SPATIAL DRIVERS OF DEFORESTATION IN SURINAME

Sara Olga Ramirez-Gomez

Picture: Kenneth Tjon

Picture: Sara Ramirez-Gomez

Picture: Kenneth Tjon

Picture: Rudi van Kanten

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SARA OLGA RAMIREZ-GOMEZ

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CENTER FOR AGRICULTURE RESEARCH IN SURINAME
TROPENBOS SURINAME

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ABSTRACT

In many tropical countries forest are destroyed to expand timber, mining and agricultural industries and are affected by infrastructure investments such roads and dams. Deforestation rates in Suriname have been historically low due to the low population pressure and relative remoteness. Suriname's status as High Forest Low Deforestation (HFLD) country is set to change if planned infrastructure investments (a hydrodam, a road to Brazil and agriculture extension with prospects for biofuels) through the heart of the country realize, moreover, if low institutional capacity and environmental regulations continue inhibiting the capacity response of governments to control the destruction of tropical forest overlapping greenstone deposits.

Analytical and empirical studies have shown that an important determinant of deforestation is the improved access to previously inaccessible forested areas alongside low governance gradients with high socio-economic value. Timely information about the underlying and proximate drivers of actual and future deforestation and on the location and extent of expected deforestation is one condition to properly manage this process of forest cover destruction. Therefore, this study uses spatial deforestation models to assess the influence of environmental drivers on forest cover change and to project future deforestation trends.

During the first stage of this project, forest cover maps were developed for 2005 and 2009 based on Landsat 5TM images. The resulting forest cover maps were used in a spatial explicit model which calculates forest change rates and simulates deforestation between 2009 and 2020 based on the spatial distribution of spatial variables and a historical deforestation scenario assuming that deforestation trajectories into the future will continue under the historical trend found between the period analyzed.

The model demonstrates how land use, infrastructure, socio-economic aspects and biophysical features drive forest loss in Suriname. With the outcomes of this research the researchers expect to be able to demonstrate the potential of this type of studies to visualize the effects of land use decisions on forest conservation along future infrastructure developments in the country, and to inform these decisions so that they minimize undue negative impacts on forest-dependent people and forest**.**

Key words: Suriname, simulation of deforestation, drivers of forest change, infrastructure investments.

1. INTRODUCTION

Forest are the most important terrestrial storehouses of carbon and play an important role in controlling the climate. In many tropical countries forest are degraded and destroyed to expand timber, mining and agricultural industries and are affected by infrastructure investments such roads and dams. Tropical deforestation has severe consequences for biodiversity, impact water quality and storage, exacerbates flooding, landslides and soil erosion and furthermore, it threatens the livelihood and integrity of forest dependent people (Foley et al 2007). Deforestation is also a major contributor to global climate change and has detriment consequences in socio-economic development and human sustainability (MEA, 2005).

Deforestation is associated to the increasing pressure in the human pursuit of economic development and gains. World demand for natural resources is increasingly driving local resource extraction and land use in developing countries that hold mining and timber deposits as well as potential for large plantations. As the global economy becomes more connected, it is progressively more difficult for developing countries to control the profitable forces of global demand in the interest of social and environmental sustainability (Laurence, 2008). To fight deforestation has been a constant challenge due to the demands on forest resources and especially when forest overlap with mining deposits which increases the conflict between the surface and subsurface land uses. Inadequate decisions, unsuitable development and misleading environmental policies are driving a decay in forest ecological integrity in the tropics (Geist and Lambin 2001; Foley et al 2005). Development policies along the tropics are encouraging economic growth by accomplishing infrastructure investments; these investments are determining the fate of important forest ecosystems, particularly across low governance zones.

In Suriname multi-faceted infrastructure projects are providing new sources of forest detriment across low governance regions in the country. At present, there is a climate of investment and use of the natural resource potential to pursuit economic development. Within recent years the issue of infrastructure investments has been given high priority among the policies of the Government of Suriname in order to endorse free trade areas between neighboring countries and furthermore to facilitate access to the economic potential of the inlands. Significant infrastructure projects include improvement of existing roads, building of the North-South Corridor, expansion of the timber and mining industry, expansion of dams and expansion of agricultural activities with prospects for palm oil.

These investments will promote economic growth; however, these factors will detonate a change that is likely to affect large areas of intact forest in Suriname which has remained as High Forested Low Deforested country (HFLD) in part due to the remoteness of its forest and due to the low population pressure. Understanding the dynamics of land use and forest cover change has increasingly been recognized as the key imperative to mitigate the synergistic effects of the drivers of deforestation (Laurence et al 2009). Furthermore, information on the vulnerability of forest areas to threats is important for prioritizing conservation action because it provides information on where deforestation is taking place, how extensive it is and what is triggering the event.

Therefore, the overarching aim of this study is to assist in understanding the proximate and underlying forces that may drive deforestation process across one of the most important areas in the country, where many economic activities take place and to demonstrate the potential of this type of studies to visualize and track the effects of land use decisions in Suriname. The specific objectives are: 1) to assess deforestation over the period 2005-2009; 2) to estimate the deforestation rate across the study area; 3) to assess the causes (drivers) of deforestation and 4) to predict future deforestation trajectories based on scenario assumptions.

The issue that this work addresses is that in view of the prospects to pursue economic development in Suriname based on natural resource exploitation and in view of the commitment of the National Government and conservation agencies for a REDD+ mechanism, it is critical to produce knowledge about the proximate and the underlying forces threatening the forest ecosystem integrity in the mid and long term.

This work describes and models deforestation processes across an area where important economic activities develop such timber, gold mining, sand mining and hydropower. The study area overlaps with the so called greenstone belt and is crossed by a road linking the capital Paramaribo with inlands settlements. The landscape in the zone is relatively high fragmented as the cumulative result of past land uses associated with agriculture, abandoned plantations, fire and mining from where deforestation has expanded outwardly.

The present study used standard approaches implemented in land use-cover change studies (Soares Filho et al 2004, 2006). First the assessment of forest cover change by applying multi-temporal analysis of satellite images and second by incorporating a spatial explicit simulation model of deforestation to assess the drivers of change and to simulate future deforestation trajectories. This work discusses the spatial patterns, process and drivers of deforestation as well as the deforestation frontier across a strategic zone in Suriname in order to help understand the side effects of land uses in the country and to encourage the use of these approaches in development planning and conservation strategies countrywide.

2 STUDY AREA

The study area is located in eastern Suriname between the settlements Paranam and Djumu (Fig 1a). The total study area was divided into two subset named Afobaka and Atjoni subset. Afobaka has a total area of 3,052 km^2 and Atjoni 7,975 km^2. Regarding geomorphology and soils, the study area comprises two major zones: the savanna belt in the northern part and the interior uplands of the Precambrian Guiana Shield toward the south. The southern part of the area overlaps with the so called greenstone belt which is an area of 24,000 km^2 located in eastern Suriname forming part of a nearly continuous, E-W to SE-NW striking green stone belt along the NE margin of the Guiana Shield, splitting into two branches from French Guiana eastwards and continuing into NE Brazil The characteristic geology of the GSB besides the deposits of gold, is reflected in its geomorphology, hydrology, and vegetation as rock composition determines weathering patterns (Ministry of Labour, Technological Development and Environment, 2003).

Within the study area the vegetation types include savanna forest, creek forest, high forest, open savanna vegetation and forest re-growth. There are two protected areas: the Brinckheuvel Nature Reserve (60km^2) in the Afobaka Subset and the Brownsberg National Park (122 km^2). The area has an extensive network of navigable creeks and two major rivers: the Saramacca and the Suriname River. Most important land uses consist of gold mining which is closely associated with the distribution of the green stone belt (GSB), timber extraction, stone and sand mining, abandoned plantation and shifting cultivation. The population is comprised by maroons groups with transient migrants from Brazil (*Garimpeiros*).

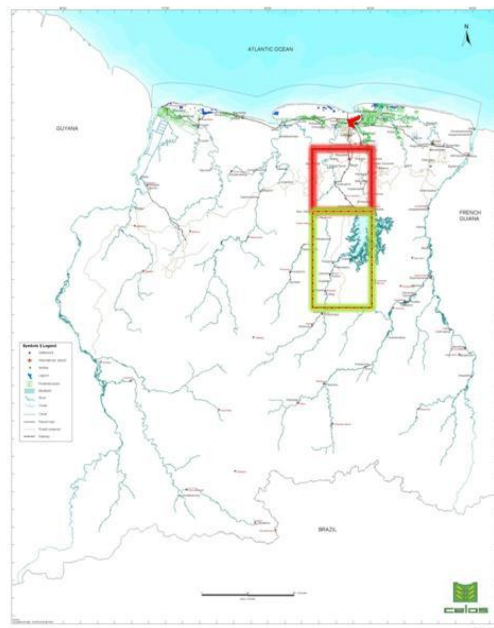

Figure 1. Study area: red box Afobaka subset, green box Atjoni (Source: Narena).

The study area is crossed by the Afobaka road which links Paranam Aluminium refinery with the hydropower dam and crossed by the road from Brownsweg to Atjoni. The entire road track from Paranam to Atjoni is one of the most important transport corridors in the country because of its current and future importance in the economic development of the country. This corridor creates access to Brokopondo dam, to mining sites and to timber concessions. It also represents the transportation corridor linking the interior human population with Paramaribo. Furthermore, the road will continue in the future from Atjoni southwards to the border with Brazil nearby the village of Vier Gebroeders at the foot of the Tumucumac Mountain range and it would eventually connect with the BR-210 and BR-163 (van Dijck 2010). The entire stretch is the so called North-South Corridor which is considered to have the potential for improving the economic competitiveness of the country. This on the other hand may expose the region to environmental change because this road will cut off though well preserved-environmentally sensitive areas of Tropical Rain Forest with high biodiversity and high availability of water resources, high ecologically and high cultural assets. Moreover, the area along the road have high socio-economic value, with rich areas of forestry resources and large reserves of gold and industrial minerals such as bauxite, copper, iron ore, marble, manganese and zinc.

3. FOREST COVER MAP

This section describes the methodology implemented to produce the forest cover maps from 2005 and 2009 by the use of satellite image and remote sensing techniques. The process starts by the acquisition of Landsat 5TM scenes followed by the clipping of the area of interest, the georeferenciation, the image classification into fractional land covers, the cloud masking, the mosaicing procedure and the automated mapping of forest cover (Fig 2).

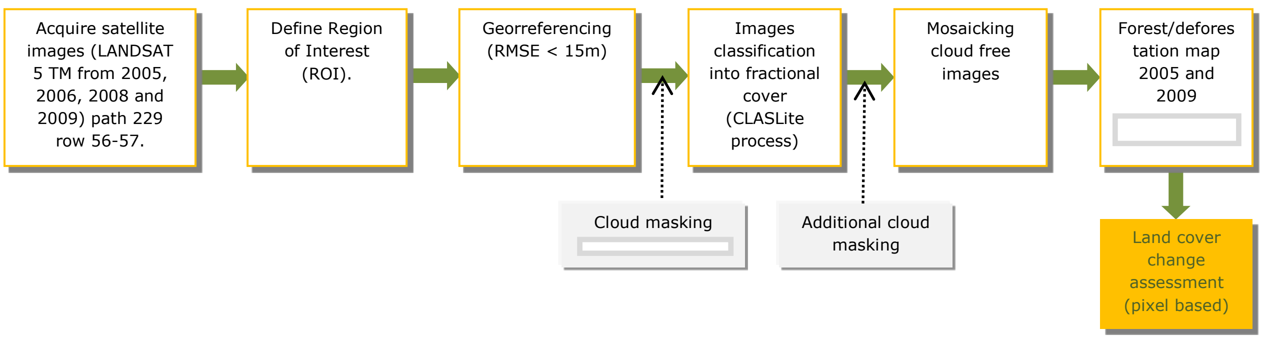

Figure 2. Flow chart forest cover assessment

3.1. Processing of satellite images and assessment of fractional cover classes.

Fourteen Landsat 5TM images of 30 m resolution were acquired for path 229 row 56 and 57 for 2004, 2005, 2006, 2008 and 2009. They were downloaded from the National Institute for Space Research (INPE) Brazil (INPE, 2010). The image bands were stacked leaving out band 6 which was used during the extra masking of clouds and shadows. A delineation of the study areas was done in GIS based on the area of interest which comprised the road between Paranam and Atjoni as well as the upper Suriname river up to Djumu, including 30km at each side of the road and river (Fig 1). The selected area was used to clip the Landsat images from the selected years, this process was done in ERDAS IMAGINE 9.1. The study area was divided in two parts according to the coverage of the satellite images. One part of the study area was named Afobaka subset for the area clipped from path 229 row 56 and the other part of the study areas was named Atjoni subset for the area clipped from path 229 row 57. The clipping process was done for images around the same study area in different years. These group of images´ subset were georeferenced with the Georeferencing tool of ArcGis 9.3 by assigning ground control points (GCP) with an accuracy of less than 15 m (approximately a satellite image pixel).

Radiometric calibration and atmospheric correction were automated performed by CLASLite version 2.0 (Asner et al 2009). Subsequently, a quantitative analysis of the fractional or percentage cover (0-100%) of the live and dead vegetation, and bare substrate within each satellite pixel was done within a CLASlite to produce fractional cover image. Fractional cover image refers to the proportion of the pixel that is covered by each land cover type and it is derived from advanced methods of Automated Monte Carlo Unmixing (AutoMCU). This process uses three spectral end member libraries to classify Photosynthetic Vegetation (PV), Non-photosynthetic Vegetation (NPV) and Bare substrate (B) (Asner et al 2009). The spectral characteristic of the PV are associated with leaf photosynthetic pigments and canopy water content; the NPV spectrum is associated with dead or senescent vegetation characteristic of plant carbon compounds and B is associated with exposed mineral soil and rocks. The AutoMCU iteratively selects a PV, NPV and B spectrum from each library, and unmixes the pixel reflectance into constituent cover fractions (see Asner et al 2009 for detailed explanation). The process of random selection is repeated until the solution converges on a mean value for each surface cover fraction. CLASLite considers 30 iterations per pixel sufficient to achieve a stable solution based on the Monte Carlo approach. Per pixel iterations produce a standard deviation for the estimates of B, PV and NPV which is used in the final analysis of the fit of the modeled spectrum.

Ten fractional cover images for both subsets in the selected years were automated generated within CLASLite. They were depicting primary forest or late secondary forest (PV >90%, NPV 0-10% and B 0-10% on a pixel basis) and deforestation (PV 0-10%, NPV >80% and B >10% on a pixel basis). These images were the main input to generate the forest cover and deforestation map after they underwent a process of secondary masking of clouds and shadows and subsequent mosaicing to generate an initial and final forest landscape for 2005 and 2009 respectively (see sessions below) which were needed during the land cover change assessment.

3.2 Model fit

To analyze the accuracy of the AutoMCU on a pixel by pixel basis, I examined the fractional cover classification to look for the total error image which shows the total error expressed as Root Mean Square (RMS) error and identify areas of concern. A pixel with a low Total Error indicates that the solution is good, whereas high Total Error suggests that the solution is not good and should either be discarded or used with cautions (Asner et al 2009). An example of this procedure is shown in figure 3. The spectral profile shows that the fractional value for B is 70% (band 1), 45% for PV (band 2) and 1% for NPV (band 3). The next three bands (4, 5, 6) indicate the standard deviation of the respective fractions, the results show that the deviation from the mean is low for the 30 iterations, showing that the solution for the three fractions (PV, NPV and B) was consistent. Band 7 indicates the total error (RMSE) which is relative low in my results, inferring that the spectral profile that was created during the Auto MCU analysis was very close to the actual spectra of the pixel, therefore, I can be confident in the ability of the fractions to reproduce the reflectance of the pixel´s spectra. I performed this analysis throughout the images; the RMSE (band 7) was generally high for clouds and water that were not properly masked out during the automated process. In that case I carried out additional masking of contaminated pixels.

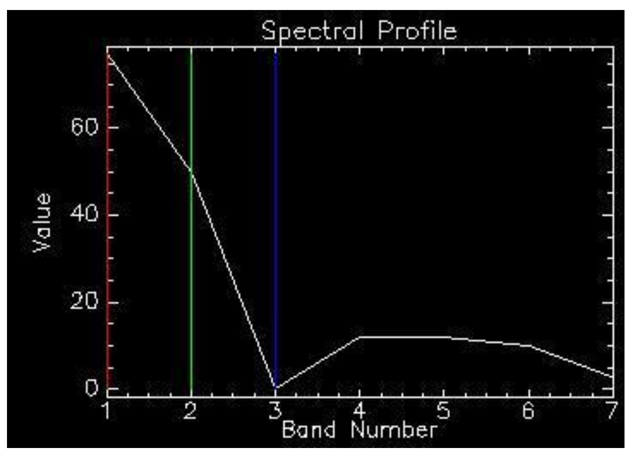

Figure 3. Band analysis-pixel fractional cover profile indicating total error image

3.3 Clouds and shadow masking

The Landsat 5TM images were covered by approximately 10 to 15% with clouds. An initial masking was performed within CLASLite before the AutoMCU runs where clouds, shadows and water are removed to prevent misclassified pixels to be included in the statistics. Water masking is achieved by detecting the unique reflectance of water. Clouds and shadows are also masked by identifying pixels that appear in the reflectance image as having negative reflectance (Asner et al 2009b). A second masking option was possible within CLASLite using the thermal band (band 6 of the Landsat 5TM image) to improve the accuracy of the fractional cover estimates since the automated process is often not sufficient. This masking step applies a user-selected threshold value to the RMSE image derived from the AutoMCU model to allow customized removal of pixels that did not comply with the preliminary masking criteria applied during the initial masking. This step did not completely mask out all clouds or pixels contaminated by clouds and shadows. Therefore, a third cloud and cloud-shadow masking was required to completely eliminate contaminated pixels. This extra masking was done manually by drawing a polygon around those areas that needed to be removed and followed by clipping those unwanted pixels (fig 4a).

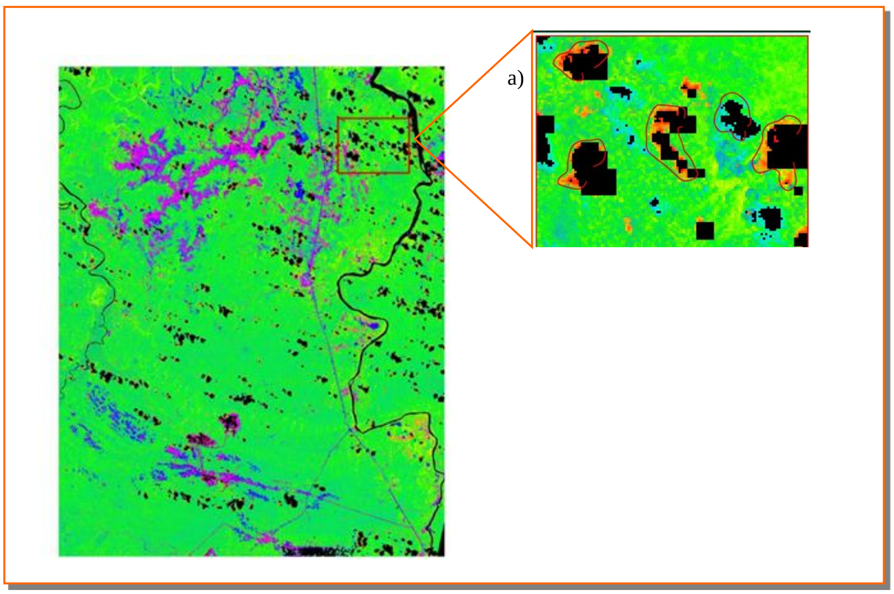

Figure 4. Fractional cover image after two masking process performed within CLASLite. a) Zoom to show need of extra masking because of the presence of contaminated pixels. Red lines around indicate polygons that were drawn to clip the undesired pixels.

3.4 Mosaicing

After the cloud and shadows were removed in all the Landsat images, the data gaps left by the clipping process (see section 1.2) were filled in with data from fractional cover images from other years produced along the process. Fractional cover images from 2004 and 2006 were used to fill the data gaps of the image of 2005. Likewise, fractional cover images from 2008 and 2009 were used to fill the gaps of an image of 2009. The result of this process is two cloud free fractional cover images from 2005 and 2009 both for Afobaka and Atjoni subsets (Fig 5 and 6). In the case of Atjoni study area, some data gaps remained because of the lack of data, therefore those gaps were classified as no data or null value.

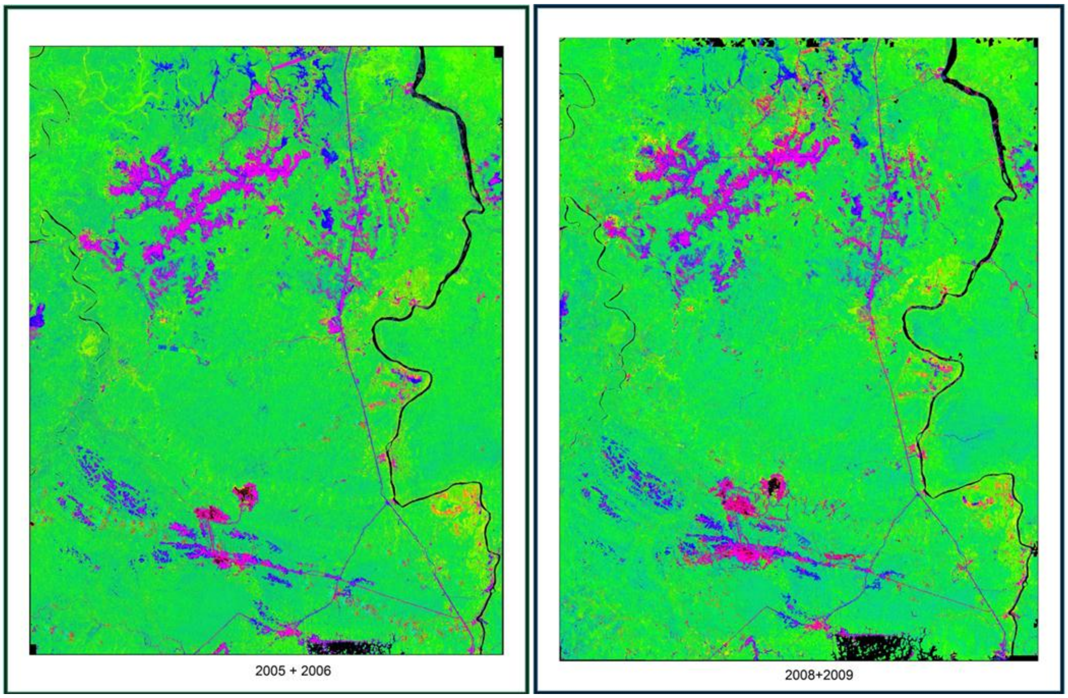

Figure 5. Cloud free fractional cover image for Afobaka subset. Black color indicates null value or non-existing data.

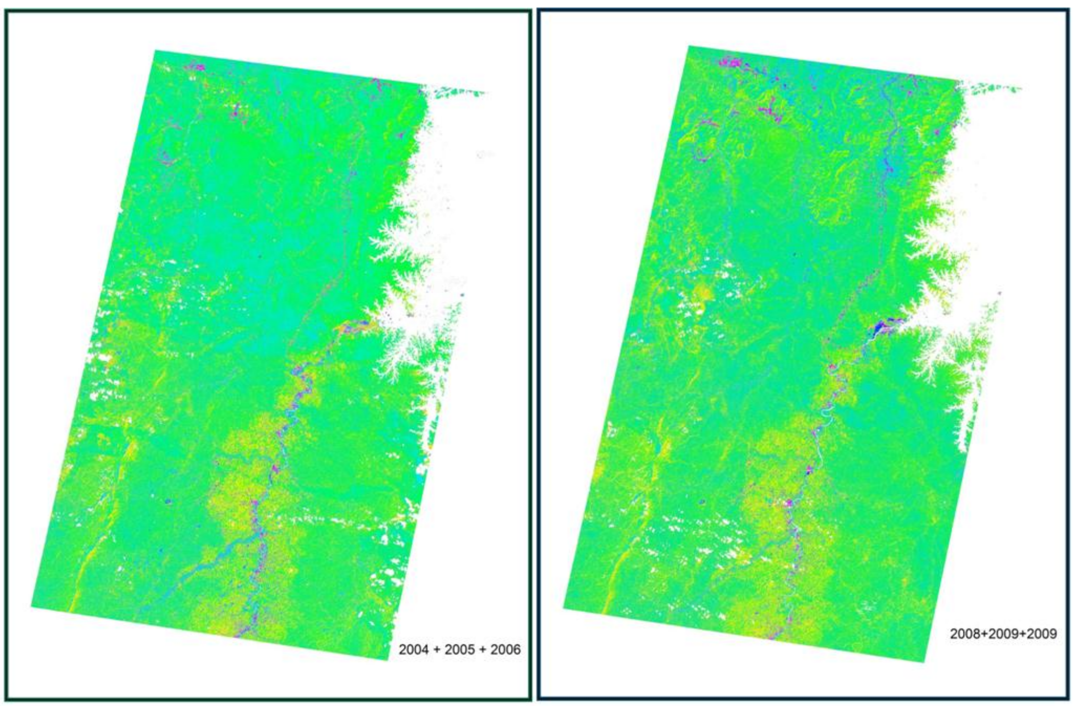

Figure 6. Cloud free fractional cover image for Atjoni subset. White color indicates null value or non existing data.

3.5 Mapping forest cover

To convert the fractional cover image into an estimate of forest cover, CLASLite implements decision tree criteria by applying the following rules (Asner et al 2009):

- Large forest clearings: PV < 56%
- Small forest clearings: 56% < PV < 80% and 14% < NPV < 34% and 0% < Bare < 17%
- OR PV < 80% and not already identified as a clearing.

From the fractional cover images presented in figures 5 and 6 it was possible to derive a classification for forest and non-forest in 2005 and 2009 in each subset of the study area. The result is a forest cover map for each year, the forest cover area per class is indicated in table 1. These maps represent the main inputs for the spatial explicit simulation of deforestation (Fig 7 and 8). High resolution Google Earth images were used to visually validate the classification performed by CLASLite. Additionally, ground truth was conducted around Brownsweg and Mindrinitie area.

Table 1. Land cover area for 2005 and 2009 in every subset of the study area

Land cover type	2005		2009	
Study area	Afobaka	Atjoni	Afobaka	Atjoni
Forest				
Hectares	266.827	673.018,00	265.645	671.518,08
%	89,21	97,09	89,05	96,75
Non-forest				
Hectares	32.275	20.187	32.663	22.540
%	10,79	2,91	10,95	3,25

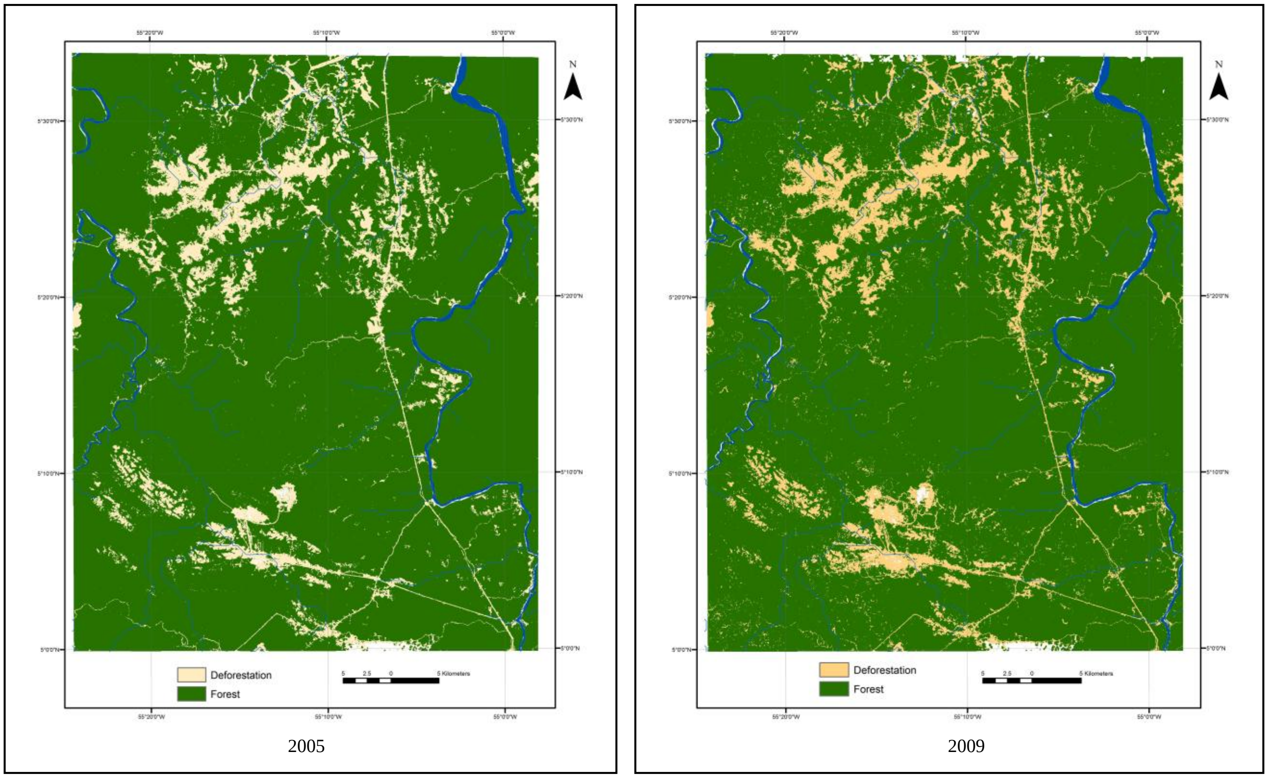

Figure 7 Forest cover maps Afobaka subset.

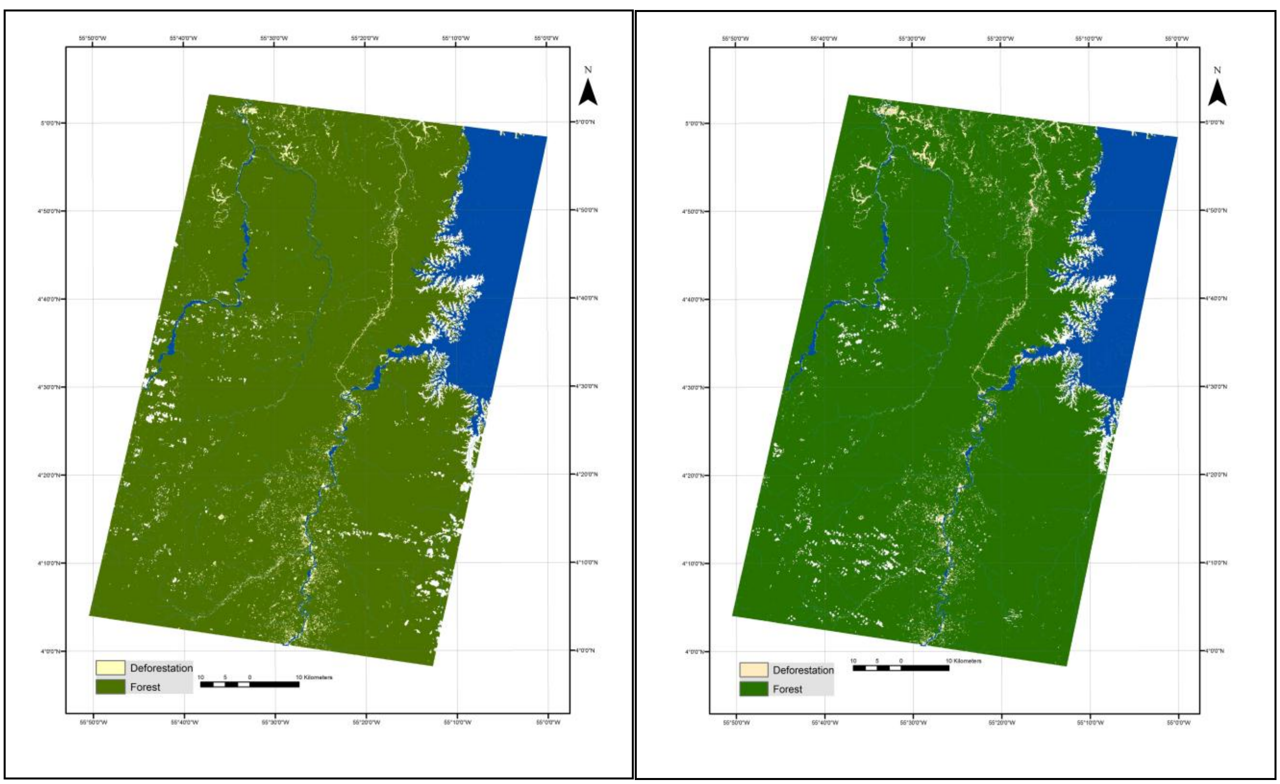

Figure 8 Forest cover maps Atjoni subset

4 SPATIAL EXPLICIT SIMULATION OF DEFORESTATION

4.1 MODEL DEVELOPMENT AND METHODS

4.1.1 General approach

In the previous chapter two forest cover maps were developed from 2005 and 2009. These two maps constitute, respectively, the initial and final landscapes during the simulation process. The spatial explicit simulation of deforestation used existing models available within *Dinamica EGO* version 1.6.2 with parameters customized for the study area. *Dinamica EGO* is a georeferenced stochastic cellular automata model that simulates deforestation and other multi-scale environmental dynamics based on the empirical relationship between spatial- explanatory variables (Soares-Filho et al 2002).

The general modeling approach encompassed two main steps. The first step comprised the calculation of annual deforestation rates , the estimation of spatial probabilities of deforestation and consequently the assessment of the drivers of forest cover change in the study areas using cartographic data for land uses, roads, settlements, protected areas and biophysical features (slope and vegetation) within a raster grid map of 30x30 m resolution. The second step involved the projection of deforestation trajectories up to 2020 based on the projection of historical deforestation rates from four years between 2005 and 2009. Deforestation trajectories based on historical trends assumed that deforestation rates remain constant through the simulation process under the assumption that neither future land use in the country nor any other policy decision will trigger an increase or decrease in the deforestation rates further than the current value.

This study support the argument that deforestation is an inertial process by which the areas most likely to be deforested are those located closer to the forest areas already intervened. Deforestation is defined in this study as the conversion from primary or late secondary forest to bare and shrubby land.

4.1.2 Model calibration, parametrisation and validation

The calculation of deforestation rates was the first step in the simulation processes. Deforestation rates are calculated within *Dinamica EGO* by comparing the initial landscape (2005) and the final (2009) for every study area measuring the percentage of forest that is changing to deforested each year between the period of analysis. *Dinamica EGO* computes deforestation rates by solving a matrix that describe a system that changes over discrete time increments, in which the value of any variable (deforestation area in this case) in a given time period t_n is the sum of fixed percentages of values in time t_{n-1} as follow (Soares-Filho et al 2009):

$$Rate = \left(t\sqrt{\frac{F2009}{F2005}} \right) - 1$$

In this case the matrix was solved for the transition forest to deforested (2 to 1 according to the land cover class values in the corresponding maps). The annualized deforestation rates for Afobaka and Atjoni subset are 0.00113864 and 0.0006838 or 0.11% and 0.06% respectively. The calculated rates reflect four year history of deforestation and are assumed here as the local historical deforestation rates for the study areas (Table 3).

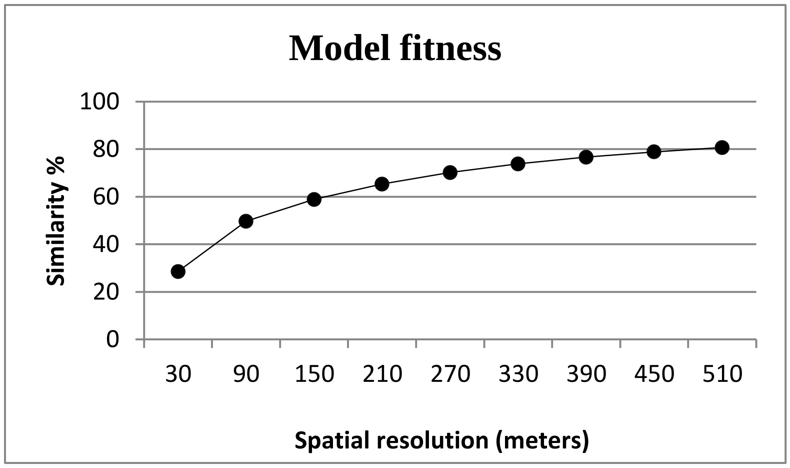

Figure 9. Model fitness based on the fuzzy similarity method**.**

The simulation of deforestation for the period between 2005-2009 receives as inputs the initial landscape (2005), the explanatory variables (Fig 13), the weights of evidence coefficients and the deforestation rate, and iterates four times (four years). In this calibration step the model produces the "distance to deforested" variable, the transition probability maps and simulated maps for each time step which are used during the model validation. The validation method used image similarity tests based on a fuzzy multiple resolution comparison between the initial and final real landscape (2005 with 2009) and the initial real landscape (2005) and the simulated one (2009). The model achieved a spatial agreement up to 80% (Fig 9) within at window size of 17 x 17 cells which is acceptable based on other results obtained using *Dinamica EGO* (Soares-Filho et al 2006, Guidice et al 2009). As the model runs, deforestation initiates adjacent to those existing deforestation patches and expands onwards depending upon the probability map. The future spatial distribution of deforestation is conditioned by the explanatory variables and by the deforestation rates used during the simulation.

Simulation of future deforestation trajectories are predicted within *Dinamica EGO* using the model parameters explained above except for the times of iteration. The simulation process starts with the real final landscape (2009) and iterates 11 times (11 years) until 2020. The model runs with the historical rate found over the period of analysis remaining constant into the future, these are 0.00113864 and 0.0006838 for Afobaka and Atjoni respectively.

Spatial distribution of deforestation

The spatial distribution of deforestation was calculated in *Dinamica EGO* by simulating the transition from forest to deforested which is determined by discrete-step-generated transition probability maps (Soares-Filho et al 2002). These spatial probabilities are produced based on a map of changes between

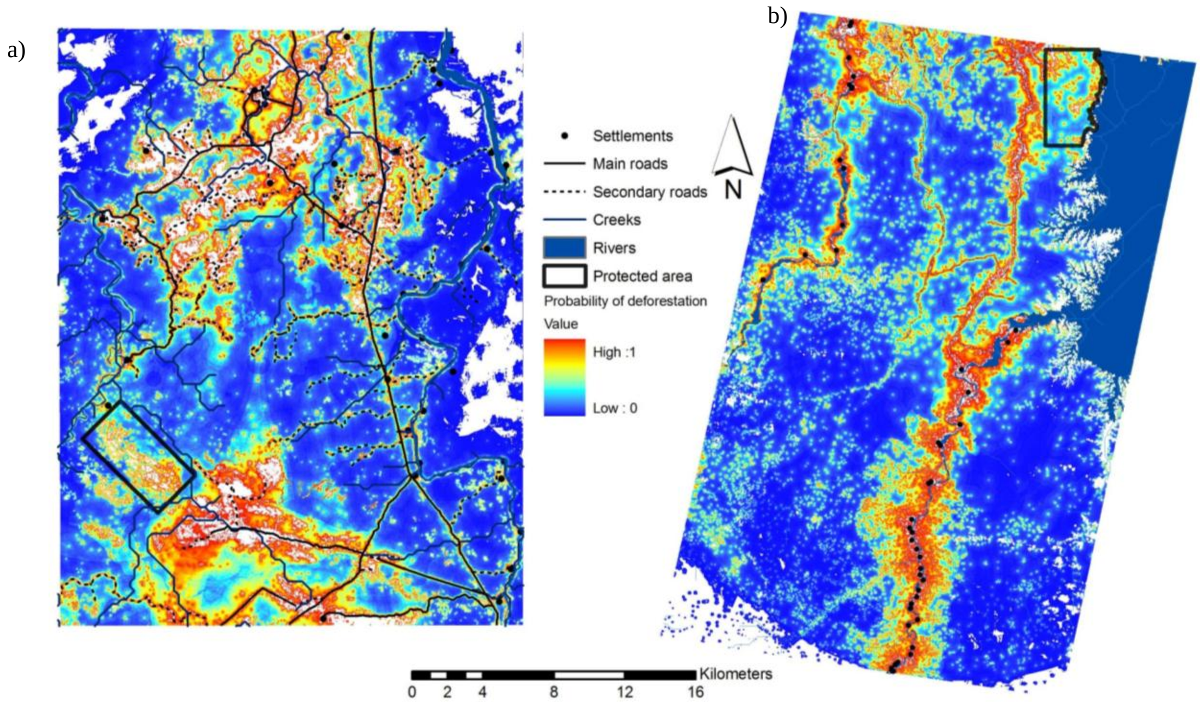

Figure 10. Spatial probability of deforestation. a) Afobaka subset, b) Atjoni subset. High probabilities area located around previously deforested areas.

2005 and 2009 and by calculating the weights of evidence of spatial variables. Weights of Evidence (WofE) is a method widely used in spatial explicit simulation to calculate, in this case, the spatial probability of deforestation occurrence based on a set of "evidence" variables (e.g distance to roads, distance to settlements, distance to navigable rivers, distance to previously deforested areas, slope, land uses, vegetation types and protected areas). The weights are calculated using Bayesian rules that explain the occurrence of an event in the light of updated evidence (Romero-Calcerreda and Luque 2006). During the process, the predictor variables are combined in a multiple map overlay operation within *Dinamica EGO*, where the posterior probability of deforestation occurs giving the presence or absence of a predictor variable (Soares-Filho et al 2010).

A WofE analysis results in a set of statistical measures of association: Weights (W^+ and W^-), Contrast (C) and Significance. The weights, W^+ and W^-, represent measures of the spatial tendency of finding one deforested pixel giving the presence of the predictor variable. If more deforested pixels occur within the spatial pattern than would be expected by chance, then W^+ is positive and W^- is negative. Conversely, W^+ is negative and W^- is positive when fewer deforested pixels occur within an evidence pattern than would be expected by chance (Giudice et al 2009). The contrast "C" provides a measure of spatial association or repelling effect between the deforested pixel and an evidence pattern. It is denoted by $C = W^+ - W^-$, therefore the larger and more positive the value, the greater is the influence of the evidence pattern in deforestation, on the other hand, the larger and more negative the value the greater is the repelling effect, near zero there is no effect at all.

The Significance is the variance of the Contrast (C) and it informs that (C) is significantly different from zero or that the association is likely to be “real”. If not significant association is found, the variable has to be removed as it was the case with the variable “protected areas”. An over or under estimation of the Weights can occur if there is no independence between the evidence variables which could affect the deforestation probability map. Therefore *Dinamica EGO* analyses the correlation between variables using a set of statistical tests to assess this assumption (Soares-Filho et al 2009). In this case was used the Joint-Uncertainty information which tests correlation between two evidence maps based on a scale 0 to 1 with higher values denoting a higher correlation (Appendix 1). A value of 0.5 was decided as the threshold based on similar studies (Giudice et al 2009). None of the evidence variables was correlated therefore all evidence variables were retained to build up the probability maps (Fig 10).

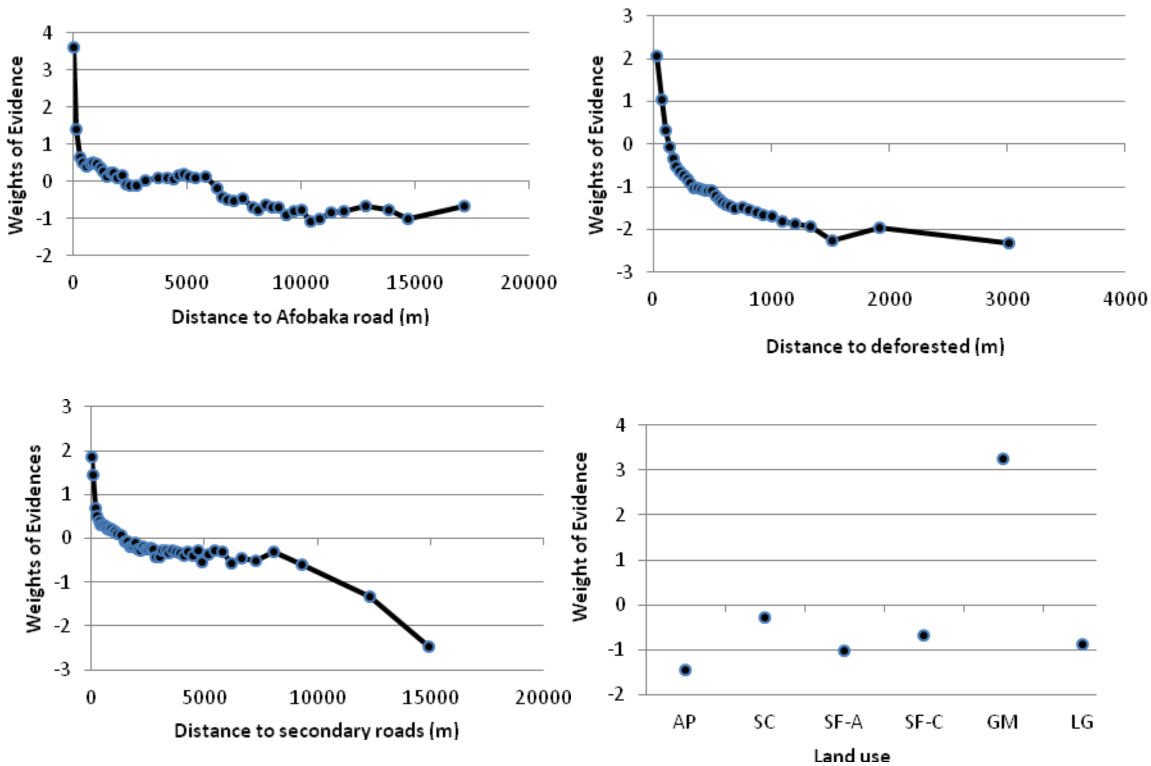

Figure 11. Weights of Evidence (W^+) Afobaka subset for the variables distance to Afobaka road, distance to secondary roads, distance to deforested and land use: AP-Abandoned plantation, SC-Shifting cultivation. SF-A-State farm agriculture. SF-C-State farm cattle. GM-Gold mining and LG-Logging.

The highest probabilities of deforestation are found in red around previously deforested patches, within short distances from roads and settlements in the case of the Atjoni subset. This result is a direct consequence of the weights of evidence coefficients (fig 11 and 12) which also reflect that the variables “distance to deforested areas”, “distance to Afobaka road”, “distance to secondary roads” and “land use-gold mining” are the main factors determining deforestation for the Afobaka subset. In the case of Atjoni subset, the main determining factors are “distance to deforested areas”, “distance to Atjoni road”, “distance to secondary roads”, “distance to settlements” and “land use-gold mining”. Likewise, the analysis showed that for both study areas, deforestation is not correlated with logging activities nor with agricultural uses and it is not strongly linked with proximity to navigable rivers over the period analyzed.

In summary, from the analysis can be retrieved that deforestation is highly probable within the first 2 km from main and secondary roads, settlements (only for the case of Atjoni) and it expands outwardly from existing deforested patches. The calculation of future deforestation (2009-2020) used the same weights and probabilities as the simulation run during the calibration procedure for 2005 and 2009, only the deforestation rate changed.

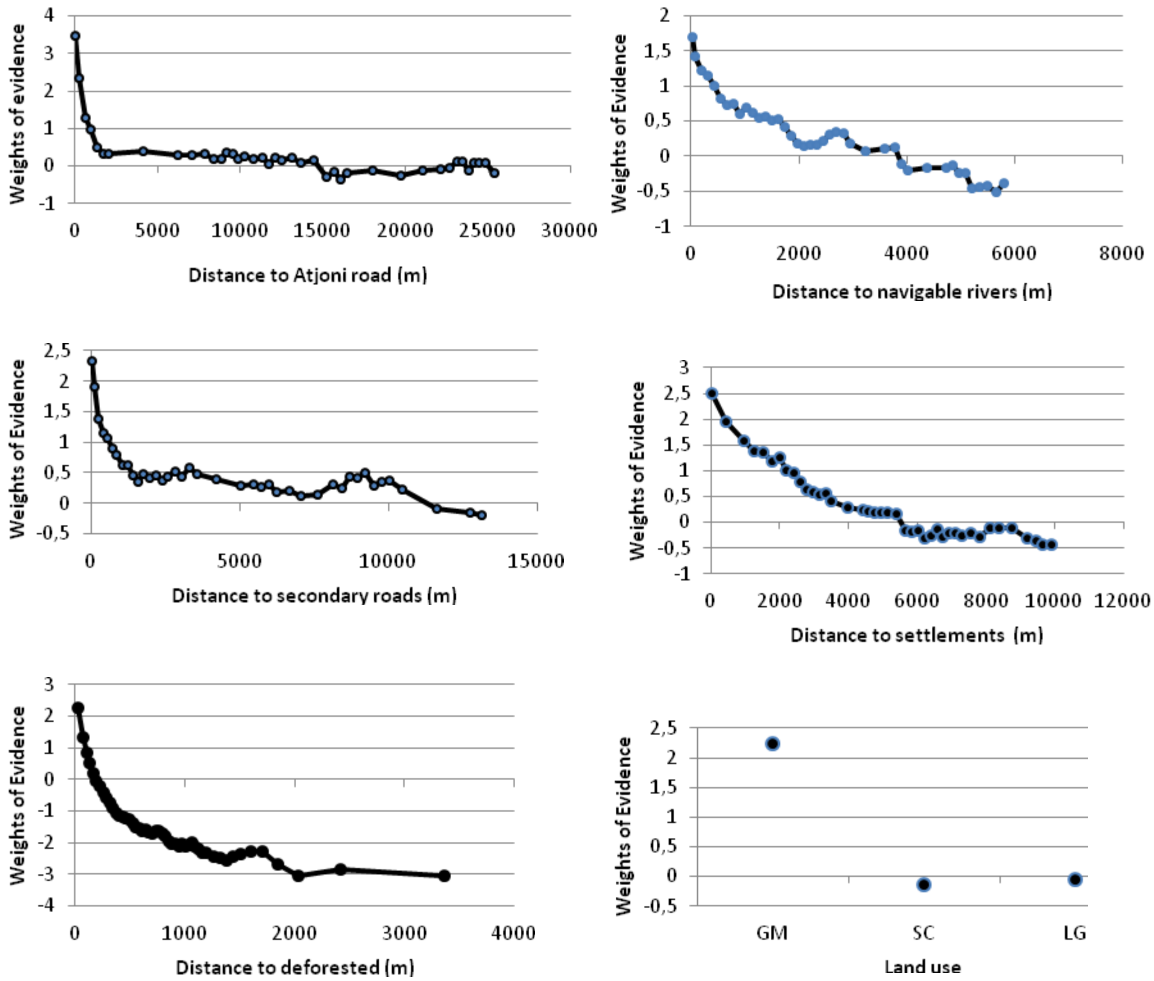

Figure 12. Weights of Evidence (W^+) Atjoni subset for the variables distance to Atjoni road, distance to navigable rivers (Suriname and Saramacca river), distance to secondary roads, distance to settlements, distance to deforested and land use: GM-Gold mining, SC-Shifting cultivation and LG-Logging**.**

4.2 CARTOGRAPHIC DATASET

The spatial explicit simulation of deforestation incorporated biophysical and proximate variables that are known for driving tropical deforestation (Geist and Lambin 2002) and that have been used in other deforestation models (SoaresFilho et al 2004, 2006; Etter et al 2006 and Guidice 2009). Ten spatial variables were considered to simulate deforestation in the study area: distance to previously deforested land (m), distance to settlements (m), distance to navigable rivers (m), distance to main roads (m), distance to secondary roads (m) and distance to railways (m). These variables were derived from maps of roads, settlements, railways and rivers and transformed to continuous distance to feature maps using *Dinamica EGO* algorithms accounting for the Euclidean distance in meters between a pixel and the closest pixel representing the feature. Other variables included slope, vegetation types, protected areas and land uses (Fig 13). The land use variable was built by appending agricultural uses (abandoned plantation, state farm agriculture, state farm cattle and shifting cultivation), gold mining and logging areas. To obtain logging areas, polygons were drawn in ArcGis 9.2 representing the highest Kernel density of logged trees.

These spatial variables were introduced in the simulation to quantify and integrate their influence on the spatial prediction of deforestation. They are known as predictor variables. To incorporate them in the simulation, all layers representing the variables were converted to raster format with 30 m resolution using ArcGIS 9.2. The cartographic dataset was stored within a raster cube dataset with all raster maps having the same number of rows and columns and tied to the same coordinate system.

Table 2. Cartographic dataset used in the simulation

LAYER	SOURCE
Forest cover maps	Elaborated within the current project.
Roads	Division of Natural Resources and Environmental Assessment of Suriname (NARENA).
Railways	NARENA
Settlements	NARENA
Rivers	NARENA
Logging	Foundation for forest management and production control SBB.
Mining	National Forest Office of French Guiana, WWF-Guianas.
Agriculture	NARENA
Vegetation	NARENA
Protected areas	NARENA
Biomass	Sarvision, Conservation International Suriname

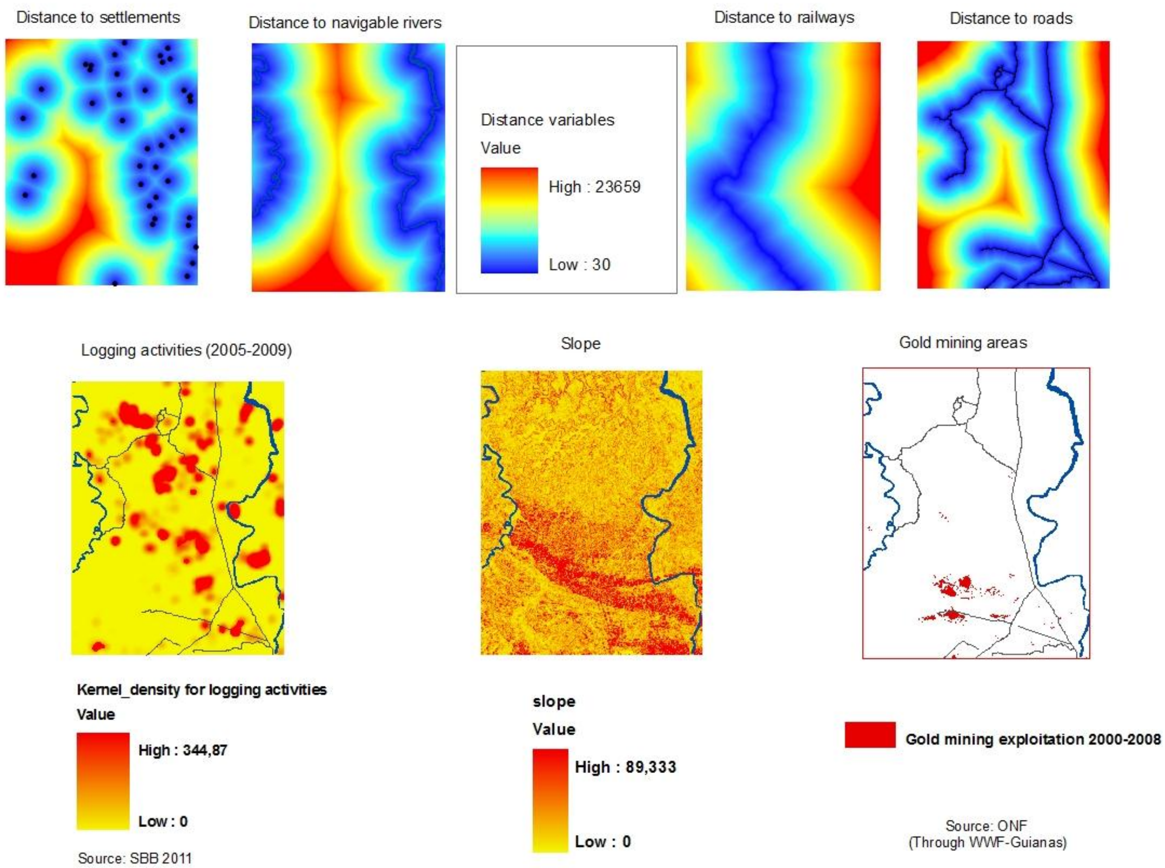

Figure 13. Some of the spatial variables used during the simulation process for Afobaka subset. The same variables were used for Atjoni area. All variables are tied to the same coordinate system and have the same number of rows and columns. The biomass layer was obtained from the Wood Hole Research Institute (2011) and used at the end of the simulation to predict emissions of Carbon dioxide (see below).

5. RESULTS AND DISCUSION

5.1. Deforestation results for the entire study area.

Forest area loss between 2005 and 2009 is spatially depicted in figure 14 with deforestation rates summarized in table 3. Figure 15 represents the forest landscape for 2020. Deforestation is growing inertially around areas of previous deforestation extending inside Brownsberg Natural Park and Brinckheuvel nature reserve. The simulated landscape in 2020 shows how far the new deforestation extends across the study area with the same spreading deforestation pattern. Locations within the so-called “Green stone belt” show a higher relation with the occurrence of deforestation. Approximately 44% of the deforestation between the period analyzed (2005-2009) was concentrated within the Gros Rosebel mines; 33% in Mindrinitie; 12% in Brownsweg and 11% distributed along roads, rivers and around the savannahs of Zanderij. These areas were acting as centers of diffusion for deforestation and are the areas that hold the largest probability of deforestation (Fig 10).

Between 2005 and 2009 there was a loss of 1182 hectares in Afobaka subset and 1500 hectares in Atjoni. The average annual deforestation rate was 295,5 and 374, 98 hectares for Afobaka and Atjoni respectively. The model estimates that after 11 years the forest will decline roughly 4000 hectares for the entire study area under a historical trend. This trend assumes an annual rate of gross deforestation in
-0,11% for Afobaka and -0.06% for Atjoni. This deforestation is still below to what is considered high (>1.5%). Some of the reasons that explain low deforestation rates in the study zones reside in demographic factors, high proportion of forest cover and relatively low economic development.

Population density across the country is 3.3 people per sq. km, one of the lowest in the world (World Bank 2010) with most population located in the coastal zone. The entire study area includes a major proportion of the interior[1] settlements along the Suriname and Saramacca river. Deforestation around these settlements, partially attributed to shifting cultivation, does not extend beyond 2 km from the village within the period analyzed (2005-2020). Additionally, deforestation rates vary spatially and are closely related to the proportion of forest cover with rates peaking if less than 80% cover (Ludeke et al 1990, Lambin and Ehrlich 1997, Etter et al 2005). Forest cover in Afobaka subset is approximately 90% of the entire area and approximately 97% of the total area in Atjoni Subset. Likewise economic development has been relatively low even though the zone is the area where many important economic activities take place: timber, mining, quarrying and hydropower generation but they have not been extensive enough as to have an effect on deforestation at the scale of this analysis.

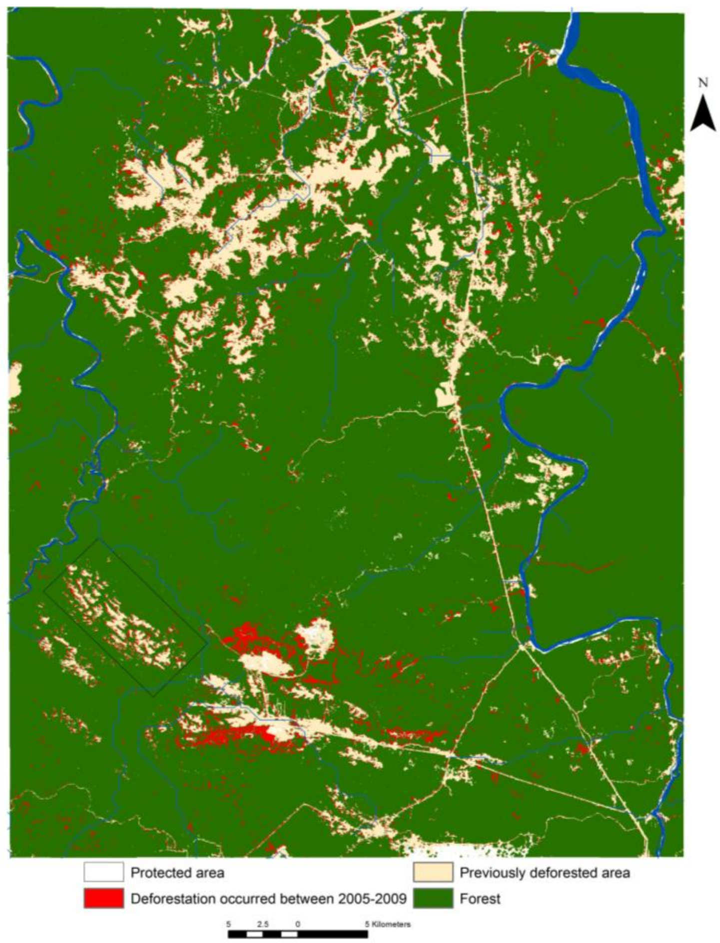

Figure 14. Deforestation occurred between 2005and 2009 for Afobaka subset (red).

However, two issues raise concern in this respect. First, gold mining activities are the main source of deforestation and it is spreading at an alarming rate across pristine forest endowed with gold deposits. In the year 2000 the area dedicated to gold mining was approximately 8295 hectares and in 2008 the gold mining area was extended to 27.253 hectares, three-fold increase in eight years (WWF 2011). Over the last decade the price of gold has increased 360% and continue to set new records raising to 1813,5 to August 2011(World

[1] Interior refers to every part of the country that is not the coastal zone.

Gold Council 2011). Similarly, in the second quartier of 2011 the gold demand was 919.8 Tonnes worth US$44.5bn, the second highest quarterly value on record with China and India as the major contributors to growth. As a response, there has been a compelling economic incentive to mass exploitation of lower grade gold deposits (Swenson et al 2011) which includes the Guiana Shiled region (Hammond et al 2007).

The second issue that raises concern is the high degree of lawleness and the difficulty of the National government to regulate this activity which prevents the country from managing how natural resources are extracted to meet a strong market demand. Deforestation is expected to increase due to gold mining in the lack of appropriate regulation and if remote forest areas become accessible with the plans to communicate Paramaribo with Santarem in Brazil which eventually would facilitate the movement of informal miners and mining companies.

Table 3. Total deforestation between 2009 and 2020.

	Afobaka	Atjoni
Annual rate of gross deforestation (%)	-0,11	-0.06
Avarage annual deforestation (Ha.yr-1)	-295.5	-374,98
Area loss 2020	1056	3805,81

Other “low-governance” regions in the Amazon where land uses are not well regulated provide with examples of increasing deforestation and ecosystem destruction in response to recent record high gold prices and extension of road infrastructure. In the department of Madre de Dios, Peru, the largest producer of gold in the country, recent mining is converting primary forest at a non-linear rate alongside increasing gold prices (Swenson et al 2011). In conjunction with annual rate of increase in gold price of ~18%, deforestation increased six-fold from 2003-2006 (292/ha/year) to 2006-2009 (1915 ha/year). According to the author, gold mining in the region seems to be relatively independent from the location of roads, however, large continental-scale multi-faceted infrastructure projects are providing new access for gold miners to Peru´s lowland Amazon.

Protected areas do not seem to counteract effectively the effects of miners across gold bearing regions in the Amazon. In Suriname, we found forest conversion inside Brownsberg Nature Park and Brinkheuvel Nature Reserve between 2005 and 2009. Within the limits of these legally protected areas we found high spatial probability of deforestation (Fig 10). Our model estimates that for 2020, deforestation increase 5% inside Brownsweg Natural Park and, in Brinkheuvel Nature Reserve deforestation will occur but some regeneration as well. The transition matrix indicates that there is regeneration during the years of the analysis, however, during the simulation; I only focused on the pixels changing from forest to deforest. The protection of legally protected areas in Suriname is hindered by the lack of law enforcement, lack of funding and lack of institutional capacity, as well as the difficulty to monitor remote land use activities. Monitoring of gold mining inside reserves, would be feasible with frequent high resolution (e.g < 10m) satellite

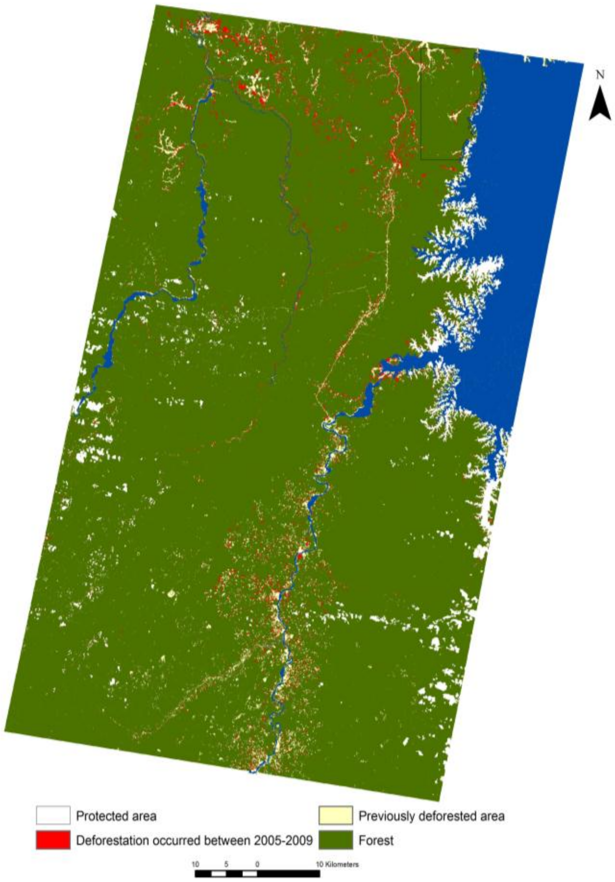

Figure 15. Deforestation occurred between 2005 and 2009 for Atjoni subset. White holes in the image are data gaps from cloud masking.

imagery. Unfortunately, steady monitoring can be costly as high resolution images are currently not freely available. Many exiting protected areas in the Guiana Shield overlap with greenstone formations. The Brownsberg Nature Park, one of the oldest protected areas in the region, has been an illustration of how gold mining has transcended the borders of the protected areas when they rest atop these primary mining targets which has resulted in 5% of forest cover loss and depletion of adjacent creek mainstreams in this protected area (Hammond et al 2007).

5.1.1. Deforestation around the savanna area

Deforestation is also observed around the savanna-forest ecotone in the Zanderij region (Fig 14) therefore the spatial probability of forest conversion is high in these transition zones (Fig 10). Bordering the open white sand savannas in the study area there is a type of tropical moist forest that reaches 20 to 30 m height with a canopy generally uniform and continuous but sometimes with patchy strata that permits light penetration. This forest type is locally known as savanna forest. Other vegetation strata around the savanna include savanna scrub which is an open areas of bare sand and herbaceous plants intermixed with shrubs and small trees up to approximately 9 m tall. There is also wood savanna with a more or less continuous cover of shrubs and trees varying in height from 9 to 16 m, dense understory of shrubs and occasional emergent trees. The structural phases of the white-sand vegetation represent a serious of formations found in transitional patterns but with similar floristic composition (Heyligers 1963; Jansma, 1994).

Climate and soil are the main factors that are influencing the vegetation in the so-called savanna belt of Suriname by an alternation of dry and wet periods in the water supply of plants. However, repeated human activities like fire can inhibit the transition stages from savanna scrub to savanna forest. Our model estimated that some deforestation took place in the savanna forest around Zanderij and that furthermore the open white sand savanna will expand gradually by 2020. The most likely reason for this process of savannization is the forest destruction by fires and sand mining which progressively spreads out the transition zone between these two ecosystems (Savanna forest and open savanna). More research is needed to better understand the effects of human activities in the loss of savanna forest and spreading out of the open sand sand savanna area in the country.

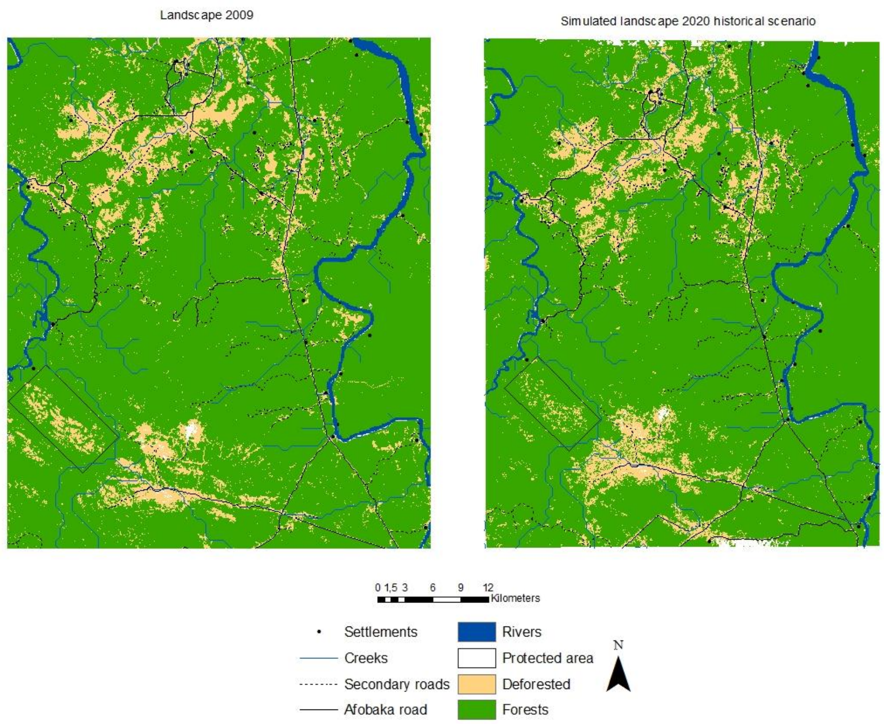

Figure 16. Simulated landscape for 2020 under the historical scenario for Afobaka subset

Information on the vulnerability of areas to threats such as forest clearing due to gold mining has been identified as important for prioritizing conservation action. Spatial explicit assessments of deforestation are important planning tools indicating where conversion of forested ecosystems is more likely to occur in the near future. Although the predictions in this study need to be refined as improved data for future projection becomes available, the areas predicted as vulnerable are consistent with the actual patterns of deforestation in Suriname.

5.1. Spatial patterns of deforestation: qualitative assessment-

According to the different types of clearance shown in figure 18 an *island*-pattern of deforestation is observed with conversion of the interior core into edge habitat particularly with deforestation mining. Along the upper Suriname river a typical *diffuse*-pattern is recognized, in which small patches are deforested for subsistence. Along roads a narrow *corridor*-pattern is identified and associated with a very slow progressing colonization frontier, especially along the Afobaka road. A more *geometric*-pattern of deforestation occurs in the "open savanna" area. This geometric case is commonly associated with large-scale clearings for modern sector activities, but in the present case this shape is connected with a combination of human factors and biophysical features related to fire prone vegetation.

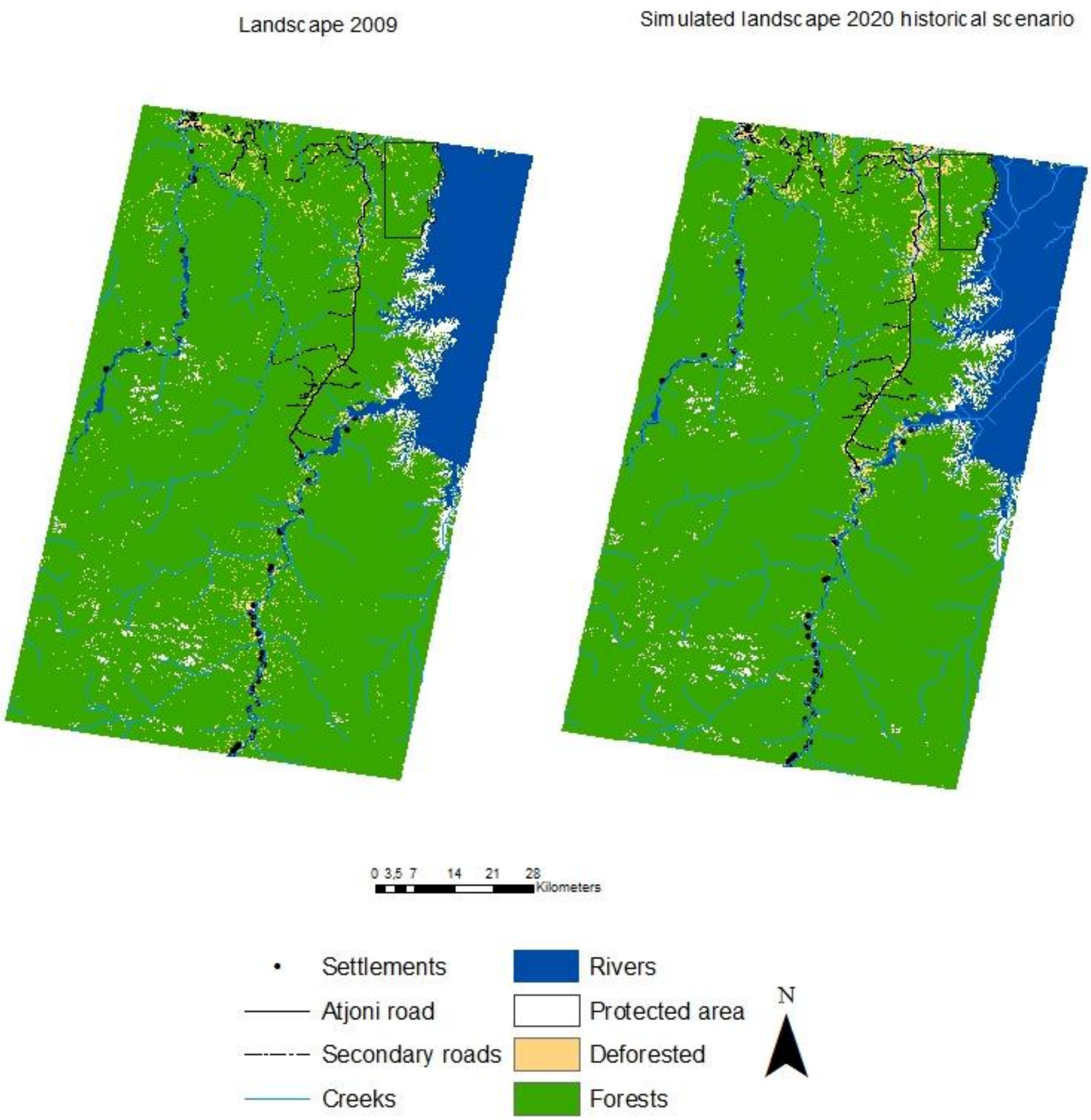

Figure 17. Simulated landscape for 2020 under the historical scenario for Atjoni subset

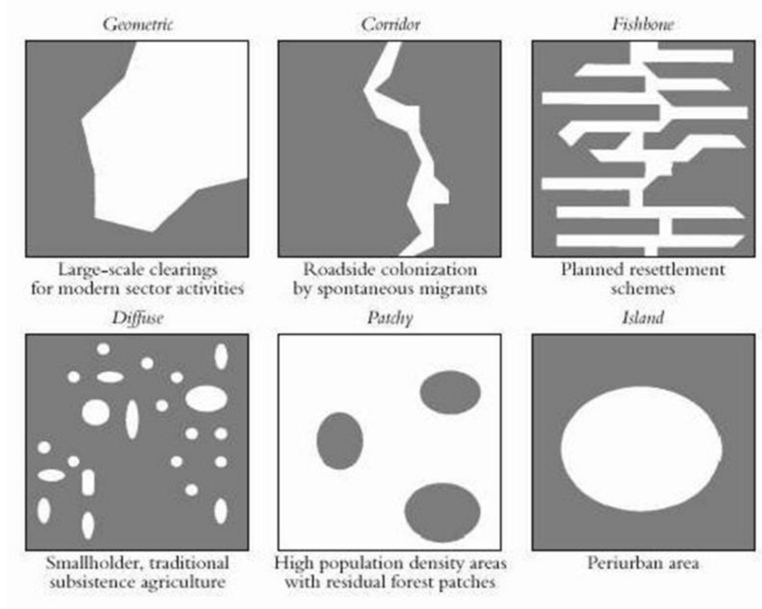

Figure 18. Characteristic spatial deforestation patterns recognized across the tropical belt (Mertens and Lambin 1997 Spatial patterns of deforestation, p 149). The patterns observed in the study area are geometric, corridor, diffuse and Island.

In general the deforestation pattern is one of a continuous matrix of forest perforated with *island* of deforestation and white sand "open savannah" areas. Deforestation patterns are spatial indicators of the deforestation processes or events that are leading the decay of the forest ecosystem and therefore an indication of the evolving deforestation frontier. Usually deforestation is localized in frontiers which are areas that respond to the dynamics of the drivers of change. In this study the deforestation frontier is localized in the forest edges surrounding Gros Rosebel, Brownsweg and Mindrinitie mining sites from where forest cover removal is progressing outwardly.

Deforestation tends to spread from previous forest clearings where more edge per unit area is exposed and thus holding a high spatial probability of forest loss (Fig 10). The results of the analysis show that by 2020 deforestation would expand up to 1 km from previously deforested patches. Continuous areas of forest overlapping with the greenstone belt in Suriname are being perforated and progressively creating edge habitat. Altered physical conditions nearby the edges may affect structure, reproduction and distribution of vegetation. Also tree fall and mortality increases and substantial effects in the reproduction of plants may occur. Sensitive plants species decline or become absent in the edges (Laurance et al. 2002).

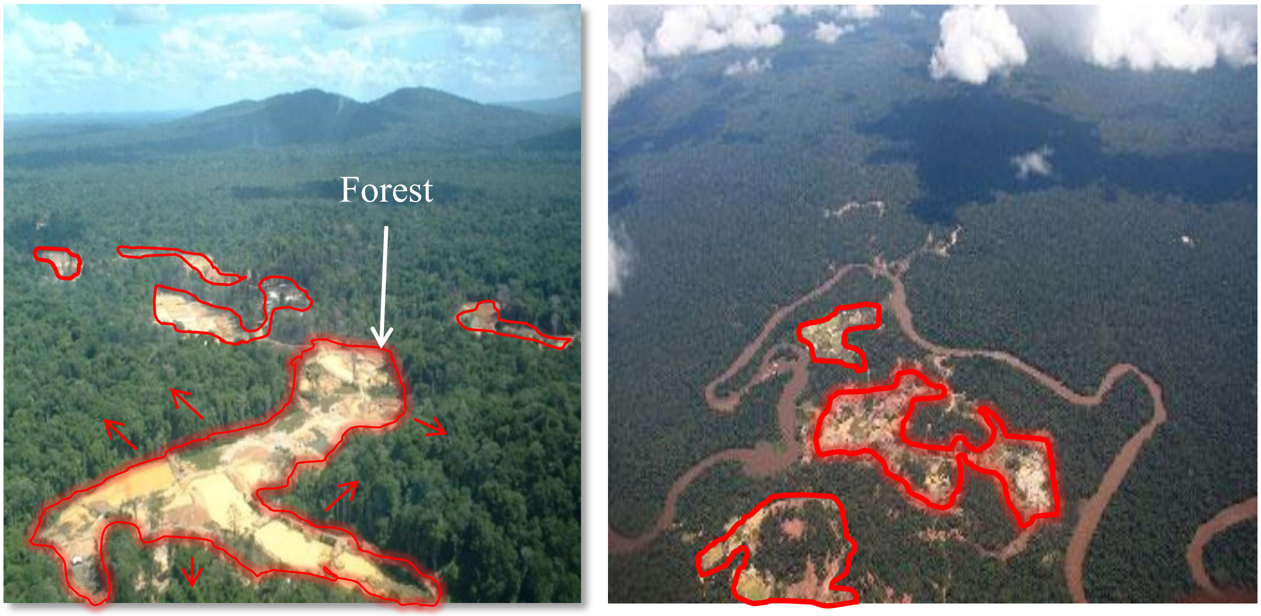

Figure 19. Representation of the fragmentation pattern due to gold mining activities

5.2. Drivers of deforestation

Proximate drivers

Proximate factors of deforestation are those originated from human activities that have an immediate direct effect on forest cover change. In other words, proximate factors are land uses that cause a change in land cover. In terms of scale they are seen to operate at the local level (Geist and Lambin 2001).

Roads

Road building has been a key determinant of deforestation in the Amazon (Mertens and Lambin, 1997; Kaimowitz and Angelsen, 1998; Nepstad et al 2001; Laurence et al 2002, 2009; Soares-Filho et al 2004, 2006,). However, roads alone do not explain deforestation; they work in combination with other proximate factors (e.g. soil fertility) and underlying forces (e.g. economic growth, production incentives, market expansions, population pressure). The effects of the roads (namely Paranam-Afobaka and Brownsweg-Atjoni roads) on forest cover change in Suriname over the period analyzed decreases rapidly beyond distances of 1 to 2 kilometer from the road (Fig 14) in contrast similar studies have found that in the Amazon (Brazil

and Peru) the probability of deforestation is high within 20 km from the main road in average (Laurence et al 2001, Soares-Filho et al 2006, Guidice et al 2009).

In Suriname, between 2005 and 2020 little correlation between deforestation and distance to main road was observed. The main reason that could explain this fact is that in the forested part of the country there is low population pressure as the 90% of the total population is located in the coastal zone. Therefore, there is very little colonization and no incentives to move the deforestation front deep into the forest interior as there is plenty of land to colonize parallel to the main road. Regarding distance to secondary roads, the situation is similar. Secondary roads in the study area are built to reach mineral exploitation sites or logging areas and due to low demographic pressure, no moving colonization front was observed.

Notwithstanding, it is important to note that this study is not observing the effect of road paving as the pavement of Afobaka road finished by the end of 2009 and the paving of the road to Atjoni is still under way. During field trips in the study area in the first semester of 2010, some land claims were detected most probable people claiming ancestral rights (Kennet Tjon, pers. Comm.). New large clearings were also observed along the paved Afobaka road for housing projects.

In synthesis, according to this analysis, the road from Paranam to Atjoni has not been a strong driver of deforestation over the period of observation (2005-2009). However, the landscape observed in 2005 reflects cumulative deforestation prior to 2005. Thus, it is likely that before 2005 the correlation between deforestation and distance to roads was stronger and explaining the deforested patches along the roads prior to that year. In a similar way, the results of the analysis regarding road could be different if we perform this study within two or three years more (e.g. 2005-2013) which could reflect the cumulative deforestation after road paving. Hence, the driving forces of deforestation, for instance roads, result from the complex interaction of socio-political and economic processes acting at multi-temporal and multi-spatial scales, therefore, it will be simplistic to conclude that roads do not exert an effect on forest cover change in Suriname; more variables over different time periods would have to be analyzed (Etter et al 2005).

Likewise, the situation could turn into a distinctive pattern as the road is extended to the Southern part of the country and furthermore if this is connected with roads in Brazil. The extension and pavement of the roads in the interior of the country would undoubtedly create access for poachers, miners, loggers, oil corporations and agribusiness to remote and well preserved forest areas of the country. This can be foreseen under a policy climate of economic growth based on natural resource extraction, since the impact of road construction on deforestation depends on the economic activities in a given region (e.g mineral exploitation vs logging) (Lambin and Ehrlich 1997). Road construction in forested areas determinately increases the incentives to convert them to other uses by offering improved marketing opportunities and lowering the cost of access and land clearing (either for productive or speculative purposes).

Indeed, the development and improvement of transportation infrastructure tends to be one of the most effective policy tools for influencing the spatial distribution of agricultural, mining and forestry activities. But the role and impact of roads will depend on the type of road, the stage of development of the frontier area and especially, it will depend on the policy-economic climate (see session below about underlying drivers).

In the case of other accessibility variables like distance to rivers, deforestation was found positive correlated at major distances from navigable rivers > 2 km. This pattern was found in the Atjoni subset and it was expected since the Suriname River is the main transportation infrastructure for inhabitants in the area. Furthermore, people can access major distance towards the forest interior using navigable tributaries. Incentives to deforest at major distances from navigable rivers are connected to shifting cultivation activities.

Gold mining

Gold mining is inside the group of proximate drivers of deforestation, particularly referring to the extension of private enterprise infrastructure (Geist and Lambin 2001). Mining is an important economic activity in Suriname where Precambrian rocks hold strategically important reserves of industrial minerals that have become essential for modern technology (gold, bauxite, iron ore, manganese, zinc and copper). Although the greatest volume of gold is produced by industrial mines, small-scale gold mining is a common activity in the Amazon where gold miners extract the mineral from alluvial sediments using rudimentary mining technology and mercury to amalgamate the gold.

Gold mining in the study area has found to be the main direct precursor of deforestation over the period analyzed (2005-2009). This can be seen in the weights of evidence coefficient (Fig 11 and 12), which reflects that most pixels changing from forest to deforested over 2005 to 2009 where located inside gold mining areas. As explained in previous sessions, these *hot spots* of deforestation coincide with the Gros Rosebel, Brownsweg and Mindrinitie mining sites.

Gold mining in the study area spans large areas of forest, leaving bare surface scars of up to 5 kilometers wide with almost no remaining tree cover. The area dedicated to gold mining in the study subsets, has increased up to 5,421.8 hectares from 2000 to 2008 (Fig 20), reflecting a threefold increase approximately. Mining is causing deforestation by tree felling and land stripping in preparation for mining (Heemskerk 2001). Results of this analysis show that mining operations often radiates beyond mining sites, the best example of it is gold mining inside Brownsberg Nature Park where during the past 10 years small scale-gold mining has been illegally practiced within this park (Arets et al 2006). It has been estimated from deforestation scars in satellite picture (Tjon and Atmopawiro 2006) that in year 1999, 571 hectares (4% of

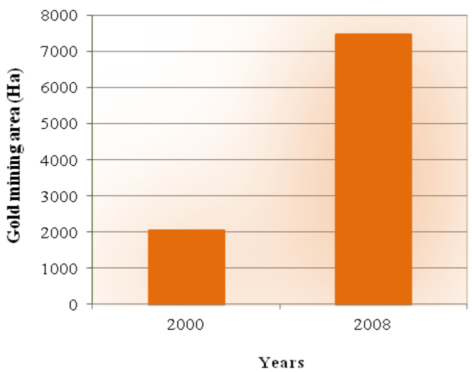

Figure 20. Area dedicated to gold mining, observations for two time periods in the study area. WWF 2010.

the total area of the park) were directly affected by gold mining, in 2002 the area expanded 43.4 hectares and in 2004 46.4 hectares more were directed impacted.

The synergies between gold mining prices and deforestation could be threatening forest ecosystem overlaying with greenstone formation in Suriname. Therefore, sound forest management effectiveness is under pressure if the surface and subsurface land uses overlap (Hammond et al 2007). The clash is exacerbated with the participation of cooperative miners from Brazil known as *garimpeiros* who have a history of creating "gold rushes" in the Amazon wilderness; the intensity of *garimpeiros* mining fluctuates with the international price of gold (Killeen 2007). Similarly, the conflict between gold mining and protected areas management is an issue that should be resolved, so that mining exempt from any sort of activity inside legally protected ecosystems.

Logging

Wood extraction is a proximate driver of deforestation of high relevance in tropical forest regions (Geist and Lambin, 2001). Unlike other Amazon countries like Brazil, in the study area there was no a positive correlation between logging operations and deforestation over the period 2005-2009. Logging operations exert an effect on deforestation when intense activity cause collateral damage to trees, canopy damage and forest impoverishment leaving the forest susceptible to fire under dry climatic conditions (Nepstad et al 2001). If canopy damage level is low, then selective logging has relatively small immediate and long term impacts on forest resources (Asner et al 2006). Likewise, deforestation and logging activities are usually positive correlated when there are other profitable incentives encouraging the conversion of forest into other land uses (e.g agriculture, large scale plantation), if roads are built and population pressure expands (Merry et al 2009).

In Suriname, logging operations have been low impact activities carried out in a selective way by small-scale companies and are characterized by low harvesting intensities. Vegetation recoveries in gaps and on skid trails have followed timber extraction because of the low timber intensity (25 years-cutting cycle). In general the forest in Suriname is underutilized regarding timber production; the sustainable potential of the forest in the country could be few times larger than the current production level of 150,000 m^3 including the present area issued for exploitation (SBB, 2006-National Forest Policy of Suriname).

Large scale timber companies (e.g. Chinese) have faced constraints to be able to operate because they have not met the required criteria from the National government and, in the other hand, local companies face difficulties because the policy climate regarding the timber sector, has not favored availability of credit. Another relevant limitation has been the lack of appropriate infrastructure (Kenneth Tjon, pers. Comm.). Timber exploitation in Suriname might be stimulated with investment capital, knowledge and access of international markets, the capacity to manage large company and enforcement of human capacity. Timber production may also be stimulated with the expansion of roads (IIRSA roads and the North-South Corridor) which is expected to improve the quality of infrastructure for heavy transport.

The above mentioned reasons could have influenced the non-existing effects of logging on deforestation during this analysis and. Deforestation was not detected because it is not carried out in large scales, because the intensity of the activities are too low to cause forest damage and consequently a forest dieback (see Nepstad et al 2008 for the dieback concept) and because there are no other variables, like fragmentation, population pressure and policy-deforestation incentive, playing a role in the synergism between timber production and deforestation.

Nevertheless, more accurate conclusions about the impact of logging on forest cover change could be drawn if the assessment is done by high-resolution satellite analysis able to detect skid trails and log landings and if the forest cover change assessment includes degradation by forest impoverishment, canopy damage and induced tree mortality. It is important to mention that these conclusions are based on the results over the period of study (2005-2009). Some relatively large logging related deforestation was detected during a field trip in 2010 to the study area inside a timber concession.

Underlying drivers of deforestation

Underlying drivers of deforestation are the political, institutional and economic factors that unchain the proximate drivers of forest cover change (Geist and Lambin, 2001). The main underlying factor defined in this work is the unstable policy climate prompting forest mismanagement.

The drivers of deforestation inadvertently pose a significant challenge in the management of natural resources because lack of capacity and appropriate policies in the country can stimulates the expanding natural resources exploitation like the ongoing gold rush across greenstone deposits. In the case of gold mining, the challenge resides in the Government capacity to mitigate this global driver of change by strengthening regulatory policies and reinforcing forest governance capacity. Overall the challenge resides, especially regarding illegal gold mining, in the alleviation of poverty, in deterring unemployment, enhancing quality of life and in improving education and social awareness (Heemskerk 2001).

Unsustainable land use practices like high-impact gold mining are fostered by a climate of poor institutional performance, lack of technical capacity and ineffective laws. Under this policy climate the effectiveness to manage large areas of intact tropical forest overlapping with primary mining targets is unlikely to succeed as the gold rush continues. In Suriname, there is an urgent need to reinforce regulation of mining concessions and operations both in protected and unprotected forest. It is relevant to design and incorporate land use zoning including the creation of protected areas of different categories. It is also relevant to develop the capacity of governmental institutions to effectively manage forest and effectively coordinate conflicting land use allocation through balanced land-use zoning process. Moreover, to enhance the management of existing protected areas overlapping with greenstone deposits. It is imperative the need of creating new areas of protection that can buffer the rapid change in forest cover due to gold mining activities. These areas could also eventually buffer the effect of future infrastructure developments which are expected to trigger the dormant impacts of roads in the study area.

6. CONCLUSIONS

Deforestation rates in the study area are closely related to the spatial patterns of forest cover encountered in the region where continuous areas of forest experience change at a relatively low rate. However, gold forest areas overlapping with the greenstone belt in Suriname are being perforated and progressively creating edge habitat. From these exposed edges the probability of deforestation maximizes pointing out deforestation hot spots in the country.

The driving forces of deforestation in this study result from the interaction of socio-political and economic processes with land uses. The major driver of deforestation is gold mining with concentration of forest cover change within the Gros Rosebel, Brownsweg and Mindrinitie regions which is consistent with the location of gold deposits. These areas might constitute the spreading source of future deforestation trajectories. Some deforestation is also found along the savanna-forest ecotone where the destruction of savanna forest is progressively spreading out a savannization process.

Little correlation was found between roads and deforestation over the period analyzed, thus roads are not the main driver of deforestation in this analysis. However, they may exert a major impact as Suriname's economy grows and moreover if road networks extent to neighbouring countries which would add a new dimension to the socio-economic dynamics of forest cover change in Suriname.

Deforestation reaches inside protected areas which reflects low level of protection. Governance can be viewed not only as a factor inhibiting the effects of economic activities along deforestation frontiers but also as a force counteracting the spreading effect of deforestation inside natural protected areas.

Deforestation in the study area is and will be stimulated by a gold rush on greenstone deposits at a scale and rates that policy interventions have not been effective to foreseen and mitigate. Deforestation tends to increase as economic forces prompting market growth exert pressure. The results of this analysis show that as this trend continues, as the force of governance grows more slowly than the force of exploitation, the forest overlapping the greenstone belt is under serious threat with all the undesirable consequences for the forest ecosystem services and livelihoods. This type of study can be used as an instrument to support conservation management of this vital ecosystem.

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APPENDIX 1:

Weights of evidence correlation between selected variables. Values above 0.5 indicate correlation.

First variable	Second variable	Joint information Uncertainty
Distance to navigable rivers	Distance to Atjoni road	0,077469
	Distance to secondary roads	0,0617479
	Distance to settlements	0,2564
	Land use	0,0741825
	Vegetation types	0,0411763
	Distance to preoviously deforested areas	0,0137744
Distance to Atjoni road	Distance to secondary roads	0,363089
	Distance to settlements	0,0866021
	Land use	0,06945
	Vegetation types	0,0230762
	Distance to preoviously deforested areas	0,0169631
Distance to secondary roads	Distance to settlements	0,0529264
	Land use	0,0914002
	Vegetation types	0,0243419
	Distance to preoviously deforested areas	0,0164596
Distance settlements	Land use	0,0964414
	Vegetation types	0,0638578
	Distance to preoviously deforested areas	0,016412
Land use	Vegetation types	0,478704
	Distance to preoviously deforested areas	0,0237892
Vegetation types	Distance to preoviously deforested areas	0,033764