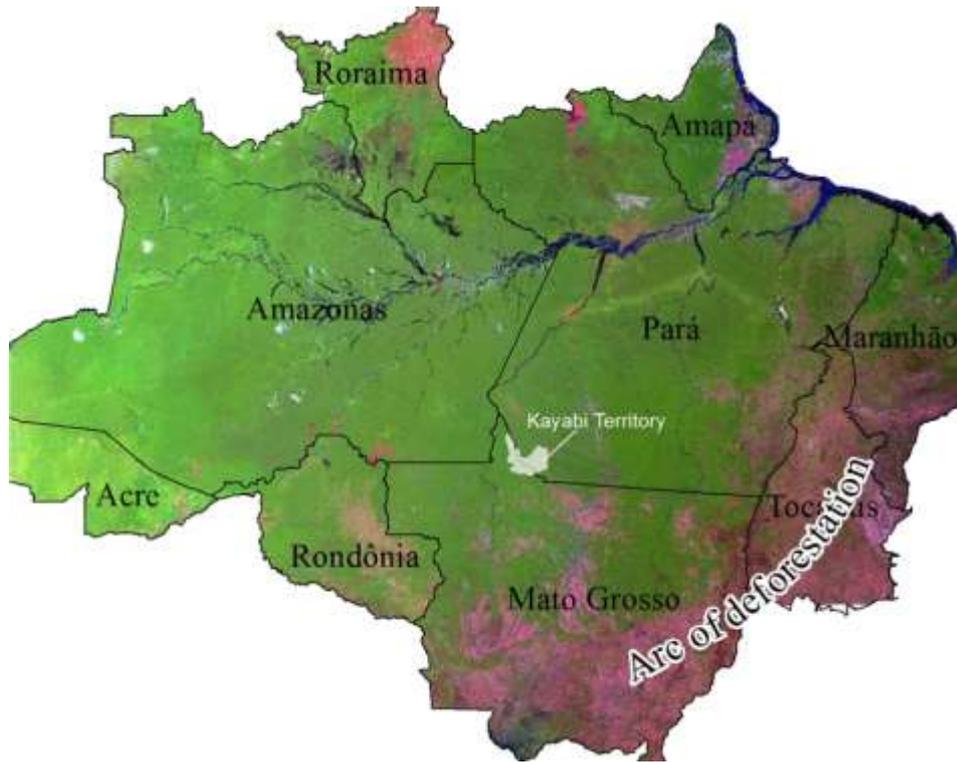


Figure 3. Location of Kayabi Territory within the ‘Arc of deforestation’

After the demarcation was declared, the process of land grabbing and deforestation intensified in the region. In October, 2004, a federal court injunction suspended the demarcation process of the land and prevented the continuation of exploration. However, even though the validity of the injunction, Indians sent several complaints pointing the acceleration of deforestation. In 2002, there were confrontations between settlers and Indians which culminate in the expulsion of some temporary occupants (IBAMA, 2006).

Through analysis of Landsat and CEBERS II imagery, IBAMA (2006) obtained the evolution of deforestation in the region for the period (1999-2005). Table 1 shows the forest loss derived from this analysis.

Table 1. Forest Lost in Kayabi Territory due deforestation (IBAMA, 2006)

Year	Deforested Area (ha)
1999	3,676
2000-2001	3,018
2002	5,551
2003	12,456
2004	6,744
2005	2,201
<i>Total</i>	<i>33,646</i>

Figure 4 shows a graph of the evolution of deforestation due to events related to the issue of Kayabi Territory. As it can be observed, upon initiation of the approval process of the area in 2002, there was a significant increase in open areas, which led to a tripling of the rate of deforestation jumping of 4,000 ha /year to 12,000 ha/ year. The deforested areas were converted almost entirely in pasture. According to IBAMA (2006), this may have occurred by the need to occupy the area by farmers in order to detach the use of the indigenous area.

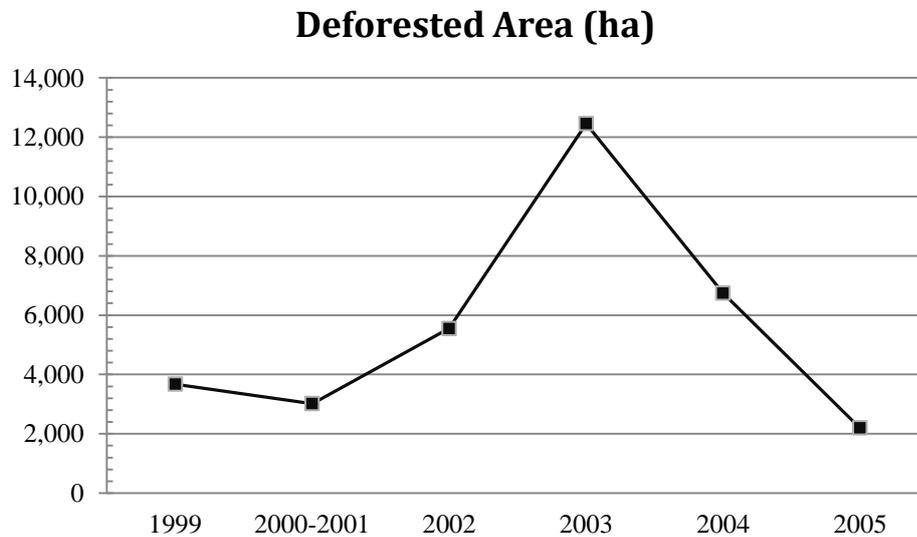


Figure 4. Deforestation Evolution in Kayabi Territory

Figure 5, below, shows Landsat imagery from different years, visual analysis corroborates IBAMA's findings which points out that the major deforestations rates occurred between 2002 and 2004.

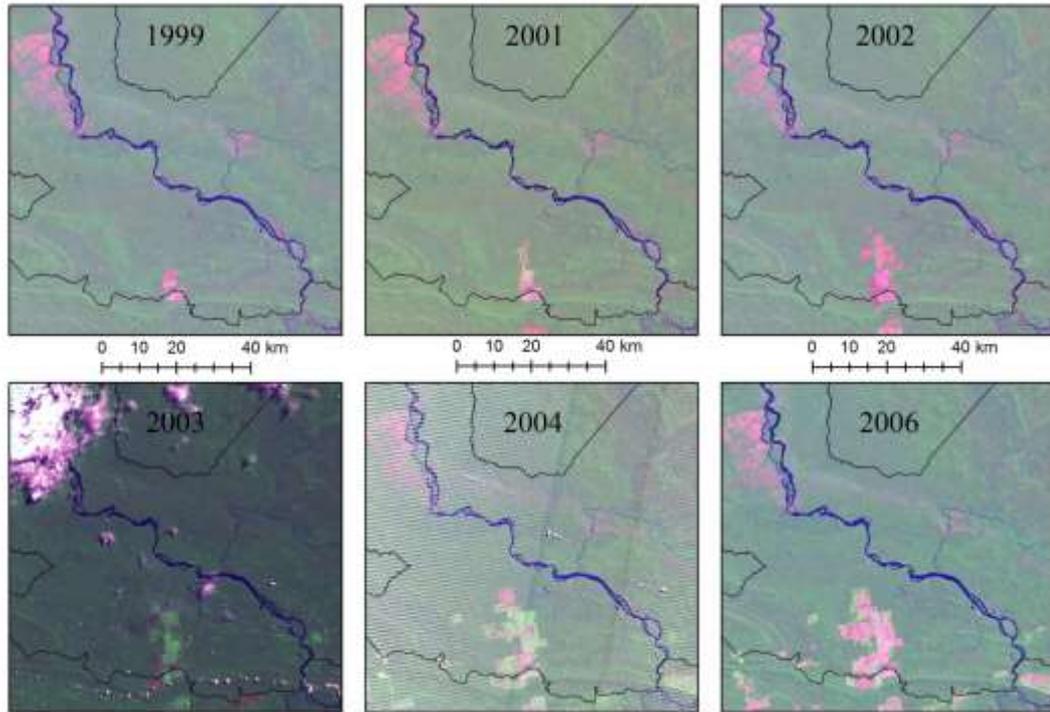


Figure 5. Deforestation Evolution in Kayabi Territory Landsat Imagery (RGB, 742)

The demarcation process resulted in a number of injunctions from companies and single land-owners that had legal land titles to the newly declared Kayabi area. In the beginning of 2003, seven single farm owners (MANDADO DE SEGURANÇA N° 8.882 - DF, 2003), a national conglomerate (MANDADO DE SEGURANÇA N° 8.882 - DF, 2003) and multinational company (MANDADO DE SEGURANÇA N° 8.873 - DF, 2003) with land titles amounting to over 450,000 hectares started an injunctions to stop the demarcation process. Figure 6 shows the land properties involved in the injunctions.

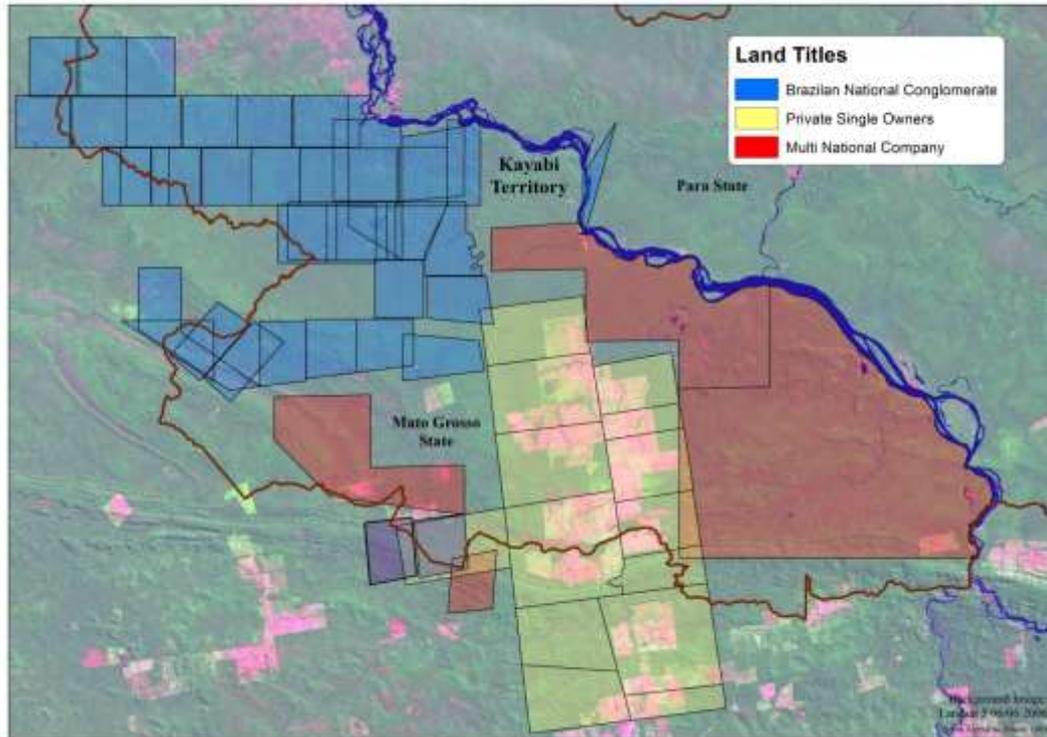


Figure 6. Private land ownership in Kayabi

In 2004, the injunction was granted suspending the demarcation and maintaining the integrity of the area. In this period, a decrease in the rate of deforestation to clear-cutting was observed, however, the number of smaller opening points increased in a scattered distributed form, indicating illegal logging and opening areas connected by narrow paths, through the forest, indicating the possibility of become the core areas of future pasture. It is believed that deforestation grew in the middle part of the east part of the territory because of the uncertainty to the farmers of their land tenure.

In 2006, IBAMA identified 61 points of deforestation in the Mato Grosso part of the Kayabi Territory and its buffer zone (10 km) and a total of 33,646 hectares deforested. As can be observed in Figure Figure 7, the deforested area in Mato Grosso portion concentrated along a dirt road from the seat of municipal Apiacás and continuing northward to the left bank of the Rio Teles Pires (IBAMA,2006).

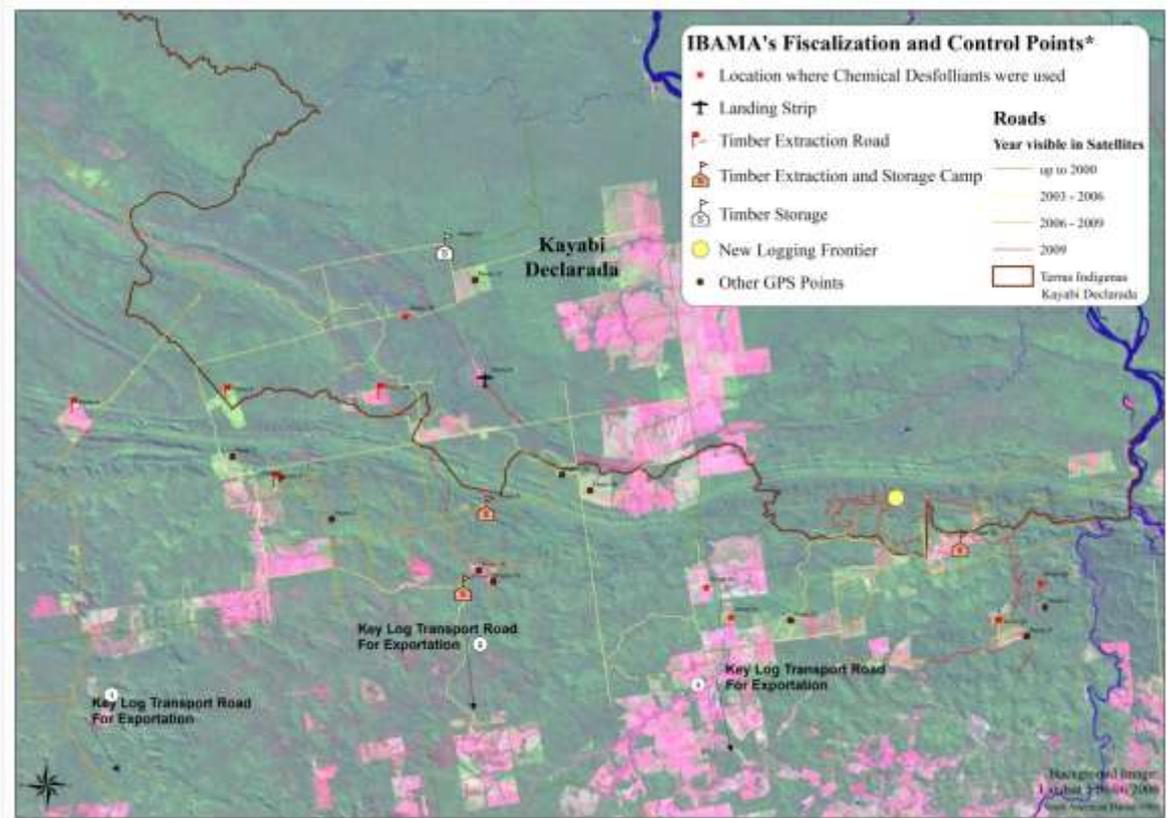


Figure 7. IBAMA fiscalization points

2.1.1 Selective Logging in Kayabi Territory

Human driven landscape change is very complex as it is dependant of several factors such as economical, institutional, political and demographic factors (Perz, et al., 2008). These have different impact and may affect time process as well as its spatial configuration. For example, availability of commercially valuable wood may trigger timber extraction processes, and consequently, the development of the required infrastructure (e.g. development of unofficial roads is required for resource extraction). Roads grant access to colonists and loggers to land or timber, but these roads not only provide access to resources but also fund development of new roads (Perz, et al., 2008). Therefore, areas that were inaccessible before are now subject to potential human exploitation. This feedback implies that as long as there is profitable resource extraction, unofficial road building will continue, even if it is not sustainable (Perz, et al., 2008). This process is called “invasive forest mobility” (Asner, et al., 2006).

The process of extraction of certain species of trees that have commercial value is called selective logging, and it is selective because markets only accept certain species for timber use (Asner, Keller, Pereira, Zweede, & Silva, 2004). Although selective logging has less forest damage than deforestation, it leaves the forest more susceptible to drought, fire and especially to anthropogenic intervention (Asner et al., 2006). In fact, forests that have already been logged have more likelihood of cleared, Asner et al. (2006) have found that logged forests would be cleared within 4 years after timber harvests. Moreover, high rates of selective logging could have great impact in natural biochemical processes (including carbon sequestration) and in long-term sustainability of forest productivity in the region (Asner, Keller, Pereira, Zweede, & Silva, 2004)

In line with the process described above, historical time analysis of satellite imagery of Kayabi Territory has shown that selective logging is only the first step in a process that leads to completely clearing of forest areas. Figure 8, below, illustrates how new unofficial logging roads in Kayabi Territory, first identified by a 2008 SPOT 5 (spatial resolution: 2.5 m), led to the clearing of 354 hectares within a period of 3 years.

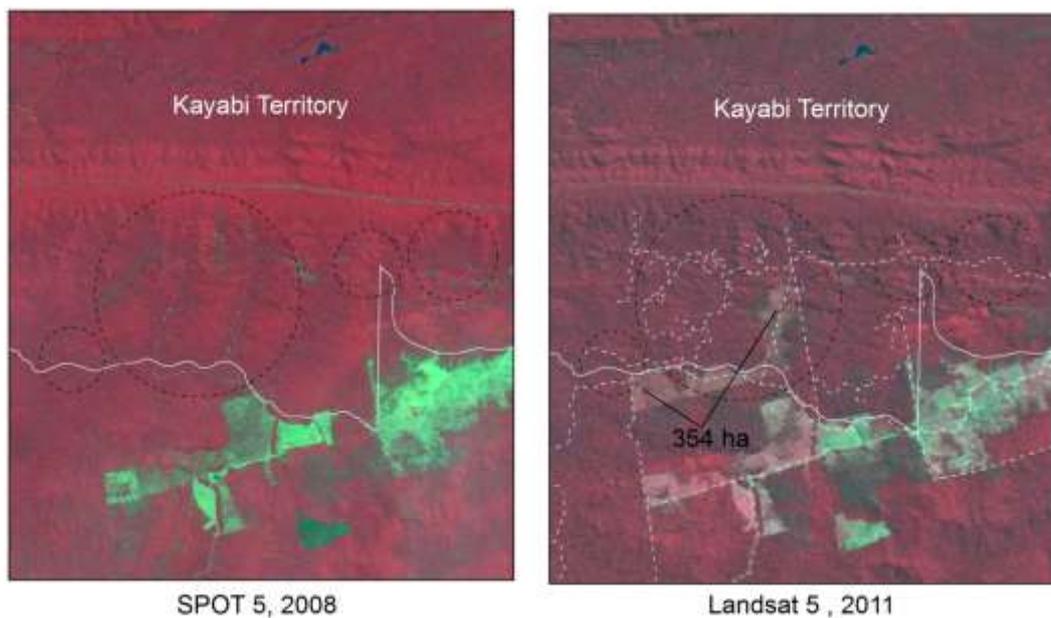


Figure 8. Logging roads preceding forest clearing.

For this reason, identification of selective logging is of most importance in order to stop further disturbance in the forest. Unfortunately, its detection and quantification with remote sensing is very difficult because of trees species diversity in the Brazilian Amazon is very high and species are locally rare (Asner, Keller, Pereira, Zweede, & Silva, 2004). In addition, rapid canopy re-growth, detection must be done within a short time period after logging activity before canopy recovers or second vegetation fills the gap.

3. Review of Literature

This chapter provides a description of the key definitions, methods that are relevant to this study. Also, it provides a brief review of the utilized software. These subjects were chosen to provide the reader with insights of the most important concepts, methods and processes carried out and to serve as reference to the followed methodology.

3.1 LUCC models

As mentioned in Chapter 1, it is very important to understand the determinants of Land use/cover change (LUCC) to develop sustainable management policies, planning and decision making. Therefore, modelling provide great means to understand the interactions land change dynamics and their driving factors.

A model can be defined as a simplified representation of a phenomenon or a system (Chang, 2010). LUCC models are used to study and predict the future states of land use patterns taking into account various biophysical and socio-economic factors. Laurance et al. (2002) have assessed the effects of biophysical and anthropogenic predictors on deforestation at the Brazilian Amazon. According to their research, three types of mayor potential predictors were identified:

- Human demographic factors (rural-population density, urban-population size)
- Factors that affect physical accessibility to forests (linear distances to the nearest paved highway, unpaved road and navigable river)
- Factors that may affect land use suitability for human occupation and agriculture (annual rainfall, dry season severity, soil fertility, soil water logging, soil depth)

These predictors are the basis to build conceptual and mathematical models and they seem to be consistent with the work carried out by Walker et al. (2004).

According to Hayelom (2009), the choice of modelling type and modelling systems depends on the purpose of the model, analyst's preferences and skills and is not an easy task to choose the model to use. For the purpose of this study, several LUCC models were reviewed and studied, IDRISI's Land Change Modeler (LCM) for Ecological Sustainability was found the most time-cost-effective. LCM provides a feature-rich environment for land analysis, planning and prediction (Clark Labs, 2009).

3.2 Definition of remote sensing and image processing

“Remote sensing is the science and art of obtaining information about an object, area or phenomenon through the analysis of data acquired by a device that is not in contact with the object area or phenomenon under investigation” (Lillesdand, Kiefer, & Chipman, 2007, p. 1). In this study, remote sensing is understood as the process of data acquisition through space borne sensors (satellites) without having any interaction with target areas. Remote sensing, in its various forms, is an essential tool for record relatively recent land change, for monitoring present changes, and for calibrating models for predicting future changes (Rindfuss, Walsh, Turner, Fox, & Mishra, 2004) . It allows the acquisition of multi-spectral, multi-spatial resolution and multi-temporal data for the land change analysis and modelling. (Hayelom, 2009). Multi-spectral sensors are those capable of record radiant energy in multiple bands of the electromagnetic spectrum. The spatial resolution is referred to measure of the smallest angular or linear separation between two objects that can be resolved by the sensor (Clarke, 2000). Temporal resolution is defined by the period of time that takes for the sensor to acquire imagery.

3.3 Description of Image Classification process

Image classification refers to the computer-assisted interpretation of remotely sensed images. In general, image classification is based on the detection of spectral signatures of land cover classes (Eastman, 2009). Real-world surface materials such as water, vegetation

and bare soil reflect different proportions of energy in the blue, green, red and near-infrared portions of the electromagnetic spectrum. A spectral signature, also called spectral reflectance curve, can be created by plotting the amount of energy reflected from each of these materials. (Clarke, 2000). Figure 9 shows spectral signatures for green vegetation, dry vegetation and soil.

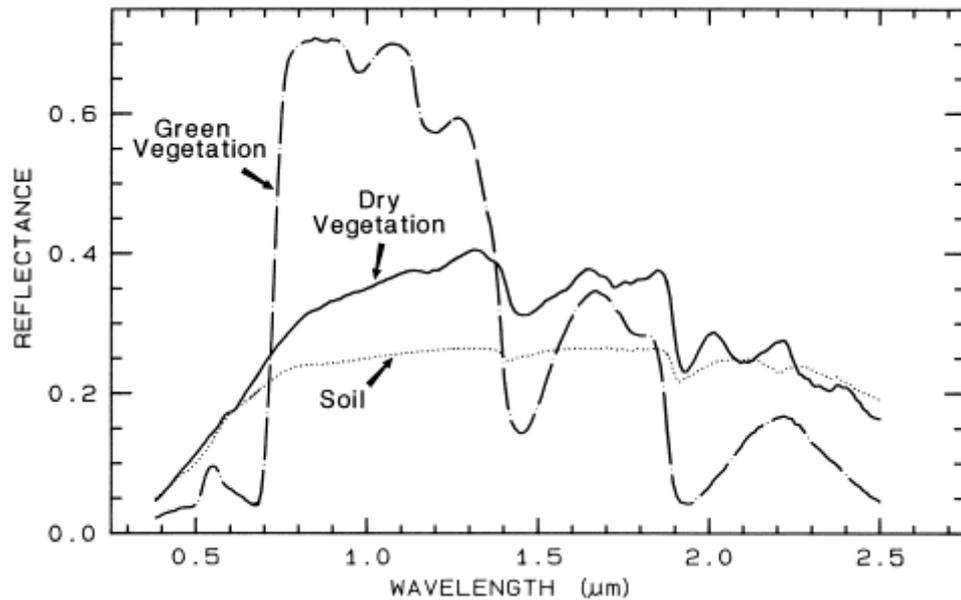


Figure 9. Example of spectral signatures (USGS, 2005)

There are two main approaches to image classification: supervised and unsupervised. The difference relays in how the classification is performed. In a supervised classification, the software system delineates specific land cover types based on statistical characterization data from known examples in the image, known as training sites. In contrast, with unsupervised classification, a clustering software is used to uncover the commonly occurring land cover types, in this case, the analyst provide interpretation of those cover types at a later stage (Eastman, 2009).

3.4 CLASlite

CLASlite is a computational package designed developed by team from the Department of Global Ecology at the Carnegie Institution for Science to identify forest degradation from

remotely sensed satellite imagery. CLASlite's algorithms identify and highlight areas where clearing, logging and other forest disturbances have recently occurred. (Asner, Knapp, Balaji, & Paez-Acosta, 2009).

There are three spectral libraries created for CLASlite. Live vegetation is referred to as photosynthetic vegetation (PV) because live vegetation maintains unique spectral properties associated with leaf photosynthetic pigments and canopy water content. The senescent or dead vegetation is termed non-photosynthetic vegetation (NPV) expressed in the spectrums as bright surface material with spectral features associated with dried carbon compounds. Finally, bare substrate (B) is frequently dominated by exposed mineral soil, but can also be human-made infrastructure (e.g. brick, asphalt, and concrete) and rocks. CLASlite includes a core sub-model called the AutoMCU¹ (Automated Monte Carlo Unmixing) that provides quantitative analysis of the fractional or percentage cover (0-100%) of live (PV) and dead vegetation (NPV), and bare substrate (B) within each satellite pixel of the image. (Carnegie Institution for Science, 2010)

According to the user's manual CLASlite's output image consists in three fractional cover images, indicating the percentage of live vegetation (technically, PV), dead vegetation (technically, NPV) and bare substrate (B) at a sub-pixel, bands 1,2 and 3 respectively (Figure 10, Figure 11, and Figure 12). In addition, three uncertainty images are created for each image described above, that gives the uncertainty of the PV, NPV and B images for each one, bands 4, 5 and 6 respectively. *“All values of uncertainty are given as standard deviations of the mean percentage cover from the initial three bands described above. The higher the number, the more uncertain that CLASlite was in estimating PV, NPV or B in that*

¹ The tropical forest spectral library provided the spectral reflectance bundles required by the AutoMCU sub-model: PV, NPV, and bare substrate. The AutoMCU is a probabilistic approach based on canopy physics to deconvolve each image pixel into these three constituent cover fractions, PV, NPV and bare substrate.

pixel. These three uncertainty images are helpful for locating areas in the image that have suspicious results. Uncertainty can be caused by clouds and cloud shadows, water bodies, atmospheric haze (e.g., from fires), unique land features, extreme terrain, and other issues. Finally, a Total Error Image (band 7) shows the total error for CLASlite image. Total Error is expressed as Root Mean Square (RMS) error. A pixel with a low Total Error indicates that CLASlite solution is probably good, whereas a high Total Error suggests that the solution was not good and should either be discarded or used with caution. Total Error image is a final check of the accuracy of the CLASlite results” (Carnegie Institution for Science, 2010, p. 8).

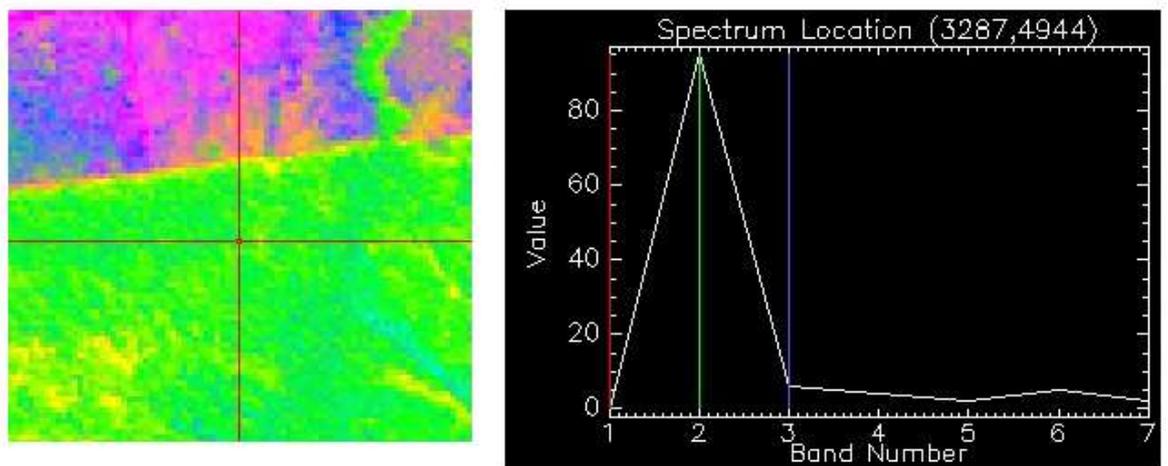


Figure 10. Pixel a high percentage of photosynthetic vegetation

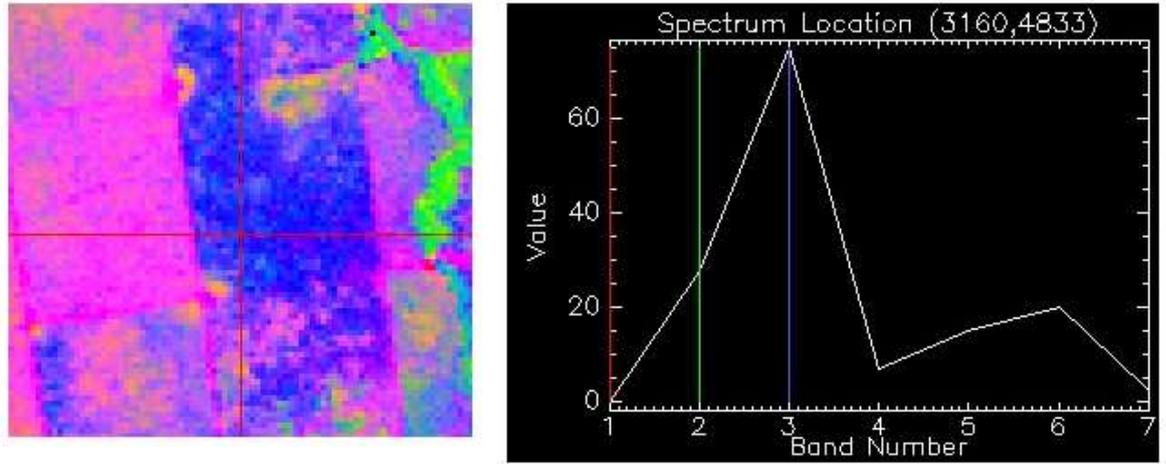


Figure 11. Pixel with a high percentage of non-photosynthetic vegetation

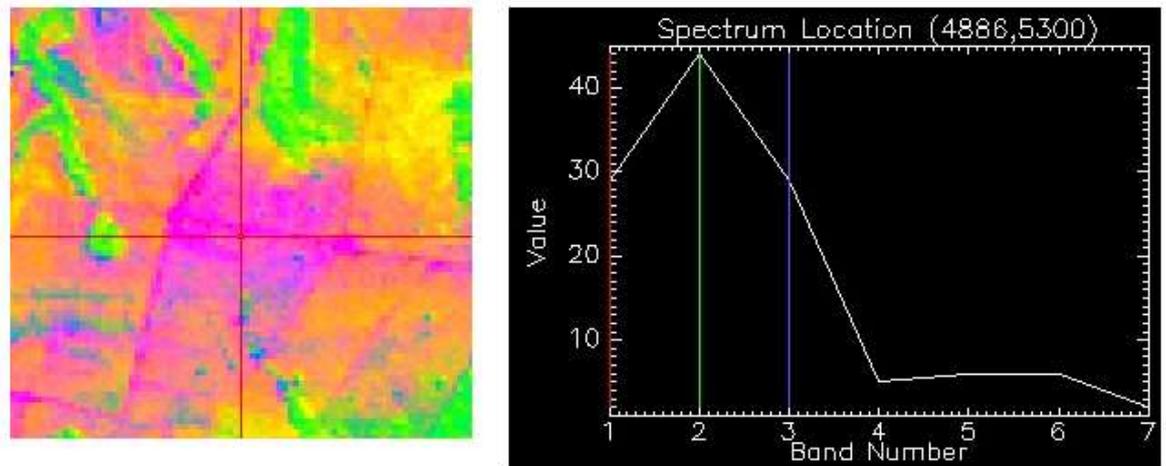


Figure 12. Pixel with a high percentage of bare substrate

In the figures above, in addition to the percentage of PV, NPV and B, the accuracy assessment for each of the 3 fractional cover image as well as for the Total Error at pixel level can be observed.

3.5 IDRISI's Land Change Modeler

IDRISI's Land Change Modeler (LCM) for Ecological Sustainability is an integrated software environment developed by Clark Labs and is oriented to the pressing problem of accelerated land conversion and the specific needs of biodiversity conservation (Eastman, 2009).

According to Clark Labs (2009)², LCM provides:

“A suite of tools for land cover change analysis, allowing the user to quickly map changes in the landscape, identify and uncover land class transitions and trends, and monitor ongoing plans;

A modeling and prediction environment to create future landscape scenarios with the integration of user-specified drivers of change, such as slope or distance maps, as well as constraint or incentive information which would impact the scenario, such as infrastructure changes or zoning regulations”

LCM is organized in a set of five major tasks areas in the form of tabs (see Figure 13):

- Analyzing past cover change
- Modelling the potential for land transitions
- Predicting the course of change into the future
- Assessing its implications for biodiversity (not used in this study), and
- Evaluating planning interventions for maintaining ecological sustainability.

² <http://www.clarklabs.org/products/Land-Change-Modeler-Overview.cfm>

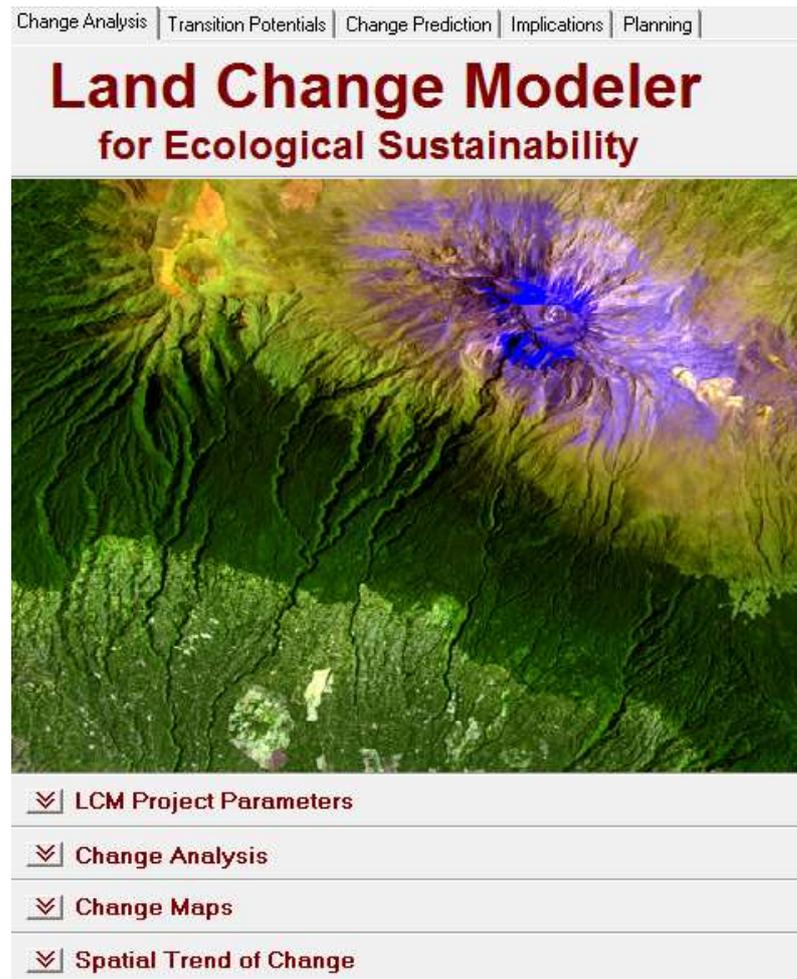


Figure 13. LCM workspace environment.

Within each tab, a series of tasks/analytical stages are presented as a series of drop-down panels.

The first three of the five tabs are concerned for the analysis of LUCC and its prediction into the future. These three panels are organized around a sequential set of operations that should be followed one after the other (Eastman, 2009).

3.6 Transition potential models

LCM provides two options for producing transition potential maps, namely logistic regression and Multilayer Perceptron Neural Network (MLP). This study uses the MLP approach and Markovian process to predict future landscape change.

3.6.1 Multi-Layer Perceptron Neural Network

“A multilayer perceptron (MLP) is a feed-forward artificial neural network model that maps sets of input data onto a set of appropriate output. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next one. Except for the input nodes, each node is a neuron (or processing element) with a nonlinear activation function. MLP utilizes a supervised learning technique called back propagation for training the network” (Wikipedia, Multilayer perceptron, 2011). Figure 14 shows a type of network is trained with the back propagation for training the network. MLPs are used for pattern classification, recognition, prediction and approximation. In addition, Multi Layer Perceptron neural networks are also used for solving problems which are not linearly separable (Neuroph, 2008).

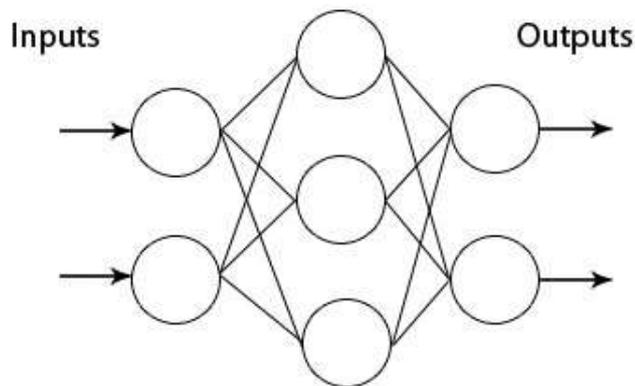


Figure 14. Multi Layer Perceptron Neural Network (Neuroph, 2008).

3.7 Markov Chain

“A Markovian process is one in which the state of a system can be determined by knowing its previous state and the probability of transition from each state to each other state” (Michalski, Peres, & Lake, 2008, p. 96).

A Markov chain is group of random variables $\{X_t\}$ (where the index t runs through 0, 1, ...) having the property that, given the present, the future is conditionally independent of the past.

In other words:

$$P(X_1 = j | X_0 = i_0, X_1 = i_1, \dots, X_{t-1} = i_{t-1}) = P(X_1 = j | X_{t-1} = i_{t-1})$$

If a Markov sequence of random variates x_n take the discrete values a_1, \dots, a_n , then

$$P(x_n = a_{i_n} | x_{n-1} = a_{i_{n-1}}, \dots, x_1 = a_{i_1}) = P(x_n = a_{i_n} | x_{n-1} = a_{i_{n-1}})$$

and the sequence x_n is called a Markov chain (Weisstein, 2011).

The *MARKOV* module in IDRISI can be used to calculate the transition probability matrix from two input maps.

4. Methodology

The prediction of the future landscape was developed using different Geographic Information Systems (GIS) and a modelling programme and followed five sequential steps:

- (1) Creation of forest land cover maps from 2000, 2006 and 2009 derived from remotely sensed data;
- (2) Land-change cover analysis by cross-tabulating forest land cover maps;
- (3) Calculation of transition potentials from forest to anthropogenic disturbance using a MLP neural network methodology;
- (4) Assessment of the model performance by predicting a 2009 land cover and comparing it with an actual 2009 land cover map; and
- (5) Predicting a 2020 land cover.

4.1 Creation of land cover maps

In order to create the multi-temporal land cover maps at different time of the Kayabi Territory, CLASlite software was utilized to create fractional cover maps for each image shown in Table 2. Finally, a supervised classification was carried out using ENVI software to create 2 class land cover maps for each year (forest and anthropogenic disturbance).

The land change analysis was based on two multi-temporal land cover maps derived from a 2000 Landsat ETM+ , a 2006 Landsat TM, a third land cover map, for the purpose validation of the model, was derived from two 2009 SPOT 5 images. Table 2 shows the characteristics of the satellite imagery used.

Table 2. Characteristics of Satellite data used

Sensor	Spectral Bands	Spectral resolution	Ground pixel Size	Acquisition date
Landsat ETM+	B1: Blue	0.45-0.515 μm	30 m	31/05/2000
	B2: Green	0.525-0.605 μm	30 m	
	B3: Red	0.63-0.69 μm	30 m	
	B4: Near-infrared	0.75-0.90 μm	30 m	
	B5: SWIR	1.55-1.75 μm	30 m	
	B6: Thermal-infrared	10.4-12.5 μm	60 m	
	B7: Mid-Infrared	2.09-2.35 μm	30 m	
	P: Panchromatic	0.52-0.9 μm	15 m	
Landsat TM	B1: Blue	0.45-0.52 μm	30 m	25/06/2006
	B2: Green	0.52-0.6 μm	30 m	
	B3: Red	0.63-0.69 μm	30 m	
	B4: Near-infrared	0.76-0.9 μm	30 m	
	B5: SWIR	1.55-1.75 μm	30 m	
	B6: Thermal-infrared	10.4-12.5 μm	120 m	
	B7: Mid-Infrared	2.08-2.35 μm	30 m	
SPOT 5	B1: Blue	0.50-0.59 μm	10 m	29/05/2009
	B2: Green	0.61-0.68 μm	10 m	12/09/2009
	B3: Near-infrared	0.78-0.89 μm	10 m	
	B4: SWIR	1.58-1.75 μm	10 m	

4.1.1 Creation of fractional cover maps using CLASlite.

Using CLASlite, fractional cover maps were created for the years 2000, 2006 and 2009. Figure 15 shows a partial 2006 fractional cover image for the Kayabi Territory and highlights examples where older and recent deforestation have occurred as well as an example of where forest is in good condition.

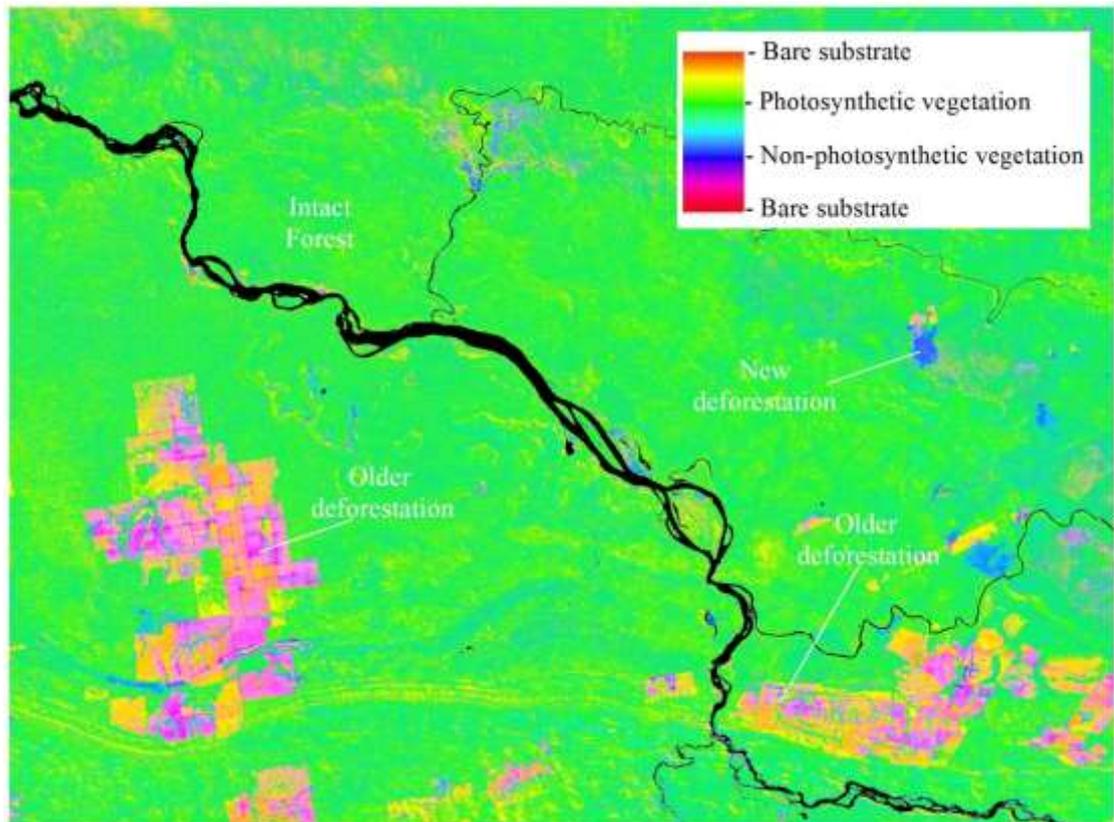


Figure 15. CLASlite's fractional Cover image of a 2006 Landsat 5.

4.1.2 Image Classification using CLASlite's fractional cover output images

In order to create the land cover maps to input in IDRISI's Land Change Modeller, CLASlite's fractional cover images were classified using ENVI software. The Kayabi Territory was used as a mask to extract only the data within this territory. A supervised classification was carried out by using as training sites the areas where anthropogenic disturbance was evident, water bodies, clouds and intact forest. A 3X3 filtering was carried out to remove extraneous pixels.

Because any classification software cannot differentiate between anthropogenic-caused bare substrates and natural bare soils (e.g. rock outcrops), a careful analysis was made by

comparing the classified images with earlier Landsat images (1986 and 1999) with the purpose to discard these natural bare soil areas.

The result of the classification was a 2 class map: Forest and Anthropogenic Disturbance for each of the analysed years. Figure 16, shows the fractional cover maps and the supervised classification made with *ENVI* for years 2000 and 2006 for the Kayabi Territory.

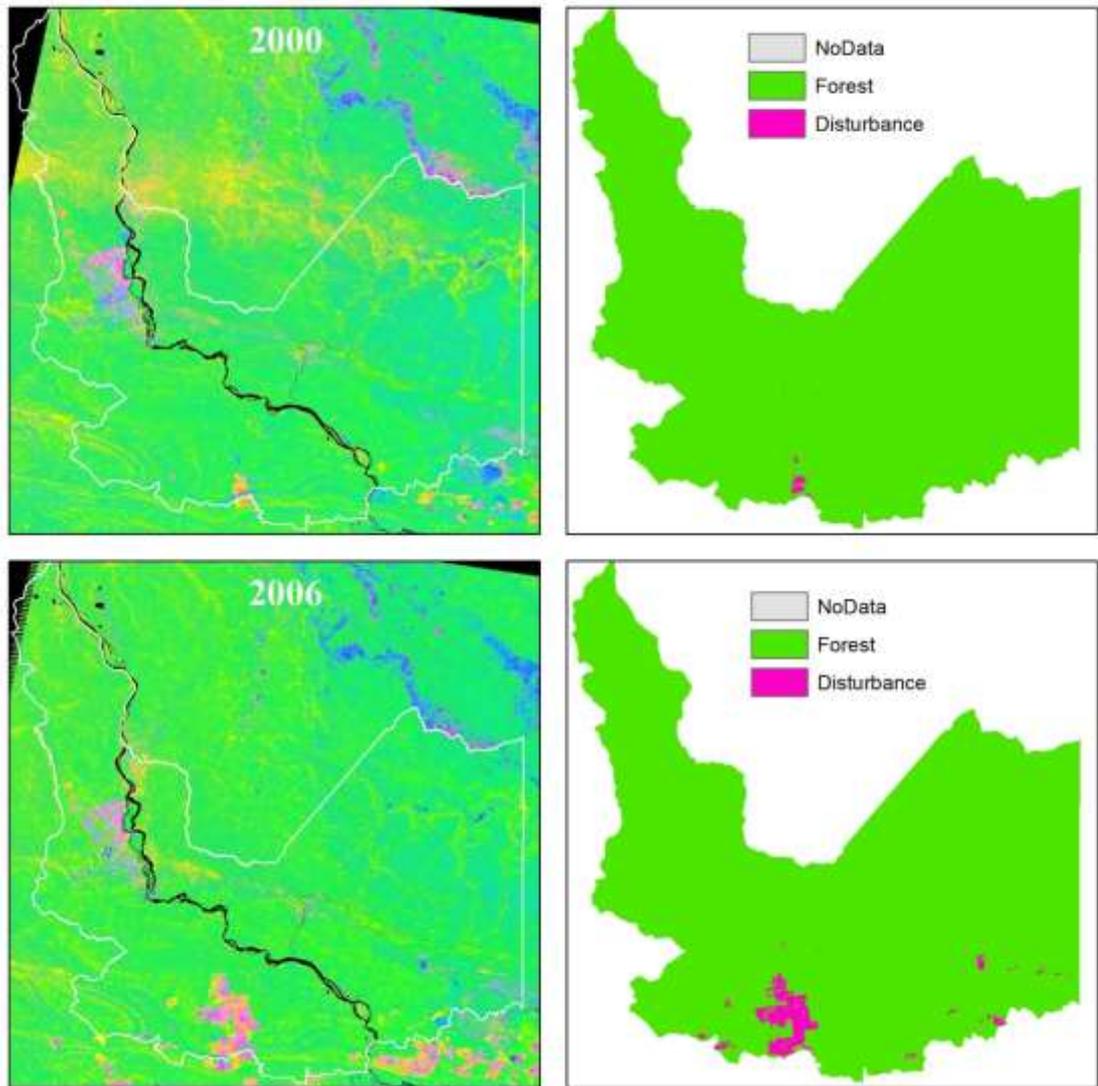


Figure 16. Resulting classification of CLASlite's fractional cover maps.

4.2 Land Change Cover Analysis

In order to assess change from forest class to disturbance between 2000 and 2006, the corresponding land cover maps were input in the Change Analysis Tab in LCM. Basically, LCM analyses each pixel in the earlier land cover map, in this case 2000, for a transition to a different class in the later land cover image (2006). Since there are only two land cover classes, there are only four possible outcomes for each pixel:

Case 1. Forest with no change (Forest persistence)

Case 2. Forest transition to Disturbance (Forest – Disturbance)

Case 3. Vegetation Re-growth (Disturbance-Forest)

Case 4. Disturbed area with no change. (Disturbance persistence)

Figure 17 shows the gains and losses experienced by each land cover class. According to this analysis, 18,018 ha of forest was lost to anthropogenic disturbance between 2000 and 2006, and 165 ha of lost forest were regained by the forest. However, this little amount of gain is much likely to be a map error, therefore, transitions less than 500 hectares were ignored in future analyses.

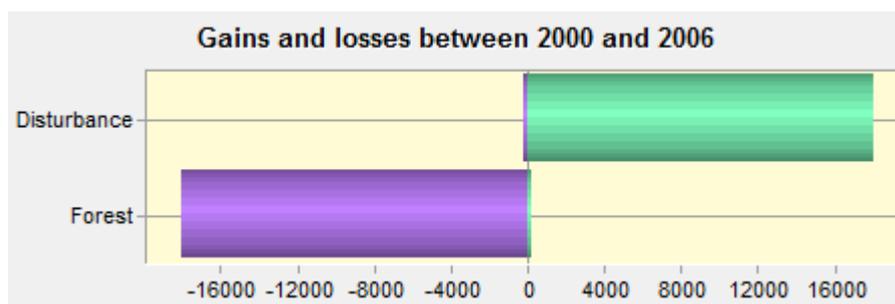


Figure 17. Gains and losses between 2000 and 2006 provided by LCM

The following figure shows a partial image of the Kayabi Territory with the transitions for each class.

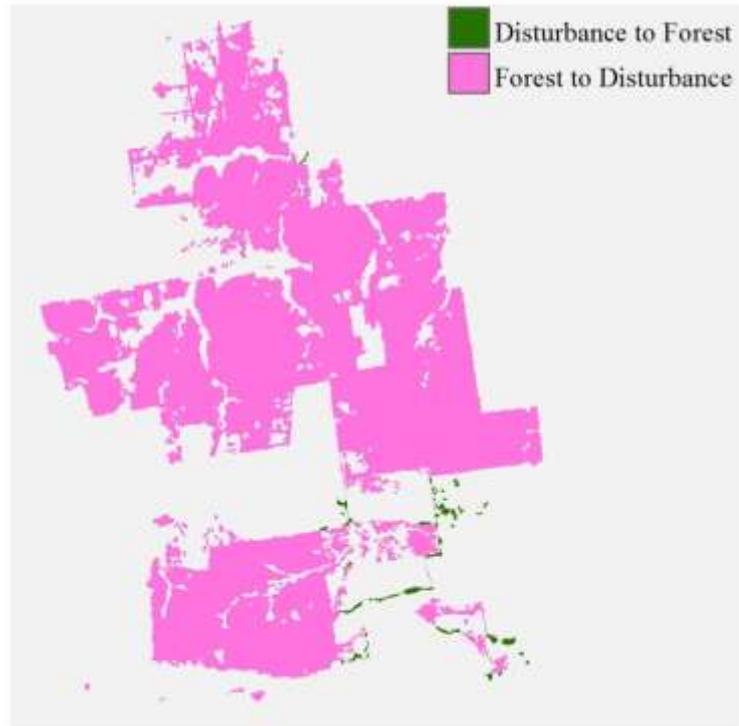


Figure 18. Class transitions calculated by LCM

In addition to create maps for all transition, maps transitions experienced by a single land cover can be created, for example, Figure 19 shows the net change from forest to disturbance between 2000 and 2006.

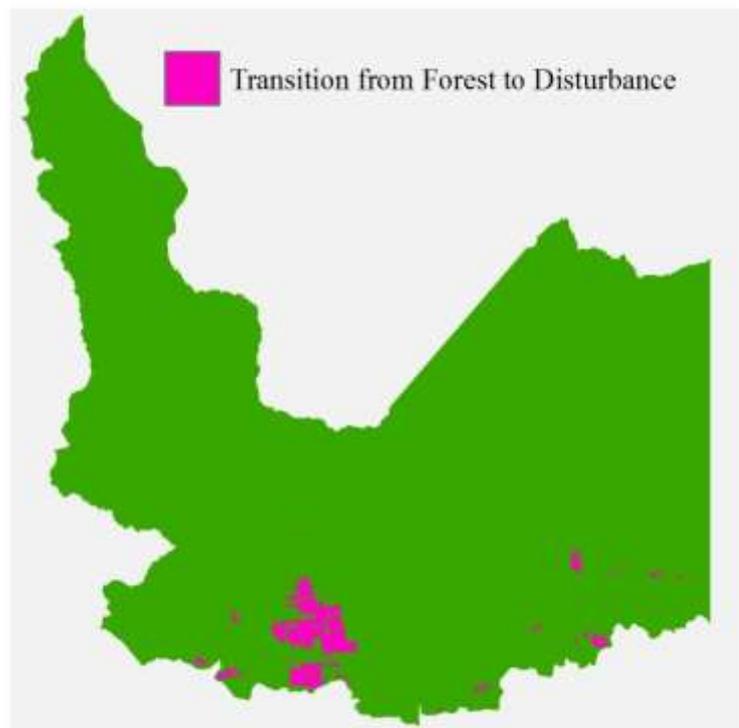


Figure 19. Transition from forest to anthropogenic disturbance (2000 - 2006)

4.2.1 Spatial trend of change

Human driven changes in landscape can be very complex and difficult to decipher (Clark Labs, 2009). For this reason as well as to facilitate interpretation, a 3rd order polynomial trend surface was created using LCM. Spatial trend analysis is an effective way of visualizing the general trend of change based on the observed change between two land cover maps. In this case, see Figure 20, it makes evident that the change from forest to disturbance is concentrated in the south part of the image; this is consistent with the deforestation tendency observed and coming from the ‘arc of deforestation’.

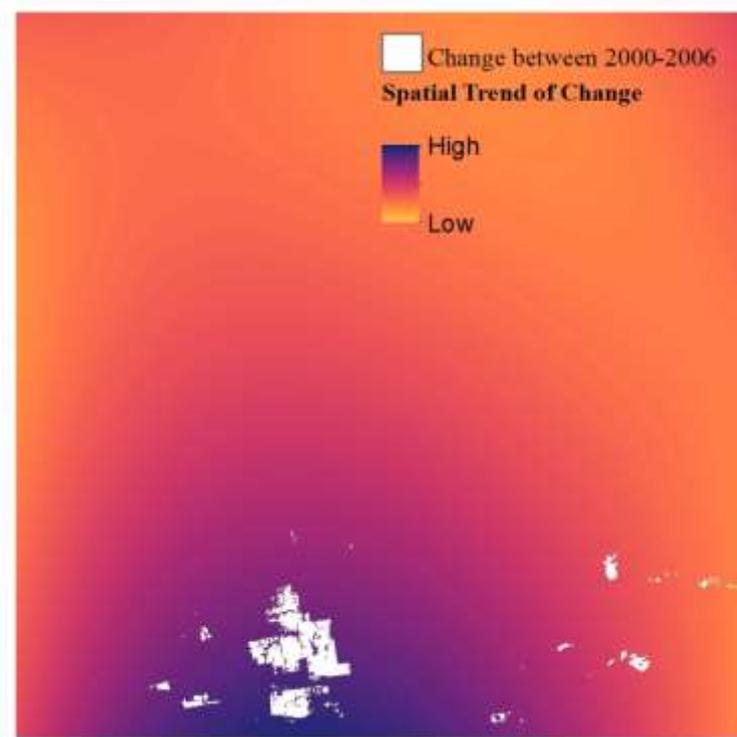


Figure 20. Spatial trend of change

Although this analysis provide effective means to visualize the general trend of change, the numeric values do not have any special significance (Clark Labs, 2009) and this image must be used only provide general sense of direction of change.

4.3 Modelling Transition Potentials

Transition potentials are expressed as the likelihood of one land cover category to another (Paegelow & Camacho Olmedo, 2008). In this case, only transition from forest to anthropogenic disturbance was to be modelled. LCM allows two approaches were used to create transition potential maps: MLP Neural Network and Logistic Regression. According to Eastman (2009), MLP has proven to have stronger capabilities particularly to model non-linear relationships between land cover change and explanatory variables, the MLP approach is used in this study.

4.3.1 Explanatory variables

As mentioned in the *LUCC models* section, some biophysical and anthropogenic factors have more effect on deforestation as they facilitate physical accessibility to forests (e.g. roads and navigable rivers). In this study, five factors were identified as major driving forces of change (explanatory variables), see

Table 3, and were assessed for correlation to deforestation. These five factors were used in the LCM transition sub-model structure as explanatory variables. LCM can differentiate between, static variables and dynamic variables, static variables are those do not change over time (e.g. terrain, slope), whereas dynamic variables do change over time (e.g. proximity to roads, proximity disturbed areas). Both types of variables have different roles on the calculation of the transition potential map. Static variables express aspects of basic suitability for the transition under consideration. In contrast, as dynamic variables change over time they are recalculated over time during the course of a prediction (Eastman, 2009).

Table 3 shows the five explanatory variables used in the transition sub-model structure. Appendix 2 contains the data, process and technical details of all used data in LCM.

Table 3. Explanatory variables in transition sub-model structure

Explanatory Variable	Type
Distance from roads	Dynamic
Distance from disturbance	Dynamic
Terrain (DEM)	Static
Distance from streams	Static
Slope	Static

The figures below show the explanatory variables in Kayabi Territory used in the sub-model structure.

For the terrain variable, a 30 metre USGS Digital Elevation Model (*DEM*) was used (see Figure 21).

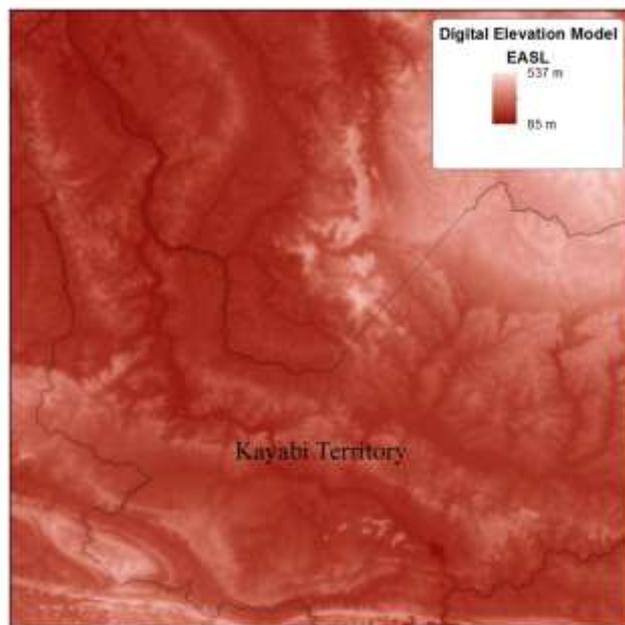


Figure 21. USGS³ Digital Elevation Model

Using ArcGIS' Spatial Analyst, a *slope model* was created using the USGS DEM as input (see Figure 22).

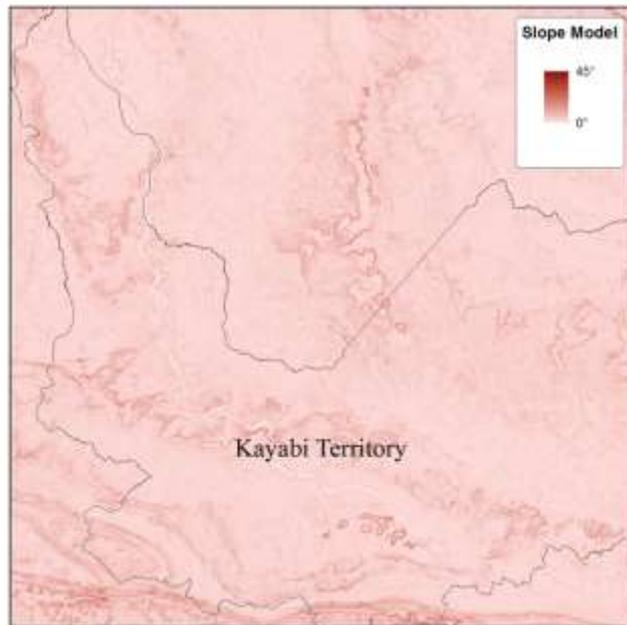


Figure 22. Slope Model derived from DEM

Using Landsat imagery from different years ranging from 1999 to 2006, the visible roads were plotted into a polyline shapefile layer using ArcGIS. The road layer was converted into a raster format and subsequently a raster with Euclidean *distance from roads* was created using the Distance module in IDRISI (see Figure 23).

³ United States Geological Survey: <http://eros.usgs.gov/#/Guides/dem>

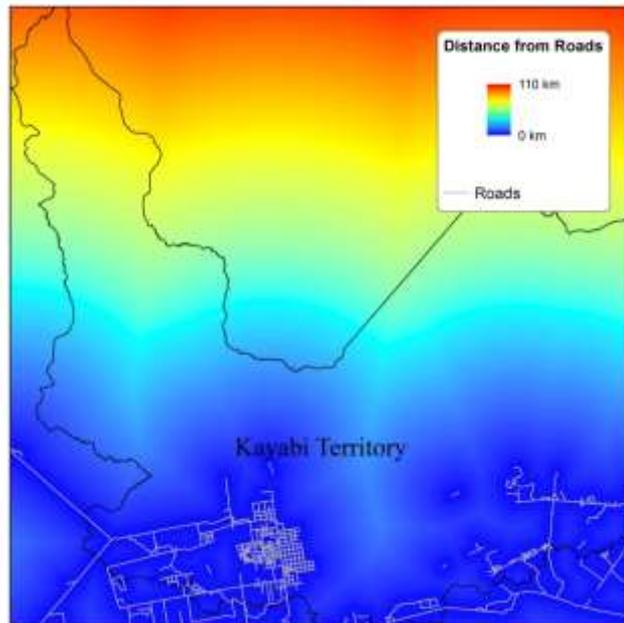


Figure 23. Distance from roads

Similarly to the roads layer, a distance module was run using a hydrology layer in order to calculate the Euclidean *distance from streams* (see Figure 24).

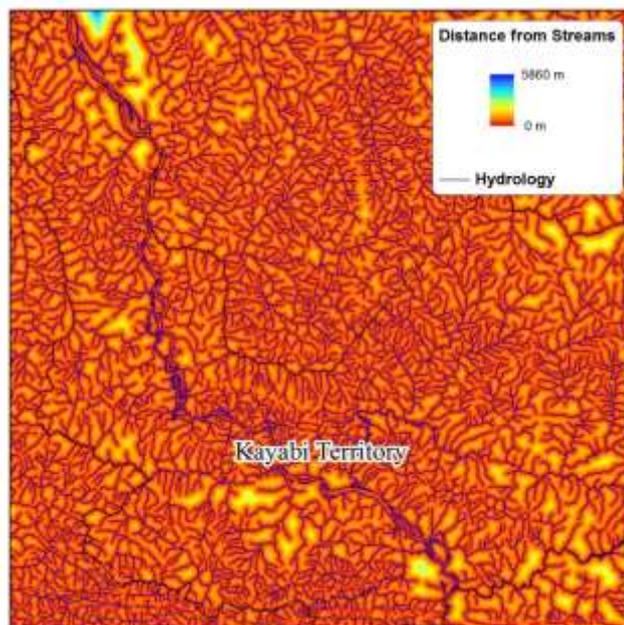


Figure 24. Distance from Streams

In order to calculate distance from previous disturbance, the 2000 land cover map was used as input to create the Euclidean *distance from disturbance* layer (see Figure 25).

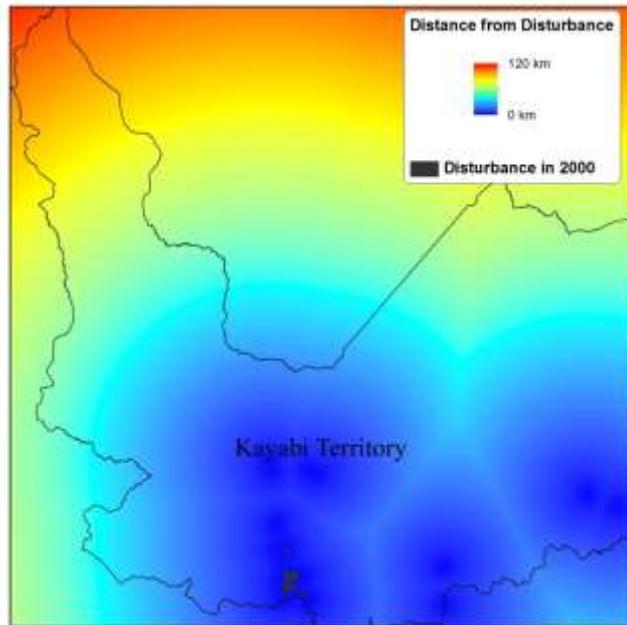


Figure 25. Distance from previous disturbance (2000)

To visualize the nature of the relationship of existing disturbance to change occurred between 2000 and 2006, a histogram was plotted using the *distance from disturbance* layer and cross-tabulated with the Boolean layer containing the change in that period (derived from layer shown in Figure 19.).

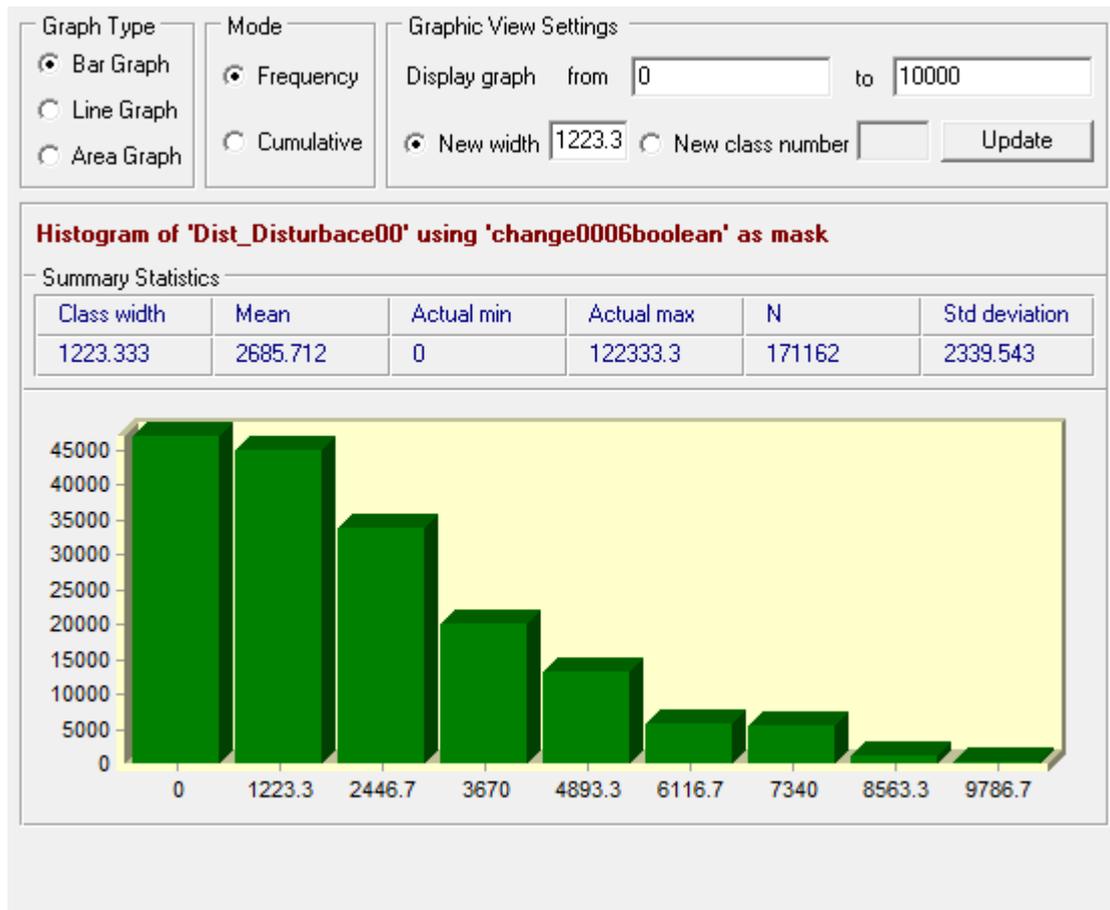


Figure 26. Frequency of change

As it can be observed in Figure 26, there is a non-linear relationship as there is sharp decline in the frequency of change as it moves away from existing deforestation, to the point where it drops to almost to zero after ten kilometres.

4.3.2 Test of explanatory variables

Cramer's V is a statistic measuring the strength of association or dependency between two categorical variables (Planetmath, 2005). In order to test the potential power of explanatory variables, the LCM's *Test and Selection of site and driver variable* module was used. Table 4 shows the Cramer's V value for each of the explanatory variables.

Table 4. Cramer's V Test for explanatory variables

Explanatory Variable	Cramer's V
Distance from roads	0.4730
Distance from disturbance	0.4572

Terrain	0.1114
Distance from streams	0.0493
Slope	0.0233

According to Eastman (2009), variables that have a Cramer's V of about 0.15 or higher are useful, whereas variables with values of 0.40 or higher are good. From Table 4, it can be observed that both, *Distance from roads* and *Distance from disturbance*, have values higher than 0.45, meaning these two variables are strongly associated with change, therefore kept in the sub-model structure. Given that the rest of the explanatory variables have a low Cramer's V values, they were taken out of the sub model in the sub-model structure, keeping only the DEM as it has a 0.1114 Cramer's V value and it represents basic terrain suitability.

4.3.3 Modelling Transition Potential using MLP

Once the explanatory variables were tested and selected as change drivers, the transition potential from forest to disturbance was modelled using the MLP neural network methodology. The LCM MLP neural network model provides an automatic mode that requires no user intervention (Clark Labs, 2009). When the model is ran, MLP creates a random sample of cells that have experienced transition from forest to disturbance and an additional set of random samples for the case of pixels that could have gone through a transition, but did not. Thus the neural network is fed with examples of the two cases, one transition class and one persistent class. Basically, the MLP uses samples to train and develops a multivariate function that can predict the transition potential based on the values at any location of the five explanatory variables. This is done by taking half of the samples it was given to train on and uses the other half to test its performance. The MLP builds a network of neurons between the five input values from the explanatory variables and the two output classes (transition and persistent classes), and a web of connections between the neurons that are applied as a set of (initially random) weights. These weights structure the

multivariate function. With each pixel it analyses from the training data, it gauges error and adjust weights, therefore improving accuracy and increasing precision.

The LMC sub model was run in order to create the transition potential map, the MLP achieved an accuracy rate of 94.56 % and a RMS value of 0.20 (see Figure 27).

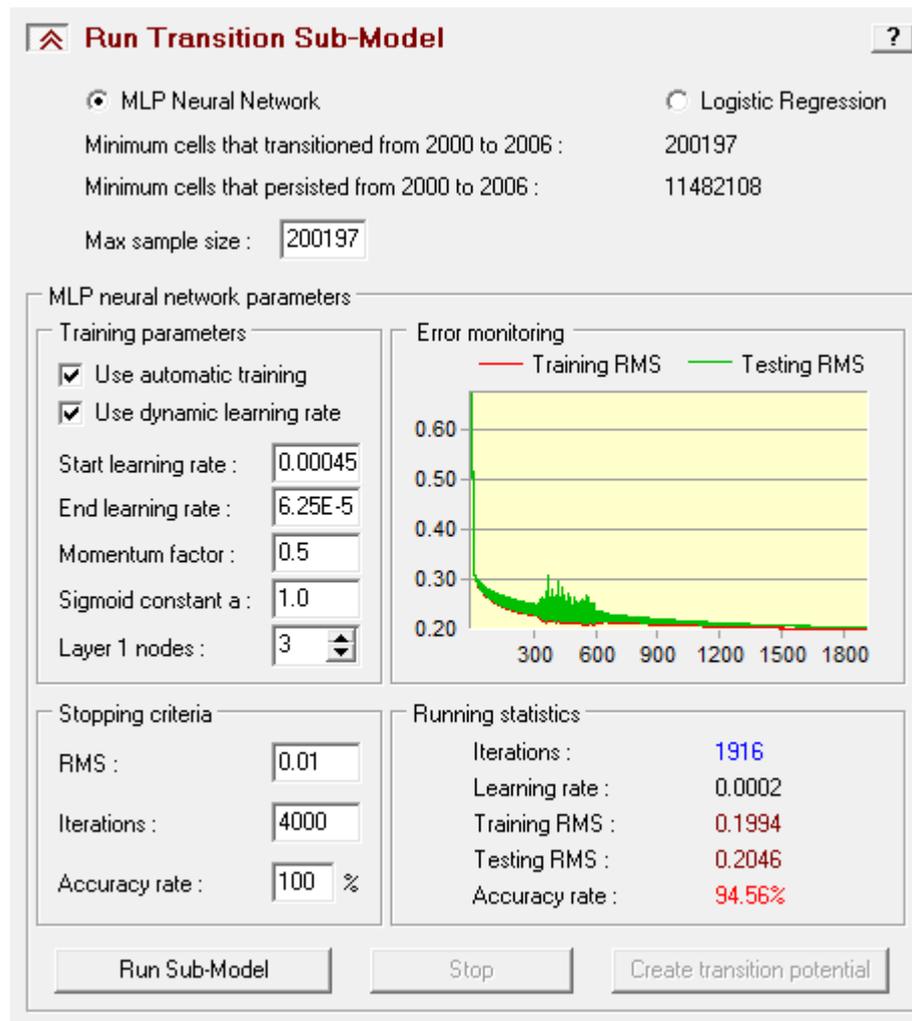


Figure 27. MLP Neural Network Sub Model.

The outcome of the model is a transition potential map for transition from forest to disturbance (see Figure 28). Each pixel on this map contains the probability value (from 0 to 1) of changing from forest to anthropogenic disturbance. It is evident that those location that are closer to roads and closer to already deforested areas, or both, have more likelihood of experience transition.

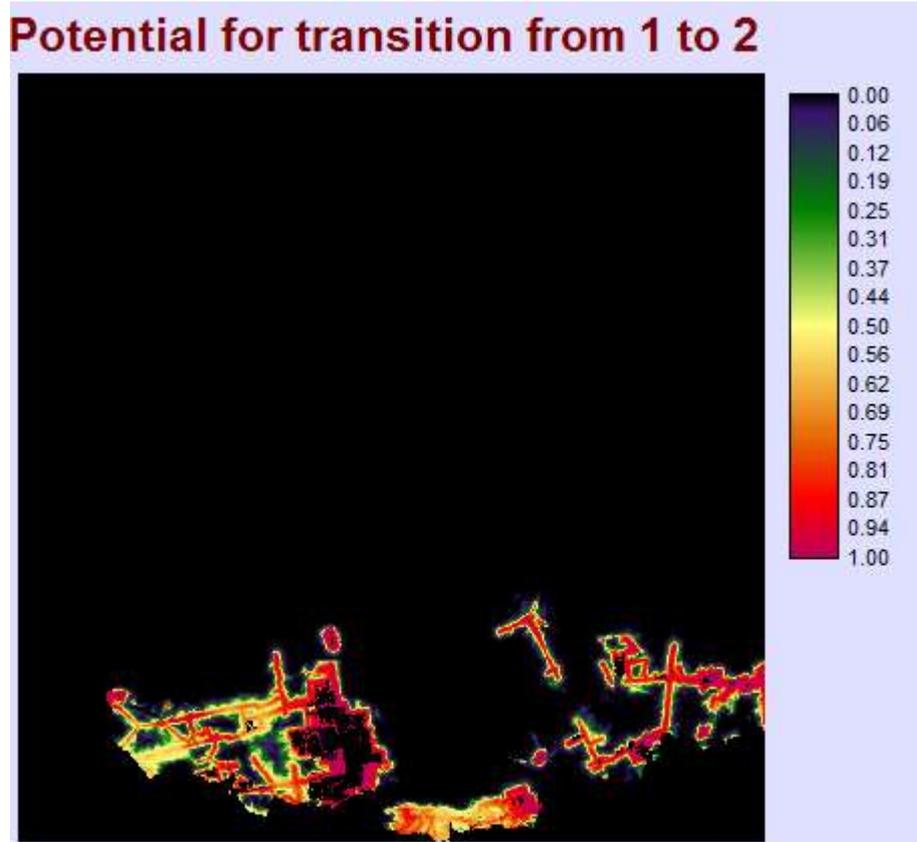


Figure 28. Transition potential from forest to anthropogenic disturbance

4.4 Model Validation

After the transition potential were calculated with the MLP, in order to validate the model a Markov chain analysis was used to predict the quantity of change in 2009 and then compared to an actual 2009 land cover map. LCM provides two basic models of prediction: a hard prediction model and a soft prediction model. The hard prediction model is based on a competitive land allocation model and the result is a specific scenario, a land cover map with the same categories as the inputs (Eastman, 2009). In contrast, the soft prediction creates a continuous map of vulnerability to change from forest to disturbance, it does not implies that will actually change, but rather, the degree in which the areas comply with the correct conditions to change (Eastman, 2009).

Once the prediction year is given, two recalculation stages were assigned to specify the frequency with which dynamic explanatory variables were to be recalculated. This means,

that for both, *distance from roads* and *distance from disturbance* variables, distance values were updated in the model every 1.5 years. Also, at each stage both static and dynamic explanatory variables are re-submitted to the MLP to calculate a new transition potential. The change predicted at each stage is in proportion to the number of defined stages.

Figure 29 shows the map of the 2009 hard prediction and the actual land cover in 2009. A quick visual inspection shows that, in general, both land cover maps are very similar to each other. However, the predicted quantity of change is greater than it really was in 2009. In addition, closer analysis shows that there are localized discrepancies, for example, the middle bottom of the image, the model fail to predict disturbance.

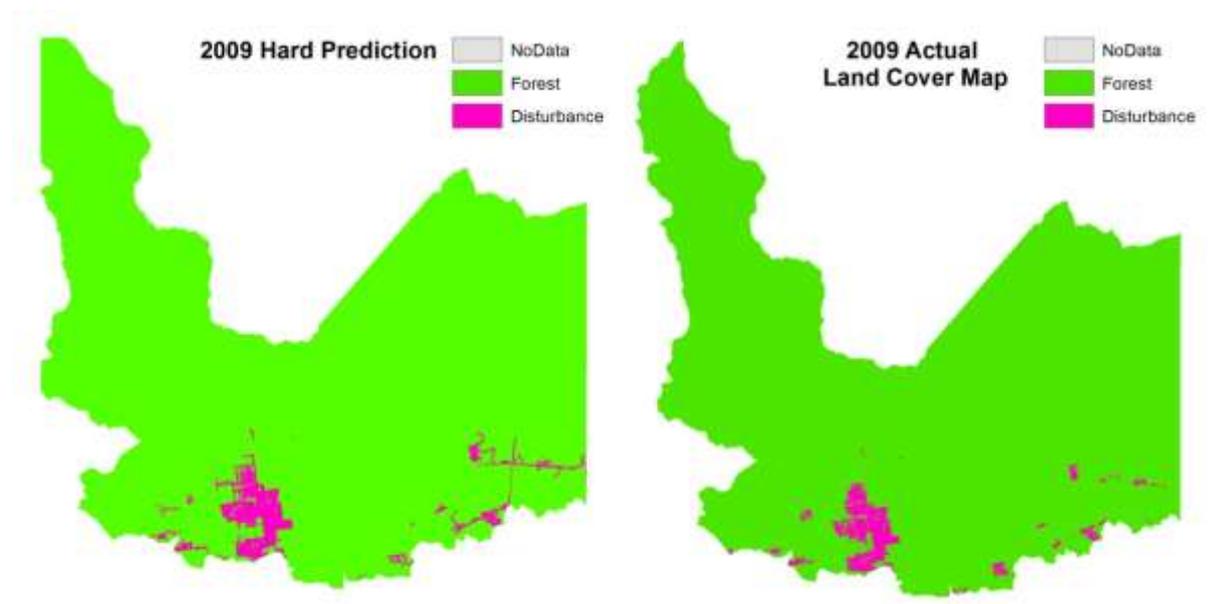


Figure 29. Hard prediction of Kayabi forest condition in 2009 and actual 2009 land cover map.

As seen in Figure 29, there are two types of disagreements in the prediction, those that relate to the quantity and those that relate to the location of the prediction. In order quantitatively assess the hard prediction; the LCM *Validate* function was used. This tool uses a three-way cross-tabulation between the later land cover map (2006), the hard prediction map and the reality map (Eastman, 2009). Figure 30 shows the resulting map of the validate function.

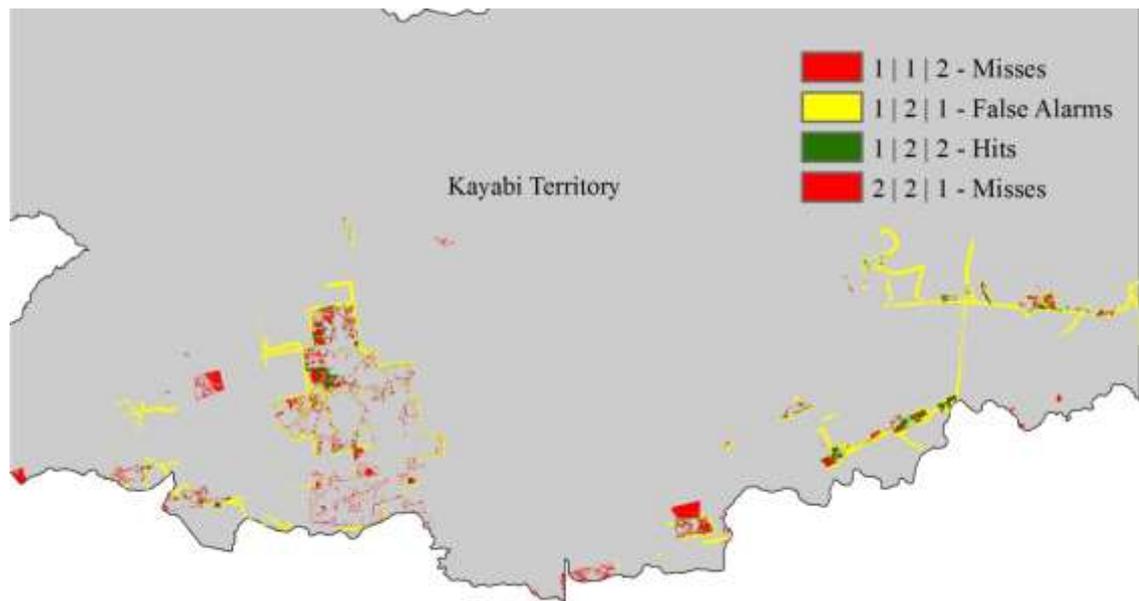


Figure 30. Validation map: *hits*, *false alarms* and *misses*

In the validation map above, the cases where the predictions are correct are called *hits* and shown in green, while change was predicted but in reality they did not are called *false alarms* and shown in yellow. Finally, the ones that where it was predicted change but in reality transitioned are called *misses*. Correct rejections are those cases where there wasn't prediction nor change (the majority of the map, in grey).

IDRISI's *Validate* module provides a method to assess and quantify agreement between two categorical images, a 'comparison' map and a 'reference map' (Clark Labs, 2011). In this case, the 'comparison' map is the simulated 2009 land cover map and the reference image is real 2009 land cover map. It offers a comprehensive statistical analysis that provide an assessments of how well do a pair of images agree in terms of the quantity of cells and how well do a pair of images agree in thermos of the location of the cells for each category (Clark Labs, 2011). Appendix 3 provides the technical description of the *Validate* module.

The result of the *Validate* module is shown in Figure 31. The percentage of correct rows, a100% for the case of the 2009 simulation, indicates that the prediction was perfect. However, this value does not seem to accord well with what is observed in Figure 30. The main reason for this result is that the validate module evaluates agreement for the entire

map, not only for class transitions, and because of the great majority of cells classified as *forest* persisted and did not change to *disturbance* a high agreement was found between the two maps.

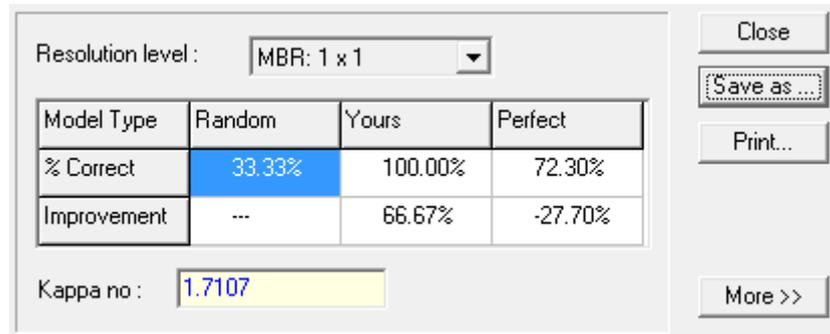


Figure 31. Validation results

The hard prediction is only a single realization of future scenario chosen from many equally plausible scenarios (Eastman, 2009). Thus, whenever there are more eligible areas for transitioning than the actual amount of change, it is very difficult to achieve an accurate hard prediction. However, the soft prediction is a comprehensive assessment of change that identifies vulnerability to change, and the predictions provide a more meaningful map because it identifies the areas that are more vulnerable to change as shown in Figure 32.

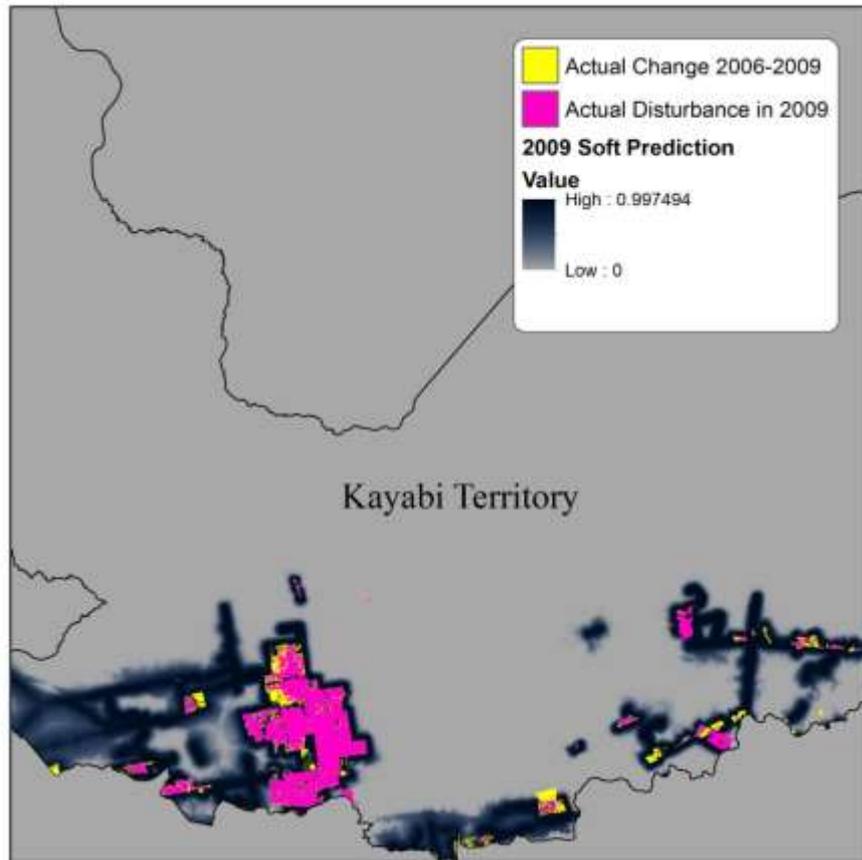


Figure 32. 2009 Soft prediction

In contrast to the hard prediction, in the soft prediction map most of the areas that had actual change in 2009 are considered to be vulnerable. In order to make a quantitative assessment of the soft prediction, a receiver operating characteristic (ROC) was used. The ROC statistic determines how well a continuous surface predicts the locations given a distribution of a Boolean variable (Eastman, 2009). In this case the soft prediction was used as the continuous surface to evaluate against the real change between 2006 and 2009. The result of the ROC statistic thrown a value of 0.987, which is a very strong value, indicating the soft prediction was very good (see Appendix 4 for more detailed results). In contrast to the validation for the hard prediction, the ROC statistic provides a real assessment of the performance of the model, as it can be observed in Figure 32. Most of the locations where change happened are mapped within the range of the soft prediction. There are only four groups of cells which transitioned from *forest* to *disturbance* that are not within the soft

prediction. However, three of them are isolated groups that are not located close to roads or previous disturbance. These developments were impossible to predict. The soft prediction was overall successful and has produced a map vulnerability to change from forest to disturbance in the Kayabi Territory.

4.5 Prediction of Kayabi Territory forest condition in 2020

Once the model was validated, both hard and soft predictions were carried out for the year 2020 in order to map possible transitions from *forest* to *disturbance* in the Kayabi Territory. Although the model was validated, it is important to have in mind, that for obvious reasons, short-term predictions are more accurate than long term predictions (Hayelom, 2009). Figure 33 shows the predicted landscape in 2020. It is important to mention that, similarly to 2009 hard prediction used to validate the model, this prediction is only a single realization of infinite number of possible spatial configurations, and that must be interpreted with care. However, the resulting 2020 prediction indicate that there will be significant changes in the future.

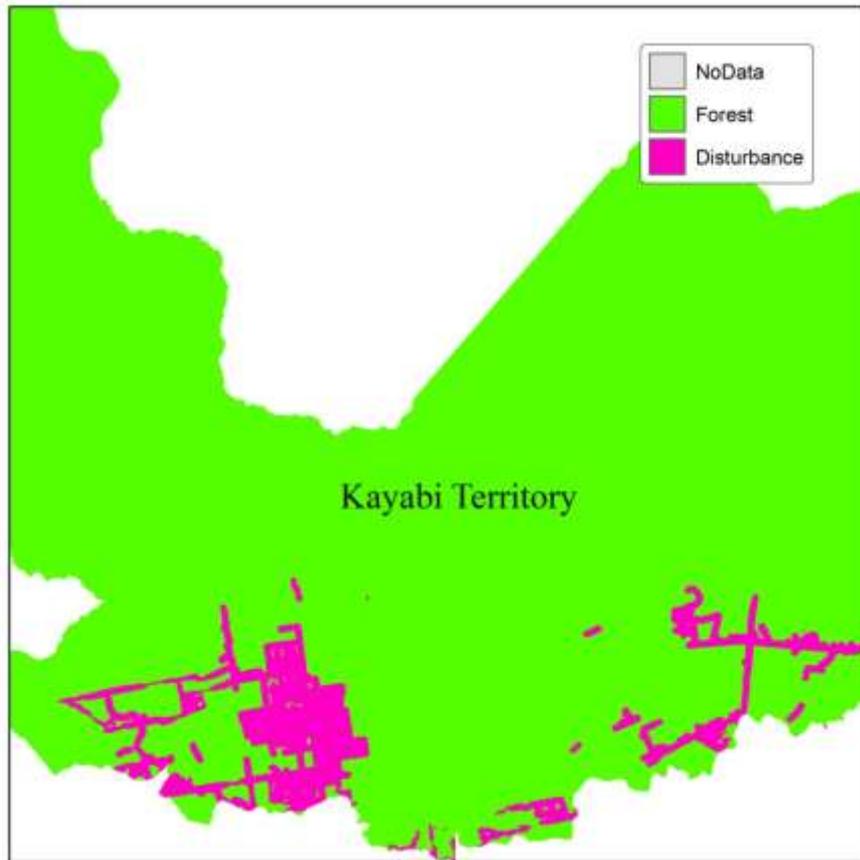


Figure 33. 2020 Hard Prediction Map

The 2020 soft prediction, shown in Figure 34, maps the vulnerability of forest areas to change into anthropogenic disturbance. Since both, the 2009 and the 2020 soft predictions, were derived from the same model, both are quite similar to each other but the 2020 soft prediction have higher values of vulnerability as it gets closed to roads and disturbance, this is due to the dynamic recalculation stages during the simulation.

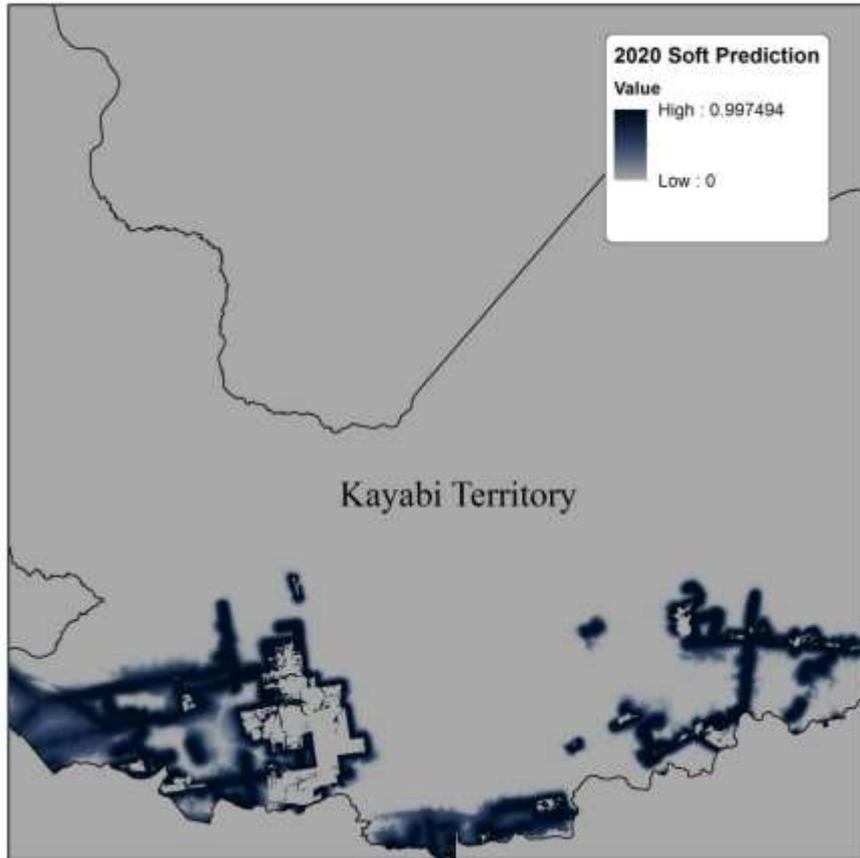


Figure 34. 2020 Soft Prediction Map

5. Discussion and Conclusions

The purpose of the previous chapter was to present the simulation of future land cover in the Kayabi Territory for 2020. To carry out this simulation, transition potentials of land cover from forest to anthropogenic disturbance were modelled using a MLP neural network approach and using explanatory variables to train the model. A Markovian process was used to predict the future land cover. Two simulations were carried out. The first (2009) allowed the model to be validated, and the second (2020) was used to predict landscape change in the Kayabi Territory.

The results of the prediction of landscape change in Kayabi Territory for 2020 indicate that by the year 2020, assuming the nature of forest development does not change, an additional 36,000 hectares of forest will be lost in the Kayabi Territory, making a total of 60,645 hectares for the period 2000-2020 (see Table 5).

Table 5. Time Analysis of forest lost in Kayabi Territory

Year	Forest Lost (ha)
2000	1,776
2006	18,018
2009	5,040
2020	35,811
Total	60,645

When comparing to reality, the predicted amount of the deforestation seems a bit too high. This can be explained, as the model uses the deforestation rate calculated to train the model. According to the change analysis 16,242 hectares were lost in six years (2000-2006), resulting an average deforestation rate of 2,707 hectares per year. If this rate is extrapolated to 20 year period, it gives a total of 54,140 hectares lost. The latter figure is consistent with the 60,645 hectares of lost forest predicted in the Kayabi Territory in 2020.

The history of analysis, however, reveals that the rates of deforestation increased from 2002 to 2004 due to the land owners' decision of developing their land and then decreased again

in 2006 because of the legal injunction process. Such events are very difficult to incorporate into the model. Nevertheless, when comparing the figures in a ten year period, analysis shows that almost 25,000 hectares of forest were lost between 2000 and 2010, the simulation predicted that an additional 36,000 hectares would be deforested, making the long term amount although still high, more reasonable. This surpassing difference (almost 10,000 hectares more for the 10 year period) is believed to be the response of the model to the "invasive forest mobility theory" meaning the more deforested areas, the more deforestation rates, in other words, deforestation leads to further deforestation.

Figure 35 shows a time series analysis of land cover maps of the Kayabi Territory, the observed pattern seems to be consistent with the hypothesis that roads and previous disturbance are the main drivers for deforestation. Moreover, the analysis confirmed that new disturbed areas serve as seeds for a more intense clearing activity in the future.

If close visual analysis is made to Figure 35, it can be observed that apparently isolated areas in 2006 are now bigger and more developed in 2009. Despite the limitations of the 2020 prediction hard prediction, the simulated landscape appears to be consistent with what has been observed in reality, for instance, the majority of the new deforested areas are close to roads and previous deforestation.

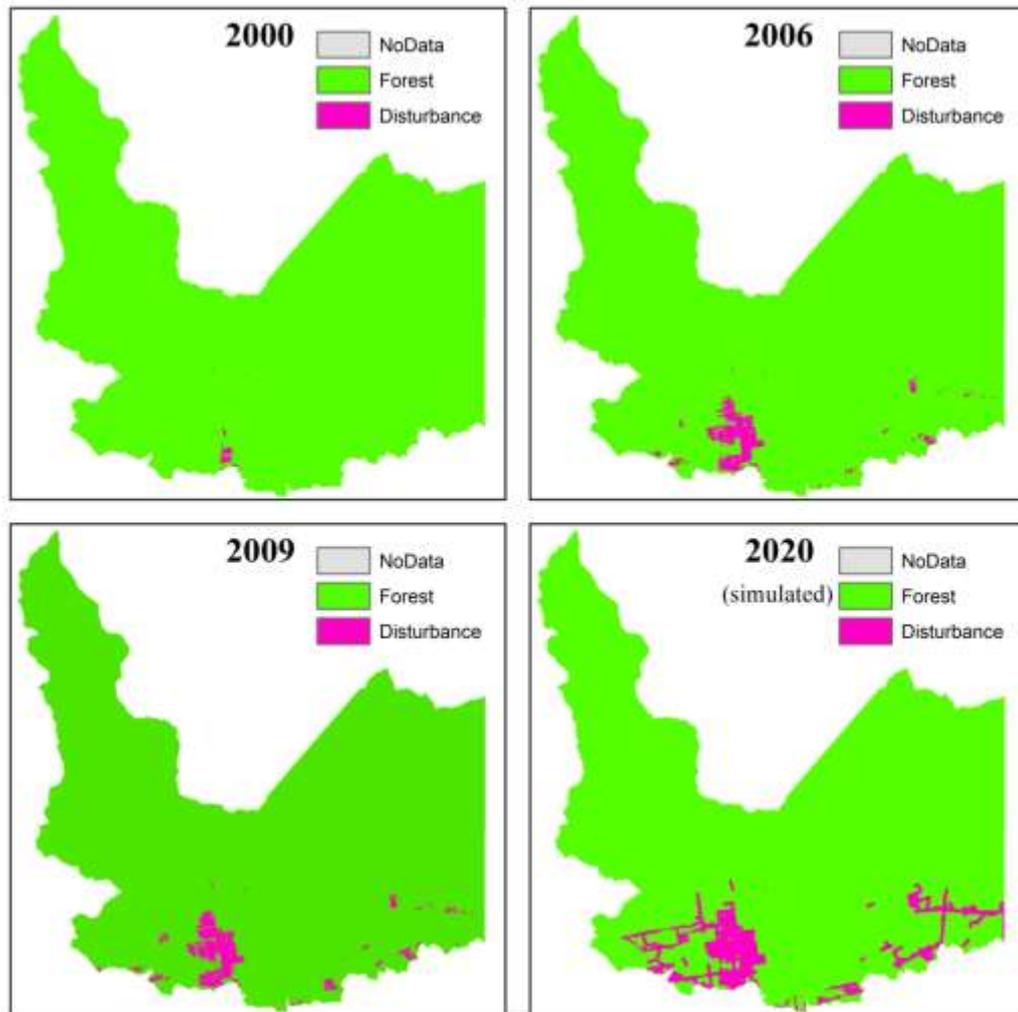


Figure 35. Time series Analysis of deforestation in Kayabi Territory

Based on visual interpretation of the simulation and the ROC criterion, it can be said that the soft predictions were produced with a satisfactory level of accuracy. Figure 36 shows the 2020 soft prediction overlaid on a 2011 Landsat image (25/07/2011), a visual analysis, shows that disturbed areas post 2009 are considered within the vulnerability range.

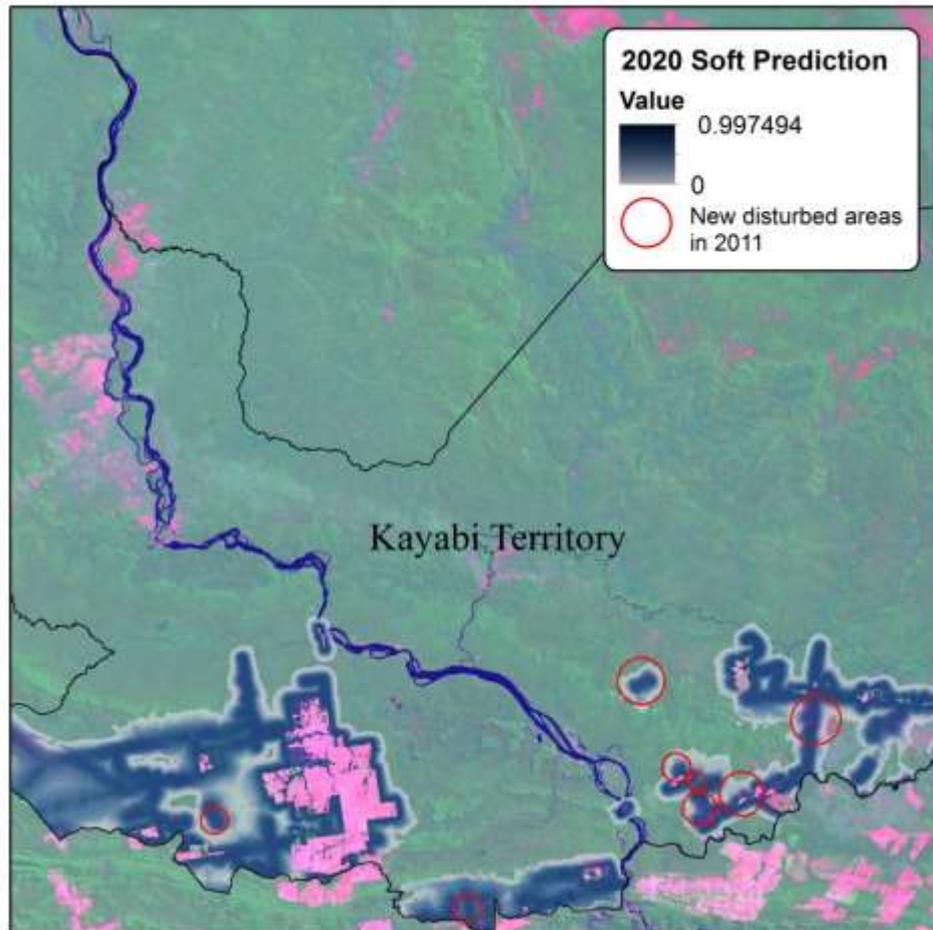


Figure 36. The 2020 soft prediction overlaid on a 2011 Landsat

The soft prediction map is very useful to understand the trend of the change in the future. Therefore it is a very valuable map for monitoring and searching for new disturbed areas within the Kayabi Territory.

5.1 Limitations

All models are a simplification of the real world; these simplifications are potential sources of error. For instance, the simulation outcomes might be affected by a number of factors, such as accuracy of image classification, registration between images, filtering processes and data aggregation.

It is important to mention, that the current version (used in this study) of LCM is experimental and most of the procedures incorporated are new and have not been widely tested, therefore these can be extended and improved in the future.

5.1.1 Human factors that affect prediction

As mentioned in Chapter 1, the deforestation history of the Kayabi Territory is very complex. The demarcation process as an indigenous territory started in 2002 but was suspended in 2004, due to land ownership disputes. Within this period, the deforestation rates increased dramatically, and it is believed this was directly related to the uncertainty of land tenure by land owners, who decided to deforest their properties before the case reached a final resolution. This is an excellent example of how some human factors are very difficult to predict in a model, and proves that the past is not always a good indicator of the future (Eastman, 2009).

5.1.2 Modifiable Areal Unit Problem.

“Geographical space can be divided in an infinite number of ways” (Lloyd, 2010, p. 61). In practice, when working on aggregated data these divisions are a potential source of error when statistical analyses on aggregated data are carried out. This problem is known as the “modifiable areal unit problem” (MAUP), and it is sub-divided in two parts. The first relates to the chosen scale for work (*scale effect*) as different results are produced over different areas of different size, and the second relates to the how the extent is divided (*zoning effect*), areas with similar size but different forms may affect the results on statistical analyses.

The predictions in study, as almost any spatial analysis, are subject to the MAUP. The land cover maps used for the simulations only cover the Kayabi Territory. However, important patterns of deforestation are happening south of the Kayabi Area, in Mato Grosso State, related to the ‘arc of deforestation’. These patterns might have effect on the training of the model, as well as in the calculated deforestation rates. These deforested areas were not

included for three main reasons. Firstly, the Kayabi Territory was used in order to have a consistent spatial extent that could be easily defined and used for future studies. Secondly, because of data availability, as an SPOT 5 scene is smaller than a Landsat scene, the 2009 SPOT 5 images used for validation purposes do not cover completely the south area below the Kayabi Territory. In addition, the *road* layer (used to create the *distance from roads* layer) did not cover the southern part from Kayabi Territory. Finally, a smaller extent was preferred in order to improve computation time.

5.2 Conclusions

The Brazilian Amazon has been subject to continuous deforestation and land use change and expansion having major environmental impacts at a global and local scale. Indigenous Territories serve as defence against the expansion of the ‘arc of deforestation’; therefore it is very important to create conditions for indigenous peoples to implement their own territorial management according to their customs.

CLASlite software has proven to be an excellent tool to provide highly detailed maps that can be used to detect deforestation, logging and other forest disturbance events by analysing tropical forest structure with fractional cover images of photosynthetic vegetation, non photosynthetic vegetation, and bare surfaces. Fractional cover analysis in CLASlite, makes it a powerful tool that allows rapid forest monitoring with error tracking (Carnegie Institution for Science, 2009).

LUCM modelling is an effective mean for adequate land use planning and the development of sustainable environmental management policies. GIS, remote sensing and modelling software are ideal tools to accomplish these tasks.

This study was able to successfully simulate future deforestation expansion in the region and also, identified the main landscape attributes driving deforestation expansion in the Kayabi Territory. Distance from roads and distance from existing disturbance were found as the key

factors driving deforestation. Nevertheless, other important aspects have great impact on LUCC. For instance, despite the demarcation of the Kayabi Territory intended conservation of the forest it seems that, far from its purpose of protecting it, it increased the deforestation rates because the uncertainty to the land owners of their land tenure. The colonization project in the 80's was effectively what brought deforestation in Kayabi Territory (see Figure 6), single farmers were the most active actors in the deforestation process. However, selective logging activities were found to happen in the territory, it is believed that these activities are product of 'opportunistic' land grabbers and loggers that seize existing roads (and develop new ones) to gain access to forest resources. The soft prediction maps simulated in this study provide excellent means for monitoring areas where selective logged has happened and therefore to protect new areas that are susceptible to be disturbed.

5.3 Future improvements of the model

This study did not use all available functionality of LCM, there are several tools that were not utilized in this study but might improve the model results. For example, the *planned infrastructure changes* tool in the *Planning* tab can be used to specify future infrastructure changes, such as major road development, and the date that they become effective. In addition, LCM is capable to model and predict how roads might develop in the future; this tool is especially useful for monitoring selective logging.

Also, the *constraints and incentive* tool in the *Planning* tab allows the user to specify an incentive or a constraint map for each of the transitions in the model. This tool can be used to model 'what if' scenarios, for instance, in one hand, it could be used to model how deforestation would decrease if the Kayabi Territory was actually recognized and declared as an indigenous territory. It could also be used to determine how much deforestation would increase if the protected status was denied.

In additional to modelling transition from forest to anthropogenic disturbance, vegetation re-growth could be model in order to assess forest recovery.

5.4 Summary

Nowadays, there is general agreement that land use and land cover change (LUCC) processes are causing significant environmental impacts at global and local scales. In this context, this dissertation has made contributions of two kinds: First, it provides evidence that models help to improve understanding of the dynamics of LUCC processes and that they are a very important tool to simulate and qualitatively predict future land change. Second, it provides an invaluable tool for monitoring existing and future change in the Kayabi Indigenous Territory, thus, helping the Kayabi people to protect its forest from further deforestation.

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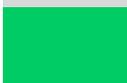
Appendix I – Northern Mato Grosso Land Ownership Map (MANDADO DE SEGURANÇA N° 8.873 - DF, 2003)



Appendix II –Characteristics and technical details of the used data

LCM uses data in IDRISI raster (.rst) and IDRISI vector (.vct) format. In order for LCM to function properly, data must be prepared with or without NoData values. In addition, it is necessary that all different year land cover maps have the exact same class number and label. For this reason ArcGIS 10 was utilized to assign the same colour map, class number and label to 2000, 2006 and 2009 land cover maps. As ArcGIS assigns extremely large NoData values, e.g. +/-3.4028235e+038, as background, missing data, or NoData, the ArcGIS reclassify tool was used to change the NoData to 0. Table 1 shows the number, class and colour assigned to the land cover maps.

Table 1. Class number, Label and Colour assigned to Land Cover Maps

Class Number	Label	Colour
0	NoData	
1	Forest	
2	Disturbance	

Land cover maps were exported as .img format and then imported in IDRISI to convert to .rst format. Table 2 shows the technical details of the used data.

Table 2. Class number, Label and Colour assigned to Land Cover Maps

Input	Technical Details
Earlier Land Cover Map (2000)	8 bit
Later Land Cover Map (2006)	8 bit
Land Cover Map for validation (2009)	8 bit
Distance from roads	32 bit
Distance from previous deforestation	32 bit
Distance from streams	32 bit
Elevation (DEM)	32 bit
Slope model	32 bit

Appendix III –Result of Idrisi’s Validate module applied to the 2009 hard

prediction map

```

Number of total runs      :      1
Multi-resolution VALIDATE :      Categorical Image Comparison
=====
Comparison image file    :      landcov_predict_2009
Reference image file     :      Dist_09_8bit
Strata/Mask image file   :      N/A

Number of valid strata:   1;  Number of valid categories:   3

//Beginning of run:      1
Resolution scale:       1 x 1
    
```

Classification agreement/disagreement
According to ability to specify accurately quantity and location

Information of Quantity			
Information of Location No[n]	Medium[m]		Perfect [p]
Perfect[P(x)]	P(n) = 0.3340	P(m) = 1.0000	P(p) = 0.7230
PerfectStratum[K(x)]	K(n) = 0.3340	K(m) = 1.0000	K(p) = 0.7230
MediumGrid[M(x)]	M(n) = 0.3340	M(m) = 1.0000	M(p) = 0.7230
MediumStratum[H(x)]	H(n) = 0.3333	H(m) = 0.7219	H(p) = 0.7219
No[N(x)]	N(n) = 0.3333	N(m) = 0.7219	N(p) = 0.7219

```

AgreementChance = 0.3333
AgreementQuantity = 0.3886
AgreementStrata = 0.0000
AgreementGridcell = 0.2781
DisagreeGridcell = 0.0000
DisagreeStrata = 0.0000
DisagreeQuantity = -0.2770

Kno = 1.7107
Klocation = 1.0000
KlocationStrata = 1.0000
Kstandard = 254.6257

//Ending of run:      1
    
```

Appendix IV –Result of ROC statistic for 2009 soft prediction map

Result of ROC**

=====

ROC = 0.987

 The following section list detailed statistics for each threshold.

With each threshold, the following 2x2 contingency table is calculated

		Reality (reference image)	
		1	0
Simulated by threshold	1	A(number of cells)	B(number of cells)
	0	C	D
For the given reference image:		A+C=56003	B+D=23168297

No.	Exp. Thrhlds(%)	Act. Thrhlds(%)	Act. raw cuts	A	True posi.(%)	B	False posi.(%)
1	0.0000	0.0000	0.0000	0	0.0000	0	0.0000
2	1.0000	1.0000	0.9742	33591	59.9807	198653	0.8574
3	2.0000	2.0000	0.9065	45637	81.4903	418849	1.8079
4	3.0000	3.0000	0.7618	49469	88.3328	647260	2.7937
5	4.0000	4.0000	0.5689	51221	91.4612	877751	3.7886
6	5.0000	5.0000	0.3245	52673	94.0539	1108542	4.7847
7	6.0000	6.0000	0.0996	54116	96.6305	1339342	5.7809
8	7.0000	7.0000	0.0151	55245	98.6465	1570456	6.7785
9	8.0000	8.0000	0.0014	55647	99.3643	1802297	7.7792
10	9.0000	9.0000	0.0001	55682	99.4268	2034505	8.7814
11	10.0000	10.0000	0.0000	55689	99.4393	2266741	9.7838
12	11.0000	11.0000	0.0000	55699	99.4572	2498974	10.7862
13	12.0000	12.0000	0.0000	55709	99.4750	2731207	11.7886
14	13.0000	13.0000	0.0000	55709	99.4750	2963450	12.7910
15	14.0000	14.0000	0.0000	55709	99.4750	3195693	13.7934
16	15.0000	15.0000	0.0000	55709	99.4750	3427936	14.7958
17	16.0000	16.0000	0.0000	55709	99.4750	3660180	15.7982
18	17.0000	17.0000	0.0000	55782	99.6054	3892350	16.8003
19	18.0000	18.0000	0.0000	55978	99.9554	4124397	17.8019
20	19.0000	19.0000	0.0000	56003	100.0000	4356615	18.8042
21	20.0000	20.0000	0.0000	56003	100.0000	4588858	19.8066
22	21.0000	21.0000	0.0000	56003	100.0000	4821101	20.8090
23	22.0000	22.0000	0.0000	56003	100.0000	5053344	21.8115
24	23.0000	23.0000	0.0000	56003	100.0000	5285587	22.8139
25	24.0000	24.0000	0.0000	56003	100.0000	5517830	23.8163
26	25.0000	25.0000	0.0000	56003	100.0000	5750073	24.8187
27	26.0000	26.0000	0.0000	56003	100.0000	5982316	25.8211
28	27.0000	27.0000	0.0000	56003	100.0000	6214559	26.8235
29	28.0000	28.0000	0.0000	56003	100.0000	6446802	27.8260
30	29.0000	29.0000	0.0000	56003	100.0000	6679045	28.8284
31	30.0000	30.0000	0.0000	56003	100.0000	6911288	29.8308
32	31.0000	31.0000	0.0000	56003	100.0000	7143531	30.8332
33	32.0000	32.0000	0.0000	56003	100.0000	7375774	31.8356
34	33.0000	33.0000	0.0000	56003	100.0000	7608017	32.8381
35	34.0000	34.0000	0.0000	56003	100.0000	7840260	33.8405
36	35.0000	35.0000	0.0000	56003	100.0000	8072503	34.8429
37	36.0000	36.0000	0.0000	56003	100.0000	8304746	35.8453
38	37.0000	37.0000	0.0000	56003	100.0000	8536989	36.8477
39	38.0000	38.0000	0.0000	56003	100.0000	8769232	37.8501
40	39.0000	39.0000	0.0000	56003	100.0000	9001475	38.8526
41	40.0000	40.0000	0.0000	56003	100.0000	9233718	39.8550
42	41.0000	41.0000	0.0000	56003	100.0000	9465961	40.8574
43	42.0000	42.0000	0.0000	56003	100.0000	9698204	41.8598
44	43.0000	43.0000	0.0000	56003	100.0000	9930447	42.8622
45	44.0000	44.0000	0.0000	56003	100.0000	10162690	43.8646
46	45.0000	45.0000	0.0000	56003	100.0000	10394933	44.8671
47	46.0000	46.0000	0.0000	56003	100.0000	10627176	45.8695
48	47.0000	47.0000	0.0000	56003	100.0000	10859419	46.8719
49	48.0000	48.0000	0.0000	56003	100.0000	11091662	47.8743
50	49.0000	49.0000	0.0000	56003	100.0000	11323905	48.8767
51	50.0000	50.0000	0.0000	56003	100.0000	11556148	49.8791
52	51.0000	51.0000	0.0000	56003	100.0000	11788391	50.8816
53	52.0000	52.0000	0.0000	56003	100.0000	12020634	51.8840
54	53.0000	53.0000	0.0000	56003	100.0000	12252877	52.8864
55	54.0000	54.0000	0.0000	56003	100.0000	12485120	53.8888
56	55.0000	55.0000	0.0000	56003	100.0000	12717363	54.8912
57	56.0000	56.0000	0.0000	56003	100.0000	12949606	55.8936
58	57.0000	57.0000	0.0000	56003	100.0000	13181849	56.8961
59	58.0000	58.0000	0.0000	56003	100.0000	13414092	57.8985
60	59.0000	59.0000	0.0000	56003	100.0000	13646335	58.9009
61	60.0000	60.0000	0.0000	56003	100.0000	13878578	59.9033
62	61.0000	61.0000	0.0000	56003	100.0000	14110821	60.9057
63	62.0000	62.0000	0.0000	56003	100.0000	14343064	61.9081

64	63.0000	63.0000	0.0000	56003	100.0000	14575307	62.9106
65	64.0000	64.0000	0.0000	56003	100.0000	14807550	63.9130
66	65.0000	65.0000	0.0000	56003	100.0000	15039793	64.9154
67	66.0000	66.0000	0.0000	56003	100.0000	15272036	65.9178
68	67.0000	67.0000	0.0000	56003	100.0000	15504279	66.9202
69	68.0000	68.0000	0.0000	56003	100.0000	15736522	67.9227
70	69.0000	69.0000	0.0000	56003	100.0000	15968765	68.9251
71	70.0000	70.0000	0.0000	56003	100.0000	16201008	69.9275
72	71.0000	71.0000	0.0000	56003	100.0000	16433251	70.9299
73	72.0000	72.0000	0.0000	56003	100.0000	16665494	71.9323
74	73.0000	73.0000	0.0000	56003	100.0000	16897737	72.9347
75	74.0000	74.0000	0.0000	56003	100.0000	17129980	73.9372
76	75.0000	75.0000	0.0000	56003	100.0000	17362223	74.9396
77	76.0000	76.0000	0.0000	56003	100.0000	17594466	75.9420
78	77.0000	77.0000	0.0000	56003	100.0000	17826709	76.9444
79	78.0000	78.0000	0.0000	56003	100.0000	18058952	77.9468
80	79.0000	79.0000	0.0000	56003	100.0000	18291195	78.9492
81	80.0000	80.0000	0.0000	56003	100.0000	18523438	79.9517
82	81.0000	81.0000	0.0000	56003	100.0000	18755681	80.9541
83	82.0000	82.0000	0.0000	56003	100.0000	18987924	81.9565
84	83.0000	83.0000	0.0000	56003	100.0000	19220167	82.9589
85	84.0000	84.0000	0.0000	56003	100.0000	19452410	83.9613
86	85.0000	85.0000	0.0000	56003	100.0000	19684653	84.9637
87	86.0000	86.0000	0.0000	56003	100.0000	19916896	85.9662
88	87.0000	87.0000	0.0000	56003	100.0000	20149139	86.9686
89	88.0000	88.0000	0.0000	56003	100.0000	20381382	87.9710
90	89.0000	89.0000	0.0000	56003	100.0000	20613625	88.9734
91	90.0000	90.0000	0.0000	56003	100.0000	20845868	89.9758
92	91.0000	91.0000	0.0000	56003	100.0000	21078111	90.9782
93	92.0000	92.0000	0.0000	56003	100.0000	21310354	91.9807
94	93.0000	93.0000	0.0000	56003	100.0000	21542597	92.9831
95	94.0000	94.0000	0.0000	56003	100.0000	21774840	93.9855
96	95.0000	95.0000	0.0000	56003	100.0000	22007083	94.9879
97	96.0000	96.0000	0.0000	56003	100.0000	22239326	95.9903
98	97.0000	97.0000	0.0000	56003	100.0000	22471569	96.9928
99	98.0000	98.0000	0.0000	56003	100.0000	22703812	97.9952
100	99.0000	99.0000	0.0000	56003	100.0000	22936055	98.9976
101	100.0000	100.0000	0.0000	56003	100.0000	23168297	100.0000

** For the given reference image, the following seven statistics are the same for all thresholds. The unit of each statistic is the proportion correct attributable to a combination of information of location and quantity.

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No info of location and no info of quantity: N(n) = 0.5000
Perfect info of location and perfect info of quantity: P(p) = 1.0000
Perfect info of location and no info of quantity: P(n) = 0.5024
No info of location and perfect info of quantity: N(p) = 0.9952

No info of location and no info of quantity: PerfectChance = 0.5000
No info of location and perfect info of quantity: PerfectQuantity = 0.4952
Perfect info of location given no info of quantity: PerfectLocation = 0.0048

No.	M(m)	N(m)	P(m)	M(p)	M(n)
1	0.9976	0.9976	0.9976	0.9952	0.5000
2	0.9905	0.9876	0.9924	0.9981	0.5014
3	0.9815	0.9777	0.9824	0.9991	0.5020
4	0.9718	0.9677	0.9724	0.9994	0.5021
5	0.9620	0.9578	0.9624	0.9996	0.5022
6	0.9521	0.9478	0.9524	0.9997	0.5023
7	0.9422	0.9379	0.9424	0.9998	0.5023
8	0.9323	0.9279	0.9324	0.9999	0.5024
9	0.9224	0.9180	0.9224	1.0000	0.5024
10	0.9124	0.9080	0.9124	1.0000	0.5024
11	0.9024	0.8981	0.9024	1.0000	0.5024
12	0.8924	0.8881	0.8924	1.0000	0.5024
13	0.8824	0.8782	0.8824	1.0000	0.5024
14	0.8724	0.8682	0.8724	1.0000	0.5024
15	0.8624	0.8583	0.8624	1.0000	0.5024
16	0.8524	0.8483	0.8524	1.0000	0.5024
17	0.8424	0.8384	0.8424	1.0000	0.5024
18	0.8324	0.8284	0.8324	1.0000	0.5024
19	0.8224	0.8185	0.8224	1.0000	0.5024
20	0.8124	0.8085	0.8124	1.0000	0.5024
21	0.8024	0.7986	0.8024	1.0000	0.5024
22	0.7924	0.7886	0.7924	1.0000	0.5024
23	0.7824	0.7786	0.7824	1.0000	0.5024
24	0.7724	0.7687	0.7724	1.0000	0.5024
25	0.7624	0.7587	0.7624	1.0000	0.5024

26	0.7524	0.7488	0.7524	1.0000	0.5024
27	0.7424	0.7388	0.7424	1.0000	0.5024
28	0.7324	0.7289	0.7324	1.0000	0.5024
29	0.7224	0.7189	0.7224	1.0000	0.5024
30	0.7124	0.7090	0.7124	1.0000	0.5024
31	0.7024	0.6990	0.7024	1.0000	0.5024
32	0.6924	0.6891	0.6924	1.0000	0.5024
33	0.6824	0.6791	0.6824	1.0000	0.5024
34	0.6724	0.6692	0.6724	1.0000	0.5024
35	0.6624	0.6592	0.6624	1.0000	0.5024
36	0.6524	0.6493	0.6524	1.0000	0.5024
37	0.6424	0.6393	0.6424	1.0000	0.5024
38	0.6324	0.6294	0.6324	1.0000	0.5024
39	0.6224	0.6194	0.6224	1.0000	0.5024
40	0.6124	0.6095	0.6124	1.0000	0.5024
41	0.6024	0.5995	0.6024	1.0000	0.5024
42	0.5924	0.5896	0.5924	1.0000	0.5024
43	0.5824	0.5796	0.5824	1.0000	0.5024
44	0.5724	0.5697	0.5724	1.0000	0.5024
45	0.5624	0.5597	0.5624	1.0000	0.5024
46	0.5524	0.5498	0.5524	1.0000	0.5024
47	0.5424	0.5398	0.5424	1.0000	0.5024
48	0.5324	0.5299	0.5324	1.0000	0.5024
49	0.5224	0.5199	0.5224	1.0000	0.5024
50	0.5124	0.5100	0.5124	1.0000	0.5024
51	0.5024	0.5000	0.5024	1.0000	0.5024
52	0.4924	0.4900	0.4924	1.0000	0.5024
53	0.4824	0.4801	0.4824	1.0000	0.5024
54	0.4724	0.4701	0.4724	1.0000	0.5024
55	0.4624	0.4602	0.4624	1.0000	0.5024
56	0.4524	0.4502	0.4524	1.0000	0.5024
57	0.4424	0.4403	0.4424	1.0000	0.5024
58	0.4324	0.4303	0.4324	1.0000	0.5024
59	0.4224	0.4204	0.4224	1.0000	0.5024
60	0.4124	0.4104	0.4124	1.0000	0.5024
61	0.4024	0.4005	0.4024	1.0000	0.5024
62	0.3924	0.3905	0.3924	1.0000	0.5024
63	0.3824	0.3806	0.3824	1.0000	0.5024
64	0.3724	0.3706	0.3724	1.0000	0.5024
65	0.3624	0.3607	0.3624	1.0000	0.5024
66	0.3524	0.3507	0.3524	1.0000	0.5024
67	0.3424	0.3408	0.3424	1.0000	0.5024
68	0.3324	0.3308	0.3324	1.0000	0.5024
69	0.3224	0.3209	0.3224	1.0000	0.5024
70	0.3124	0.3109	0.3124	1.0000	0.5024
71	0.3024	0.3010	0.3024	1.0000	0.5024
72	0.2924	0.2910	0.2924	1.0000	0.5024
73	0.2824	0.2811	0.2824	1.0000	0.5024
74	0.2724	0.2711	0.2724	1.0000	0.5024
75	0.2624	0.2612	0.2624	1.0000	0.5024
76	0.2524	0.2512	0.2524	1.0000	0.5024
77	0.2424	0.2413	0.2424	1.0000	0.5024
78	0.2324	0.2313	0.2324	1.0000	0.5024
79	0.2224	0.2214	0.2224	1.0000	0.5024
80	0.2124	0.2114	0.2124	1.0000	0.5024
81	0.2024	0.2014	0.2024	1.0000	0.5024
82	0.1924	0.1915	0.1924	1.0000	0.5024
83	0.1824	0.1815	0.1824	1.0000	0.5024
84	0.1724	0.1716	0.1724	1.0000	0.5024
85	0.1624	0.1616	0.1624	1.0000	0.5024
86	0.1524	0.1517	0.1524	1.0000	0.5024
87	0.1424	0.1417	0.1424	1.0000	0.5024
88	0.1324	0.1318	0.1324	1.0000	0.5024
89	0.1224	0.1218	0.1224	1.0000	0.5024
90	0.1124	0.1119	0.1124	1.0000	0.5024
91	0.1024	0.1019	0.1024	1.0000	0.5024
92	0.0924	0.0920	0.0924	1.0000	0.5024
93	0.0824	0.0820	0.0824	1.0000	0.5024
94	0.0724	0.0721	0.0724	1.0000	0.5024
95	0.0624	0.0621	0.0624	1.0000	0.5024
96	0.0524	0.0522	0.0524	1.0000	0.5024
97	0.0424	0.0423	0.0424	1.0000	0.5024
98	0.0324	0.0323	0.0324	1.0000	0.5024
99	0.0224	0.0223	0.0224	1.0000	0.5024
100	0.0124	0.0124	0.0124	1.0000	0.5024
101	0.0024	0.0024	0.0024	0.9952	0.5000

No.	Kno	Klocation	Kquantity	Kstandard
1	0.995	0.000	1.005	0.000
2	0.981	0.596	0.985	0.230
3	0.963	0.811	0.965	0.172
4	0.944	0.880	0.945	0.128
5	0.924	0.911	0.924	0.100
6	0.904	0.937	0.904	0.082
7	0.884	0.964	0.884	0.070
8	0.865	0.985	0.864	0.061
9	0.845	0.993	0.844	0.054
10	0.825	0.994	0.824	0.047
11	0.805	0.994	0.804	0.042
12	0.785	0.994	0.784	0.038
13	0.765	0.994	0.764	0.035
14	0.745	0.994	0.744	0.032
15	0.725	0.994	0.723	0.029
16	0.705	0.994	0.703	0.027
17	0.685	0.994	0.683	0.025
18	0.665	0.995	0.663	0.023
19	0.645	0.999	0.643	0.022
20	0.625	1.000	0.623	0.020
21	0.605	1.000	0.603	0.019
22	0.585	1.000	0.583	0.018

23	0.565	1.000	0.563	0.017
24	0.545	1.000	0.543	0.016
25	0.525	1.000	0.523	0.015
26	0.505	1.000	0.502	0.014
27	0.485	1.000	0.482	0.014
28	0.465	1.000	0.462	0.013
29	0.445	1.000	0.442	0.012
30	0.425	1.000	0.422	0.012
31	0.405	1.000	0.402	0.011
32	0.385	1.000	0.382	0.011
33	0.365	1.000	0.362	0.010
34	0.345	1.000	0.342	0.010
35	0.325	1.000	0.322	0.009
36	0.305	1.000	0.301	0.009
37	0.285	1.000	0.281	0.009
38	0.265	1.000	0.261	0.008
39	0.245	1.000	0.241	0.008
40	0.225	1.000	0.221	0.008
41	0.205	1.000	0.201	0.007
42	0.185	1.000	0.181	0.007
43	0.165	1.000	0.161	0.007
44	0.145	1.000	0.141	0.006
45	0.125	1.000	0.121	0.006
46	0.105	1.000	0.100	0.006
47	0.085	1.000	0.080	0.006
48	0.065	1.000	0.060	0.005
49	0.045	1.000	0.040	0.005
50	0.025	1.000	0.020	0.005
51	0.005	1.000	-0.000	0.005
52	-0.015	1.000	-0.020	0.005
53	-0.035	1.000	-0.040	0.004
54	-0.055	1.000	-0.060	0.004
55	-0.075	1.000	-0.080	0.004
56	-0.095	1.000	-0.100	0.004
57	-0.115	1.000	-0.121	0.004
58	-0.135	1.000	-0.141	0.004
59	-0.155	1.000	-0.161	0.003
60	-0.175	1.000	-0.181	0.003
61	-0.195	1.000	-0.201	0.003
62	-0.215	1.000	-0.221	0.003
63	-0.235	1.000	-0.241	0.003
64	-0.255	1.000	-0.261	0.003
65	-0.275	1.000	-0.281	0.003
66	-0.295	1.000	-0.301	0.003
67	-0.315	1.000	-0.322	0.002
68	-0.335	1.000	-0.342	0.002
69	-0.355	1.000	-0.362	0.002
70	-0.375	1.000	-0.382	0.002
71	-0.395	1.000	-0.402	0.002
72	-0.415	1.000	-0.422	0.002
73	-0.435	1.000	-0.442	0.002
74	-0.455	1.000	-0.462	0.002
75	-0.475	1.000	-0.482	0.002
76	-0.495	1.000	-0.502	0.002
77	-0.515	1.000	-0.523	0.002
78	-0.535	1.000	-0.543	0.001
79	-0.555	1.000	-0.563	0.001
80	-0.575	1.000	-0.583	0.001
81	-0.595	1.000	-0.603	0.001
82	-0.615	1.000	-0.623	0.001
83	-0.635	1.000	-0.643	0.001
84	-0.655	1.000	-0.663	0.001
85	-0.675	1.000	-0.683	0.001
86	-0.695	1.000	-0.703	0.001
87	-0.715	1.000	-0.723	0.001
88	-0.735	1.000	-0.744	0.001
89	-0.755	1.000	-0.764	0.001
90	-0.775	1.000	-0.784	0.001
91	-0.795	1.000	-0.804	0.001
92	-0.815	1.000	-0.824	0.000
93	-0.835	1.000	-0.844	0.000
94	-0.855	1.000	-0.864	0.000
95	-0.875	1.000	-0.884	0.000
96	-0.895	1.000	-0.904	0.000
97	-0.915	1.000	-0.924	0.000
98	-0.935	1.000	-0.945	0.000
99	-0.955	1.000	-0.965	0.000
100	-0.975	1.000	-0.985	0.000
101	-0.995	0.000	-1.005	0.000

No.	CorrectChance	CorrectQuantity	CorrectLocation	ErrorLocation	ErrorQuantity
1	0.500	0.498	0.000	0.000	0.002
2	0.500	0.488	0.003	0.002	0.008
3	0.500	0.478	0.004	0.001	0.018
4	0.500	0.468	0.004	0.001	0.028
5	0.500	0.458	0.004	0.000	0.038
6	0.500	0.448	0.004	0.000	0.048
7	0.500	0.438	0.004	0.000	0.058
8	0.500	0.428	0.004	0.000	0.068
9	0.500	0.418	0.004	0.000	0.078
10	0.500	0.408	0.004	0.000	0.088
11	0.500	0.398	0.004	0.000	0.098
12	0.500	0.388	0.004	0.000	0.108
13	0.500	0.378	0.004	0.000	0.118
14	0.500	0.368	0.004	0.000	0.128
15	0.500	0.358	0.004	0.000	0.138
16	0.500	0.348	0.004	0.000	0.148
17	0.500	0.338	0.004	0.000	0.158
18	0.500	0.328	0.004	0.000	0.168
19	0.500	0.318	0.004	0.000	0.178

20	0.500	0.309	0.004	0.000	0.188
21	0.500	0.299	0.004	0.000	0.198
22	0.500	0.289	0.004	0.000	0.208
23	0.500	0.279	0.004	0.000	0.218
24	0.500	0.269	0.004	0.000	0.228
25	0.500	0.259	0.004	0.000	0.238
26	0.500	0.249	0.004	0.000	0.248
27	0.500	0.239	0.004	0.000	0.258
28	0.500	0.229	0.004	0.000	0.268
29	0.500	0.219	0.003	0.000	0.278
30	0.500	0.209	0.003	0.000	0.288
31	0.500	0.199	0.003	0.000	0.298
32	0.500	0.189	0.003	0.000	0.308
33	0.500	0.179	0.003	0.000	0.318
34	0.500	0.169	0.003	0.000	0.328
35	0.500	0.159	0.003	0.000	0.338
36	0.500	0.149	0.003	0.000	0.348
37	0.500	0.139	0.003	0.000	0.358
38	0.500	0.129	0.003	0.000	0.368
39	0.500	0.119	0.003	0.000	0.378
40	0.500	0.109	0.003	0.000	0.388
41	0.500	0.100	0.003	0.000	0.398
42	0.500	0.090	0.003	0.000	0.408
43	0.500	0.080	0.003	0.000	0.418
44	0.500	0.070	0.003	0.000	0.428
45	0.500	0.060	0.003	0.000	0.438
46	0.500	0.050	0.003	0.000	0.448
47	0.500	0.040	0.003	0.000	0.458
48	0.500	0.030	0.003	0.000	0.468
49	0.500	0.020	0.003	0.000	0.478
50	0.500	0.010	0.002	0.000	0.488
51	0.500	0.000	0.002	0.000	0.498
52	0.490	0.000	0.002	0.000	0.508
53	0.480	0.000	0.002	0.000	0.518
54	0.470	0.000	0.002	0.000	0.528
55	0.460	0.000	0.002	0.000	0.538
56	0.450	0.000	0.002	0.000	0.548
57	0.440	0.000	0.002	0.000	0.558
58	0.430	0.000	0.002	0.000	0.568
59	0.420	0.000	0.002	0.000	0.578
60	0.410	0.000	0.002	0.000	0.588
61	0.400	0.000	0.002	0.000	0.598
62	0.391	0.000	0.002	0.000	0.608
63	0.381	0.000	0.002	0.000	0.618
64	0.371	0.000	0.002	0.000	0.628
65	0.361	0.000	0.002	0.000	0.638
66	0.351	0.000	0.002	0.000	0.648
67	0.341	0.000	0.002	0.000	0.658
68	0.331	0.000	0.002	0.000	0.668
69	0.321	0.000	0.002	0.000	0.678
70	0.311	0.000	0.001	0.000	0.688
71	0.301	0.000	0.001	0.000	0.698
72	0.291	0.000	0.001	0.000	0.708
73	0.281	0.000	0.001	0.000	0.718
74	0.271	0.000	0.001	0.000	0.728
75	0.261	0.000	0.001	0.000	0.738
76	0.251	0.000	0.001	0.000	0.748
77	0.241	0.000	0.001	0.000	0.758
78	0.231	0.000	0.001	0.000	0.768
79	0.221	0.000	0.001	0.000	0.778
80	0.211	0.000	0.001	0.000	0.788
81	0.201	0.000	0.001	0.000	0.798
82	0.191	0.000	0.001	0.000	0.808
83	0.182	0.000	0.001	0.000	0.818
84	0.172	0.000	0.001	0.000	0.828
85	0.162	0.000	0.001	0.000	0.838
86	0.152	0.000	0.001	0.000	0.848
87	0.142	0.000	0.001	0.000	0.858
88	0.132	0.000	0.001	0.000	0.868
89	0.122	0.000	0.001	0.000	0.878
90	0.112	0.000	0.001	0.000	0.888
91	0.102	0.000	0.000	0.000	0.898
92	0.092	0.000	0.000	0.000	0.908
93	0.082	0.000	0.000	0.000	0.918
94	0.072	0.000	0.000	0.000	0.928
95	0.062	0.000	0.000	0.000	0.938
96	0.052	0.000	0.000	0.000	0.948
97	0.042	0.000	0.000	0.000	0.958
98	0.032	0.000	0.000	0.000	0.968
99	0.022	0.000	0.000	0.000	0.978
100	0.012	0.000	0.000	0.000	0.988
101	0.002	0.000	0.000	0.000	0.998

** : A ranked image (Tmp\$Rank_landcov_predict_2009_soft) based on the input image was created in the working directory.
In addition, a percentile map(Tmp\$percentile_landcov_predict_2009_soft) based on the threshold bands user specified was also created in the working directory.