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# Carbon and Co-Benefits from Sustainable Land-Use Management

**Deliverable 10: Quantification of carbon benefits in conservation project activities through spatial modeling: Republic of Congo as a Case Study**

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# EXECUTIVE SUMMARY

The goal of this phase of the Carbon and Co-Benefits Initiative project is to develop an approach that can be used to estimate the impact of forest protection activities on net greenhouse gas (GHG) emissions. For instance, in many protected areas, the threat of deforestation may be high in some sections, while near zero in others. To estimate the effect of protecting such an area on the net reduction of GHG emissions, it is important to determine the likelihood that a given area will be deforested. Projected rates of deforestation can subsequently be combined with estimates of the carbon stocks in the forests to produce estimates of the net GHG emissions that would occur if the area was not protected. The specific goal of the work reported here is to demonstrate this approach by applying each of the key steps to an area in the Republic of Congo. The selected study area is located in the southern part of the Republic of Congo and situated between the USAID's Central African Regional Program for the Environment (CARPE)-defined landscapes of Lope-Chaillu-Louesse on the north, Gamba-Mayumba-Conkouati on the west and Leconi-Bateke-Lefini on the east.

Many of the activities of CARPE are related to the protection of forest areas under threat from variety of human activities, such as forest clearing for agriculture, logging, and bushmeat hunting. The potential impact of these human activities on forest carbon stocks, and thus GHG emissions, varies. For example, forest clearing generally produces the highest quantity of GHG emissions, whereas bushmeat hunting produces the lowest, and could be practically zero impact.

To develop a framework for reporting carbon benefits from forest protection activities, a spatial modeling approach of deforestation and quantitative analysis of future modeled deforestation was used. One of the key motives for using spatial modeling within the scope of carbon projects is that future land use change can be associated with carbon stocks. The three specific objectives were: (1) to test different deforestation driver combinations in the spatial modeling process, using statistical validation techniques, to identify the most critical drivers that explain the patterns of deforestation in the study areas; (2) to stratify the threat of deforestation based on the spatial modeling into low, moderate and high threat classes; and (3) to model potential $CO_2$ emissions from the simulated deforestation in the study area. The baseline $CO_2$ emissions in two existing protected areas—the Loudima Faunal Reserve and Aubeville Boko Congo, modeled without protection, were estimated and used to demonstrate how emissions reductions under protection are estimated. An additional area is under discussion for future protection (Sources de Ogooue Zanaga) but its boundary is not exactly fixed at of this writing; however, we estimate the potential deforestation threat to this area and the potential emissions savings that would accrue from protecting it.

Spatial modeling is used widely in studies of land change to simulate a landscape classified from satellite images and to predict changes in the future, helping decision makers in their intent to keep ecosystems sustainable. In this work GEOMOD model was used to simulate a transition from forested to non-forested categories. The model depicts the location and quantity of the simulated land use change, or in this case change from forest (closed forest, degraded/open forest, and savanna) to non-forest. Geographic Information Systems (GIS) technology (raster base with a 28 m cell size) was used in the two distinct steps in spatial modeling. The first step simulates the existing landscape mosaic based on different biophysical, socio-economic and demographic factors. For example, factors such as elevation, slope [biophysical factors], distance to existing roads, rivers and towns [socio-economic factors], and population density [demographic factor] were used to model the impact of human activities that lead to deforestation. The second modeling step that defines areas of future deforestation threat takes the results from the first step and extrapolates them, using a national rate of deforestation, into the future.

We assumed that the protected areas were established to prevent further deforestation and degradation. The potential carbon credits from such an action would be the difference between the baseline emissions and the assumed zero emissions that would result by well-regulated protection. The first step estimated the projected baseline deforestation for the whole region, where deforestation was allowed to occur in the protected areas. According to the GEOMOD simulation, much of the Loudima reserve was under high threat from deforestation resulting in almost 30% of the reserve projected to be deforested by 2022, or about 2,200 ha. Most of this loss was projected to occur in the low biomass savanna system. Because of the location of Loudima reserve, the projected deforestation rate is considerably higher than the national average (0.2%/yr). In contrast, the GEOMOD projection of the threat of deforestation in the Aubeville Boko

was very low and only about 6 ha were projected to be deforested, mostly in the savanna and degraded forest.

The baseline emissions from Aubeville Boko were only about 367 t $CO_2$ over the 20-yr period simulated. The situation for Loudima was significantly different. Given the high threat from deforestation, the total carbon impact for protecting Loudima would be about 50,250 t $CO_2$ over 20 years. These examples illustrate how some protected areas such as Aubeville Boko, even though relatively large, have very little carbon impact because the threat for further deforestation was practically zero. However, for areas such as the Loudima reserve, which is projected to be under high threat for further deforestation due to its location, can have a larger carbon impact. The new potential protected area under discussion –Sources de Ogooue Zanaga and located near the border with Gabon—is in an area projected to be under high threat in the south and moderate to low threat moving north towards the border with Gabon. The total area projected to be deforested over a 20-yr period is about 814 ha or about 0.6% of the total area. Thus if the final location is in this area, there would potentially be a reduction in emissions of about 139,000 t $CO_2$ over a 20-yr period from protecting such an area as long as it was well guarded.

# CHAPTER 1: CARBON BENEFITS FROM FOREST PROTECTION ACTIVITIES: REPUBLIC OF CONGO AS A CASE STUDY

## INTRODUCTION

The goal of this phase of the Carbon and Co-Benefits Initiative project is to develop an approach that can be used to estimate the impact of forest protection activities on net greenhouse gas (GHG) emissions. For instance, in many protected areas, the threat of deforestation may be high in some sections, while near zero in others. To estimate the effect of protecting such an area on the net avoidance of GHG emissions, it is important to determine the probability that a given area will be deforested (Brown, 2002, 2003; Brown et al., 2006). Likely rates of deforestation can then be applied to areas projected to be under high threat (high potential). These rates of deforestation can subsequently be combined with estimates of the carbon stocks in the forests to produce estimates of the net GHG emissions that would occur if the area was not protected. The specific goal of the work reported here is to demonstrate this approach by applying each of the key steps to an area in the Republic of Congo. That the analysis in this study used geographic information system (GIS) technology imparts several advantages over traditional techniques, including spatial analysis of threat distribution, the ability to overlay other spatial data bases such as impacted watersheds or ranges of critical species, and the potential to use resulting maps to optimize development goals when designating new protected areas.

The Republic of Congo is part of the USAID's Central African Regional Program for the Environment (CARPE). The CARPE is a 20-year regional initiative that began in 1995, and was created to increase knowledge of Central African forests and biodiversity, and to build institutional and human resources capacity in the region. During the first phase of CARPE, from 1995 to 2002, key lessons were generated by partners regarding the conditions and practices required to reduce deforestation and biodiversity loss in nine Central African countries. The overall goal of the second phase of CARPE is to help establish sustainable natural resource management practices throughout Central Africa, thereby promoting sustainable economic development and alleviating regional poverty. CARPE's operational objective for its programs in its second phase (2003–2010) is to reduce the rate of deforestation and biodiversity loss through increased local, national, and regional natural resource management capacity.

Many of the activities of CARPE are related to the protection of forest areas under threat from a variety of human activities, such as forest clearing for agriculture, logging, and bushmeat hunting. The potential impact of these human activities on forest carbon stocks, and thus GHG emissions, varies. For example, forest clearing generally produces the highest quantity of GHG emissions, whereas bushmeat hunting produces the lowest, and could be practically zero impact.

## OBJECTIVES

This chapter summarizes the framework of reporting the carbon benefits from forest protection activities through modeling tropical deforestation. To develop a framework for reporting carbon benefits from forest protection projects we used spatial modeling of deforestation and quantitative analysis on future modeled deforestation, focusing on three objectives. The first objective was to test different deforestation driver combinations in the spatial modeling process, using statistical validation techniques, to identify the most critical drivers that explain the patterns of deforestation in the study areas. The second objective was to stratify the threat of deforestation, based on the spatial modeling, into low, moderate and high threat classes. The third objective was to model potential $CO_2$ emissions, or the basline, from the simulated deforestation. The simulated baseline $CO_2$ emissions in existing protected areas were used to demonstrate how emissions reductions under protection can be estimated.

## STUDY SITE

The selected study area is located in the southern part of the Republic of Congo and situated between the CARPE-defined landscapes of Lope-Chaillu-Louesse on the north, Gamba-Mayumba-Conkouati on the west and Leconi-Bateke-Lefini on the east. The study area was selected after initial review of the regional TREES dataset (SAI 2004), the spatial modeling work of Justice et al. (2001) and Zhang et al. (2006), and personal communication with Paul Elkan, Director of the Wildlife Conservation Society in the Republic of

Congo. The study area covers an area defined by two Landsat satellite imagery scenes from 2002 that cover parts of the Niari, Bouenza and Lekoumou regions (UNEP-GRID; Deichmann 1997) (**Fig. 1**). Two isolated patches of protected lands exist in the study area: the Loudima Faunal Reserve and Aubeville Boko Congo protected area (**Fig. 1**). A new protected area has been added to the World Conservation Monitoring Center's list and very little information is available at this time other than a tentative name of Sources de Ogooue Zanaga.

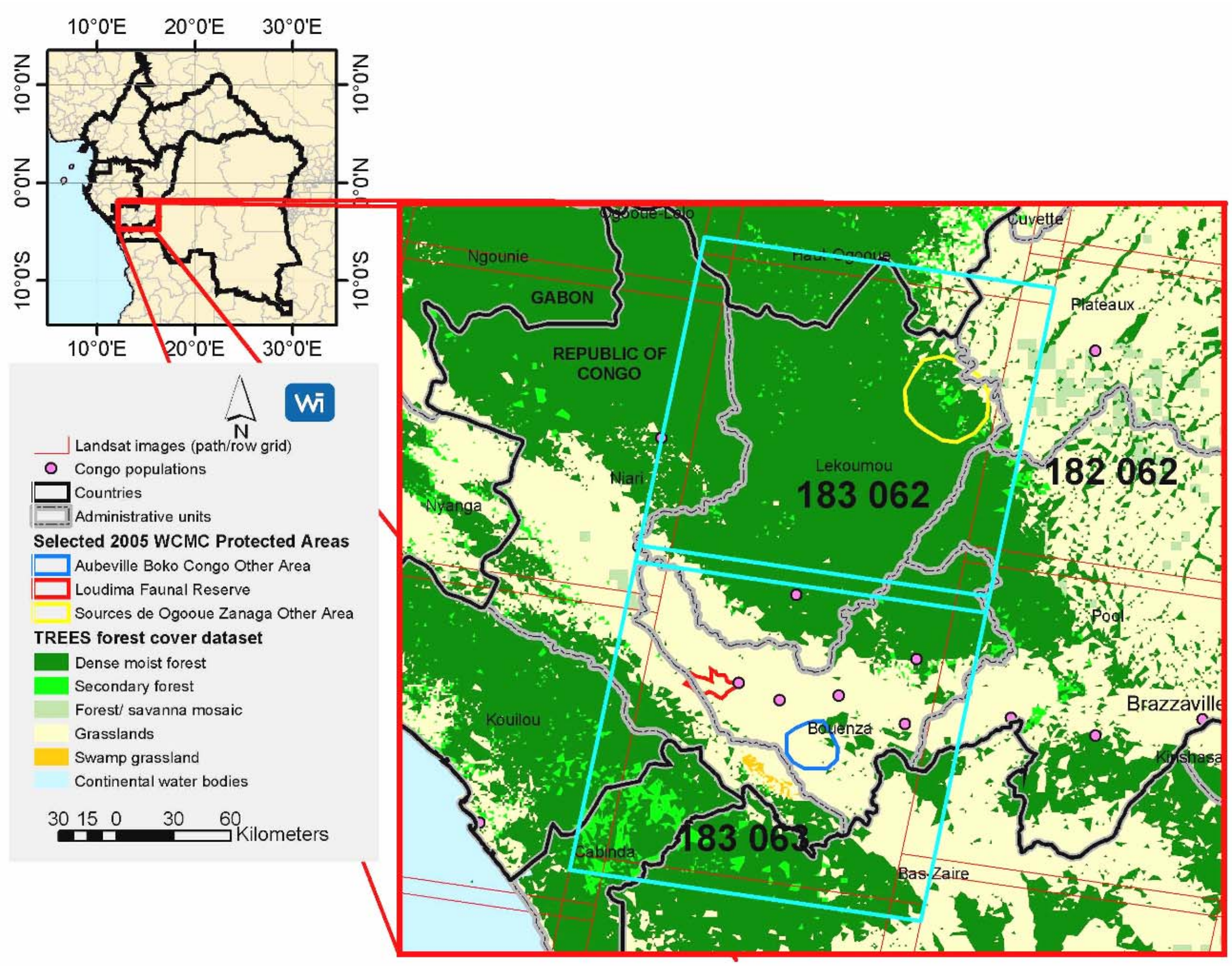



**Figure 1. Location of the study area delineated by the World Reference System path183 rows 062 and 063. The three polygons identified as 2005 World Conservation Monitoring Center protected areas are discussed further in the report.**

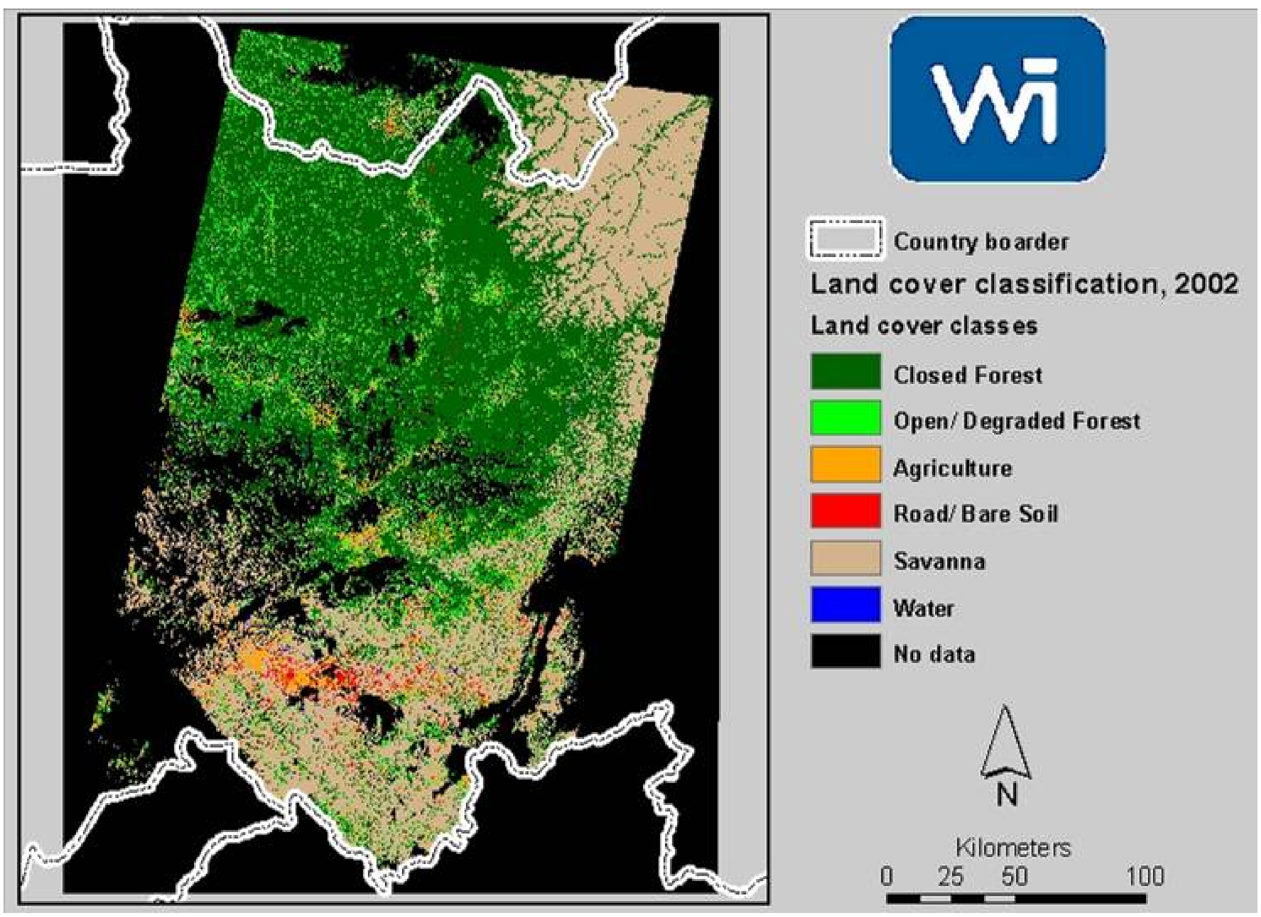
The large block of remaining forest is part of the Chaillu Massif Mountains of Gabon and comprises most of the Lekoumou Region. This forest block tapers to a point as it approaches the Congolese capital of Brazzaville. According to Justice et al. (2001) and Zhang et al. (2006), the coarse deforestation models for the CARPE region from 1990-2050 show heavy deforestation projected to occur on its southwestern edge as early as 2010. They also estimate that in 40 years the Congolese forests there will be cut off from the main forest body to the north in Gabon.

According to the database on protected areas from World Conservation Monitoring Center (WCMC) (WDPA Consortium 1993), the Loudima Faunal Reserve, established in 1979, is a category IV protected area, assigned by the International Union for the Conservation of Nature and Natural Resources (IUCN)[1], situated in the Congo Rain Forest Biogeographical Province (number 3.02.01). The vegetation type is listed as 'Savanna' and the reserve is home to the buffalo species *Syncerus caffer*, the *Potamochoerus porcus* bushpig and various monkey species. Under 'Management constraints', it is mentioned that eucalypts and pine are planted and harvested there, and that the pine provide shelter for the fauna of the savanna and should be protected.

The WCMC database has less information concerning the Aubeville Boko Congo and Sources de Ogooue Zanaga protected areas. They are listed in the database as 'Other area' and there is no IUCN category assigned to them. There is no information on altitude, size, notes, information, sources, historical details, land area, administration or ownership. Aubeville Boko Congo is classified under Udvardy's Afrotropical Realm and Congo Woodland/Savanna Province, biome as tropical dry forests/woodland; and Sources de Ogooue Zanaga is classified as Congo Rain Forest province and biome as tropical humid forest.

# METHODS

An image mosaic composed of World Reference System (WRS) 183-62 and 182-63 frame for April 24, 2002 was classified and used in the analysis. The images were classified into six categories: closed forest, open/ degraded forest, agriculture, road/ bare soil, savanna and water, using unsupervised classification technique that puts into categories pixels with similar reflectance characteristics from a multi-band image without prior knowledge of what these categories might be (**Fig. 2**). Accuracy assessment of the classified map was not performed due to limitation of ground truth data.




1 IUCN categorizes protected areas by management objective and has identified six distinct categories of protected areas: I - Strict Natural Reserve/Wilderness area; II – National Park; III – Natural Monument; IV – Habitat /Species Management Area; V - Protected Landscape/ Seascape; VI – Managed Resource Protected area. The IUCN defines category IV as protected area managed mainly for conservation through management Intervention (IUCN, 1994).

**Figure 2. Top—land cover map for 2002 created from unsupervised classification from Landsat images (no data are areas under clouds or outside the images); bottom—some limited ground-truth data obtained by aerial digital imagery.**

According to the interpretation of the imagery, less than 5% of the landscape was classified as human-disturbed area (agriculture and road/ bare soil). We aggregate these categories into one category called deforested. Water accounted for 0.25% of the whole landscape and was not considered in the spatial modeling process. The majority of the landscape—95% or about 3.87 million ha—was classified as forested category: closed forest, open/ degraded forest and savanna (**Table 1**). A reference map of two categories: deforested and forested, was used later in spatial modeling as a reference land use map of 2002.

**Table 1. Area for each land cover class according to the image classification.**

| Land cover class | Area (ha) | Percent of the landscape |
|---|---|---|
| Closed forest | 2,039,699 | 50 |
| Open / Degraded forest | 318,222 | 8 |
| Savanna | 1,512,175 | 37 |
| Agriculture | 148,717 | 4 |
| Road/ Bare soil | 48,627 | 1 |
| Water | 10,012 | 0.25 |
| Total | 4,077,452 | 100 |

Spatial modeling is used widely in studies of land use and land change to simulate a landscape classified from satellite images and to predict changes in the future, helping decision makers in their intent to keep ecosystems sustainable. In this work GEOMOD model was used to simulate a transition from one land use category to another [from forested to non-forested category]. The model depicts the specific location and quantity of the simulated land use category (Hall et al, 1995, Hall et al., 2000). Geographic Information Systems (GIS) technology is used in the two distinct steps in spatial modeling. The first step involves simulation of the existing landscape mosaic based on different biophysical, socio-economic and demographic factors. For example, factors such as elevation, slope [biophysical factors], distance to existing roads, rivers and towns [socio-economic factors], and population density [demographic factor] can be important for understanding human activities that lead to deforestation. The second step of the spatial modeling takes the results from the first step and extrapolates them into the future; this step can define areas of future deforestation threat. One of the key motives for using spatial modeling within the scope of carbon projects is that future land use change can be associated with carbon stocks. The spatial modeling and carbon emission modeling was performed on a raster base (28m, cell size) with the capabilities of the GIS software Idrisi Kilimanjaro (Eastman 2003).

An overview of the approach and methods is presented in this section (**Fig. 3**) while information on decision rules implied in the methodology is explained in detail in the technical report (**Chapter 2**).

## *1. Step One of Spatial Modeling*

### *1. 1. Calibration procedure*

Calibration and validation of the spatial model are of high importance for the credibility of the modeled output (Brown et al., 2006). Calibration is the procedure that uses information from an initial or prior time to calibrate the spatial model. The calibration procedure involves following steps: choosing decision rules for creating driver maps and choosing techniques for weighting these maps in a process of creating a suitability map. Two decision rules, empirical and heuristic, were applied in the process of creating driver maps. The first decision rule was *Empirical*, where empirical knowledge was used to create driver maps. For example a slope map was categorized into classes, where each class represents the area that falls within a range of one percent of the original slope map. For each range category a percent deforested area within this class was assigned to indicate the relationship between the slope maps and deforested class in the reference map. The hypothesis used in the *Empirical* rule assumed that the slope category with high percent deforested area will be most likely to be deforested in the future. The empirical rule was applied to create a set of empirical driver maps of slope and distance to roads, rivers, and towns.

The second decision rule, *Heuristic,* assumed that with increasing distance from a feature (roads, rivers, towns etc.), the distribution of the deforestation decreases. A set of heuristically derived driver maps of

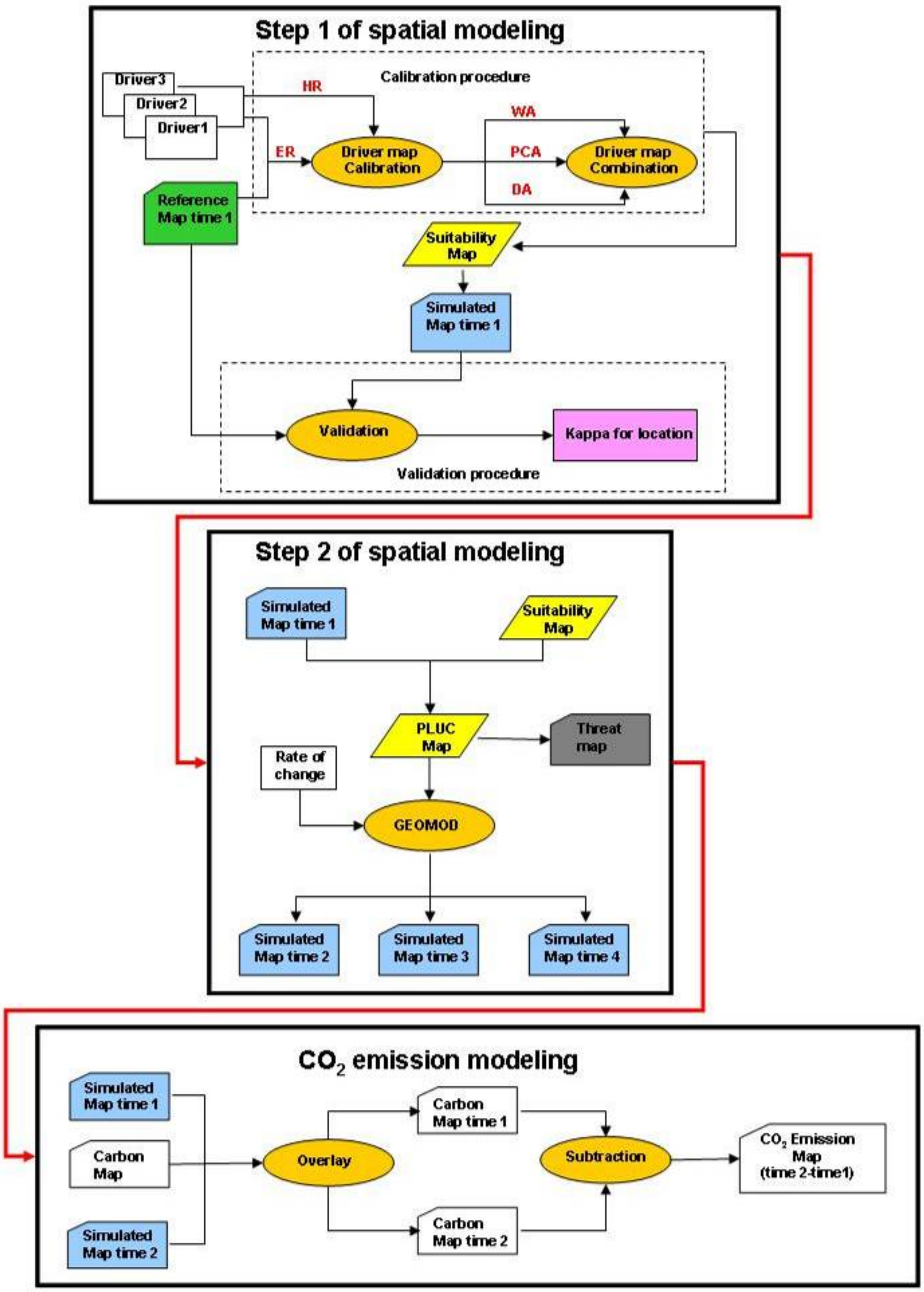



**Figure 3. Flow chart of the steps used to simulate changes in land use/land cover using GEOMOD. Step 1 simulates the existing landscape and compares it to the reference land use map of time one. Step 2 simulates future land uses based on the Potential Land Use Change map (PLUC). Step 3 creates a carbon emission map over time based on a carbon map and simulated land use maps. (All spatial procedures are shown in the flow chart with orange oval shapes, simulated land use maps in blue shapes, reference land use map in green shapes, threat map of future deforestation in gray shapes and PLUC and suitability maps in yellow shapes). ER=empirical rules, HR = heuristic rules, WA=weighted average, PCA=principal components analysis, DA=discriminant analysis.**

accessibility to roads, rivers, towns and deforested areas was created. Detailed information on how empirical and heuristic drivers were applied is presented in **Chapter 2**.

A suitability map is a map where each cell has a value based on the weight of each driver included in a specific driver combination. To create a suitability map, driver maps were combined by applying three techniques: weighted average (WA), principle component analysis (PCA) and discriminant analysis (DA). These techniques were applied to different combinations of driver maps, created according to the empirical and heuristic decision rules. Detailed explanations of the three weighted techniques are given in **Chapter 2**.

### *1. 2. Validation procedure*

Validation is the procedure for assessing the predictive power of the model by comparing the simulated map to the reference map. The six land-use classes on the classified map of 2002 (**Fig. 2)** were aggregated into two categories: forested, representing category with high carbon stock, and deforested, representing category with low carbon stocks. The two category map was used as a reference map in the model validation process. GEOMOD was used to simulate deforestation pattern in the study area for 2002 using suitability map produced from the calibration procedure and quantity of deforested pixels in the reference map of 2002. Statistics, such as Kappa for location, are used to perform the validation (Pontius, 2002). Kappa for location statistic was calculated for all simulated outputs of GEOMOD to choose a driver map combination that explains most of the dynamics on landscape in 2002. Detailed explanation of the applied validation procedure is given in **Chapter 2**.

## *2. Step Two of Spatial Modeling*

This step of the spatial modeling process determines the rate of land use change, and simulates a future deforestation pattern based on the potential land use change (PLUC) map. In addition, the PLUC map is used to create a threat map of future deforestation.

When land use maps of two points in time are available, they are usually used to determine a rate of land use change. The rate of change is then extrapolated into the future and used to simulate future land use change. In many cases a land use map for only one date for the study area is available, and assumptions of rates of land use change are derived from other published sources for the same country or region.

The suitability map that yielded the highest Kappa for location statistic was used to create a PLUC map that shows the most suitable areas for deforestation beyond 2002. The PLUC map was created by masking out all areas classified as deforested in the reference map of 2002 from the suitability map. This step allowed simulating future deforestation only in the forested areas. GEOMOD was used to simulate a future deforestation pattern in the study area based on the PLUC map.

A threat map of future deforestation was created by stratifying the PLUC map into three classes: low, moderate and high threat class. Equal interval decision rule was used to divide all pixels from the PLUC map into the three classes using the histogram of the pixel-value distribution to define the boundaries of the threat classes. Detailed information on the step two of spatial modeling is given in **Chapter 2.**

## *3. Step Three: CO2 emission modeling*

To estimate carbon emissions from simulated deforestation, a map of carbon stocks for the forest classes in the reference map of 2002 was created using a 1980 map of the spatial distribution of total biomass carbon density (above and below ground) for forests, woodland/woody savanna and grass/shrub savanna in tropical Africa (Gaston at al, 1998). It was assumed that this map of biomass carbon density was still applicable to the current situation given that no further data are available. To estimate potential $CO_2$ emissions for each five-year period, the carbon stock per land use category at the beginning of the period was subtracted from the amount of carbon stock per land use category at the end of the period[2]. Combining the simulated deforestation map and the estimated potential $CO_2$ emissions for the 20-year period of simulation, we estimate the net $CO_2$ emissions that would occur under a projected business-as-usual or <u>baseline</u> case. More detailed technical information is given in **Chapter 2**.

[2] CO2 emissions were calculated by multiplying the C stock difference by 3.667

# RESULTS AND DISCUSSION

## *1. Step One of Spatial Modeling*

Thirty suitability maps were created to determine which driver maps combination and which technique of weighting would gives the best result in terms of measuring the goodness-of-fit for validation (see **Table 9** in **Chapter 2**). GEOMOD used the quantity of deforested area in the reference land use map of 2002 and each of the thirty suitability maps to simulate thirty land use maps of 2002. Kappa for location statistic, measuring the goodness-of-fit for validation, was calculated for each of the thirty simulated maps of 2002 (Pontius and Pacheco, 2004). The first method used to create a suitability map was the weighted average (WA) approach, and the highest measurement of Kappa for location was 0.12. The second method used PCA weights, and the goodness-of-fit for validation yielded a very low result for Kappa for location statistic of -0.05. The third method used discriminate analysis (DA) that outperformed the other two methods, with a Kappa for location of 0.47 (see **Table 8** in **Chapter 2**). The empirical driver maps of accessibility to roads, rivers and towns, and slope as well as the heuristically created driver maps of accessibility to already deforested area and concession area were used to create the suitability map (**Fig. 4**).

Distributions of deforested pixels in the reference map of 2002 and in the simulated map of 2002 [simulation based on the suitability map in **Fig. 4**] are shown in **Figure 5**. GEOMOD placed deforested areas primarily along the roads and near populated places. There are more scattered deforested pixels [in red] in the reference map (**Fig. 5 - A**) compared to the pattern of deforestation simulated from GEOMOD (**Fig. 5 - B**). This pattern is a common result as it is difficult for a model such as GEOMOD to simulate this more random scattered pattern. Also it is possible that there are errors in the imagery data due to misclassification of pixels with similar reflectance value in the process of image classification.

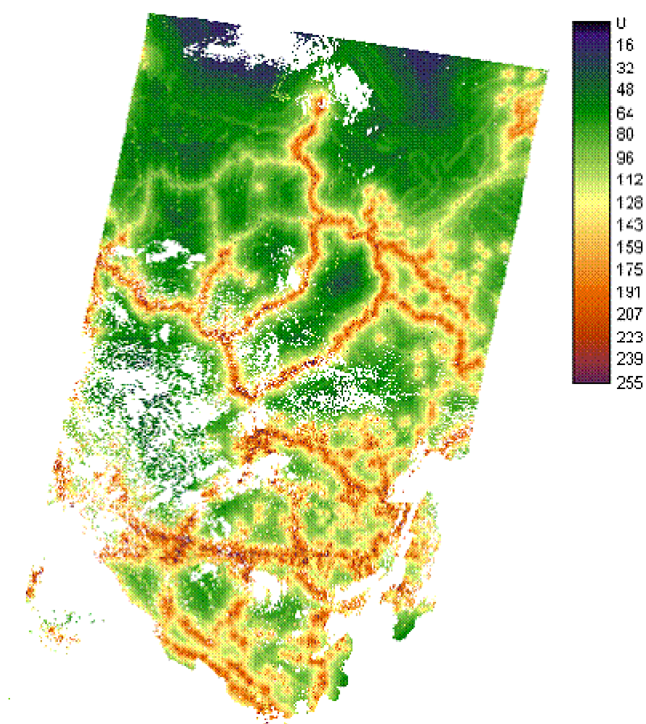



**Figure 4. Suitability map created by using standardized coefficients from discriminant analysis as weights (Table 7, row 27-DA). The highest value on the map represents the highest likelihood of conversion from forested to deforested category.**

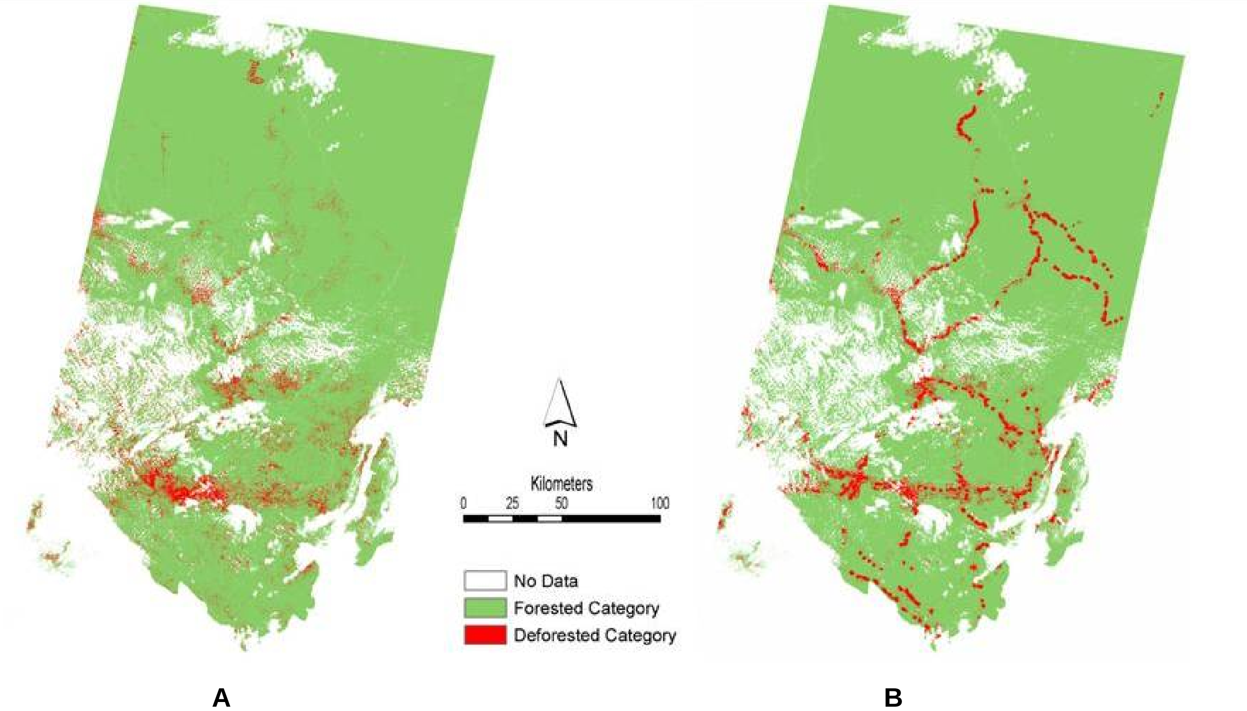



**Figure 5. Reference map for 2002 (A) and simulated map for 2002 (B) of the study area in two categories: forested and deforested.**

## *2. Step Two of Spatial Modeling*

Justice at al. (2001) cites an annual deforestation rate for the Republic of Congo as 0.2 %. Although the rate of deforestation is higher in the southern part of Congo, it was considered to be a conservative assumption to use the nationwide rate for our analysis. The rate of annual deforestation of 0.2% was linearly extrapolated to calculate the quantity of potential deforested area for each year through 2022 (**Fig. 6**). This quantity of deforestation was used later with GEOMOD to simulate deforestation through 2022.

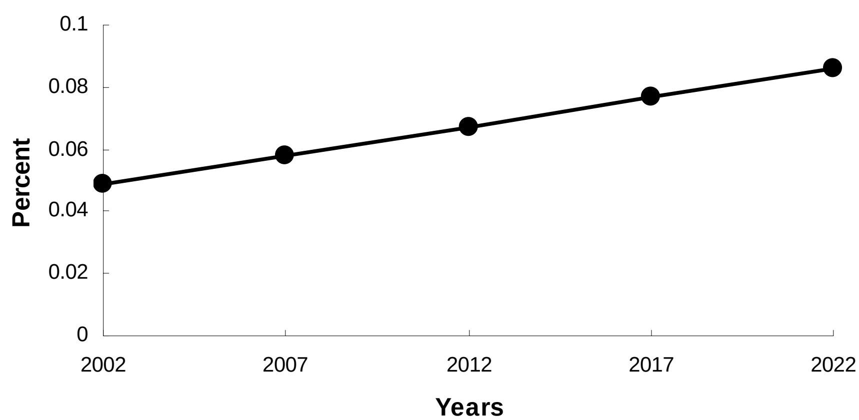



**Figure 6. Cumulative quantity of deforested areas as a percent of the landscape.**

Potential land-use change (PLUC) map (**Fig. 7**) was created by masking out all deforested pixels in the reference map from the suitability map (**Fig. 4**), and deforestation beyond 2002-reference-map was simulated using GEOMOD. Pixels with high values shown on the PLUC map are most likely to be deforested on the simulated maps of deforestation through 2022 (**Table 2**).

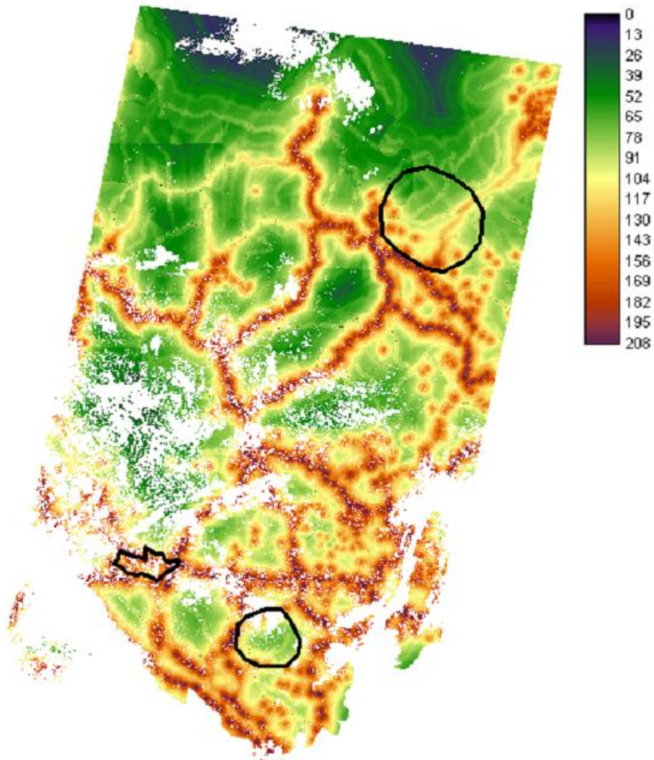



**Figure 7. Potential land use change (PLUC) map. The higher numbers on the scale show that these areas are most likely to be deforested beyond 2002. The black outlined polygons are WCMC protected areas.**

**Table 2. Simulated deforested area, in hectares per 5-year periods. All numbers are rounded to the nearest hundred.**

| | Deforested area (ha) per 5-yr period | | | | |
|---|---|---|---|---|---|
| Vegetation Class | 2002-2007 | 2007-2012 | 2012-2017 | 2017-2022 | Total area (ha) |
| Savanna | 22,300 | 17,800 | 19,200 | 18,200 | 77,500 |
| Closed Forest | 11,000 | 14,600 | 13,000 | 13,300 | 51,900 |
| Degraded Forest | 4,700 | 5,100 | 5,000 | 5,300 | 20,100 |

The PLUC map was stratified into three classes, representing a future deforestation threat: low, moderate and high threat class (**Fig. 8**). Using equal interval decision rule, pixels from the PLUC map were divided into three equal classes based on their values (For detailed information on decision rules see **Chapter 2**.) The equal-interval decision rule assigns a larger proportion of the pixels to the moderate threat class [light yellow].

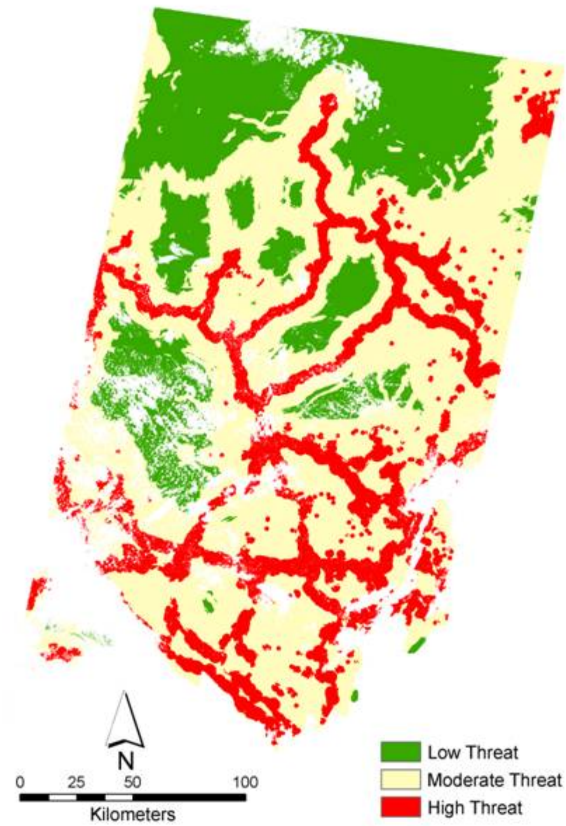



**Figure 8. Threat map of deforestation created by using equal interval decision rule, where pixels from the Potential Land Use Change (PLUC) map were divided into three threat classes (low, moderate and high threat) based on pixel values.**

### *3. Step Three: $CO_2$ emission modeling*

To estimate the carbon stocks of the forest categories (closed forest, open/ degraded forest and savanna), a biomass value from the biomass map was assigned to each pixel (**Fig. 9**). Because of the difference in scale between the land cover map (Landsat land cover classification map, with resolution of 28.5 m) and the biomass map (resolution of 5km), we found that areas, e.g., mapped as closed forest in the land cover map of 2002 often fell in pixels mapped as savanna in the coarse biomass map; other similar anomalies were also found.

The actual biomass value for the closed forest category varied from 41 to 391 t/ha (**Table 3**). For those pixels that were mapped as closed forest in the land cover map of 2002 and fell within the savanna class on the coarse biomass map (e.g. this could be riparian or gallery forests), a value from the mid range of the biomass scale (223 t/ha) was assigned. In a similar manner, the value for the open/ degraded forest was given a value from the lower range of this scale (88 t/ha). The actual biomass value for the savanna category ranged from 5.5 to 10 t/ha. The savanna category from the land cover map of 2002 that falls within the forest block of the coarse biomass map was assigned a value in the higher range of the savanna biomass scale (10 t/ha). Carbon stock maps were created for 2002[3] and for all simulated years.

[3] Carbon is calculated as 0.5 x biomass

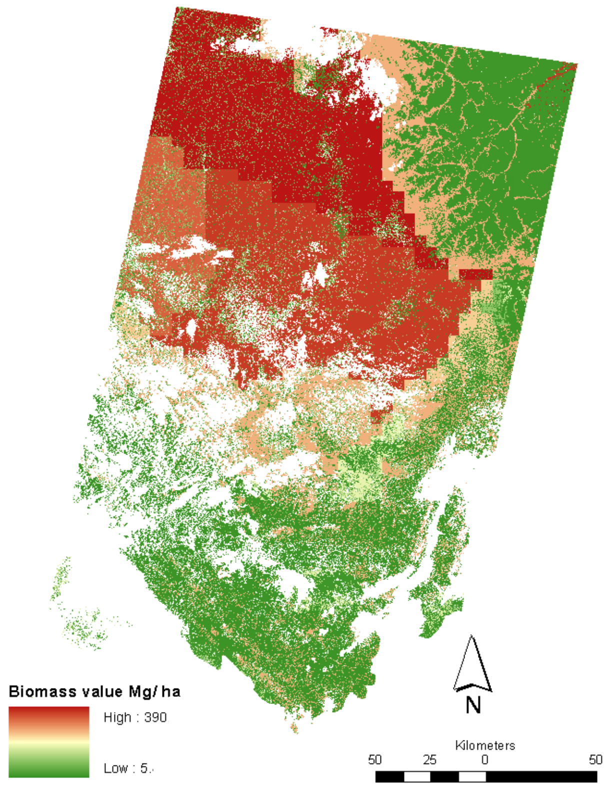



**Figure 9. Map of biomass in above and below ground pools in 2002 for the study region (from Gaston at al., 1998).**

**Table 3. Range of biomass (t/ha) and carbon stocks (t C/ha) per land cover class in the study area according to Gaston at al, 1998.**

| Land cover class | Range of Biomass (t/ha) | Range of C stocks (t C/ha) |
|---|---|---|
| Savanna | 5.5 – 10 | 2.75 – 5 |
| Closed Forest | 41 - 391 | 21. - 195 |
| Open/ Degraded Forest | 88 | 44 |

The potential $CO_2$ emissions for each simulated period were dominated by changes in the closed forest category and swamped the emissions from degraded forests and savannas (**Fig. 10**). Total carbon emissions projected over the 20 year period for the study region are about 8.7 million t C or 31.9 million t $CO_2$ or about 1.6 million t $CO_2$ per year. This change in carbon stock represents a projected baseline scenario for this region and indicates estimated emission avoidance if no further deforestation occurred in the region. The initial carbon stock of the area was estimated to be about 321.2 million t C, and the change in stock over the total period was about 2.7%.

During the entire twenty years period, the $CO_2$ emissions were relatively stable for degraded forest and savanna classes, while the $CO_2$ emissions from closed forest class fluctuated. Emissions from closed forests are substantially higher than the other two forest classes with a large increase within the first five years and relatively small variations over the last three five-year periods. . Even though the deforestation of the savanna was much higher than that for the closed forest (**Table 2**), its lower carbon stocks resulted in low emissions. Deforestation rate of the degraded and open forest class was about one-forth of the savanna, yet the carbon emissions were more than double those from the savanna, once again illustrating the importance of the carbon stock estimates to the total emissions.

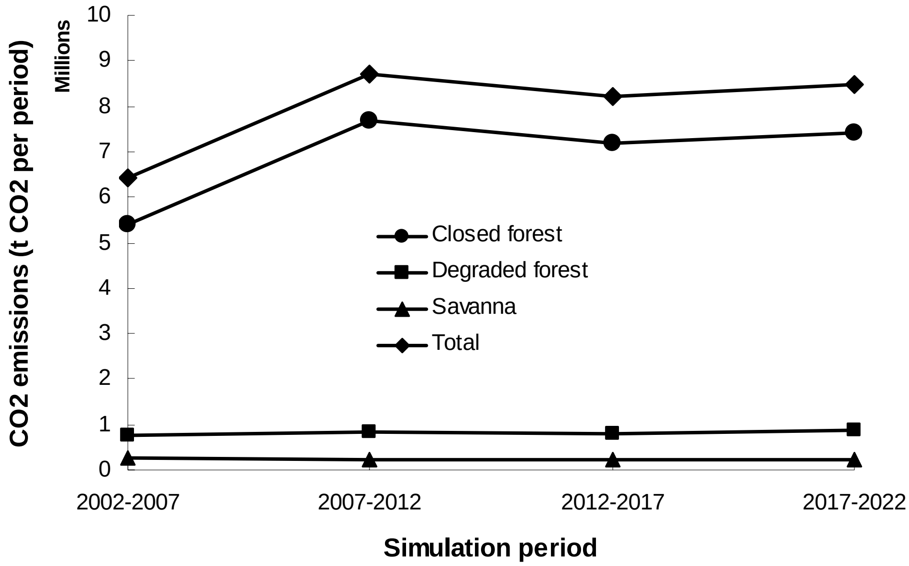



**Figure 10. Simulated $CO_2$ emissions for the study area (t $CO_2$ per 5-yr interval) by the three vegetation classes: closed forest, degraded forest and savanna and total $CO_2$ emissions for the study area.**

## *4. Estimating the potential carbon benefits from protecting forest areas*

In this section, we illustrate how the model simulations can be used to estimate the potential reductions in carbon emissions by establishing protected areas. The focus will be on the analysis for two reserves shown in **Figure 1**—the Loudima Faunal Reserve and Aubeville Boko Congo (**Table 4**), with implications for Sources de Ogooue Zanaga whose boundary is not exactly fixed at of this writing[4]. We will assume that the protected areas were established to prevent further deforestation and degradation. The potential carbon credits from such an action would be the difference between the baseline emissions and the assumed zero emissions that would result by well-regulated protection.

**Table 4. Area per land cover class, percentage of land cover class and percentage of deforested area according to the land cover classification of 2002 within the Loudima Faunal reserve and Aubeville Boko Congo protected areas.**

| | Loudima Faunal reserve | | Aubeville Boko Congo protected area | |
|---|---|---|---|---|
| **Land cover classes** | **Area (ha)** | **Area (%)** | **Area (ha)** | **Area (%)** |
| Closed Forest | 180 | 1 | 6,480 | 17 |
| Open/ Degraded Forest | 380 | 2 | 3,170 | 8 |
| Savanna | 9,470 | 53 | 26,440 | 70 |
| Agriculture | 6,240 | 35 | 1,480 | 4 |
| Road/ Bare soil | 1,500 | 8 | 470 | 1 |
| Water | 150 | 1 | 0 | 0 |
| Total area (cloud free) | 17,920 | 100 | 38,030 | 100 |
| Total deforested area | **7,740** | **43** | **1,950** | **5** |

[4] Sources de Ogooue Zanaga was added to the WCMC data base recently.

The first step is to estimate the carbon emissions resulting from the projected baseline deforestation. The analysis for the whole region above results in the development of a baseline projection of deforestation and corresponding carbon emissions; the two protected areas were not treated any differently in that analysis and deforestation was allowed to occur in them.  A more detailed look at how the deforestation in the two areas is projected to proceed is shown in **Figure 11**.

The deforested area within the Loudima protected area decreases during the simulation period 2002-2022, and the deforested area within the Aubeville Boko Congo protected area increases, although the amount in Loudima was considerably larger than the amount in Aubeville Boko (**Fig. 12**). According to the GEOMOD simulation, almost 30% of the Loudima reserve was projected to be deforested by 2022, or about 2,200 ha, and most of this loss was projected to occur in the low biomass savanna system. Because of the location of Loudima reserve, the projected deforestation rate is considerably higher than the national average (0.2%/yr). In contrast, the GEOMOD projected about 6 ha to be deforested, mostly in the savanna and degraded forest, in the Aubeville Boko Congo area.

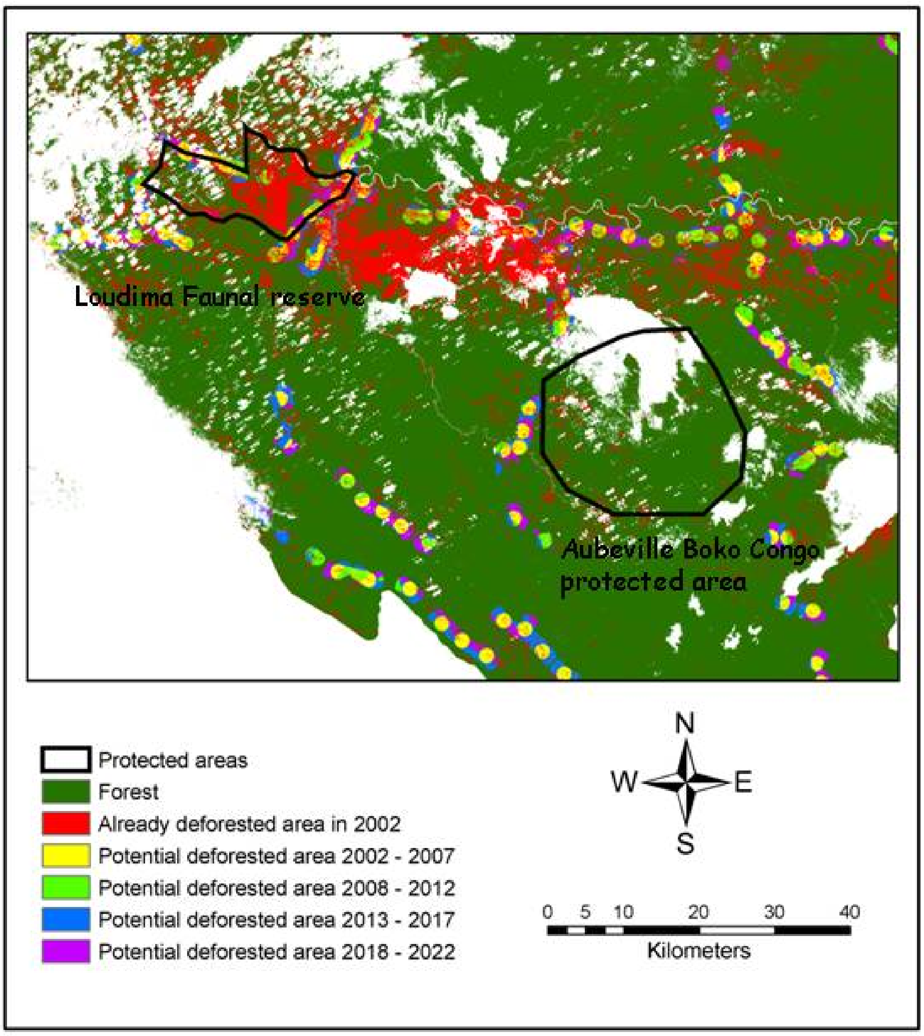



**Figure 11.  Potential deforestation within the Loudima Faunal reserve and Aubeville Boko Congo protected area according to 'Baseline Case' scenario (no protection from deforestation).**

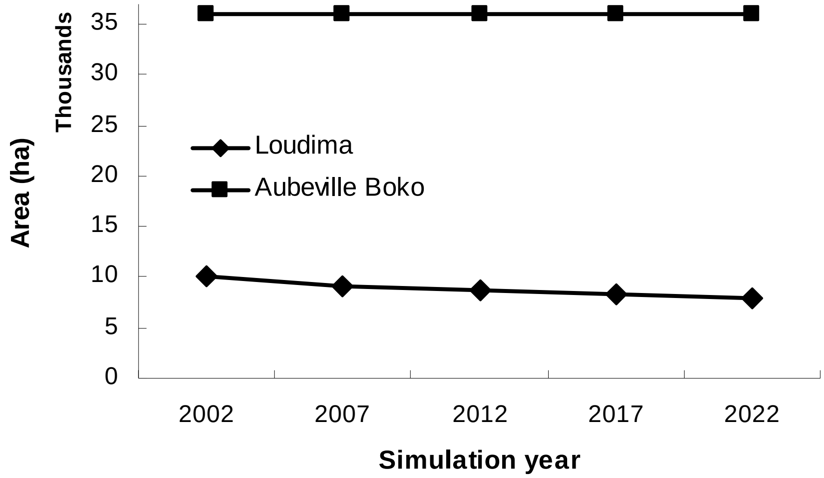



**Figure 12. Simulated total change in forest cover (closed, degraded and closed, and savanna classes) over the 20 year period for the two protected areas.**

The total carbon stock in the Aubeville Boko area is about 13 times higher than in the Loudima, and the difference increases through time as Loudima loses more forest area and carbon (**Table 5**) even though the area is only about four times larger (**Table 5**). Aubeville Boko area contains an average carbon stock of 23 t C/ha compared to 6.4 t C/ha in Loudima.

**Table 5. Total carbon stocks (t C) per simulated year for Aubeville Boko Congo protected area and Loudima Faunal Reserve for a 'Baseline Case' scenario (deforestation is allowed to occur in protected areas).**

| Simulated Year | Total carbon stocks (t C) | |
|---|---|---|
| | Aubeville Boko Congo Protected area | Loudima Faunal Reserve |
| 2002 | 850,651 | 63,791 |
| 2007 | 850,651 | 57,912 |
| 2012 | 850,651 | 55,242 |
| 2017 | 850,542 | 52,772 |
| 2022 | 850,542 | 50,089 |

The baseline emissions from Aubeville Boko are zero during the first 10 years and then increase to about 100 t C (366.67 t $CO_2$) during the third 5-year period, and there are no emissions for the last 5-year period. It is clear that the protection of this area had very little carbon impact, and only about 100 t C over 20 years could be reported (**Figure 13**). The situation for Loudima is significantly different. Emissions from deforestation range from 5,500 to 2,500 t C per 5-year interval over the whole 20-year period. The total carbon impact for protecting Loudima would be about 13,700 t C or 50,250 t $CO_2$ over 20 years. Thus the protection of the smaller Loudima Faunal reserve has almost a fourteen times larger carbon impact than protecting the larger Aubeville Boko reserve, even the latter area was four times larger.

The analysis showed the impact of the deforestation on the $CO_2$ emissions, but in reality we do not expect immediate $CO_2$ emissions from deforestation. Some of the logged trees would be used for timber and the carbon would be stored in the wood products, so no $CO_2$ emission would be expected immediately in this case. Also, depending on the logging practice the roots of the trees might decompose slowly, which leads to slow emissions of $CO_2$.

This example illustrates how some protected areas, even though relatively large, have very little carbon impact because the threat for further deforestation was practically zero. However, for areas such as the Loudima reserve, which is projected to be under high threat for further deforestation due to its location, can have a larger carbon impact.

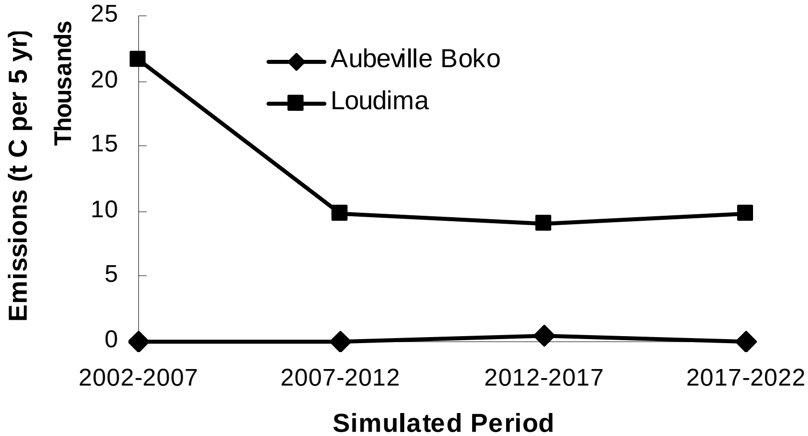



**Figure 13. Potential $CO_2$ emission (t $CO_2$) per simulated period of deforestation for both protected areas: Aubeville Boko Congo protected area and Loudima Faunal Reserve, for a 'Baseline Case' scenario.**

The new potential protected area under discussion –Sources de Ogooue Zanaga and located near the border with Gabon—is in an area projected to be under high threat in the south and moderate to low threat moving north towards the border with Gabon (**Figure 14**). About 8% of the area is under high threat for further deforestation, 17% under low threat (essentially no threat) and 75% under moderate threat (**Table 6**).

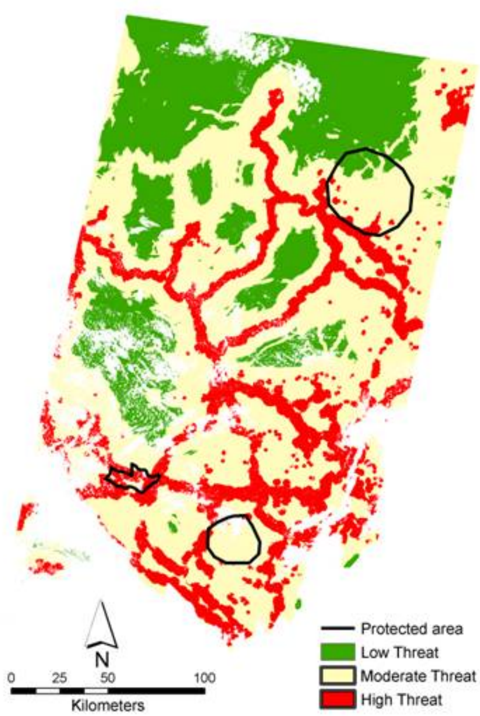



**Figure 14. Locations of existing protected areas – Aubeville Boko Congo and Loudima Faunal reserve (bottom) – and a potential new protected area – Sources de Ogooue Zanaga (top right corner) – in relation to the simulated threat for future deforestation.**

**Table 6. Area (ha) of closed forest, open/degraded forest and savanna according low, moderate and high threat classes in proposed protected area Sources de Ogooue Zanaga.**

| | Sources de Ogooue Zanaga | | |
|---|---|---|---|
| Threat Class | Area (ha) Closed Forest | Area (ha) Open/Degraded Forest | Area (ha) Savanna |
| Low | 5,700 | 0 | 19,000 |
| Moderate | 42,200 | 400 | 67,000 |
| High | 6,800 | 100 | 4,400 |

The total area projected to be deforested over a 20-yr period is about 814 ha or about 0.6% of the total area. Thus if the final location is in this area, there would potentially be a reduction in emissions of about 139,000 t $CO_2$ over a 20-yr period from protecting such an area as long as it was well guarded.

# CHAPTER 2: TECHNICAL REPORT

This chapter explains in detail technical aspects of the proposed framework for reporting carbon benefits from forest protection projects through modeling forest deforestation. The first section explains data sources and deforestation drivers, and the second sections includes details of methods used in the framework of modeling deforestation and reporting carbon benefits for projects considering forest protection (**Fig.3** in **Chapter 1**).

## DATA SOURCES AND DEFORESTATION DRIVERS

The following factors and their corresponding spatial datasets were considered as critical deforestation driving forces that could explain the landscape mosaic on the reference map of 2002, and were considered to play a significant role in future deforestation:

- Slope map - derived from a digital elevation model (DEM);
- Accessibility to roads – created as a distance map from existing roads;
- Accessibility to rivers – created as a distance map from rivers;
- Accessibility to towns – created as a distance map from towns;
- Accessibility to existent deforested area – created as a distance map from classified deforested areas for 2002;
- Concession areas;

These driver maps were derived from the original GIS data (**Table 7**), and were resampled to match the resolution of the Landsat mosaic (pixel size 28.5 m). Data processing and GEOMOD modeling were done with the GIS software Idrisi Kilimanjaro (Eastman 2003). All spatial data, collected in different coordinate systems, were projected to Transverse Mercator Projection in WGS 1984 UTM zone 33 south. The resolution of 28.5m for the Landsat image determined the resolution at which the analyses were carried out.

**Table 7. GIS data, data sources, format and scale.**

| GIS data | Data source | Availability | Format | Scale / resolution |
|---|---|---|---|---|
| DEM | Global Land Cover Facility (http://glcf.umiacs.umd.edu) | Free | Grid | 90 m |
| Rivers | CARPE (http://carpe.umd.edu) | Free | shape file | 1:1,000,000 |
| Roads | CARPE (http://carpe.umd.edu) | Free | shape file | 1:1,000,000 |
| Towns | GIS Data Depot (http://data.geocomm.com) | Free | ASCII text | |
| Concession areas | Forest Monitor (http://www.forestsmonitor.org) | Purchased | shape file | 1:1,000,000 |

## METHODS USED IN PROPOSED FRAMEWORK

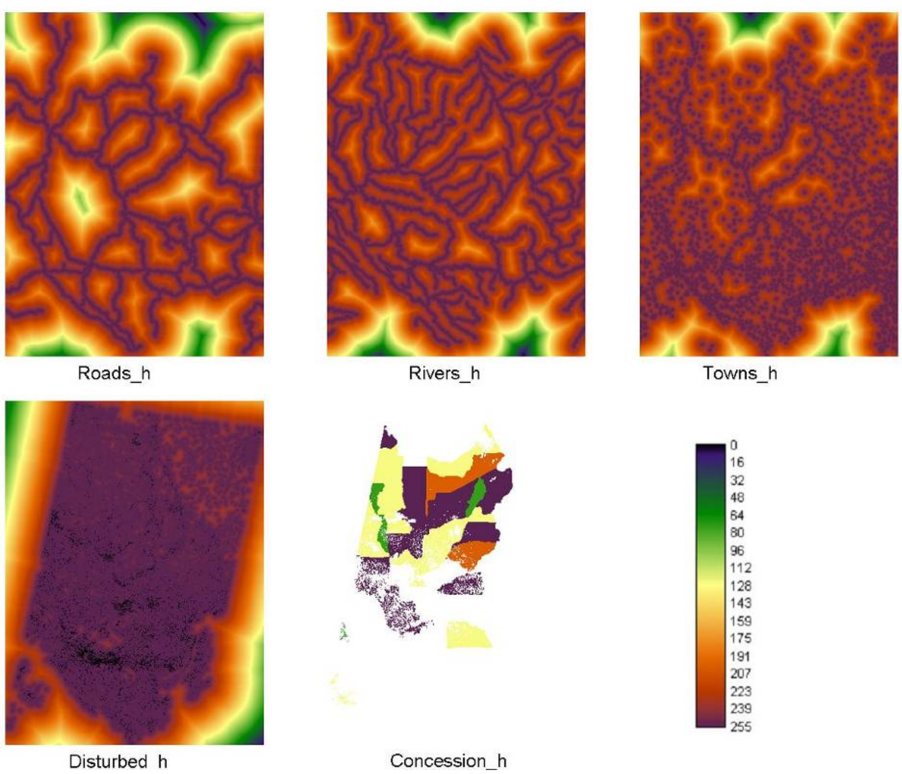
### *1. Step One of Spatial Modeling*

This section describes decision rules for creating driver maps, techniques used for weighting these maps in a process of creating a suitability map, and validation of the simulated maps.

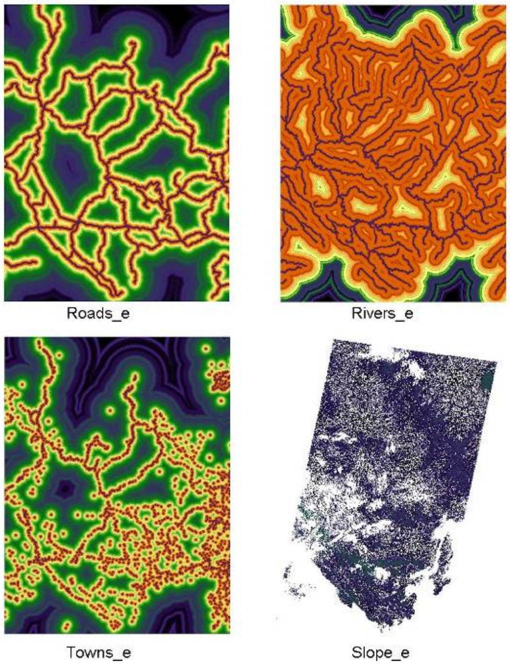
### *1. 1. Decision rules for creating driver maps*

Using the *Empirical* rule, the percent slope map was categorized into 132 classes: class '0' is for no data; class '1' is for slope between 0 and 1 percent; class '2' is for slope between 1 and 2 percent, etc. As the deforested area accounted for only 5% of the total area it was expected that this area would be limited to shallow slopes, however deforested areas occur on almost any slope up to 70 percent, with the highest proportions of disturbed lands on steeper slopes. The "accessibility to river" map was categorized into 42 classes with width of 1 km for each class as follows: class '0' representing pixels of rivers; class '1' representing a distance between 0 and 1 km from a river; class '2', representing a distance between 1 and 2 km from a river, etc. Percent deforested was assigned to each class. High proportions of the deforested areas were located closer to the rivers. Following the same procedure the "accessibility to roads" map was categorized into 53 classes and a road driver map was created with values of the proportion of the deforested area within each class. The deforested areas tended to be closer to the roads. Accessibility to town driver map that represents a proportion of deforested area in each of 57 classes was also created. All empirically created driver maps were standardized to a scale from 0 to 255, where areas with a value of 0 are not likely to be deforested and areas with value of 255 are the most likely to be deforested.

Using the *Heuristic* rule, driver maps of accessibility of roads, rivers, disturbed area and towns were created using a fuzzy classifier in the scale of 0 to 255. A different *Heuristic* decision rule was used to create driver maps of concession areas. The status information for the concession GIS dataset was not defined for all polygons. Most of concession areas had unknown status, while some indicated the time of allocation or the expiration year of a logging company's activity. However, assuming that the degree of logging activity could be different for these concession areas, a heuristic driver map associated with concession areas was created by giving a rate to each category of concession area according of their status. On the continuous scale of 0 to 255, a rating of 255 was given to areas with active allocation status, because in these areas logging activity is still under the way and threat for deforestation is high. A rate of 200 was given to the concession areas with expired status. A rate of 125 was applied to the concession areas with uncertain status, and the lowest rate of 75 was given to areas with no information about the status. All driver maps created by empirical and heuristic decision rule are shown on **Figure 16**.




**A -- Heuristic driver maps**




**B – Empirical driver map**

**Figure 16. Driver maps created by (A) *Heuristic* decision rule, based on prior knowledge and by (B) *Empirical* decision rule, based on assumption that with increasing the distance from a feature, the distribution of the deforestation decreases.**

### *1. 2. Weighted techniques used to produce a suitability map*

Three techniques were applied: weighted average (WA), principle component analysis (PCA) and discriminant analysis (DA), to different combination of driver maps, created according to the empirical and heuristic decision rules. Suitability maps were produced for each of these driver map combinations and were used from GEOMOD to simulate a landscape of forested and deforested categories in 2002.

The first technique for determining the weight of each driver and creating a suitability map uses the WA approach. This technique calculates “suitability” in each cell according to the following equation:

$$R(i) = \left[ \sum_{a=1}^{A} WaPa^{(i)} \right] \Big/ \left[ \sum_{a=1}^{A} Wa \right]$$

Where *R(i)* is suitability value in cell*(i);a* is particular driver map*; k* is an index of a category in map ‘a’ *; A* is the number of driver maps*; Wa* is the weight of driver map ‘a’ where cell(I) is a member of category $a_k$. Twenty-four suitability maps were calculated using different combinations of driver maps from heuristic and empirical created driver maps (Eastman, 2003).

The second technique uses a PCA approach. The PCA technique uses a set of driver maps to produce a set of principle components. The first principal component accounts for as much of the variance in the data as possible, and each succeeding component accounts for less of the remaining variance. The output of this module provides us with loadings for each component representing the percentage of variance for each variable in the original set of driver maps (Eastman, 2003). Weights for each driver map were calculated as a percentage of the total variance explained by the first principle component for each driver map. Each of the driver maps was multiplied by its corresponding weight and the weighted average sum was used to produce a suitability map.

The third technique was discriminant analysis (DA), which models the value of dependent categorical variables (forested and deforested category in the reference map of 2002) based on the relationship of each to a set of independent variables (driver maps). The DA was performed using SPSS statistical software (SPSS for Windows, version 12.0, Chicago, SPSS Inc.). Random sample data from the reference map (equal number of pixels from forested and deforested categories) were used as dependent variables, and the corresponding values of these pixels from all driver maps were used as independent variables. Half of the sample data were used in the validation process. In the output, standardized coefficients allow a comparison between variables measured on different scales, and they were used as weights to calculate a suitability map. Each of the driver maps was multiplied by corresponding standardized coefficients and combined together to produce a suitability map.

To determine which driver combination and which technique of weighting would give the best result in terms of measuring the goodness-of-fit for validation, thirty suitability maps were created (Table 8). They were used to simulate deforestation in 2002 using the same quantity of deforested area as in the reference land use map of 2002. Kappa for location statistic, measuring the goodness-of-fit for validation, was calculated for each of the simulated maps of 2002.

### *1. 3. Importance of Calibration and Validation procedure*

When land cover maps of two points in time are available, GEOMOD predicts change in the landscape from point one to point two in time based on topography (slope, aspect, elevation etc.), accessibility (distance from roads, rivers, towns etc.) and socio-economical (concession areas, population density, population growth, etc.) factors. Calibration and validation of the model are of high importance for the eligibility of modeled output (Hall and Dushku, 2005). Calibration is the procedure that uses information from time one, or prior, to calibrate the GEOMOD model, while validation is the procedure for assessing the predictive power of the model by comparing the predicted map of time two to the reference map of time two. Statistics, such as Kappa for location, are used to perform this assessment (Pontius, 2002). These two procedures have to be distinct in the analysis in order to avoid “intentional fitting” of the GEOMOD model to the data. Pontius and Pacheco (2004) introduced a statistical method to quantify the goodness-of-fit of calibration and validation for land use change models. When maps of two points in time are available, goodness-of-fit for calibration is measured by calculating Kappa for location statistic for the comparison between simulated map of time one and reference map of time one, and goodness-of-fit for validation is measured by calculating Kappa for location statistic for the comparison between the simulated map for time two and the reference map of time two. Our study was constrained by the availability of satellite images for the study area – only one time point was acquired – and therefore only a land use map from 2002 was used to measure goodness-of-fit of calibration and goodness-of fit of validation, assuming that the first point is defined as a “time prior human arrival” in the area (Brown at al, 2006). The flowchart of calibration and validation procedures using the land cover map of 2002 (time one) is shown in the first step of spatial modeling in **Figure 3**, **Chapter 1**.

**Table 8. Combination of drivers for creating a suitability map. E=empirical and H = heuristic drivers; WA = weighted average approach, PCA = principle component analysis, and DA = discriminate analysis; # = number of driver maps in the combination; code = row.**

| | | Accessibility | | | | | | | Socio-Economical | Topography | Kappa for Location |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Code** | **#** | **Roads** | | **Rivers** | | **Towns** | | **Disturbed area** | **Concession area** | **Slope** | |
| | | **E** | **H** | **E** | **H** | **E** | **H** | **H** | **H** | **E** | |
| 1-WA | 6 | X | | X | | X | | X | X | X | 0.12 |
| 2-WA | 6 | | X | | X | | X | X | X | X | -0.05 |
| 3-WA | 5 | X | | X | | X | | X | X | | -0.05 |
| 4-WA | 5 | | | X | | X | | X | X | X | -0.05 |
| 5-WA | 5 | X | | | | X | | X | X | X | -0.05 |
| 6-WA | 5 | X | | X | | | | X | X | X | -0.05 |
| 7-WA | 5 | X | | X | | X | | X | | X | -0.05 |
| 8-WA | 4 | X | | X | | X | | X | | | -0.05 |
| 9-WA | 5 | | | X | | X | | X | X | X | -0.05 |
| 10-WA | 3 | X | | X | | | | | | X | -0.05 |
| 11-WA | 4 | X | | X | | X | | | | X | 0.12 |
| 12-WA | 3 | X | | X | | | | | | X | 0.10 |
| 13-WA | 3 | | | X | | X | | | | X | 0.11 |
| 14-WA | 2 | X | | X | | | | | | | 0.11 |
| 15-WA | 2 | | | X | | X | | | | | 0.10 |
| 16-WA | 2 | X | | | | | | | | X | 0.10 |
| 17-WA | 2 | | | X | | | | | | X | 0.05 |
| 18-WA | 2 | | | | | X | | | | X | 0.09 |
| 19-WA | 2 | X | | X | | | | | | | 0.08 |
| 20-WA | 4 | X | | | | X | | X | | X | -0.05 |
| 21-WA | 3 | X | | X | | | | X | | | -0.05 |
| 22-WA | 3 | | | X | | X | | X | | | -0.05 |
| 23-WA | 3 | X | | X | | X | | | | | 0.11 |
| 24-WA | 3 | | | X | | X | | X | | | -0.05 |
| 25-PCA | 6 | X | | X | | X | | X | X | X | -0.05 |
| 26-PCA | 6 | | X | | X | | X | | X | X | -0.05 |
| 27-DA | 6 | 0.403 | | 0.308 | | 0.568 | | -0.320 | -0.121 | 0.013 | 0.47 |
| 28-DA | 4 | 0.390 | | 0.337 | | 0.631 | | 0.053 | | | 0.11 |
| 29-DA | 6 | | 0.640 | | 0.355 | | 0.242 | -0.020 | -0.011 | 0.112 | 0.43 |
| 30-DA | 4 | | 0.640 | | 0.357 | | 0.243 | | 0.111 | | 0.12 |

Suitability maps created by one of the aforementioned techniques were used to simulate a pattern of deforestation for 2002. Kappa for location statistic was measured for all simulated outputs in order to choose a driver map combination that explains most of the dynamics on landscape in 2002. The suitability map that yielded the highest Kappa for location statistic was used in the second step of the GEOMOD modeling to predict future deforestation. The suitability map that yielded the highest Kappa for location statistic was created by using combination of drivers from row **27-DA** in **Table 8** is shown in **Figure 17**.

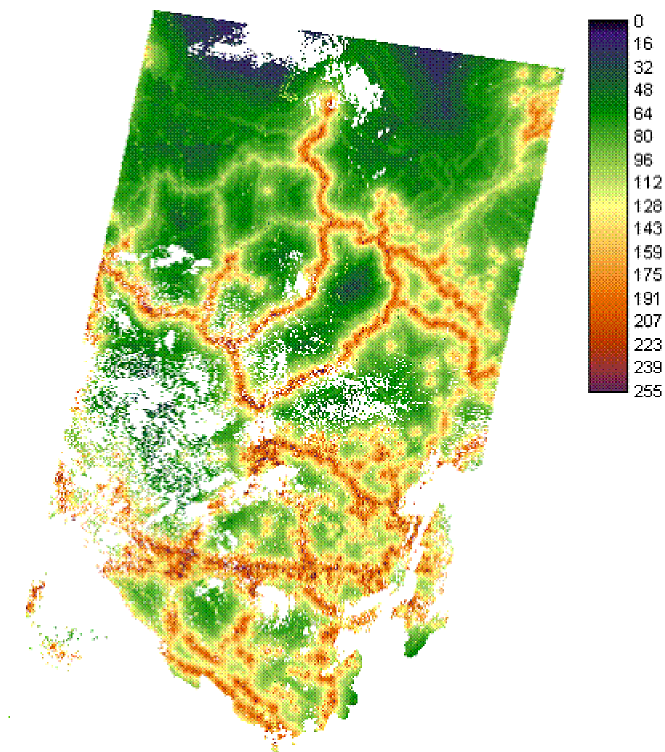



**Figure 17. Suitability map created by using standardized coefficients from discriminant analysis as weights (27-DA row in table 7). The highest value on the map represents the highest likelihood of conversion from forest to non-forest.**

## *2. Step Two of Spatial Modeling*

### *2. 1. Rate of change in forest cover*

The rate of deforestation of 0.2 % adopted from Justice at al., 2001 was linearly extrapolated to calculate a quantity of deforested area for each year through 2022 (**Fig. 18**). The rate of deforestation is highest in the southern part of Congo, so it was considered to be a conservative assumption to use the nationwide rate of 0.2%.

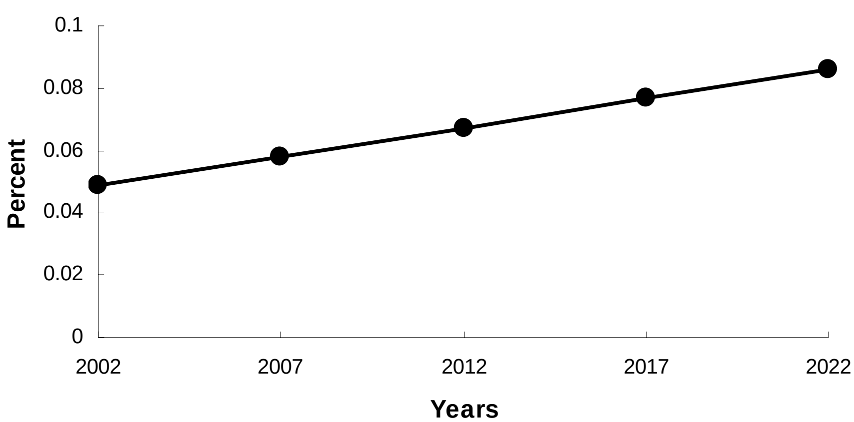



**Figure 18. Cumulative deforested areas as a percent of the forested landscape.**

### *2. 2. Potential land use change map*

A potential land use change (PLUC) map shows the most suitable areas for deforestation beyond 2002 (**Fig. 19**). This map is created by masking out areas mapped as deforested categories in the reference map of 2002 from the suitability map (**Fig. 17**). The PLUC map was used to create a land use change map for the every five-year period from 2002 to 2022 - baseline projection of deforestation.

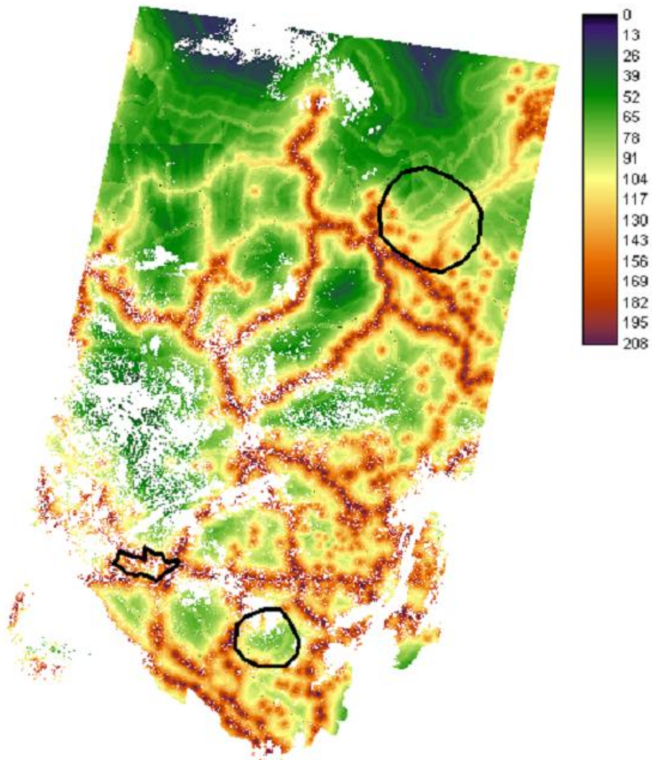



**Figure 19. Potential land use change (PLUC) map for a 'Baseline Case' scenario where deforestation is allowed to occur in the existing protected areas .The higher numbers on the scale show that these areas are most likely to be deforested in the future. The black outlined polygons are WCMC protected areas.**

The PLUC map (**Fig. 19**) was stratified into three classes representing the threat of deforestation: low, moderate and high threat class. The boundaries of these threat classes were defined by using equal interval decision rule. The maximum value in the PLUC map was 208, and the low threat class was defined as a range from 1 to 69, the moderate threat class was defined from 70 to 139 and the high threat class was defined as above 139 (**Fig. 20**).

Threat maps of deforestation for a 'Baseline Case' scenario, which allows deforestation to occur in the existing protected areas, is shown in **Chapter 1, Fig. 8**.

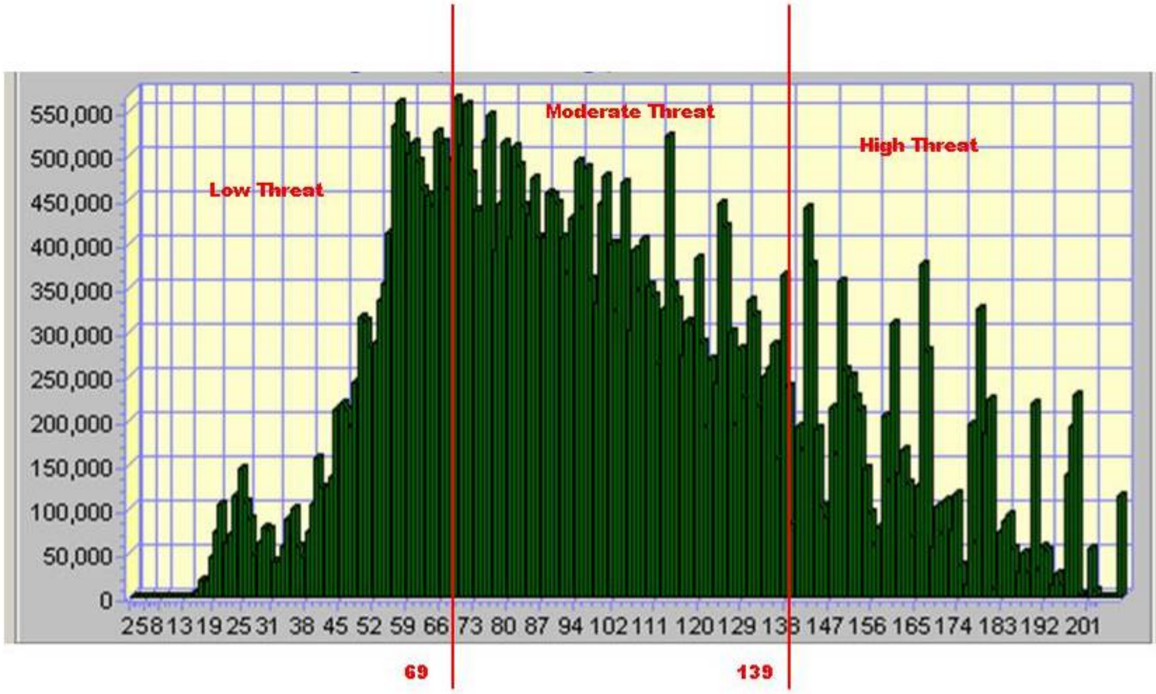



**Figure 20. Histogram of distribution of pixels in Potential Land Use Change (PLUC) map for a 'Baseline Case' scenario. The red vertical lines defined the three threat classes: low, moderate and high according equal interval decision rule.**

### *3. Step Three: $CO_2$ emission modeling*

One of the key motives for using spatial modeling within the scope of carbon initiative projects is that future land use change can be associated with potential $CO_2$ emission. To estimate $CO_2$ emissions for every five years of simulated deforestation or forest degradation, a map of carbon stocks for the reference map of 2002 was created. A 1980 map of spatial distribution of total biomass carbon density (above and below ground) for forests, woodland/ woody savanna and grass/ shrub savanna in tropical Africa (Gaston at al, 1998) was used to assign value of biomass carbon density to the classified categories of forest, open/ degraded forest and savanna in the map of 2002. It was assumed that this map of biomass carbon density was still applicable to the current situation given that no further data are available. Further details on the map and specific carbon stocks are given in **Chapter 1** and will not be repeated here.

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