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

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Summary:
Land use/cover change practices in the 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 across scales, such as land fragmentation and degradation, biodiversity loss, alteration in atmospheric composition and climate change. The future landscape for the Kayabi Indigenous Territory in the Brazilian Amazon was simulated using GIS, Remote Sensing and the IDRISI's Land Change Modeler. 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.

KEYWORDS: Amazon, deforestation, modelling, remote-sensing, prediction.

1. Introduction

During 2007, over 80% of both clearing and cumulative clearing in Amazon 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. It seems that is the process of Land use/cover change (LUCC) that is bringing a fast deforestation processes; the most common LUCC practices in the Brazilian Amazon include cattle ranching, logging, agriculture, mining, and urbanization (Asner et al, 2004).

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. 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. This paper aims to understand the determinants of LUCC by using a modelling approach

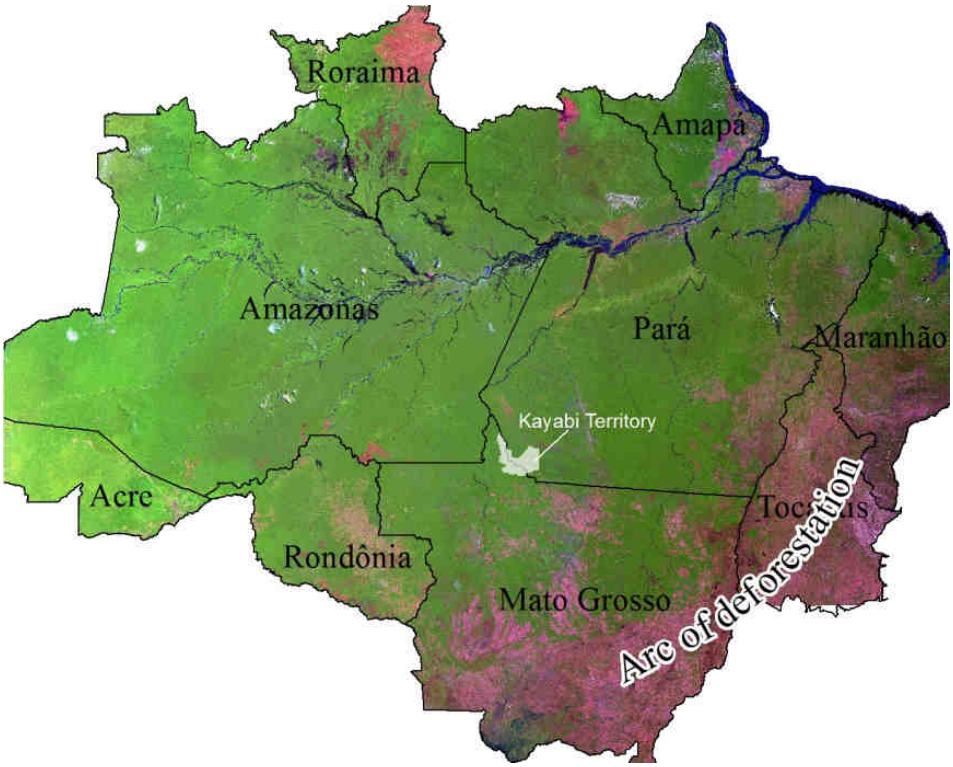


Figure 1. Location of Kayabi Territory within the 'Arc of deforestation'

2. Modelling LUCC in the Kayabi Indigenous Territory

The prediction of the future landscape was developed using different GIS and IDRISI's Land Change Modeler and followed five sequential steps, presented as follows.

(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.
Each of these steps will be presented as follow.

Step 1: Creation of land cover maps 2000, 2006 and 2009 derived from remotely sensed data

CLASlite software was utilized to create fractional cover maps for each image shown in Table 1, followed by a supervised classification using ENVI software to create 2 class land cover maps for the years 2000, 2006 and 2009 (forest and anthropogenic disturbance). The result of the classification was a 2 class map: Forest and Anthropogenic Disturbance for each of the analysed years (see Figure 2).

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 (see details in Table 1).

Table 1. 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	

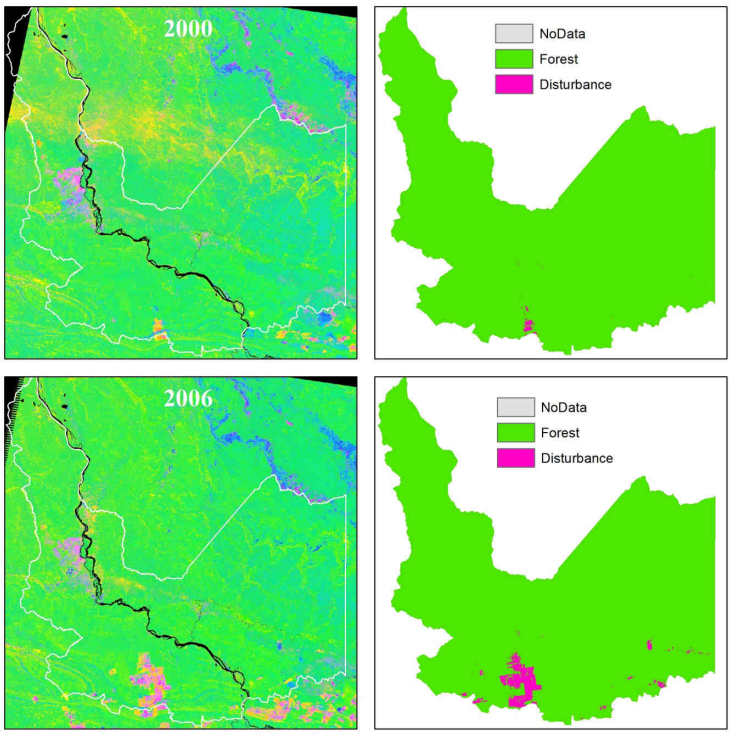


Figure 2. Resulting classification of CLASlite's fractional cover maps.

Step 2: Land Change Cover Analysis by cross-tabulating forest land cover maps

Change from forest class to disturbance between 2000 and 2006 was assessed by using Change Analysis Tab in LCM. LCM analyses each pixel in the earlier land cover map for a transition to a different class in the later land cover image. Since there are only two land cover classes, there are four possible outcomes for each pixel (see Figure 3):
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)

A 3rd order polynomial trend surface was created using LCM to aid interpretation. Spatial trend analysis is an effective way of visualizing the general trend of change based on the observed change between two land cover maps and, as can be seen in Figure 4, makes evident change from forest to disturbance is concentrated in the south part of the image which is consistent with the deforestation tendency observed on the 'arc of deforestation'.

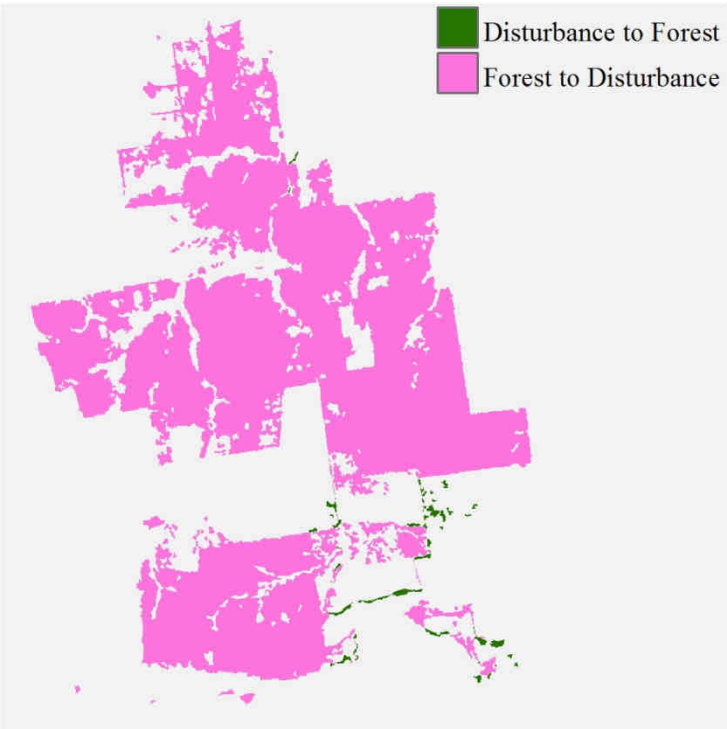


Figure 3. Class transitions calculated by LCM[1]

[1] Transitions of less than 500 hectares were ignored in the model as they were produced by a map error in image co registration process.

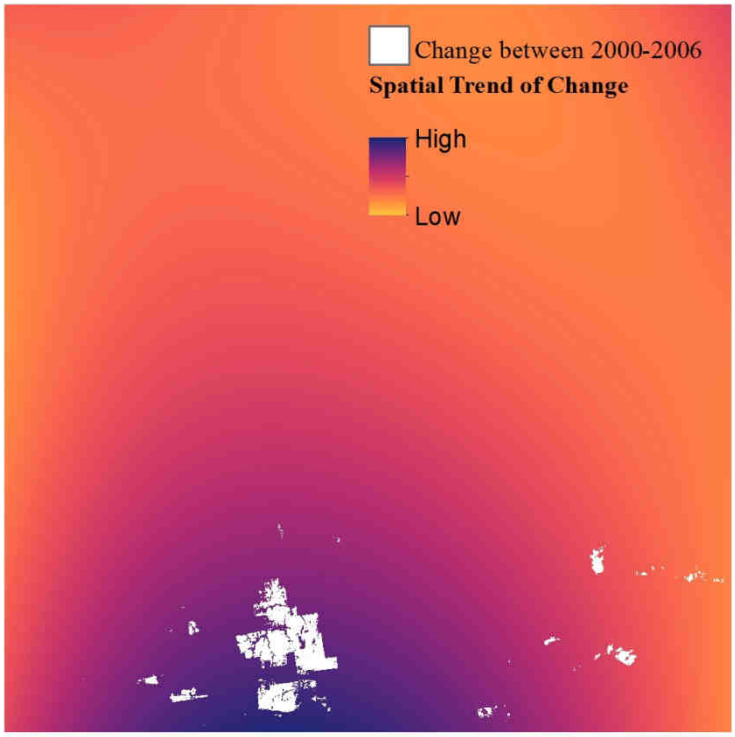


Figure 4. Spatial trend of change

Step 3: Calculation of transition potentials from forest to anthropogenic disturbance using a MLP neural network methodology;

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 modelled. A MLP Neural Network approach was used to create transition potential maps. Five factors were identified as major driving forces of change (see Table 1) and were assessed for correlation to deforestation.

Table 2. 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

LCM's Test and Selection of site and driver variable module was used to test the potential power of explanatory variables (see

Table 3). Only variables with values higher than 0.45 (strong association with change) were kept in

the sub-model structure.

Table 3. 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

The transition potential from forest to disturbance was modelled using the MLP neural network methodology. The LMC sub model was used to create the transition potential map (MLP achieved an accuracy rate of 94.56 % and a RMS value of 0.20). The outcome of the model is a transition potential map for transition from forest to disturbance (see Figure 5). Each pixel on this map contains the probability value (from 0 to 1) of changing from forest to anthropogenic disturbance.

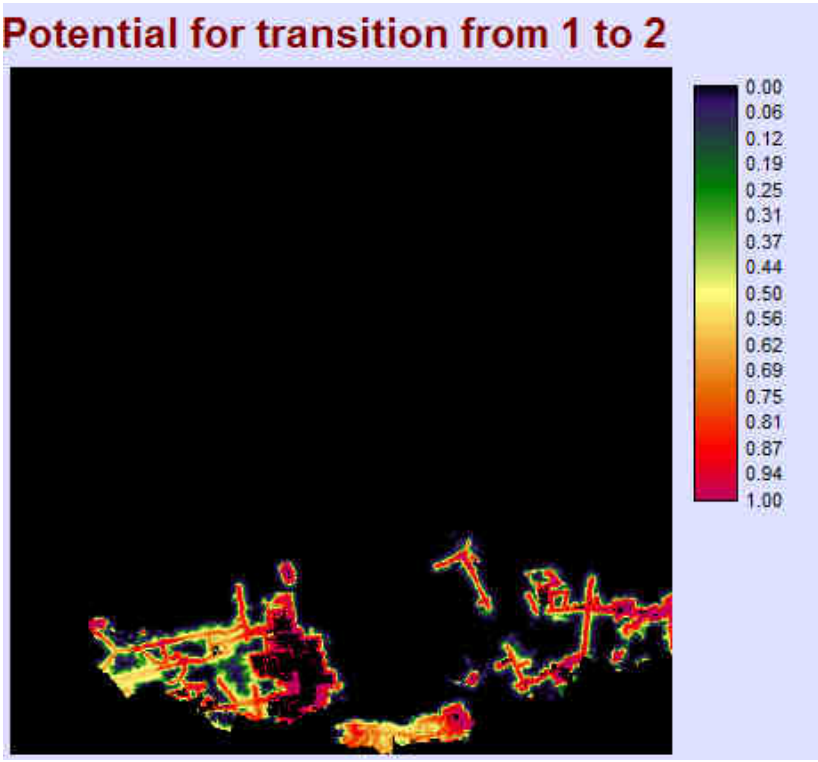


Figure 5. Transition potential from forest to anthropogenic disturbance

Step 4 Assessment of the model performance by predicting a 2009 land cover and comparing it with an actual 2009 land cover map

Markov chain analysis was used to predict the quantity of change in 2009 and then compare to an

actual 2009 land cover map. LCM provides two basic models of prediction: a hard prediction model and a soft prediction model.

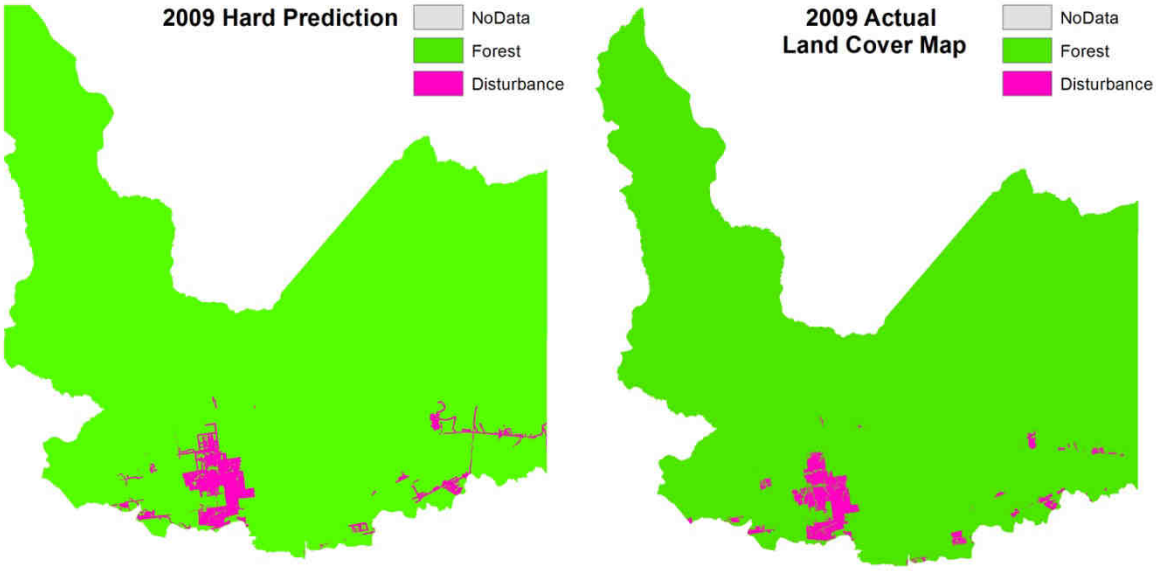


Figure 6. Hard prediction of Kayabi forest condition in 2009 and actual 2009 land cover map.

Figure 6 shows two disagreements in the prediction are either concerned with quantity or with location of change. The assessment of the hard prediction was carried out with the LCM Validate function (see the resulting map in Figure 7 and output of function in Figure 8).

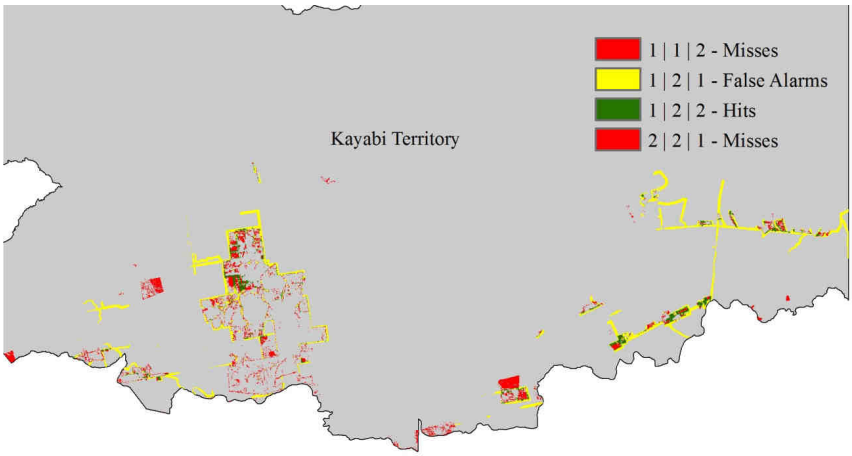
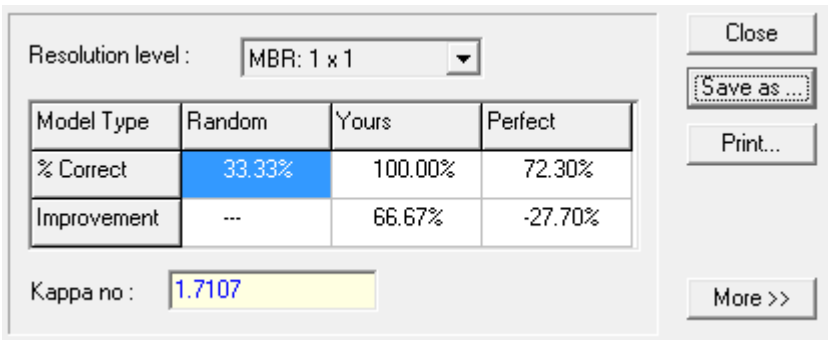


Figure 7. Validation map: hits, false alarms and misses



Model Type	Random	Yours	Perfect
% Correct	33.33%	100.00%	72.30%
Improvement	---	66.67%	-27.70%

Figure 8. Validation results

As the hard prediction is a single realization of a future scenario chosen from many equally plausible scenarios (Eastman, 2009), it is very difficult to achieve an accurate hard prediction. The soft prediction identifies vulnerability to change, and thus provide a more meaningful map (see Figure 9).

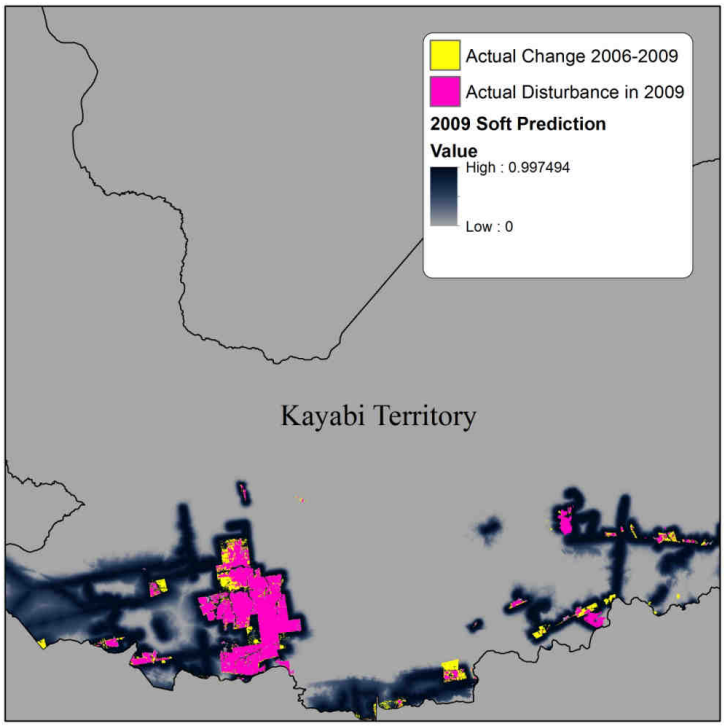


Figure 9. 2009 Soft prediction

A quantitative assessment of the soft prediction was carried out using receiver operating characteristic (ROC) statistics. The result of the ROC statistic was 0.987, which is a very strong value and indicates the soft prediction was very accurate.

Step 5: Predicting the Kayabi Territory forest condition in 2020

Both hard and soft predictions were produced for the year 2020 (see Figure 10).

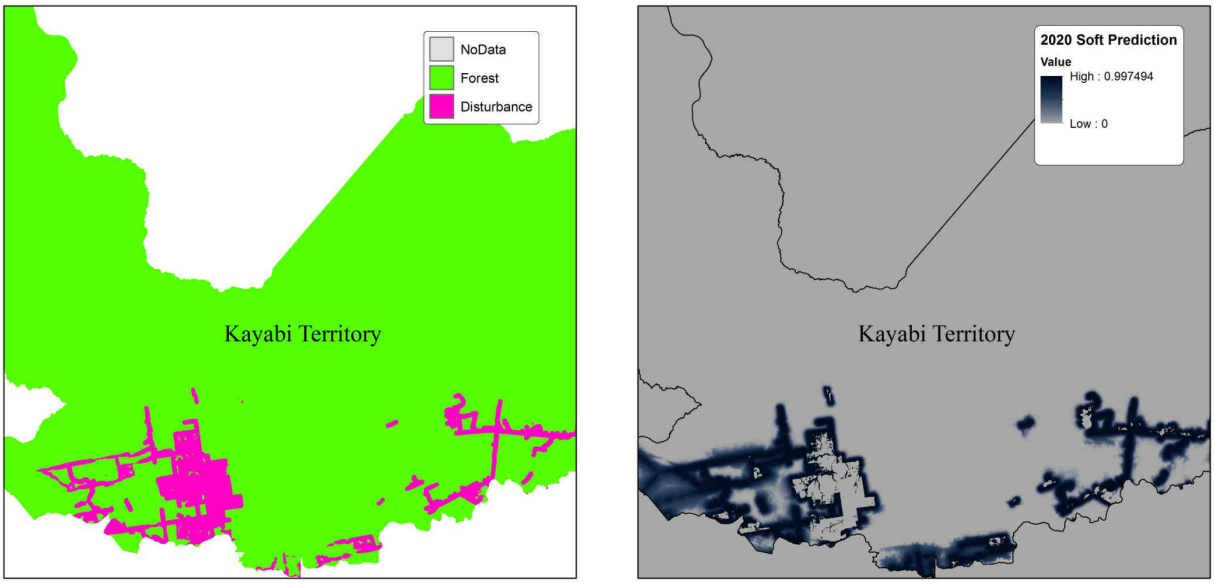


Figure 10. Map Predictions for 2020: hard prediction (left-hand side) and soft prediction (right-hand side).

3. Discussion and Conclusions

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 4).

Table 4. 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 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. External factors play an important role in interpreting the results. In this case, it is known rates of deforestation were impacted by legal injunction process. Such events are very difficult to incorporate into the model.

Figure 11 shows a time series analysis of land cover maps of the Kayabi Territory, which is consistent with the hypothesis that roads and previous disturbance are the main drivers for deforestation. The analysis also confirmed new disturbed areas serve as seeds for a more intense clearing activity in the future.

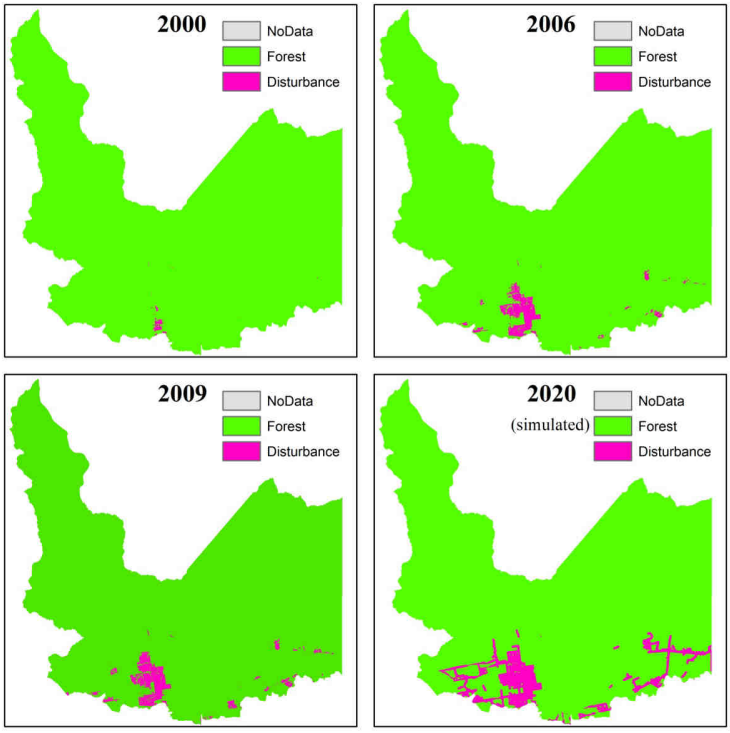


Figure 11. Time series Analysis of deforestation in Kayabi Territory

Based on visual interpretation of the simulation and the ROC criterion, it is clear the soft predictions were produced with a satisfactory level of accuracy. Figure 12 shows the 2020 soft prediction overlaid on a 2011 Landsat image (25/07/2011), where it is clear post 2009 disturbed areas are vulnerable.

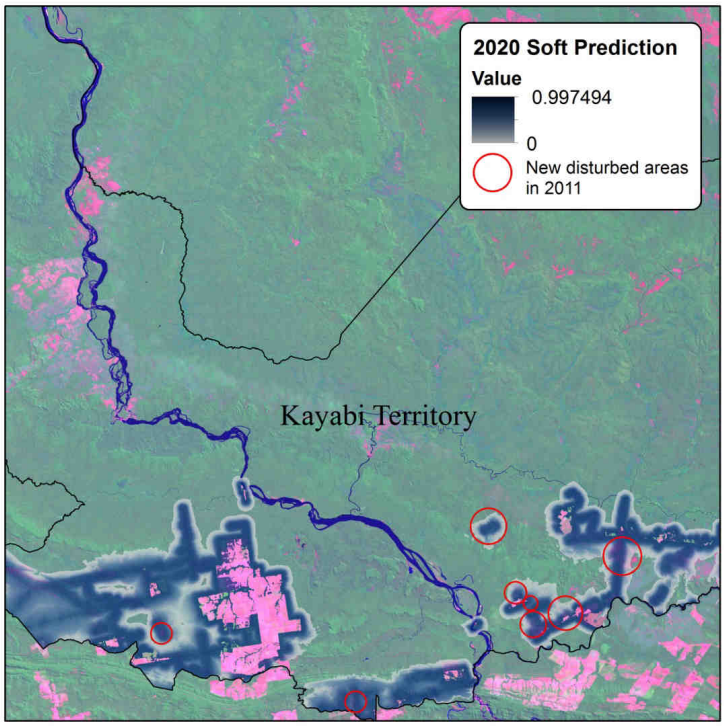


Figure 12. The 2020 soft prediction overlaid on a 2011 Landsat

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. 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.

4. References

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5. Biographies

Hugo de Alba has an MSc in GI Science from Birkbeck, University of London. He has work experience in the environmental assessment field. His research interests include landscape modelling, GI applications in clean energy projects and spatial analysis.

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