Collaborative Project

Role Of Biodiversity In climate change mitigatioN

Effects of land use changes on ecosystem processes, carbon storage and climate change mitigation

GA number: 283093

FP7-ENV-2011.2.1.4-1

SEVENTH FRAMEWORK PROGRAMME

Start date of project: 01 November 2011 | Duration: 48 months

Due date of deliverable: 13/11/2015 (month 45) | Actual Submission date: 18/11/2015

Lead partner for deliverable: WU

Authors: Herold, M.; García Esteban, M.; Lau Sarmiento, A.; Hoosbeek, M.; Adam, K.; Morton, D.; Martorano, L.G.; Lisboa, L.S.; Muniz, R.; Sotta, E.; Beltrão, N.E.S.; Vettorazzi, C.A.; do Nascimento, N.C.; Guadalupe, V.; de Aguiar, L.J.G.; dos Santos, V.F.; Simoes, M. and Ferraz, R.

Dissemination Level		
PU	Public	**X**
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the Consortium (including the Commission Services)	
CO	Confidential, only for members of the Consortium (including the Commission Services)	

Executive Summary and main conclusions

Land use change is the biggest driver of changes affecting tropical forests in Latin America and the ecosystem services that these provide. In this report we examine recent changes in land use and land cover and their effects on some indicators of biodiversity. This includes work to quantify interactions between biodiversity, land use options, and land use change in relation to climate change mitigation capacity by: (1) quantifying the direct effect of land use change on biodiversity, carbon storage, sequestration; (2) determining the direct effect of changes in biodiversity on climate change mitigation capacity as expressed in lowered sequestration rates of carbon, and ecosystem integrity; and (3) assessing the potential of biodiversity over a range of REDD relevant ecosystems to boost carbon sequestration and maintain carbon pools.

Results of the project concerning effects of land use changes on ecosystem processes, carbon storage and climate change mitigation are summarized in this deliverable and include studies on:

1. **Local scale:** including feasibility studies on how new technologies such as terrestrial laser scanning, drones, and advanced analysis of remote sensing to better predict biomass related forest structure variables and assess the impacts of land changes on forest structure and biomass. Research demonstrates that including the soil carbon pool is important in assessing the effects of forest-related land changes on carbon budgets.
2. **National examples:** with case studies from Mexico and Brazil highlight strategies on how new tools and approaches result in a better integration of carbon and biodiversity issues in measuring and monitoring land changes and their impacts on ecosystems. The concept of ecosystem integrity as a measure of ecosystem health related to biodiversity and ecosystem functions has been successfully tested in the context of Brazil and Mexico.
3. **Continental analysis:** demonstrate how the integration of ground data, remote sensing and spatial modelling allows for an assessment of deforestation patterns and the impacts on carbon (emissions) and changes in biodiversity.

The results are summarized in the context on the ongoing discussions on REDD+ implementation include a set of key messages that have also been presented at the ROBIN final meeting at the European parliament:

Key outcomes on tropical forests and climate change:

1. Forest-related mitigation includes both sinks and sources and potential is ~25% of total greenhouse gas emissions
2. No successful climate smart development/agriculture in tropical countries will be possible without considering forests

Key outcomes of biodiversity and REDD+:

3. Reducing carbon emissions also preserves biodiversity but varies regionally **(co-benefit)**
4. Biodiversity fosters forest resilience to climate change and reducing risk of reversals **(safeguard)**
5. Enhancing forest (carbon stocks) requires functioning forest ecosystems **(requirement)**

Key outcomes from knowledge to action:

6. New data, for example on carbon sequestration, forest carbon tocks and tree species diversity, available to underpin national and sub-national mitigation strategies and the implementation of REDD+.

Effects of land use changes on ecosystem processes, carbon storage and climate change mitigation

Created and maintained by Mauro García Esteban

Version control	Edited by	Date of revision
Version 1.1 – Final draft version	MGE	29-10-2015
Version 1.2 – After comments from Melanie Kolb	MGE	04-11-2015
Version 1.3 – Addition of the Mexican contribution	MGE	11-11-2015
Version 1.4 – Addition of abstract and extra Brazil contribution	MGE	18-11-2015
Version 1.5 – Edited by co-ordinator	TWP	21-12-2015
Approved by co-ordinator	TWP	05-01-2016

Contents

1. General Introduction

1.1. Background and objectives

Land use change is the biggest driver of changes affecting tropical forests in Latin America and the ecosystem services that these provide. In this report we examine recent changes in land use and land cover and their effects on some indicators of biodiversity.

As part of the ROBIN project (Role Of Biodiversity In climate change mitigation), Work Package (WP) 1.2 builds on the findings and data collected in WP1.1 on the spatial relationships between biodiversity and climate change mitigation to assess the temporal changes in biodiversity as a result of the effect of land use (change) on climate mitigation and ecosystem processes. Furthermore, it uses the indicators and functional diversity definitions made in WP 1 to quantify the temporary changes in biodiversity.

The general aim of WP 1.2 is to quantify interactions between biodiversity, land use options, and land use change in relation to climate change mitigation capacity and its specific objectives are to:

- Quantify the direct effect of land use change on biodiversity, carbon storage, sequestration based on national forest inventory data, plot data, and chronosequences.
- Quantify the direct effect of changes in biodiversity on climate change mitigation capacity as expressed in lowered sequestration rates of carbon, and ecosystem integrity
- Quantify the potential of biodiversity over a range of REDD relevant ecosystems to boost carbon sequestration and maintain carbon pools.

The specific tasks covered by this report are to:

- Assess the temporal changes in biodiversity resulting from land use (change) on climate mitigation and ecosystem processes.
- Analyse for a range of REDD+ relevant land uses (actions) and over different land use intensity measures and indicators to carry out temporal analysis of biodiversity trends in the region.
- Analyse temporal changes in biodiversity and climate change mitigation potential for different land use systems. Time series based on land cover

change monitoring and biophysical variables will be converted to spatial degradation measures (fragmentation/connectivity on landscape level) and used to derive biodiversity loss estimates in linkage with available specimen data bases.

- Assess historic changes in land-use and natural and human-induced disturbance through remotely sensed time series analysis.
- Establish the effects of changes in land use and biodiversity on carbon and nutrient stocks of litter and soil and their effects on soil respiration.

Land use change and climate change are expected to have local impacts on the integrity of ecosystems. However, data on biodiversity change are particularly uncommon in Latin America. This report builds on a previous ROBIN report describing how dose-response-relationships (DRR) will be used to link the main indicators in ROBIN's socio-ecological framework (Kolb et al. 2013). It reported on some specific examples of DRRs linking: (i) ecosystem degradation and biodiversity, (ii) infrastructure and biodiversity and (iii) habitat fragmentation on birds and mammals. In particular, it also defined and developed the use of a general indicator of ecosystem integrity as a unifying approach to quantify and model the effects of changes in biodiversity and the "health" of ecosystems on ecosystem services across the broad range of tropical forest landscapes in Latin America.

We define ecosystem integrity as a composite indicator made up of component indicators (also composites) such as structural diversity, functional diversity, taxonomic diversity and landscape level characteristics. The first three are measures of biodiversity, while landscape diversity is a measure of structure on a broader scale. In this report we develop the application of the "ecosystem integrity" indicator as a basis for understanding recent impacts of land use change on biodiversity and as a practical approach for monitoring large scale patterns of change in biodiversity.

1.2.Report overview

As part of the ROBIN WP 1.2, this report focusses on assessing the effects of land use changes by quantifying the effects of past changes in land use on ecosystem processes, carbon storage and climate change mitigation. The assessment of these effects was performed at three different scale levels, covering the local, national and continental levels. The structure of the report will cover these levels individually. The aspects studied at each level were:

- Land use change
- Effect of land use changes on carbon and greenhouse gasses emissions

- Effect of land use changes on biodiversity and ecosystem integrity via a Dose Response Relationships (DRR) analysis.

At the local level, the changes in land use were assessed for Guyana by means of terrestrial LIDAR. Next to that, the effect of land use changes on the carbon and nutrient stocks was assessed by evaluating the changes in the composition of litter and soil in different locations in Mexico, Guyana, Brazil and Bolivia. The effect of these changes on the local biodiversity and ecosystem integrity was performed by a DRR analysis on site data under a land use gradient.

At the national level, the changes in land use and their effect on carbon emissions and biodiversity were assessed for Mexico and Brazil. In both cases, the concept of Ecological Integrity (EI) is used to analyse the Dose-Response Relations (DRR) between land use change and biodiversity. In the case of Brazil it was further analysed how the provision and maintenance of ecosystem services can contribute to local and regional sustainable development.

At a continental level, changes in land use were measured in terms of forest extension and the drivers triggering these changes analysed. The effects of these changes on carbon emissions were directly linked to the area of deforestation. The effects on biodiversity and ecosystem integrity were assessed by modelling the vulnerability to changes and the recovery capacity of the different locations.

2. Local level

2.1. Land use change and impacts (T-LIDAR)[1]

An accurate estimation of anthropogenic changes in the tropics is relevant for establishing of measurements, reporting and verification (MRV) systems and adaptation policies. One of the greatest challenges to successfully establish policy mechanisms such as REDD+ (Reducing Emissions from Deforestation and forest Degradation) is to measure and monitor forest above ground biomass (AGB) and its changes effectively and accurately (Kankare et al. 2013; Holopainen, Vastaranta, and Kankare 2011). For this purpose, remote sensing techniques are considered as essential tools in the REDD+ context. In combination with ground measurements they provide a cost-effective approach to assess the impact on forest carbon in REDD+ projects.

Improving current tropical forest emission estimates requires accurate biomass measurements before and after the impact events at local level, and the effective use and integration with remote sensing techniques to monitor impacts over larger areas. Traditional methods involve the establishment forest inventories, which are often time consuming, labour-intensive and expensive to implement at large scale. However, recent remote sensing technologies have shown potential for automated and objective measurements of canopy structure.

Terrestrial laser scanning (TLS) has the ability to collect data efficiently with very fine spatial resolution and accuracy (Calders et al. 2015; Raumonen et al. 2011). Furthermore, some studies have explored the capabilities of TLS to capture the complex shape and structure of trees and focused on modelling individual trees (Bienert et al. 2007; Pfeifer, Gorte, and Winterhalder 2004; Raumonen et al. 2013). These 3D tree models can be used to estimate tree volume without the need of allometric equations (Hosoi, Nakai, and Omasa 2013; Calders et al. 2015; Raumonen et al. 2013).

On the other hand, Unmanned Aerial Vehicles (UAV) provide a flexible platform to provide local scale remote sensing data. Currently, UAVs are already a readily available technology that is routinely used in imaging and mapping operations. Most commonly UAVs are equipped with standard consumer cameras which allow acquisition of high resolution RGB imagery as well as photogrammetric 3D models.

---

[1] This section summarises the research of Lau Sarmiento, A. (2015)

The more advanced technologies include usage of also hyper-/multispectral cameras, which allow more advanced radiometrical analysis. Such spectral data can be found useful in tasks including tree species classification, estimation of leaf biochemistry, and extraction of forest structural parameters. For this campaign we found most appropriate to use an octocopter UAV with the WUR HYMSY camera system (Suomalainen1 et al. 2014). The HYMSY consists of a hyperspectral pushbroom sensor, a consumer camera, and a GPS-INS unit. It allows us to produce for each flight a high resolution RGB orthoimage, a digital surface model/3D point cloud of the area, and a hyperspectral datacube.

For the Guyana campaign in November 2014, we assembled two expert teams: a TLS team lead by Alvaro Lau Sarmiento and a UAV team lead by Dr Juha Suomalainen. The objectives of this campaign were:

1. Assess the impact of selective logging in terms of biomass and change of canopy structure.
2. Quantify the recovery rates of different forest attributes with a chronosequence approach and the combination of different approaches (TLS).
3. Use hyperspectral techniques and find hyperspectral indicators that can predict taxonomical and functional foster attributes (UAV).

The whole campaign lasted 38 days and was based in the Vaitarna Holding Concession, located at N 6.031591 ° ,W 58.71199 ° in the Cuyuni-Mazaruni region about 40 km south of Bartica (Guyana). For the selective logging objective we acquired TLS scans, field inventory and data (tree height, diameter at breast height and branch architecture) from destructive logging at local level. We sampled a total of 10 selective logging plots (0.12 ha each), with 26 scan positions per plot acquired pre- and post-logging. In Figure 1 we see the digital point cloud from the logged trees in Guyana. For the chronosequence we acquired TLS scans using logging compartments that have been harvested in different years. A total of 24 stump scans were acquired: 10 stumps for recent harvest, 7 stumps with an age of 2-3 years and 7 stumps with an age of 3 years before, and 14 control plots.

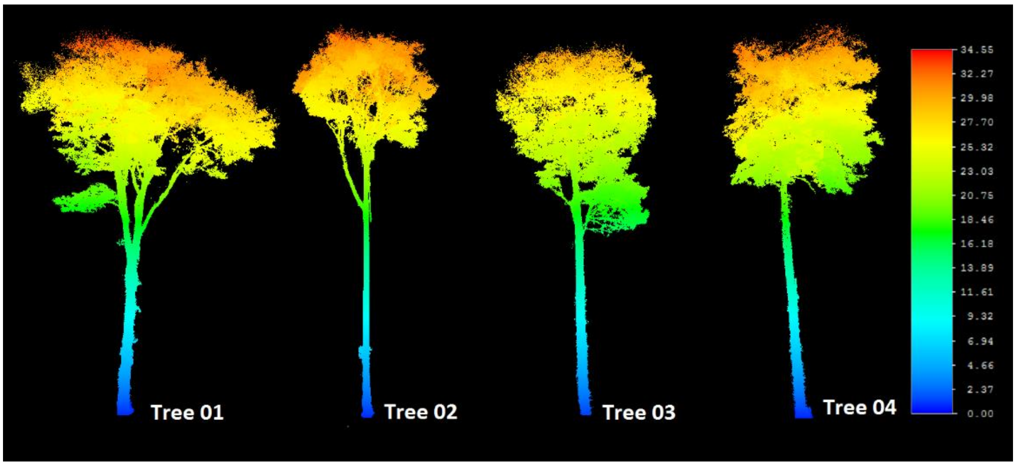


Figure 1. Digital tree pointcloud from selective logging in Guyana. Tree 01, 03 and 04 are Wallaba ituri (Eperua glandiflora) and Plot 02 is Huruasa (Pithecellobium jupunba).

Results/examples from T-LIDAR data on logging impact

The processing of TLS data uses available methodologies for processing point cloud data and employs a tree modelling algorithm: Quantitative Structure model – QSM (Raumonen et al. 2011) to estimate volume and canopy structure. Results from previous research in deciduous trees proved that AGB estimates from TLS showed a high agreement (concordance correlation coefficient - CCC of 0.98) compared to reference values from destructive sampling, while AGB estimates from allometric equations against reference showed a lower agreement (CCC of 0.68 – 0.78) (Calders et al. 2015). The novel QSM approach has not been applied to tropical forest trees yet. Further TLS analysis is expected to result in direct biomass change measurements that will be validated and compared to those from the available traditional forest methods for inventories and harvest estimates.

Preliminary results clearly show visual changes in logging plots (Figure 2). Immediate changes in forest structure can be seen and further analyses on how logging activities affects forest structure and its quantification is under way.

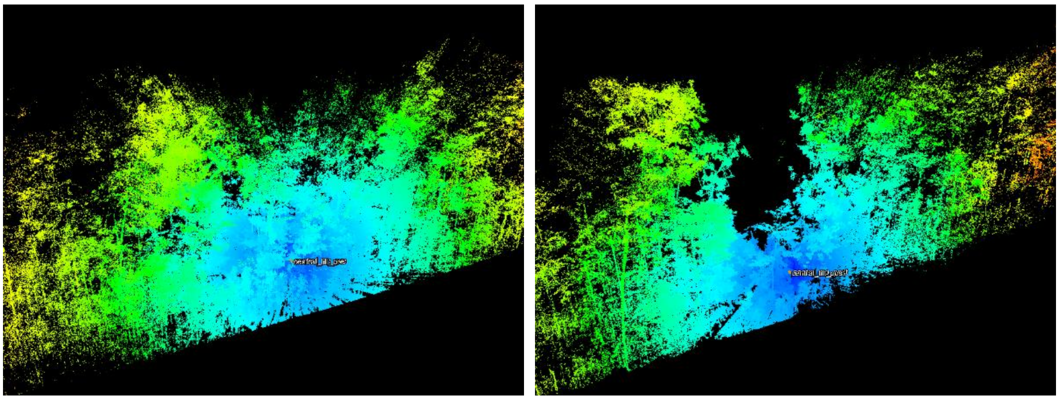


Figure 2. Guyana Plot 04 pre-logging (left) and same plot post-logging (right). Data was visualized using RiScan Pro software.

Results/examples from UAV data on changes due to logging impact

The UAV/HYMSY data was pre-processed into georectified data products: a high resolution RGB orthophoto (about 2cm pixels), a digital surface model/3D point cloud of the area (about 5cm pixels and accuracy), and a hyperspectral data cube (450–950nm, 101 bands, about 20cm pixels - Figure 3).

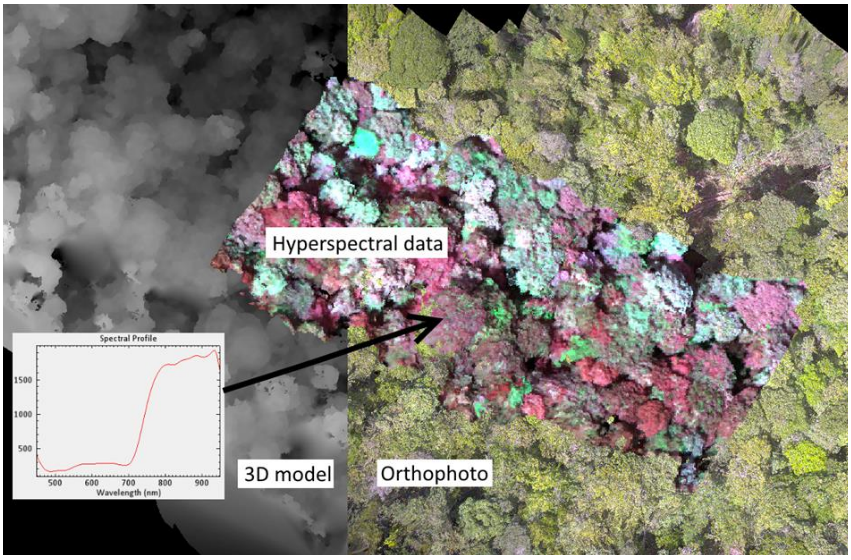


Figure 3. High resolution RGB orthophoto (about 2cm pixels), a digital surface model/3D point cloud of the area (about 5cm pixels), and a hyperspectral datacube (450–950nm, 101 bands, about 20cm pixels).

The preliminary inspection of the results has showed that the data was successfully collected and the dataset can be analysed for further studies. We can clearly see in the 3D model the changes caused by logging. Currently the UAV data is being used in development of an opto-geometric forest de-shadowing method for improving accuracy of the spectral signature determination (MSc thesis of Andrei Mirt) and in a trial of linking and comparing the UAV 3D model with the TLS point clouds for improving 3D model coverage (MSc thesis of Sabina Rosca). Later the hyperspectral and structural data and will be used in studies on tree species classification and radiative transfer modelling of the forest plots.

2.2. Land use and impacts on soil carbon stocks[2]

The effects of land use and other disturbances have been evaluated at several long term ecological research sites in Mexico, Guyana, Brazil and Bolivia. These experiments involved monitoring of plant species diversity and in some cases a survey of litter and soil characteristics followed by some type of experimentally induced land use change or other type of disturbance applied to selected plots. The effects on plant biodiversity have been monitored at least once previously to the ROBIN project. As part of the current project selected sites have been visited and were sampled for litter layers (above ground litter of leaves and small branches either fresh (L litter), fragmented (F litter) or (partly) decomposed (H litter)) and mineral soil at two depth increments (0 – 10 and 10 – 20 cm depth). For each site a detailed sampling and analysis protocol was developed in order to assure compatibility among partners and data integration among sites. All samples were analysed for carbon, nitrogen and phosphorous contents and expressed as weight per m^2. In addition, extracellular enzyme activities (EEA) have been measured in order to gain insight into the nutrient status of each site and how plants and microbial communities responded to changes in diversity as a result of induced land use change or disturbance. Altogether, the relation between land use change and disturbance, plant diversity and the cycling of C, N and P is evaluated. As to date (October 15, 2015), not all pre-existing plant biodiversity data has been made available and not all lab analysis (EEA) are finalized.

Mexico – Las Joyas
Located in the Manantlán Biosphere, the selected plots represented the three major forest types: pine forest, mesophilic deciduous forest, and a mixture between those two. Per forest type, three sites were selected and there were three sample sets taken per site (a total of 9 sites, each sampled three times).

[2] This section summarises the research of Hoosbeek, M. (2015)

Diversity was hypothesized to affect litter quality in terms of C:N, C:P and N:P ratios. These litter input ratios were related to the corresponding C-, N- and P-EEA ratios. Above (leaf) and belowground (root) litter with relatively low P contents (high C:P) caused significant increases in phosphatase activities (the enzyme which makes P available for uptake by plants and micro-organisms). We found a significant link between litter quality and cycling of C, N and P in litter and soil. Moreover, C contents of the litter layers (C storage) were negatively related to N and P nutrient litter contents, i.e. low litter quality, as to be expected with high plant diversity, increased C sequestration.

Mexico – Chamela

The sampling sites are plots in several small watersheds and were well monitored regarding biomass, litter fall and species diversity. The sampling in five watersheds happened on pre-existing plots in the middle of each of them, allowing each plot to be sampled six times (three on one slope, three on the opposing slope; both perpendicular to the brook draining the watershed).

Figure 4 shows a weak relation between plant diversity (number of species) and C:N and C:P ratios of leaf litter. Other measures of biodiversity (e.g. Shannon) did not improve this relationship. The steep slopes within the watersheds resulting in marginal litter layers and shallow soils may explain these weak relationships. As at Las Joyas, low litter quality expressed as high litter C:P caused low C:P related enzyme activities. Carbon contents in litter and soil were positively related to N and P contents of above and belowground litter inputs. Still, topography is the dominant factor with respect to soil C sequestration.

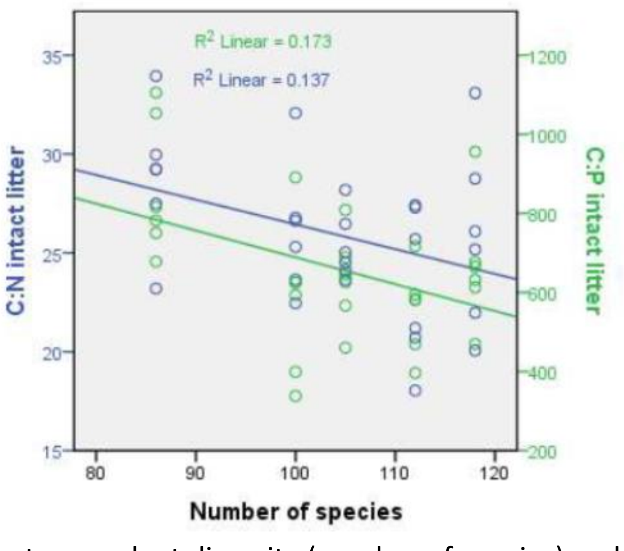


Figure 4. Relation between plant diversity (number of species) and C-N and C:P ratios of leaf litter.

Guyana – Pibiri

The 15 permanent sample plots were set up in 1993 and are 1.96 ha (140 x 140 m) with a buffer zone of 50 m surrounding the plot. In 1994, the plots were experimentally logged using five different treatments: control (no logging), 4 trees ha-1, 8 trees ha-1, 16 trees ha-1, and 8 trees ha-1 followed by post-harvest liberation thinning. Van der Sande et al. (submitted) related existing biodiversity data with measured plant trait data by using structural equation model (SEM). For community trait composition, eight leaf and stem traits associated with carbon uptake and retention were measured for the most abundant species, and weighted by species' basal area.

Species richness did not increase productivity and biomass stocks. Instead, soil P increased aboveground productivity and aboveground biomass stocks, whereas soil N increased fine root biomass stocks, indicating that P is most limiting and that N is needed for root investment and P uptake. High litter quality (i.e., high N) decreased soil C contents due to increased decomposition. The underlying mechanisms will be further explored once the EEA data are available (expected by the end of October 2015)

Brazil – Tapajos

In December of 2013 a protocol for sampling litter and soil at two locations in the Tapajós National Forest was developed. The actual sampling took place in May of 2014. At site "km 67" 6 control, 10 ">dbh55" and 10 ">dbh45" were selected and sampled. Logging disturbance did not affect C, N or P contents of the mineral soil. A possible explanation may be the long recovery time (since 1979) which is 35 years.

At experimental area "km 114" 6 control, 6 ">dbh55" and 6 ">dbh45" were selected and sampled. C and N contents of both soil depths (0-10 and 10-20 cm) were higher with increased disturbance. Extra regrowth after the disturbance in 1982 may explain this effect. However, soil P contents were not affected which may be due to the limited availability of P in these ecosystems.

Bolivia – INPA

A detailed litter and soil sampling protocol was developed in September of 2013 in Bolivia. The INPA permanent biodiversity plots include 2 blocks with 4 treatments per block (testigo, normal, mejorada, intensive). Each treatment plot includes 4 1-ha subplots (4 replicates). Per subplot 5 samples were taken and pooled into one composited sample in October of 2014. Two depth increments were sampled (0-5 and 15-20 cm).

Soil C and N was largest under the “normal” treatment as compared to “mejorada” (0 – 5 cm soil depth increment). However, soil P was not affected by treatment which may be due to the growth limiting nature of P. The deeper soil was not affected by treatment.

As for several of the other sites, the relation between plant biodiversity data, plant functional traits and soil biogeochemical data will be analysed once all data are available. These data and analysis will provide further insight into land use change (disturbance) and biogeochemical cycling of C, N and P.

2.3. Using remote sensed texture metrics to predict biomass related forest structure variables [3]

The potential of satellite remote sensors for identifying areas of ecological significance (for example regions of high biodiversity or carbon storage) and their response to anthropogenic change is an important area of research. Modern very high resolution sensors (<5 m pixel resolution) have the potential to provide direct measures of ecological variables (for example, the number of trees per unit area, vertical and horizontal canopy structure) but computational complexity, swath size and limited image availability restrict geographic scope. So, for the time being, regional to global scale analyses will rely on indirect measures derived from coarser (10-500 m) satellite images. Underlying this approach is the assumption that certain ecological parameters are associated with detectable biophysical properties. For example, vegetation indices such the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) have found to show significant correlations with vegetation health, drought stress and productivity.

It has long been recognised that the ecological value of habitats is a function of structure (Cody 1981, MacArthur & MacArthur 1961, MacArthur 1964). Vegetation indices such as EVI and NDVI may be capable of capturing elements of forest structure at the level of the pixel, but the ecological value of any location is likely to depend upon its wider regional context. To increase opportunities for finding ecological correlates with remotely sensed data a method that embodies neighbourhood structure (texture) within a single pixel is therefore desirable. Haralick (1979) proposed a suite of image texture metrics and these are shown to capture components of foliage structure across a range of habitats (Wood et al. 2012). In this study we derive several Haralick texture indices for Landsat satellite

[3] This section summarises the research of Adam K. and Morton, D. (2015)

images representing densely forested regions in South-Eastern Mexico. We also develop a novel texture index designed to exploit the full range of spectral information within an image. We assess these texture indices against maps of ecological variables to explore their ecological potential. We also examine their potential for temporal change detection.

Methods

Image Selection

We report on analyses from coincident Landsat images (path 20, row 47) corresponding to an area of 30,740.7 square kilometres in South-Eastern Mexico (Figure 5). This area was identified from satellite images and interpolated forest structure maps as containing large areas of dense forest, along with cleared areas and regions of lower quality habitat.

Figure 5. Location of the study area in South Eastern Mexico.

Images were selected to minimize the effect of cloud and haze, and for change analysis, seasonality. Remote sensed metrics can respond to seasonal variation in chlorophyll and illumination angle (Zhang et. al. 2003) so to minimise these effects in annual measures of change using anniversary images are required. High levels of cloudiness in forest biomes limit the frequency of images meeting these criteria.

Image 1, representing 27th of March 2000 (Figure 6), was used in comparisons with interpolated maps of ecological variables. The interpolated maps correspond to 2004. Ideally comparisons should be temporally coincident, but with data limitations this was not possible. Whilst this compromise may reduce the strength of relationships we expect the dynamic of many forest variables to be slow enough relative to this interval for negative effects to be unimportant. To detect change an anniversary image from the 22nd of March 1995 was also obtained. A larger interval would increase the signal of change relative to image noise but suitable data were not available.

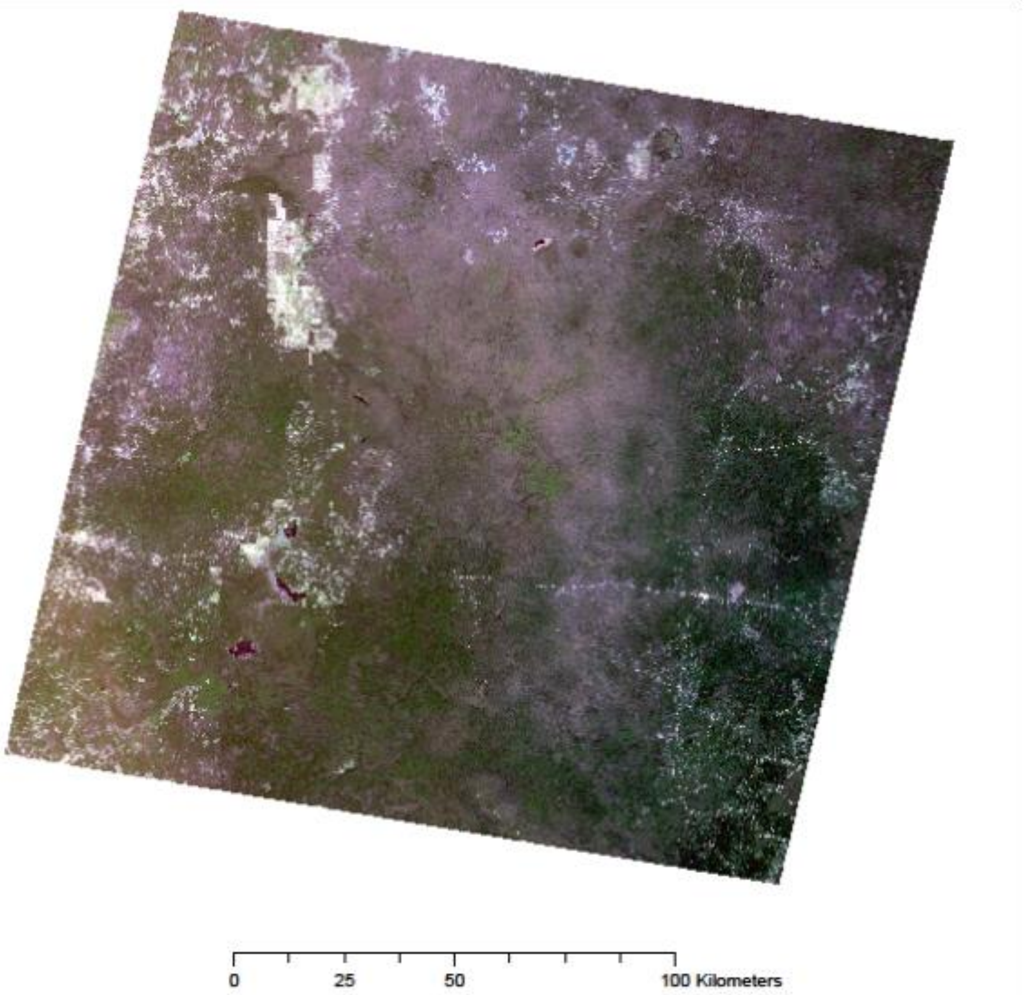


Figure 6. Study area and Landsat image used to derive texture metrics.

Forest structure variables

Interpolated maps of nine forest biophysical variables covering the whole of Mexico, derived from models containing a wide range of plot, climate and remote sensed data , were used to provide estimates of forest structure within the study areas. These contained information on mean crown diameter, DBH, tree height and stem height, standard deviations in crown diameter, DBH, tree height and stem height and number of trees per hectare at a 1 km resolution. Our aim was to investigate the relationship between these metrics and measures of texture derived from Landsat images.

GLCM Texture

Structure is an important attribute for characterizing habitat. However, measuring structure over large areas is logistically difficult, so our goal here is to evaluate the degree to which image texture from remotely sensed data are associated with ecological variables. Haralick (1973) presented techniques for image texture analysis based on a grey-level co-occurrence matrix (GLCM). GLCM functions characterise the texture of an image by calculating how often a pixel with an intensity (grey-level) of value i occurs in a specific relationship to a pixel with the value j. The number of grey levels in the image determines the size of the GLCM. To illustrate this Figure 7 shows how a GLCM is derived from 5 by 4 image matrix. The GLCM is a square matrix with indices representing the number of grey levels. Intersects are populated according to the frequency of co-occurrence. In this example, co-occurrence is defined as the pixel to the right, but other co-occurrence relationships can be specified. The top-left cell in the GLCM therefore represents the frequency of a 1 occurring to the right of 1.

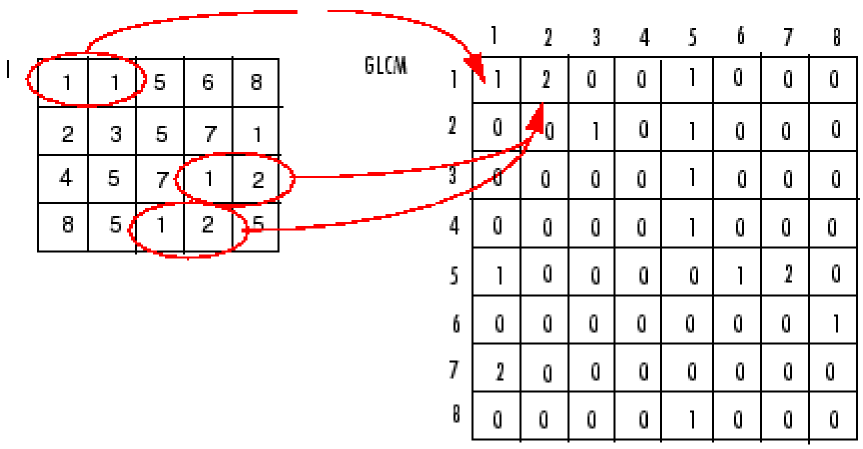


Figure 7. Example derivation of a Grey Level Co-occurrence matrix from a 5 by 4 image matrix.

Properties of the GLCM can reveal information about the spatial distribution of pixels in the image. For example, if the frequency of all grey-level pairs was equal in the

GLCM, this would indicate that any value had an equal probability of occurring next to any other; in other words pixels are perfectly mixed, entropy/disorder is maximised. If GLCM scores are high along the diagonal this indicates that grey levels are clumped into groups with similar values.

To compute GLCM texture statistics, a single raster band is required. GLCM texture analysis using a near infrared channel has shown significant correlations with vegetation structure (Wood et. al. 2012), but Landsat 7 provides seven optical bands with potentially useful information in each. Principal component analysis (PCA) of a satellite image examines the covariance of spectral channels within an image to construct new orthogonal compound axes that minimize the covariance. These are used to convert the original bands into a set of linearly uncorrelated bands, the principal components. The principal components are ordered according to their information content (variation reduction). High ranked principal components compress information across all bands into a single band and should therefore have potential within textural analyses. Examination of the first principal component showed little contrast within forest regions. In a multispectral image the brightness values of any pixel in one band are highly correlated with the brightness values of other bands. This correlation represents a major source of data redundancy and we suspect therefore that PC1 is representative of image brightness. This tallied with an observed high contrast between non-vegetated highly reflective surfaces (typically clear-cut and settlements) and dense vegetation areas. The PC2 image shows significant contrast within vegetation regions, so this was used for GLCM analyses.

We used the Orfeo toolbox (Christophe, Inglada & Giros 2008), to compute eight simple Haralick texture features (Table 1). Initial examination of these variables found that many were highly correlated with each other and therefore redundant as predictors of ecological variables. As a result, only Entropy, Correlation, Cluster Shade and Cluster Prominence were used to model forest structure. While some collinearity remained between these predictors, examination of the variance inflation factor of resulting models found no adverse effect of their inclusion. Although Energy, Inverse Difference Moment Inertia and Haralick Correlation were not included here due to their close correlation with Entropy, they are still potentially valid as alternative predictors of forest structure.

Table 1. Haralick texture metrics

Texture Metric	Interpretation
Energy	This is a measure of image homogeneity
Entropy	This is a measure of disorder
Correlation	This is a measure of linear dependency of grey levels on those of neighbouring pixels.
Difference Moment	This measures local homogeneity of an image. The incidence of co-occurrence of pixel pairs when they are close in grey-scale value and thus increases the difference moment value
Inertia (a.k.a Contrast)	This is a measure of the local variations within an image. If there is a large amount of variation contrast will be high.
Cluster Shade	This is a measure of skewness of the GLCM. When the cluster shade is high the image is asymmetric.
Cluster Prominence	This is also a measure of skewness
Haralick's Correlation	Similar to correlation

K-means Shannon Diversity

In order to generate an additional measure of texture, designed to capture information across all bands, the information contained in the first 6 bands of the satellite image was compressed into a single categorical band through the use of unsupervised K-means classification. The number of k-mean classes was determined by investigating the total within group sum of squared error when randomly sampled points were classified in different numbers of groups. The smallest number of classes for which the within group sum of squared error was less than 10 percent of the total sum of squared error (11 classes for the 2000 image and 24 classes for the 1995 image) was chosen. K-means classification was carried out using the Orfeo toolbox tool in QGIS.

The spectral diversity of this classified image was then derived by passing a moving window over the k-means result. The Shannon Diversity of classes within a 90 m (three pixel) radius around each pixel was calculated, then assigned to the focal pixel

(Figure 8). The resulting statistic is therefore a measure of neighbourhood spectral diversity. Where the resulting value for a pixel is low, only a small number of different classes are present in the surrounding window, indicating a more homogeneous area. Where this value is high, a larger number of classes are present, suggesting a heterogeneous area. Inspection of the resulting raster indicates that this analysis is effective in picking up linear features and patch edges, as well as disturbed forest areas.

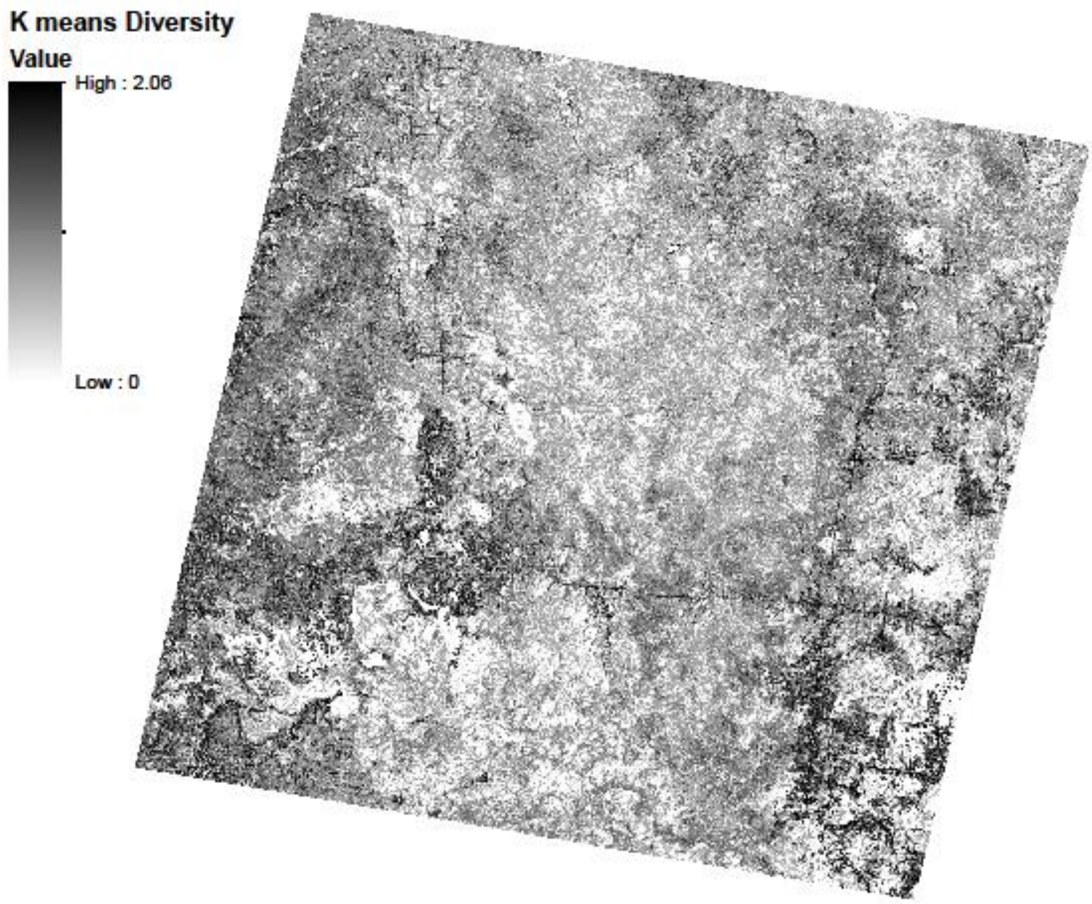


Figure 8. K-means Shannon Diversity within a 3 x 3 cell radius of pixels.

Modelling approach

In order to investigate the relationships between the interpolated ecological maps and the remote sensed measures of texture, data were extracted for all variables of interest at 1000 randomly sampled points. For each forest structure variable, a linear model was constructed which used K-means Shannon Diversity and Haralick texture metrics (Entropy, Correlation, Cluster Shade and Cluster Prominence) within pixels to explain variation in predicted condition. In order to evaluate these models, the parameter estimates, significance, R squared and relative importance values were all calculated (Table 2). Only a weak correlation between Shannon Diversity and the Haralick statistics was observed in the points sampled and the variance inflation factor for the models containing the two variables was low (<3) (Zuur, Ieno & Elphick 2010). This suggests the two sets of variables represent distinct aspects of the satellite data and supports the inclusion of both terms in the modelling process. The R package "relaimpo" was used to calculate fractional variable relative importance values.

In order to investigate change over time, the above process was repeated for a second Landsat scene, dated March 1995. The change in texture over this period should therefore also relate to changes in forest structure, provided these metrics are correlated with observable ecological patterns.

Table 2. Results of linear models

Response	Predictor	Estimate	P	R^2	Importance
Crown diameter (sd)	K-means diversity	0.039	**0.003**	0.030	0.281
	Entropy	0.034	**<0.001**		0.517
	Correlation	-0.003	0.081		0.046
	Cluster Shade	0.034	0.094		0.061
	Cluster Prominence	-0.011	0.245		0.095
Crown diameter (mean)	K-means diversity	0.099	**<0.001**	0.089	0.202
	Entropy	0.066	**<0.001**		0.382
	Correlation	-0.002	0.624		0.014
	Cluster Shade	0.169	**<0.001**		0.114
	Cluster Prominence	0.050	**0.010**		0.289
DBH (mean)	K-means diversity	0.002	0.987	0.023	0.011
	Entropy	-0.025	0.744		0.057
	Correlation	-0.016	0.284		0.025
	Cluster Shade	0.816	**<0.001**		0.662
	Cluster Prominence	0.233	**0.005**		0.246
DBH (sd)	K-means diversity	-0.234	**0.022**	0.026	0.313
	Entropy	-0.044	0.520		0.090
	Correlation	-0.028	**0.028**		0.206
	Cluster Shade	0.392	**0.012**		0.282
	Cluster Prominence	-0.021	0.769		0.109
Trees per hectare	K-means diversity	-130.233	**<0.001**	0.162	0.311
	Entropy	-66.525	**<0.001**		0.352
	Correlation	-2.386	0.376		0.038
	Cluster Shade	-50.962	0.115		0.011
	Cluster Prominence	-45.027	**0.003**		0.287
Stem height (mean)	K-means diversity	-0.195	**0.003**	0.080	0.214
	Entropy	-0.115	**0.010**		0.326
	Correlation	-0.014	0.098		0.081
	Cluster Shade	-0.008	0.938		0.017
	Cluster Prominence	-0.137	**0.004**		0.361

Stem height (sd)	K-means diversity	-0.032	0.149		0.170
	Entropy	-0.016	0.277		0.227
	Correlation	-0.005	0.100	0.035	0.119
	Cluster Shade	0.056	0.097		0.130
	Cluster Prominence	-0.033	**0.038**		0.354
Tree height (mean)	K-means diversity	-0.296	**<0.001**		0.261
	Entropy	-0.158	**0.005**		0.306
	Correlation	-0.019	0.076	0.087	0.082
	Cluster Shade	0.134	0.289		0.048
	Cluster Prominence	-0.136	**0.022**		0.302
Tree height (sd)	K-means diversity	0.026	0.394		0.027
	Entropy	-0.001	0.961	0.010	0.011
	Correlation	-0.007	0.081		0.172
	Cluster Shade	0.160	**<0.001**		0.753
	Cluster Prominence	0.019	0.369		0.038

Results

Relationships with forest structure maps

Although the models varied in their performance across forest structure variables (as seen in Table 2), all nine response variables were significantly related to at least one of the remote sensed texture metrics ($p > 0.05$), and in seven cases two or more metrics had significant terms in the model. This suggests that these measures of local image texture are correlated with forest structure and are therefore likely to prove useful in evaluating area of high quality forest habitat. Despite this, none of the measures of texture used were found to have significant effects on all aspects of forest structure. The K-means Shannon Diversity metric, along with the Cluster Prominence performed best (significant in 6 out of 9 models), while correlation was only found to have a significant effect on a single response variable. This is important because it suggests that the successful use of image texture to predict forest structure variables will be dependent on the application of the correct metric for the biophysical variable of interest.

The various measures of texture showed a negative relationship with a number of forest structure variables. Highest tree density and mean tree height were found where Entropy and K means diversity was lowest. This may be due to areas of mature forest, where the greatest number of large trees are found, appearing relatively homogeneous to the satellite image. Since such areas are the location of much biomass and biodiversity, measures of texture such as Shannon Diversity derived from a K means classification of a satellite image may be useful tools in identifying areas of high value forest.

While a number of significant relationships were found, R squared values were generally low. This may be partly due to the difference in time periods between the interpolated maps and the Landsat image used, but also likely reflects that there are a number of other factors which are not accounted for by the measures of texture. For example, vegetation indices such the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) have useful correlations with vegetation health, drought stress and productivity (Sims et al. 2006; Ogaya et al. 2014). Although NDVI is highly chlorophyll sensitive and tends to saturate in high biomass regions, which limits its utility, EVI enhances the vegetation signal to overcome limitations of NDVI and is more responsive to canopy structure, including leaf area index (LAI), canopy type and architecture, so has greater potential within productive forest biomes. Furthermore, the inclusion of climate and topography variables could also improve predictive power. Since such variables were used in the production of the interpolated response variables used here, these factors had to be omitted to avoid introducing circularity to the analysis. Variables describing image texture are therefore likely to be most useful as additional tools alongside other important metrics. Analysis of variable relative importance found that in general, the significant predictors showed similar contributions. This suggests that the inclusion of several different measures of texture is necessary to produce the best models of forest structure.

Change over time

Comparison of Landsat images from 2000 and 1995 identified a number of areas of change in Shannon Diversity over this time period (Figure 9). Given the relationships between this metrics and forest structure described above, this suggests that some change has occurred in the forest habitat to cause the shift in Shannon Diversity values. A number of areas appear to have undergone a reduction in Shannon Diversity. This may reflect a maturing canopy resulting in a more uniform area of habitat. Conversely the area to the North of the images has undergone an increase in Shannon Diversity. This suggests a clearing of some of the forest area and the creation of more fragmented habitat.

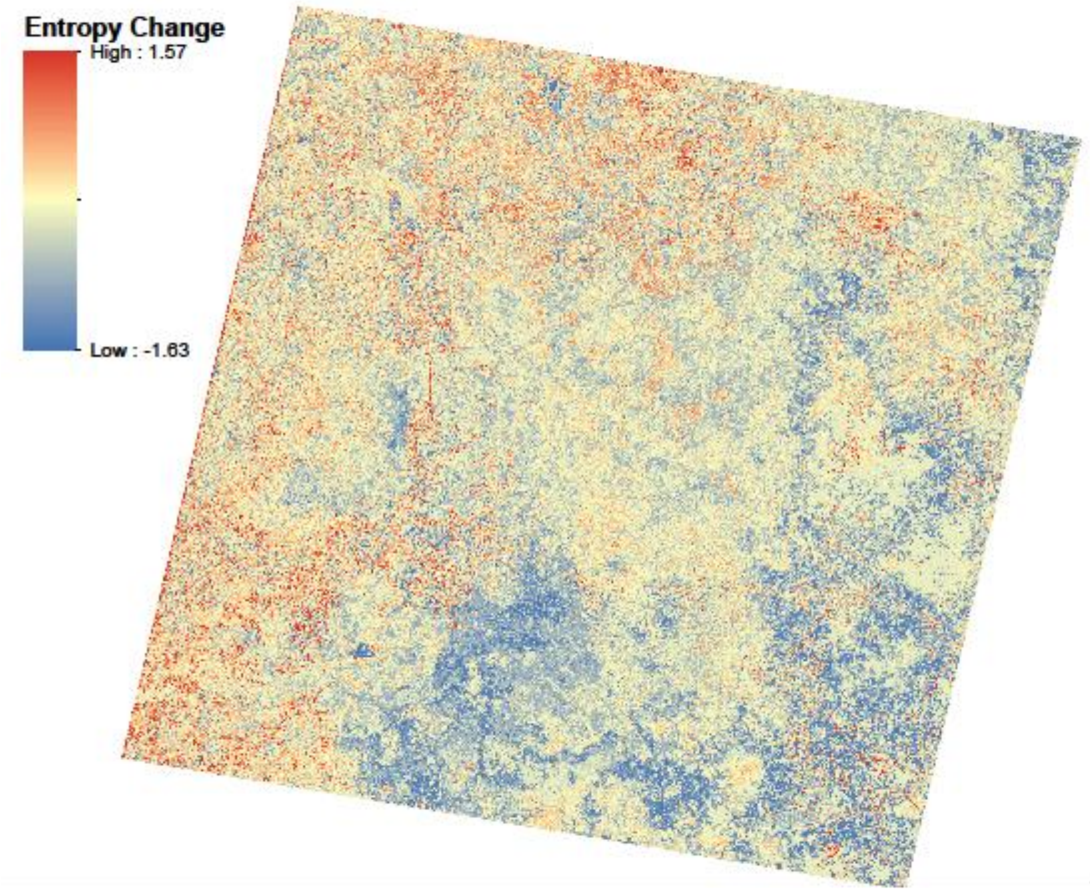


Figure 9. Change in K means Shannon Diversity between 1995 and 2000.

Change in the four GLCM metrics varied across the two time periods (Figure 10). Entropy showed a similar pattern to K-means Shannon Diversity, with large increases and decreases seen across the landscape. The same was not true of the other metrics however, with only a relatively small degree of change apparent in most areas. This may indicate that K-means Shannon Diversity and Entropy are the texture metrics most sensitive to change in forest structure. Alternatively it may be that the biggest changes in this landscape between 1995 and 2000 have been in variables which are best predicted by Entropy and K-means diversity (e.g. trees per hectare, mean tree height), while those better predicted by Cluster Shade and Prominence such as mean DBH have stayed relatively constant.

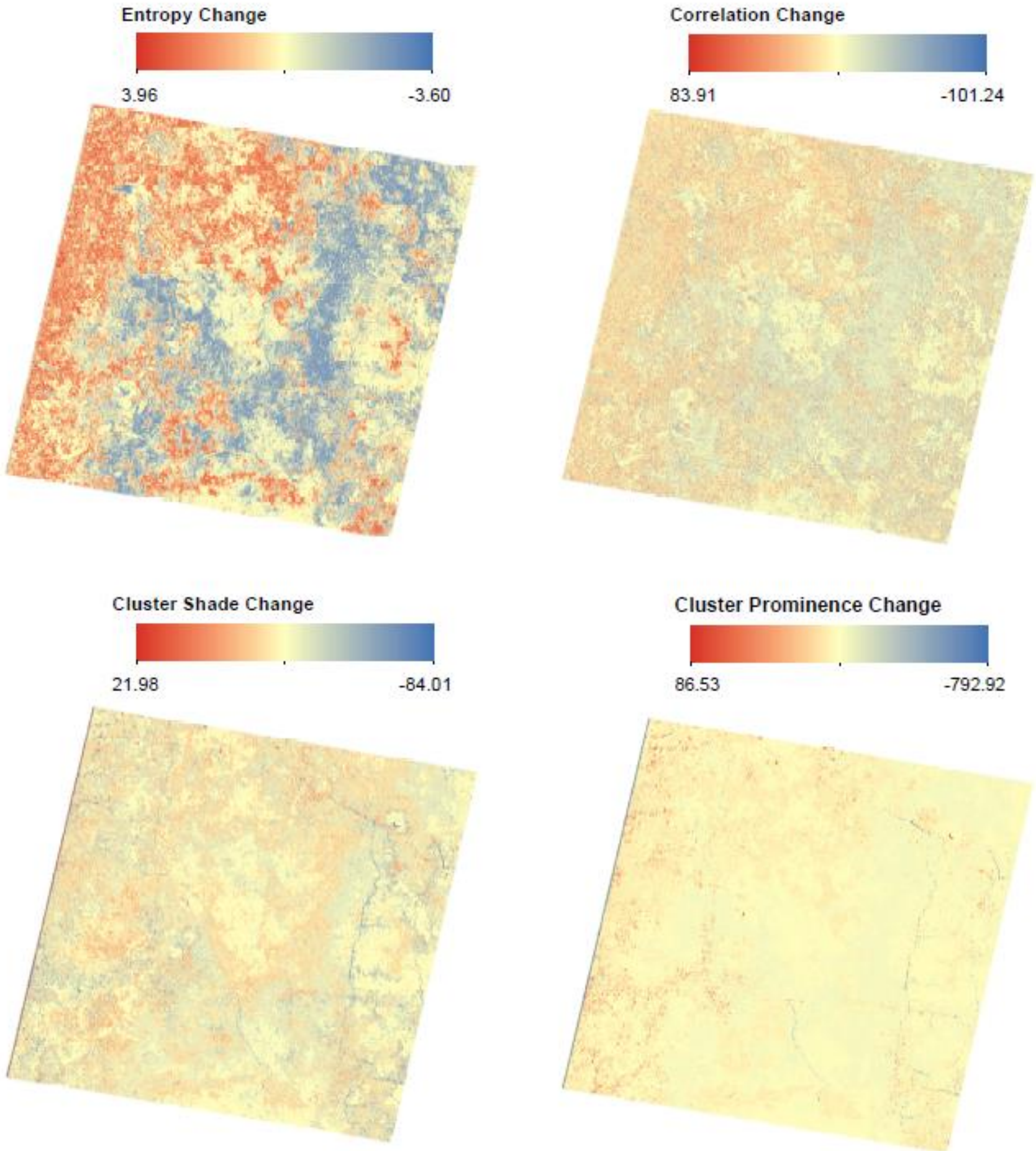


Figure 10. Change in pixel Haralick Entropy (top left), Correlation (top right), Cluster Shade (bottom left) and Cluster Prominence (bottom right) between March 1995 and March 2000.

While a lack of available ground data meant that it was not possible to validate this observed change in remote sensed metrics, further investigation into the ability of these texture metrics to map changes in biomass and biodiversity through detecting alterations in different aspects of tree density and structure is needed. Given the relationships between EVI and entropy and forest interpolated maps observed here, it seems likely that these simple metrics are capable of mapping changes in forest quality over large spatial scale. The inclusion of other variables in these models, such as climate and topology, is also likely to improve the ability to detect differences in forest habitat (Matsushita et al. 2007; Saleska et al. 2007).

Conclusions

Measures of texture such as K means Shannon Diversity and second order entropy statistics are both correlated with interpolated maps of forest structure. Image texture therefore appears to be capable of detecting important variation in forest canopy structure. Different forest structure variables were better predicted by different measures of texture, suggesting that choosing the correct metric is essential in order to accurately estimate forest condition. Changes in textural metrics over time can be detected and are therefore likely to be related to changes in forest cover and maturity. Landsat derived texture measures may therefore be an effective way of assessing the structure and status of tropical forest habitat and changes in this over time, particularly where combined with other sources of spectral, climate and topographic data.

3. National level

3.1. Mexico[4]

Introduction

The main goal of ROBIN is to investigate the effect of biodiversity on ecosystem services, especially climate mitigation. As part of the results of Work Package (WP) 1.1, it has been shown that biodiversity actually has a positive effect on carbon stocks and carbon sequestration. Thus, one of the conclusions of ROBIN is that biodiversity should be considered as an integral component of policies and practices focussed on reducing the impact of climate change (e.g., REDD+). Despite these important findings, major problems persist, such as: How to handle the complex concept of biodiversity and how to measure what aspects of biodiversity? In ROBIN the general approach has been to use a set of biodiversity proxies generated by combining field data with remote sensing based products. In this context, a biodiversity indicator based on the concept of ecosystem integrity (EI) has been introduced (Kolb et al., 2013). We define EI as a composite indicator made up of component indicators (also composites) such as structural diversity, functional diversity and taxonomic diversity. In this report we develop the application of the EI indicator as a basis for understanding recent impacts of land use change on biodiversity and as a practical approach for monitoring large scale patterns of change in biodiversity.

Our concept of EI is based on the approach of complex systems and ecosystems are considered as self-organized entities according to the thermodynamic logic of dissipative structures (Equihua et al. 2014, Kay 1991; Regier 1995; Holling 2001; Manuel-Navarrete & Kay 2004). In this context, the “optimal” operational condition of an ecosystem can be characterized by several proxies of ecosystem health. The measure of integrity must include the capacity to attain and maintain an optimal operational point both under “normal” conditions and when subject to tension (operational points that certainly cannot be equal) (Kay 1991). An ecosystem with a high level of integrity must be capable of continued evolution and development as a natural consequence of the continued operation of the processes of self-organization. Under this perspective, if a system is maintained close to an optimal

[4] This section summarises the research of Equihua, J.; Equihua, M.; Pérez-Maqueo, O.; Díaz, P.; Kolb, M.; García Alaníz, N. and Schmidt, M. (2015)

operational point, processes of self-organization can be interpreted as the mechanistic basis of what is known as the “resilience” of ecosystems.

In short, EI arises from processes of self-organization derived from thermodynamic mechanisms that operate through the locally existing biota, as well as the energy and materials at their disposition, until attaining optimal operational points which are not fixed, but rather vary according to variations in the physical conditions or changes produced in the biota. It must be recognized, however, that while the processes of self-organization can lead to very diverse conditions, to the eyes of human experience, ecosystems present certain constancies, such as identifiable configurations. Here we present the practical application of this concept to model EI for Mexico.

Methodology

Ecosystem integrity (EI) is an underlying indicator of the state of ecosystems that manifests itself in specific characteristics of structure, composition and function that are actually measurable. We generated a set of variables with existing information to provide data for structure, composition and function of ecosystems as a way to infer the EI. These variables are used as covariates (nodes) for inference on and prediction of EI from three different sources. We produced one block of covariates by interpolating Mexican National Forestry and Soil Inventory (INFyS), which provides in situ measurements. The second block we derived from MODIS products distributed by NASA. We developed a third one based on MAD-Mex land cover classification maps (Figure 11).

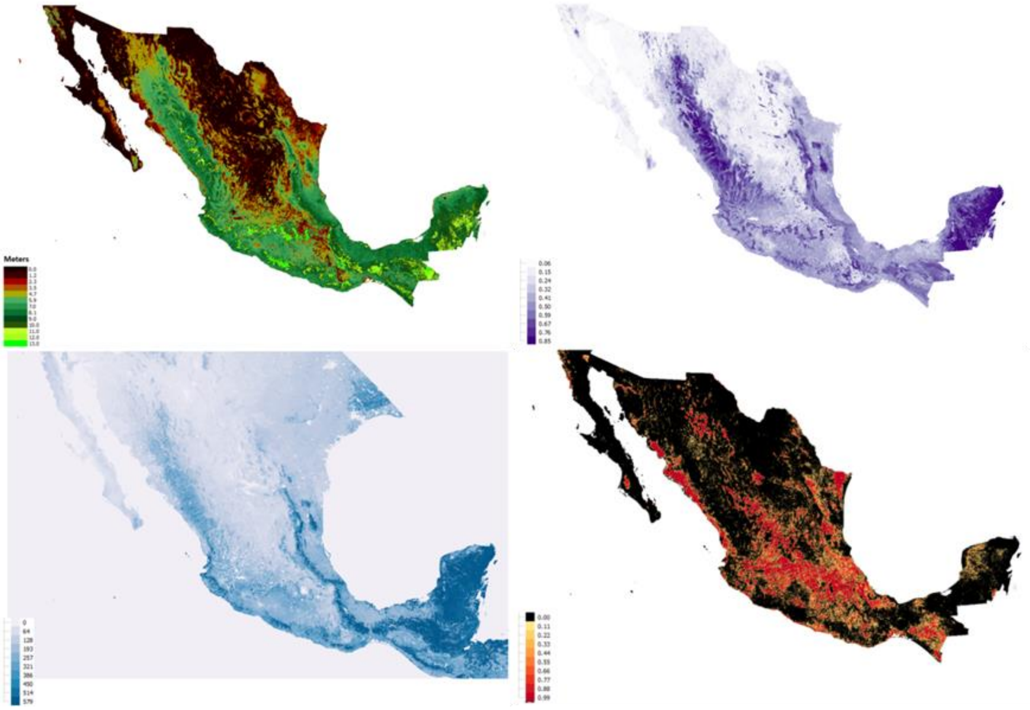


Figure 11. Examples of variable maps generated as input for modelling ecosystem integrity. a) average tree height/km2 (2004), b) probability of litter/km2 (2004), c) mean gross primary productivity (2004-2005), d) proportion (%) of land use per 1 km pixel.

Compilation and generation of input variables

Most of the variables are based on systematic field data from the INFyS 2004-2013. INFyS measurements take place in cycles that sample 22,000 plots over a period of 5 years. These plots are located on a regular grid with a spacing of 5 km, although certain types of locations can be further spaced, for example, plots on arid and semi-arid communities have a distance of 20 km. INFyS includes the re-collection of 152 variables on each plot. Thirty-none of these are at a tree level; for example tree height, tree condition (alive, dead but standing or stump), presence of insect plagues, etc. From the 17 variables originally considered from the national forest inventory for Mexico, we produced nine wall-to-wall maps for structural variables using machine learning techniques (the vanilla implementation of random forests as well as quantile regression forests from the R programming language, Kolb et al. 2014). For this purpose, a total of 170 explanatory variables were introduced into the spatiotemporal models, of which 150 covariates were generated based on remote sensing data like MODIS. Other variables like altitude and other topographic information were considered constant over time.

The Terra/MODIS Gross Primary Productivity product (MOD17A2) is a cumulative composite of GPP values based on the radiation-use efficiency concept which has been used to represent biomass. It is produced globally with an 8-day periodicity with a 1 km spatial resolution. Composites based on pixel-wise means and standard deviations were generated for periods of three years (year of interest +- 1 year) and for the wet and dry seasons of each year.

Medium resolution (30 m) MAD-Mex land cover classification maps based on Landsat imagery (Gebhardt et al. 2014) were used to generate maps depicting the proportion of cover at 1 km. First the original MAD-Mex scheme was aggregated to IPCC classes, with the difference that forest and shrub land were separated. Then the proportion of each class contained in each 1 km pixel was calculated.

Probabilistic model (Bayesian network

To create the EI Model, a Bayesian network approach was applied, since it is not only an inference mechanism but a predictive model in itself. The general structure of the network is composed by four tiers: precondition, hidden, instrumental, and contextual (Figure 12). This structure resembles those used in medical diagnostics arranged by preconditions, diseases, symptoms, along with a layer of reference values. Hence, our proposal does not necessarily clarify causation (etiology) of the condition of integrity. In fact, the condition of integrity "causes" the status of the instrumental variables, just like a disease causes the result of a clinical test or a symptom. In this case, preconditions are represented by the proportion of natural vegetation per pixel, the hidden tier represents the difference between natural and actual land cover, the instrumental tier is the core variables that indicate ecological integrity and the contextual tier is the reference framework for the model to adjust to topographic and climatic circumstances.

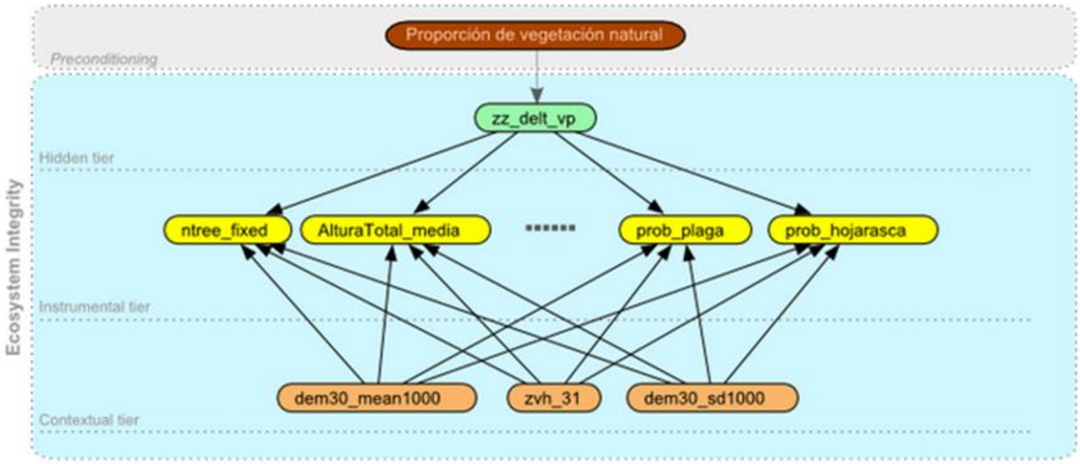


Figure 12. Generic model of ecosystem integrity with four tiers: Preconditioning, hidden, instrumental and contextual variables.

We did an initial exploration of different set-ups of networks, including naive arrangements. Besides the magnitude of difference between natural and actual land cover, the models were progressively conditioned by a set of different Holdridge life zones (Díaz Maeda 2015) aggregates and by variations of digital elevation (mean and standard deviation/km2, ASTER GDEM 2009). Mexico is an extremely beta-diverse country due to its biogeophysically heterogeneity. Thus a hidden variable was introduced to be able to stratify model fitting according to those ecological differences. Based on this preliminary analysis we selected the combination of hidden variable Holdridge life zones of 31 categories and nodes discretized into 10 levels.

With this basic setting we conducted a step-wise search of a Bayesian Network to minimize the total error rate using a scoring learning algorithm. The resulting node selection was then used in further exploration. These new networks were trained with the scoring algorithm, and once a satisfactory configuration was achieved, we trained that Bayesian Network with the algorithm eliminating the previous estimates of the conditional probability tables. Furthermore the conditional probability tables were further treated by the NETICA option of smoothing them up to degree four.

By means of a series of calibration and sensitivity analysis, the importance of different variables and their effect on the models was tested. This way, for the final EI model, only a subset of the variables was used in the Bayesian Network.

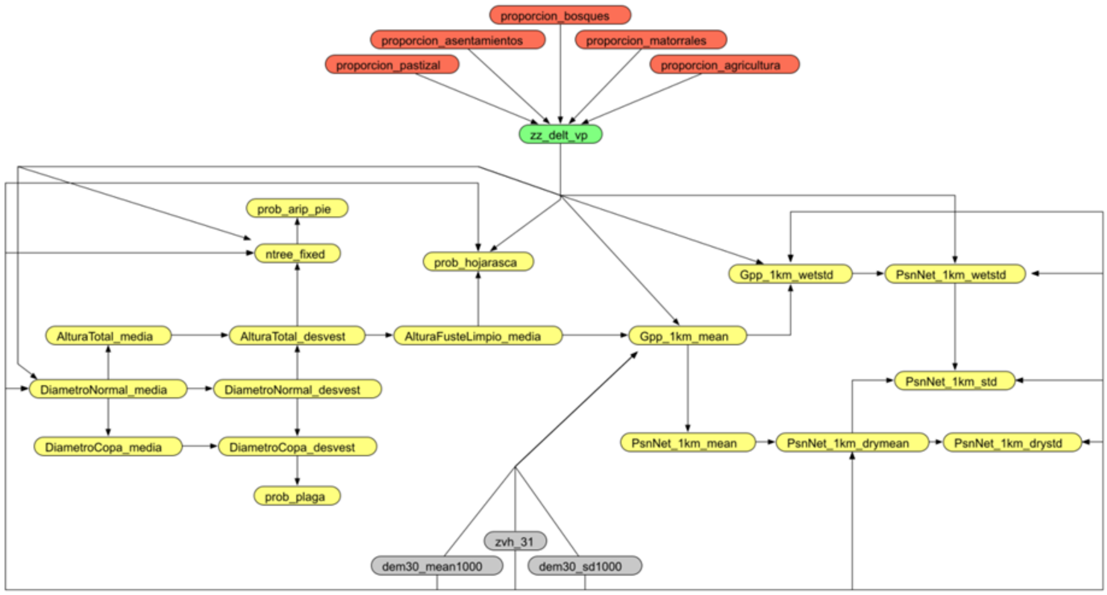


Figure 13. Structure of the final Bayesian network used to model EI.

Ecological integrity over time

Once a satisfactory Bayesian Network model was fitted, input variables for this structure were created to study EI trends in time. As mentioned, INFyS–MODIS based maps corresponding to the year 2004 are fit upon data from the years 2003 to 2005. To produce EI maps of successive time steps the window on which the set of node-covariates is calculated is shifted 1-month into the future. This takes place from January 2004 (which is built upon the window January-2003 to January-2005) to December 2013 (which is built upon the window December 2012 to December 2014) to sum up a total of 120 time steps. The Final Bayesian Network is then used as a predictive model to generate a new EI map for each of these time steps. If one stacks the previous EI maps one has a 120 point time series which can be used for trend analysis.

To formalize the study of EI trends, a model based analysis of the pixel-wise was produced for all the country. First the IE-image time series stack is whitened to remove autocorrelation from each pixel-time series. A Mann-Kendall test and a Thiel-Sen regression is generated on the previous pre-whitened pixel-time series. The slope estimated by the Thiel-Sen regression is used as an estimator of the time series trends and the Mann-Kendall test is used to discard insignificant slopes.

Results

A visual comparison of the resulting maps of EI with other available data sets on the condition of ecosystems on a national scale (Kolb 2009, González-Abraham et al. 2015) show a very good correlation of the general pattern. Most severe degradation can be seen in and around major cities, while in Central Mexico and the Gulf of Mexico coastal plain the historical patterns of land use are clearly apparent (Figure 14). Additionally, the EI map shows patterns of integrity of natural vegetation, that has not been revealed by other products, because of the before not available data sets of the INFyS. Natural vegetation with lower values of integrity can be found in the N part of the Yucatán Peninsula and the Pacific slope of Jalisco, Michoacán, Guerrero and Oaxaca. A sensitivity analysis of the effect of different variables in the model revealed that land use and roads is a very important driver for EI dynamics.

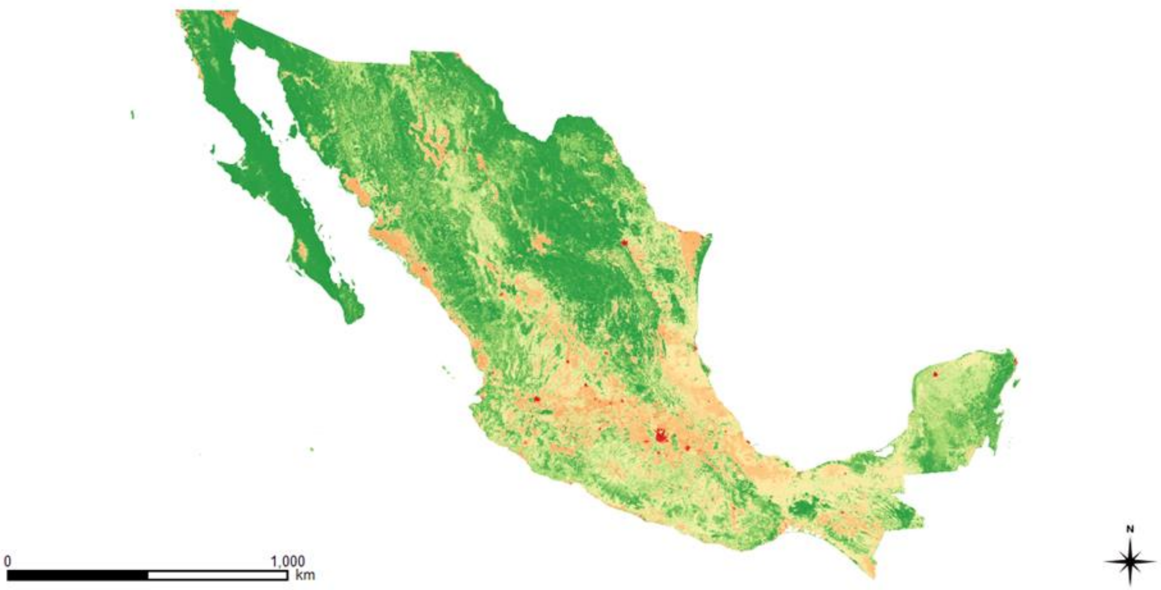


Figure 14. Ecological integrity for Mexico (2004). Red: low EI, green: high EI.

A preliminary review of temporal tendencies of the median of EI over time for per Holdridge life zone reveals increasing and decreasing trends which was not considered to be statistically significant (Figure 15). As a regional example, a zoom on the Yucatan Peninsula is presented (Figure 16), where all slopes not significant at 0.95 for the Yucatan peninsula were disregarded. Most negative trends are located around cities and highways. The results are plausible but a further investigation is required to make sense of and formally validate these results.

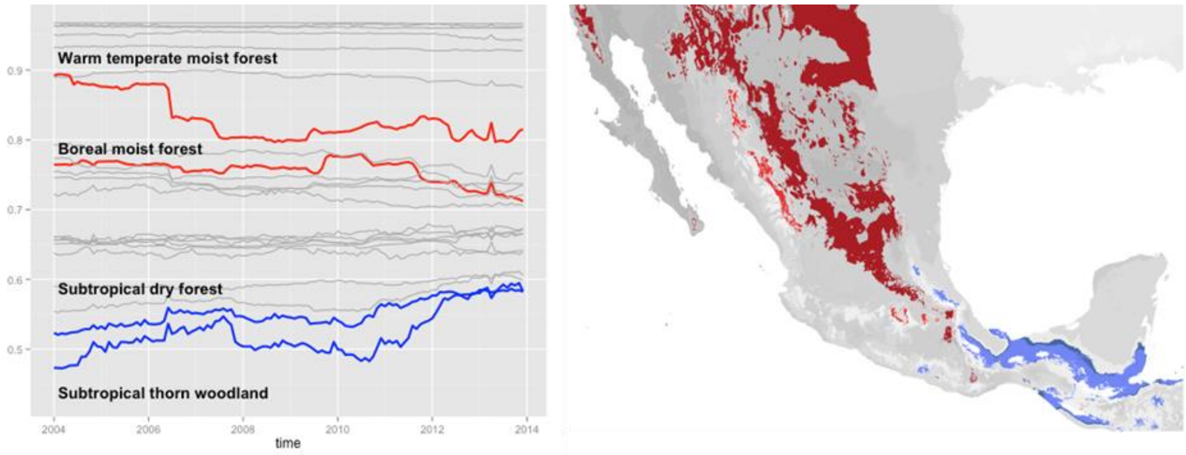


Figure 15. Ecological integrity for Mexico per Holdridge life zone over time (2004-2013). a) tendencies of the median value (red: descending, blue: increasing) and b) their spatial distribution.

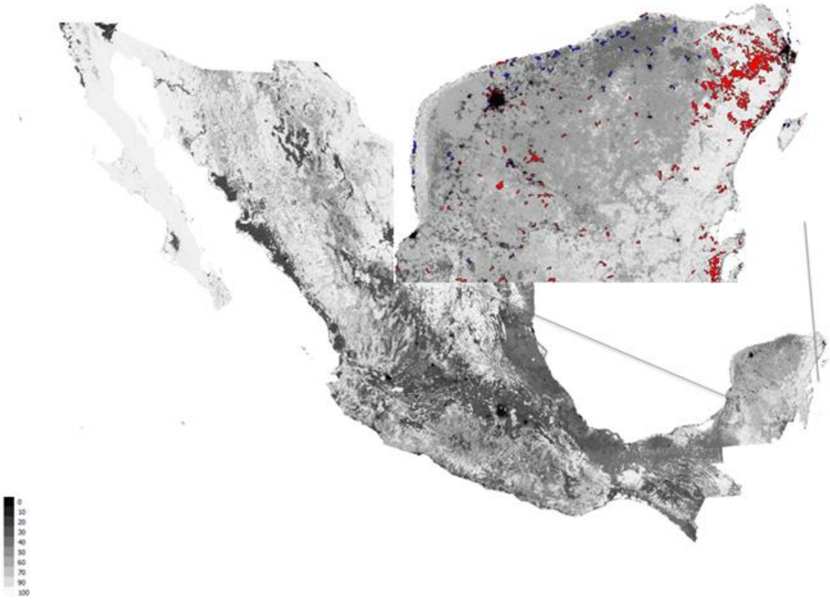


Figure 16. Regional example Yucatán Peninsula: Tendencies of the median value (red: descending, blue: increasing) of ecological integrity per Holdridge life zone over time (2004-2013).

Discussion

The adopted methodological approach offers a unified platform for modelling EI as a measure of biodiversity. It allows for integrating different kind of datasets and makes it possible to process them in a flexible framework on a national scale. Given the broad conceptual and dynamic structure, the indicators and variables for EI that we have developed can be seen as a very useful tool to evaluate and interpret data in a very accessible form for many diverse stakeholder groups and for the public in general. EI clearly depends on local biophysical conditions (e.g. vegetation type, soil

and climate). So the patterns of association of variables and EI are not generic but vary between local contexts shaped by the thermodynamic forces that govern the ecological dynamics, as well as the actual biota.
Since there is no baseline information available and biodiversity monitoring only exists for very few locations, validation has to be done through a process of "inter subjectivity" conciliation. This means that the system is seeking to fit the model as much as possible to the expert judgment. Availability of relevant information is another limitation, but the development of a synthesizing tool like EI is encouraging the gathering of new information to better inform us about the status of EI.
The conceptual approach adopted for EI is adequate to further evaluate managing scenarios so to give recommendations on how to design policies for sustainable development and other countries in the Americas are picking-up the idea of using EI to evaluate environmental policies.

3.2. Brazil

3.2.1. Introduction

In this section, five studies are shown. The first of them “Probabilistic Bayesian model from Remote Sensing data applied to mapping the Ecosystem Integrity in Brazilian Amazon” focuses on mapping the ecological integrity in the Brazilian Amazon and where it is critically disrupted by deforestation. The following three studies focus on modelling the dose response relations between land use change and climate change and biodiversity, as well as ecosystem integrity and ecosystem services indicators in Brazilian Amazon.

The second study focuses on an area in Brazilian Amazon, the Tapajós National Forest (Flona Tapajós), as presented in the third work “Multi-temporal cover patterns using Landsat TM in the Tapajós National Forest and its surroundings: a case study”. In this work, the spatial distribution patterns of land use and cover change in the landscape using data from spatio-temporal remote sensing sources have been identified and mapped. The method of assessment of natural and non-natural landscapes can support the understanding of the observed dynamics of land use and cover change. Results from data analysis show that between 1989 and 2005 there was a higher percentage of deforestation patterns than occurred from 2005 to 2009. The data indicate that the area still has an extensive forest cover but, within the analysed period, it became obvious that human pressures, especially activities related to agriculture and livestock were considerably changing the landscape in the study area. Reductions in deforestation showed the effects of management actions by the Chico Mendes Institute for Biodiversity Conservation (iCMBio) to ensure the sustainable use of the Flona Tapajós, created in 2007.

Threats regarding the maintenance of the Native Forest are associated with a period from 1989 to 2005. Signs of rupture between the conservation unit and the São Jorge Community are clear in the loss of occupation and use patterns, already in the period from 1989 to 2005, which intensified between 2005 and 2009, reaching its climax with that Community’s emancipation and a loss of area in the Flona Tapajós in 2012. The spatial-temporal dynamic of native forest loss in the Buffer Zone (10 km) weakened its function of anthropogenic forces mitigation, thus threatening the Conservation Unit’s sustainability or, in other words, compromising goods and services provided by the forest to the region’s population and biodiversity. The spatial-temporal dynamics in Flona Tapajós and its surroundings indicates the importance of legally protected areas for the conservation of goods and services offered by the people as part of the Amazon Forest Strategy.

Taken as a whole, this set of studies provides a description of changes over time, but also points out future trends and identifies higher-pressure areas. This is accomplished by the third study on “Scenario Analysis of the Main Drivers forces threatening the conservation of the Tapajos National Forest, Brazilian Amazon”. This study addresses efforts to investigate landscape changes in the Flona Tapajós and its surroundings by considering the infrastructure and selected roads, municipal offices, land tenure (settlements, Conservation Units and Indigenous Lands) and localities. The biophysical elements included climate variables such as rainfall and annual water deficit, altimetry and slope. Data were spatialized by using the geostatistical analysis, modelling and scenario generation were operated in the DINAMICA software that provided a detailed analysis for each vector element of change in the landscape, in addition to its role in the spatial dynamics of the study area. In addition, the advancing agricultural frontier in the zone of transition of the ecotone Cerrado-Amazon biomes, which present different environmental and legal aspects, has potential to promote pressures in another legally protected areas in Amazon. Thus, the studies accomplished on the framework of other regional projects were integrated within the ROBIN project in order to add competences in the assessments of the role of biodiversity in the climate change mitigation.

In this sense, future trends and scenarios were also carried out in other areas in Amazon as presented in the last work “Future scenarios for the north of Amapá state considering REDD+ as a conservation tool”, which assessed how the provision and maintenance of ecosystem services can contribute to local and regional sustainable development. This study allowed creating three future scenarios of deforestation considering different levels of forest governance for the northern region of Amapá to 2030. Further, it was estimated the opportunity cost of avoiding forest conversion using information of the net present value (NPV) of four land use activities, namely, forest, cattle ranching, and gold mining, and the average carbon stock values of these land use categories. The output was the graphical representation of the differences derived from the returns of the forest and those land uses that will replace it, with differences in carbon stocks of the emissions avoided by not converting the forest to other uses. Finally, the results contribute to the discussion of a policy to subsidize programs aiming at reduction of emissions from deforestation and degradation (REDD) and payment for ecosystem services (PES) implementation, by defining priority areas in the border region between Amapá and French Guiana.

Therefore, such results in Brazilian Amazon are able to subsidise the forecasts interpretations from the simulations achieved by the applied models in the WP 1.2 and WP 2.2.

3.2.2. Probabilistic Bayesian model from Remote Sensing data applied to mapping Ecosystem Integrity in Brazilian Amazon[5]

Introduction

According to the Convention on Biological Diversity (CBD) there are clear interlinkages between biodiversity and climate changes, because biodiversity supports many ecosystem services that are very important for climate change mitigation and adaptation, like carbon uptake and storage as well as regulation of evapotranspiration flux. But, the relationship between biodiversity loss and the impacts on ecosystem services of tropical forests, in face of the ongoing global climate change needs to be better quantified. Although quite intuitive, the biodiversity concept can be apprehended from many points of view, like: functional, structural and taxonomic approaches. For this reason, it's not simple to get a single indicator that can evaluate or represent the biodiversity of a given ecosystem. On the other hand, what matters in fact, in terms of environmental services, it's not biodiversity itself but the equilibrium state of biodiverse ecosystems, called: Ecosystem Integrity (EI). Ecosystem Integrity can be understood as a dynamic state of natural ecosystems in which it's observed maximum capacity of resilience and self-organization of its original components that maintains many ecosystem processes related to most terrestrial biogeochemical cycles. The EI state is own of balanced systems in which one observe expressive biodiversity, in terms of functional, structural and taxonomic features. Then the variables that describe biodiversity can be used as EI indicators and, in turn, EI of a given ecosystem can be considered as a proxy of biodiversity and the specific ecosystem services it provides. Nevertheless, land use changes and agriculture expansion reduce the ecosystems integrity modifying the functions related directly to the ecosystem services. The relationship between biodiversity loss and the ecosystem services in tropical forests, in face of the ongoing global climate change, has been quite accepted by the scientific community, but needs to be better quantified and understood.

Objectives

The general objective of this report to present briefly the methodological approach and the results of the Probabilistic Bayesian model from Remote Sensing data applied to mapping the Ecosystem Integrity in Brazilian Amazon. It is intended to present also the relationships between ecosystem integrity and the land use

[5] This section summarises the work of Simoes, M. and Ferraz, R. (2015)

patterns, as well as, the relationships between ecosystem integrity/biodiversity loss with the carbon stock and evapotranspiration fluxes regulation ecosystem services.

Methodology

In this work, we considered the concept of Ecosystem Integrity (IE) as a proxy of the biodiversity, meaning the state in which a given ecosystem is able to sustain the processes of self-organization. The methodological approach of this work consists in the generation of an “ecosystem biodiversity loss” spatial model based on probability distribution of evidence parameters (Bayesian theory - Lindley 1972). The modelling was based on learning process (dada-driven model) using the Expectation Maximization algorithm (Buntime 1994). Bayesian network has been established from an expert conceptual model that related different spatial data (Thematic maps and Remote Sensing data: (i) EVI; (ii) LAI- Leaf Area Index (MODIS/ USGS – NASA); (iii) Tree Cover (MODIS/ USGS – NASA); (iv) GPP- Gross Primary Productivity (MODIS/ USGS – NASA) (Figure 17). Then, the Bayesian Networks (BBN-Bayesian Belief Network) can provide metrics for the generation of ecosystem integrity index, from the training of probabilistic relationships of evidence obtained through, in the case of Brazil, remote sensing data. In order to decreasing the environmental heterogeneity was used, as a landscape segmenter, a phyto-ecologic landscape zoning that was elaborated at the regional scale for the whole Brazilian Amazon. For the validation of this probabilistic model, an evaluation was carried out in controlled areas (Figure 18), with field observation and comparison with the IE model based on knowledge (knowledge driven), prepared by experts.

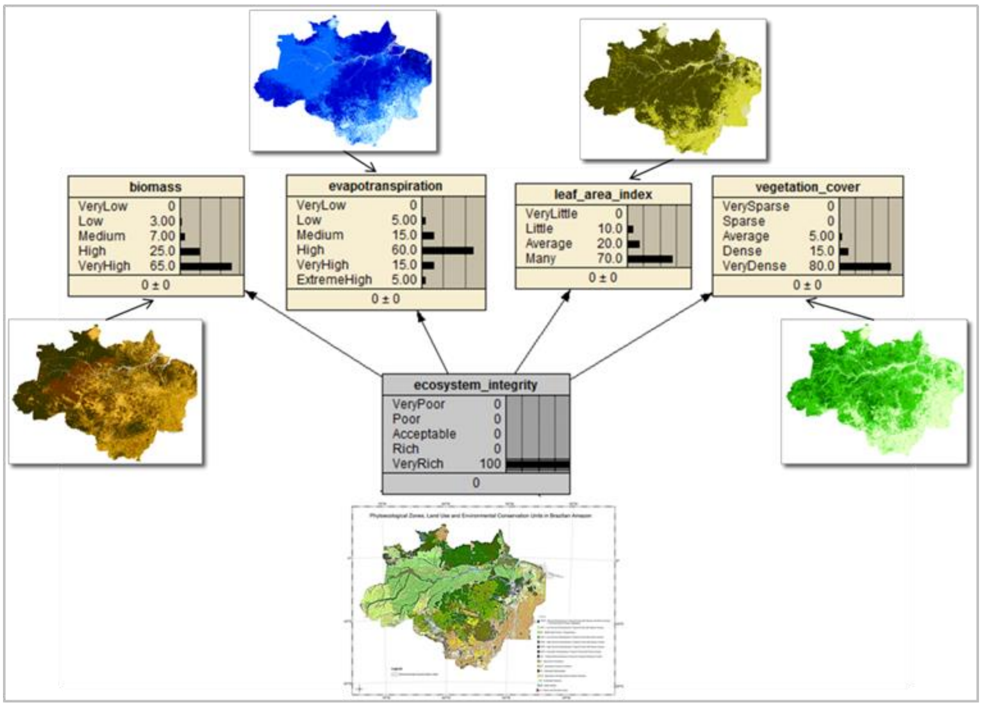


Figure 17. Bayesian network established from an expert conceptual model: Spatial Remote Sensing data: (i) EVI; (ii) LAI- Leaf Area Index (MODIS/ USGS – NASA); (iii) Tree Cover (MODIS/ USGS – NASA); (iv) GPP- Gross Primary Productivity (MODIS/ USGS – NASA)

In order to study the relationships between ecosystem integrity/biodiversity loss with the land use landscape patterns, was held a comparative study between the biodiversity loss" spatial model based on probabilistic distribution of evidences (Bayesian theory - Lindley 1972) and the Land Use and Cover data from PROBIO (Figure 20).

In order to study the relationships between ecosystem integrity/biodiversity loss with the evapotranspiration fluxes regulation ecosystem services, was held a comparative study between the biodiversity loss" spatial model based on probabilistic distribution of evidences (Bayesian theory - Lindley 1972) and the evapotranspiration fluxes ecosystem service estimated from MODIS Surface Resistance and Evapotranspiration (MOD 16), data developed by Numerical Terradynamic Simulation Group (NTSG), College of Forestry & Conservation - University of Montana. (Mu et al., 2007) (Figure 21). In order to study the relationships between ecosystem integrity/biodiversity loss with the carbon stock ecosystem service was held a comparative study between ecosystem integrity and the Aboveground Carbon Stocks (ACS) estimated from spatial model developed by Baccini et. al. (2004) within the Pantropical National Level Carbon Stocks Project held by the Woods Hole Research Center – WHRC, Boston University and the University of

Maryland (MA, USA). The methodology was based on ground data, MODIS 500m imagery and GLAS LiDAR data.

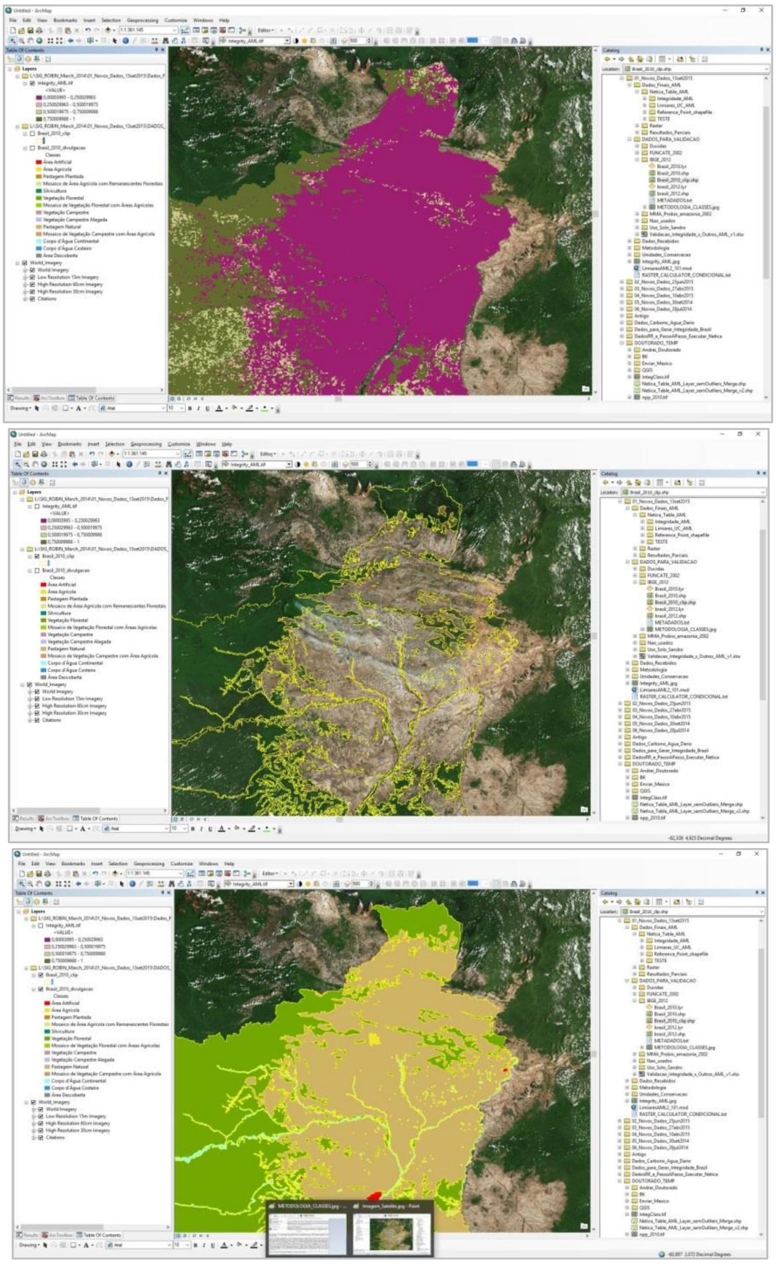


Figure 18. Ecosystem Integrity (EI) probabilistic model validation (from top to bottom): Ecosystem Integrity model results; Satellite visual observation and field data; Land Use Map.

Results

The Figure 19 shows the results of Ecosystem Integrity Bayesian model, where one can observe the spatial distribution of the ecosystem integrity or biodiversity loss (delta EI).

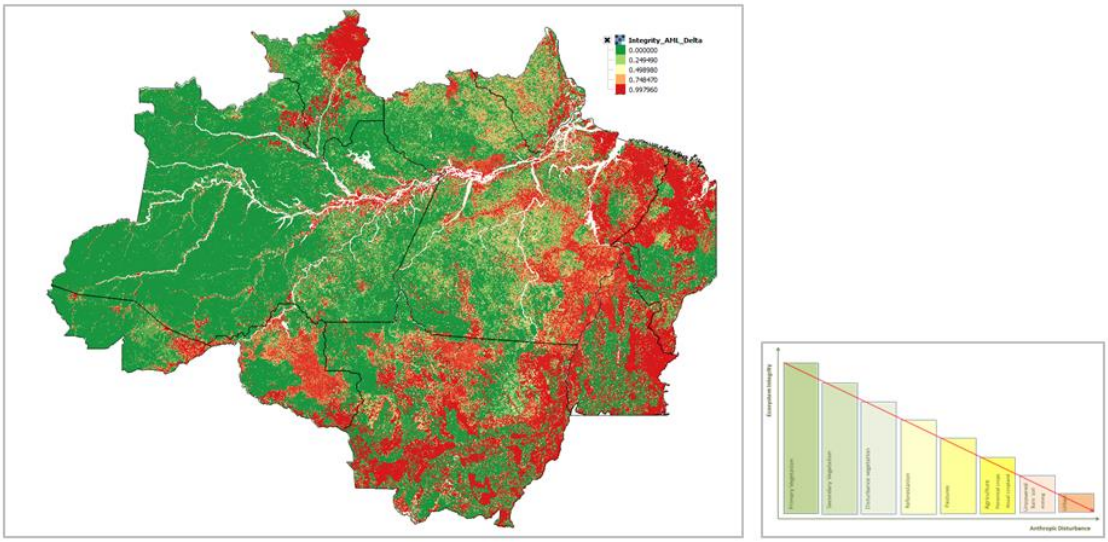


Figure 19. Ecosystem Integrity Bayesian model: spatial distribution of the ecosystem integrity or biodiversity loss (delta EI).

Land use changes (LUC), in large-scale and high-intensity, are intrinsically related with biodiversity loss and integrity decrease of natural systems, which keep the ecosystem services (ES). Land use landscape patterns can be correlated with different levels of ecosystem integrity (EI) and consequently with the potential environmental services provision. The Figure 20 shows the EI and the LU maps where one can observe a strict relationship between the land use patterns and the results expressed by EI index.

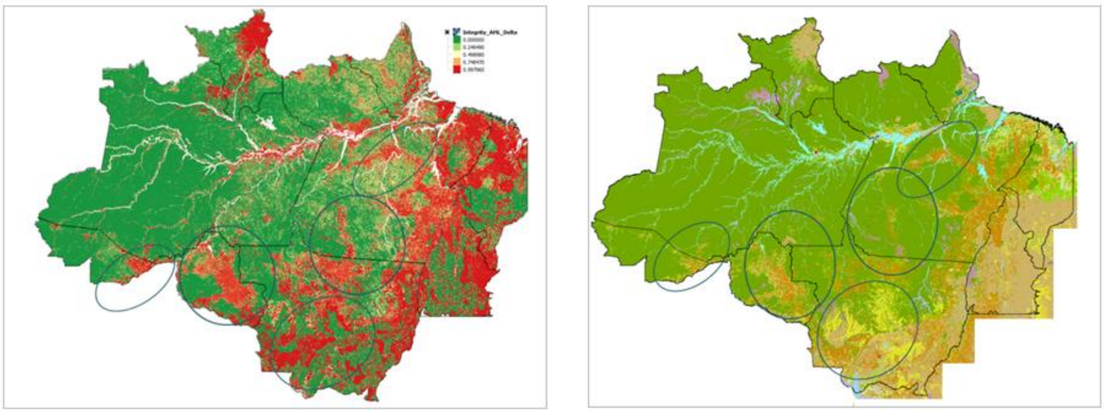


Figure 20. Left: Ecosystem Integrity (EI) and right: Land Use (LU) maps. Strict relationship between the land use patterns and the results expressed by EI index.

One of the most important ecosystem services refers to capacity of natural forests in regulating the water fluxes between the soil surface and the atmosphere (water balance) and by consequence stabilizing the climate seasonality. So studies of the relationship between land use changes, tropical forests biodiversity loss and the water ecosystem services, in face of the ongoing global climate change, are very important. In this work, it was used, as water fluxes ecosystem service, an evapotranspiration (ET) model estimated from MODIS Surface Resistance and Evapotranspiration (MOD 16). The Figure 21 shows the EI and the ET maps where one can observe a strict relationship between the ET different levels and the results expressed by EI index.

There is a functional link between the tropical forest ecosystem biodiversity and their capacity for carbon uptake and storage. But land use changes and the expansion of agriculture practices reduce the ecosystems integrity modifying the functions related directly to the ecosystem services. The Figure 21 also shows the the Aboveground Carbon Stocks (ACS) map, where one can observe a strict relationship between the ACS different patterns and the results expressed by EI index.

Conclusion

The results were promising, allowing the establishment of biodiversity loss probabilistic distribution spatial patterns and also the relationship with the carbon stocks (Aboveground Biomass) and with the water fluxes ecosystem service (Evapotranspiration).

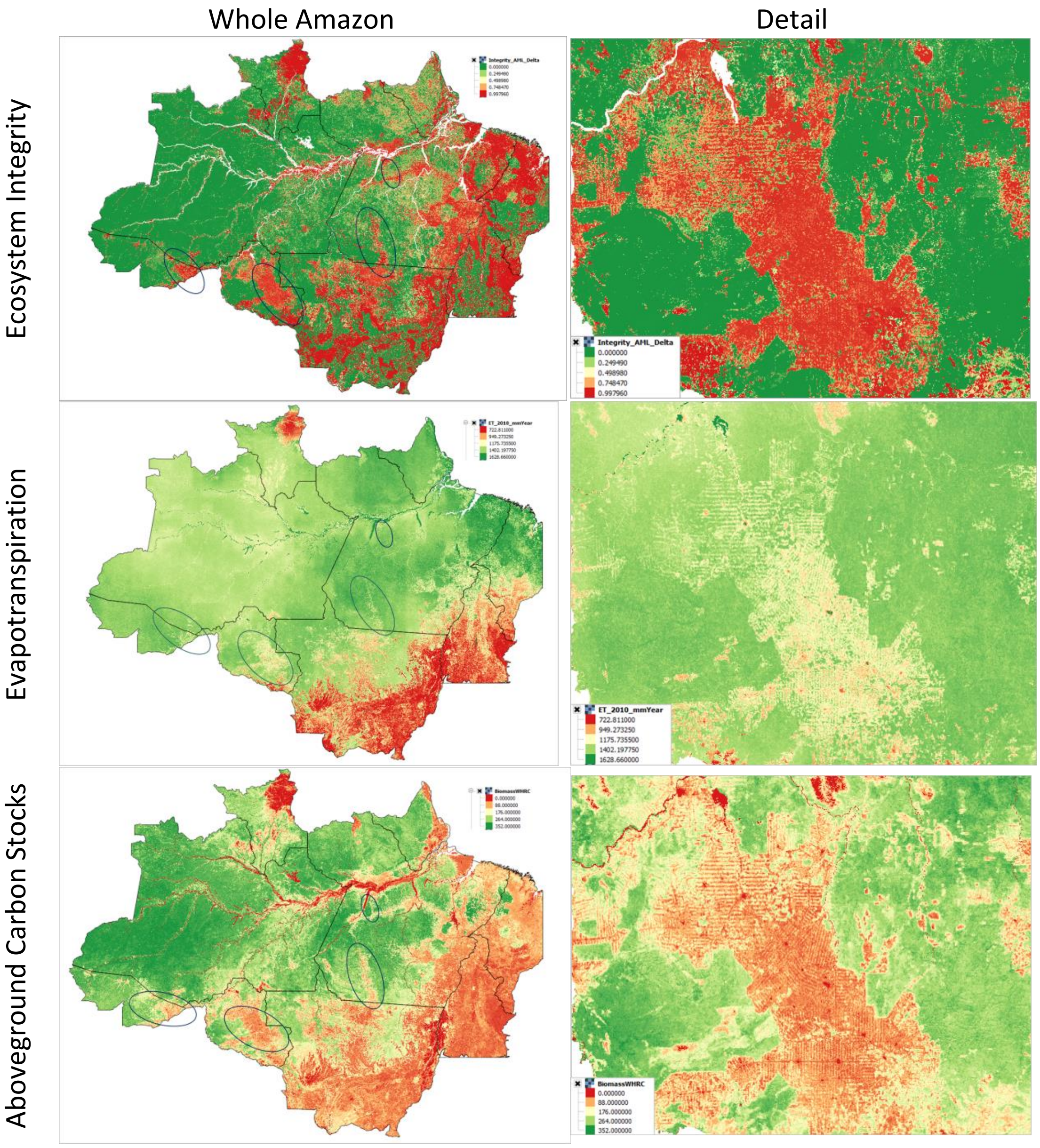


Figure 21. Up: Ecosystem Integrity (EI), middle: Evapotranspiration (ET), down: Aboveground Carbon Stocks (ACS). Left column images show the whole Brazilian Amazon while right column a zoomed area (second oval from the left).

3.2.3. Multi-temporal cover patterns using Landsat TM in the Tapajós national forest and its surroundings: a case study[6]

Introduction

Tapajós National Forest (Flona Tapajós) — a designated Conservation Unit (CU) created by Decree No. 73,684/1974. This CU has undergone constant changes in usage patterns and ground cover, especially in its surroundings, due to activities related to agriculture, livestock and timber harvesting. In June 2012, Federal Law No. 12,678 reduced the area of Flona Tapajós by approximately 4% of its original size (Figure 22). According Batista et al. (2013), this reduction may lead to possible threats in the maintenance of goods and services that FLONA offers, provoking with the passing of years changes in the livelihoods of surrounding communities, thus increasing pressure on the protected area. Therefore, the aim of this work was to identify and map spatial distribution patterns of use and ground cover after the alterations in the landscape using data from spatio-temporal remote sensing sources.

Materials and methods

Satellite images from the TM sensor aboard the Landsat-5, from July and August of 1989, 2005 and 2009 were used. Digital processing was performed: atmospheric correction, geometric correction, mosaic, classification and post-classification. We used the Geographic Information System (GIS) ArcGIS v.9.3 to construct thematic maps of the study-case, along with the following procedures: conversion of classified images to vector format for calculating the areas of thematic classes adopted this work; assembly and manipulation of geographic database and map algebra to detect changes between the years studied.

[6] Lisboa, L.S.; Vettorazzi, C.A.; Martorano, L.G.; de Almeida Muniz, R.; Beltrão, N.E.S. (2015)

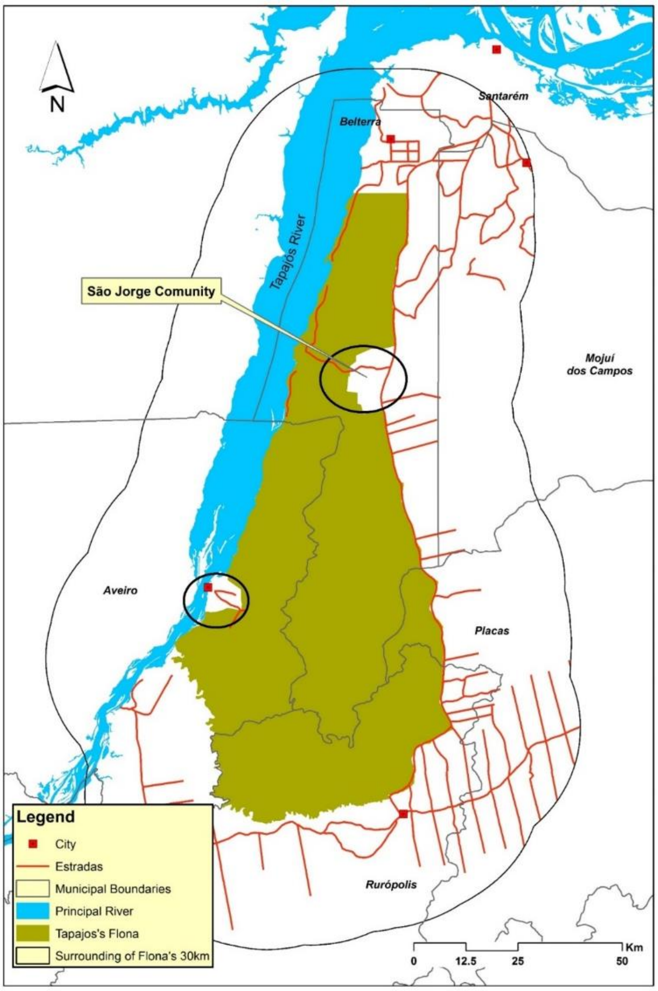


Figure 22. Flona Tapajós and surroundings, with ellipses in black indicating where the territorial reduction occurred.

Results and discussion

In Flona Tapajós and its surroundings, between 1989 and 2005, the areas with Native Forest (NF), Regeneration (R), Recent Deforestation (RD) and Exposed soil (ES) that remained unchanged comprised respectively 62%, 3%, 2% and 2%. The altered areas (17%) underwent their most drastic changes in areas with NF (9%) and in 2005 were identified as R (2%), RD (3%) and ES (4%), while (2%) areas belonging to class RD had not been removed. In the period 2005-2009, the areas with NF, R, RD and ES that remained unchanged comprised 61%, 6%, 3% and 6% (Table 3) respectively. In the period 1989-2005 there was an 11% reduction in NF areas. In the second period, this reduction was approximately 1%. On the other hand, the area (R) made up only 4.4% in 1989 and grew to 7.6% in 2005, reaching about 11% of the area in 2009. Areas with RD represented 5% in 1989 and 7% in 2005 and 2009, indicating that the "Government Programme Zero Deforestation in the Amazon" shows evidence of consolidation in study-case. This fits with the trend in ES, which went from 4% in

1989 to 19% in 2005 and 2009 (Figure 23). It is noteworthy that despite the reduced fragments located within Flona Tapajós, its environment, in particular its buffer zone, underwent a robust process of human disturbance. By analysing only the changes in NF and spatializes them for two periods, it was verified that in the 2nd period the greatest changes occurred in neighbouring areas of the Community São Jorge (Figure 24), indicating the weakness in maintaining forest by anthropogenic pressure. To reinforce the evidence of these losses, the Community São Jorge left the jurisdiction this CU.

Table 3. Transition matrix of change of the main land uses in the Flona Tapajós, PA and its surroundings. The number in bold is the percent of the area at period: 1989-2005. The number in italics is the percent at period: 2005-2009.

	Time2			
CLASS	NF	R	RD	ES
Time1				
NF	**62**	**2**	**3**	**4**
	61	*1*	*1*	*1*
R	**0**	**3**	**1**	**1**
	0	*6*	*1*	*1*
RD	**0**	**2**	**2**	**2**
	0	*2*	*3*	*2*
ES	**0**	**1**	**1**	**2**
	0	*1*	*2*	*6*

Note: NF = Native Forest, R= Regeneration, RD=Recent Deforestation, ES = Exposed Soil

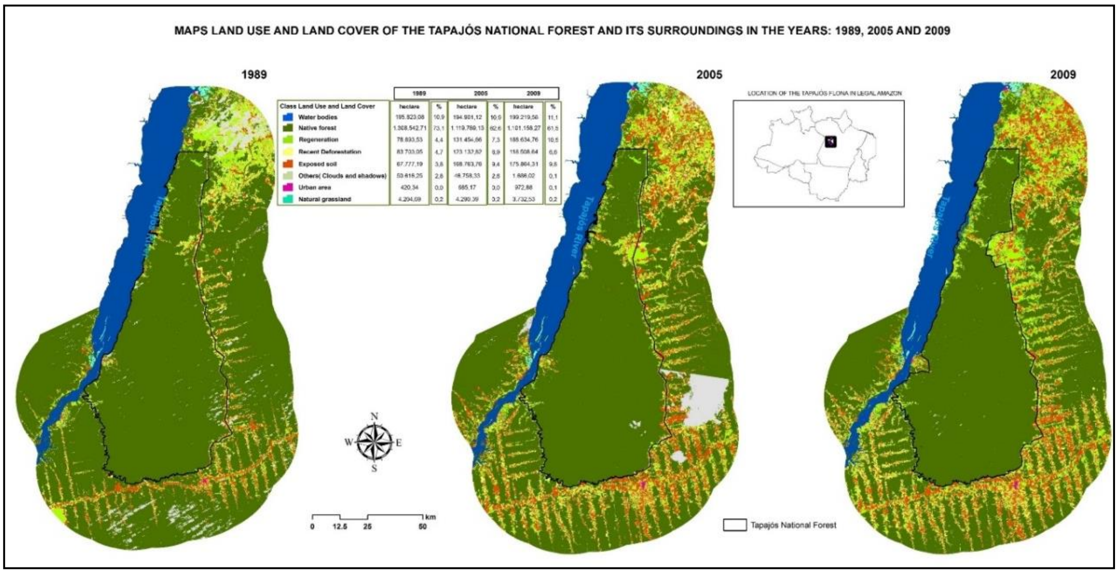


Figure 23. Mapping and quantitative analysis of the use and land cover in Flona Tapajós and surroundings. Years: 1989, 2005, and 2009.

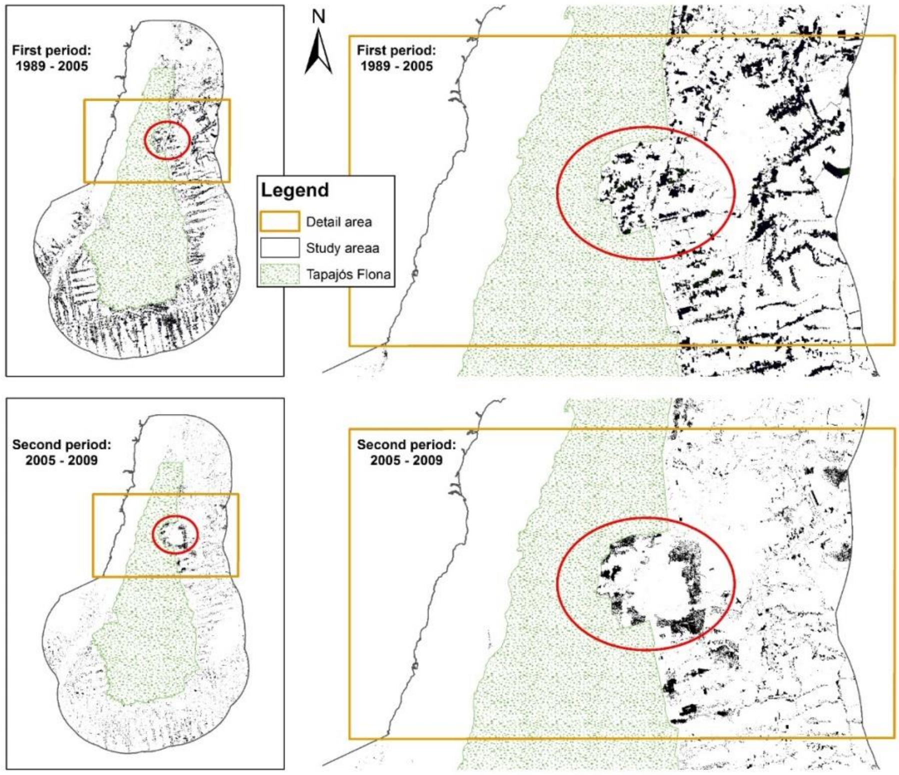


Figure 24. Flona Tapajós and surroundings (right), with ellipses in red indicating the Community São Jorge. Detail (left).

Conclusions

Between 1989 and 2005 there was a higher percentage of loss patterns in the Native Forest than occurred from 2005 to 2009; the method of assessment of natural and non-natural landscapes can support the understanding of the observed dynamics of use and coverage. In addition, the assessment provides support for analysis of the effects of fragmentation in this landscape. The spatio-temporal dynamics in Flona Tapajós and its surroundings indicates the importance of legally protected areas for the conservation of goods and services offered by the people as part of the Amazon Forest Strategy. In integration with other information and analysis, these dynamics may uncover possible threats to the maintenance of goods and services that sustain the biodiversity of the region.

3.2.4. Scenario analysis of the main drivers forces threatening the conservation of the Tapajos national forest, Brazilian Amazon[7]

Introduction

Several public policies were released in an attempt to integrate the Amazon to the other regions of Brazil in the 1960s. Amongst the main engagements on infrastructure, the government built ports, hydroelectric facilities, and opened highways such as the Transamazônica (BR 230), Cuiabá-Santarém (BR 163) and Belem-Brasilia (BR 316), triggering an aggressive process of landscape transformation and deforestation. At the same time, however, the government instituted legally protected areas in the region, such as the Tapajos National Forest (FLONA), in 1974. The road was extended in 2012 and is now part of a regional complex, between two major highways in the region.

The Tapajós National Forest suffers influence of the Transamazônica highway (BR-230) in the South, and the Cuiabá- Santarém highway (BR-163) located in its Eastern side, which leads to Santarém and Itaituba. Despite all the pressures generated by its surroundings, the protected area has presented suitable conservation indicators. However, it is noteworthy that the west side of Pará concentrates the greatest number of projects, as the seven hydroelectric power plants, the Cargo Transhipment Stations (ETC), and also the paving of highways BR-163 and BR-230. Thus, the spatiotemporal analysis intends, not only to provide a description of changes over time, but also to point out future trends and identify higher-pressure areas. This study addresses efforts to investigate landscape changes in the Tapajós National Forest and its surroundings, which covers a total area of 19,627 km², including the municipalities of Belterra, Santarém, Aveiro, Rurópolis, and Placas. The literature review supported the selection of change drivers.

Materials and methods

Considering the infrastructure, we selected roads, municipal offices, land tenure (settlements, Conservation Units and Indigenous Lands) and localities. Biophysical elements included climate variables such as rainfall and annual water deficit, altimetry and slope. All variables were crossed with land use data made available by the project TerraClass (INPE) for 2008 and 2010. For each municipality was sought information on crop, livestock and plant extraction through production to subsidize economic data provided by the results of spatial analysis process. Data were spatialized by using the geostatistics analysis, modelling and scenario generation

[7] do Nascimento, N.C.; Martorano, L.G.; Beltrão, N.E.S. (2015)

were operated in the DINAMICA software that provided a detailed analysis for each vector element of change in the landscape, in addition to its role in the spatial dynamics of the study area.

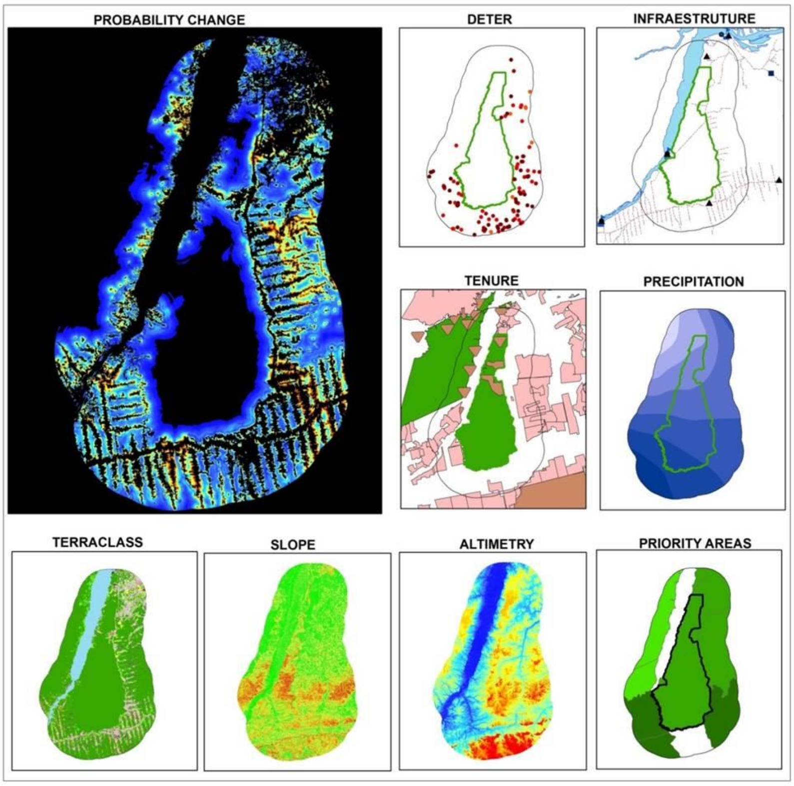


Figure 25. Model Database.

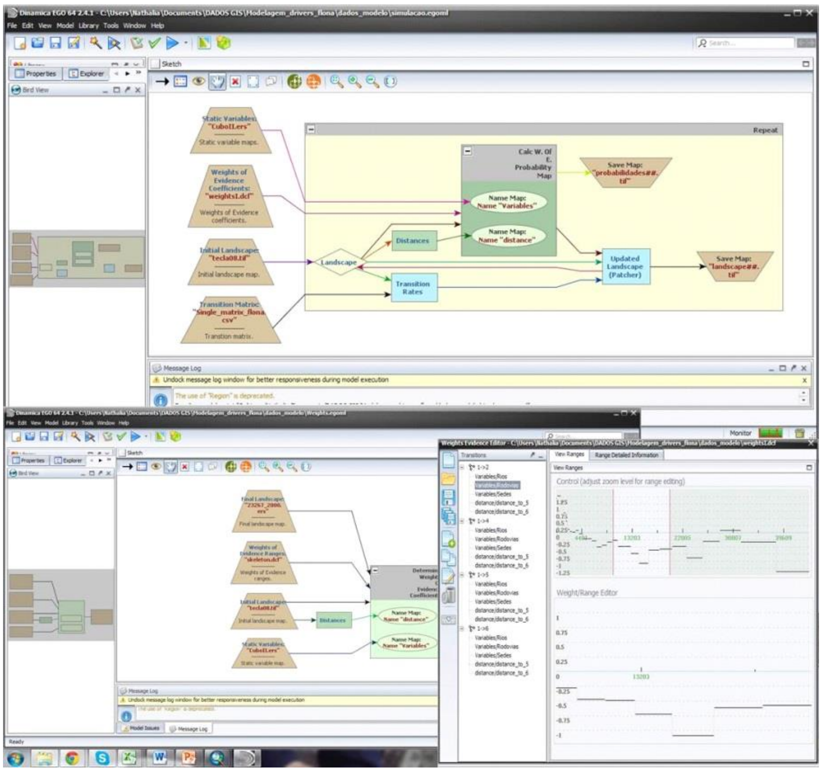


Figure 26. Steps of the process in spatial modelling DINAMICA EGO software

Results and discussion

The results showed that amongst the variables used as landscape transformation vectors, the roads appear to be the main drivers of change in every scenario, which means a change in the forest with different production systems. Taking into account the total area analysed, sites from Rural Settlement present more probability for transitions. The remaining areas with most probability for transitions are those with the lowest declivity values, who use agricultural machinery on the yearly cultivation of soy and corn. The remaining transitions follow the deforestation pattern, known as fishbone, along the Transamazonica highway. Inside the National Forest, the road that connects the São Jorge Community to the Tapajos across the Forest, at the Km 67 on Highway 163, is a major anthropic pressure. The evidence to this fact is that in 2012 this community was no longer under the control of ICMBio. In the map, the yellow and red dots indicate the places with higher chance of changing in the year 2030. According to the map, there are two zones of concern: the South side of FLONA, for the settlements controlled by INCRA (National Institute of Colonization and Agrarian Reform); the West side, where the Santarem-Cuiaba road is being renewed. The South side is a major concern for biological conservation given the intense use of the soil by farmers from the Settlements. The altitude, intense rainfall rates, the areas for settlements, and the predicted scenario for the year 2030 are elements that strengthen the need of Integrated Crop-Livestock-Forestry Systems to relieve the pressure on the south side of the Tapajos National Forest.

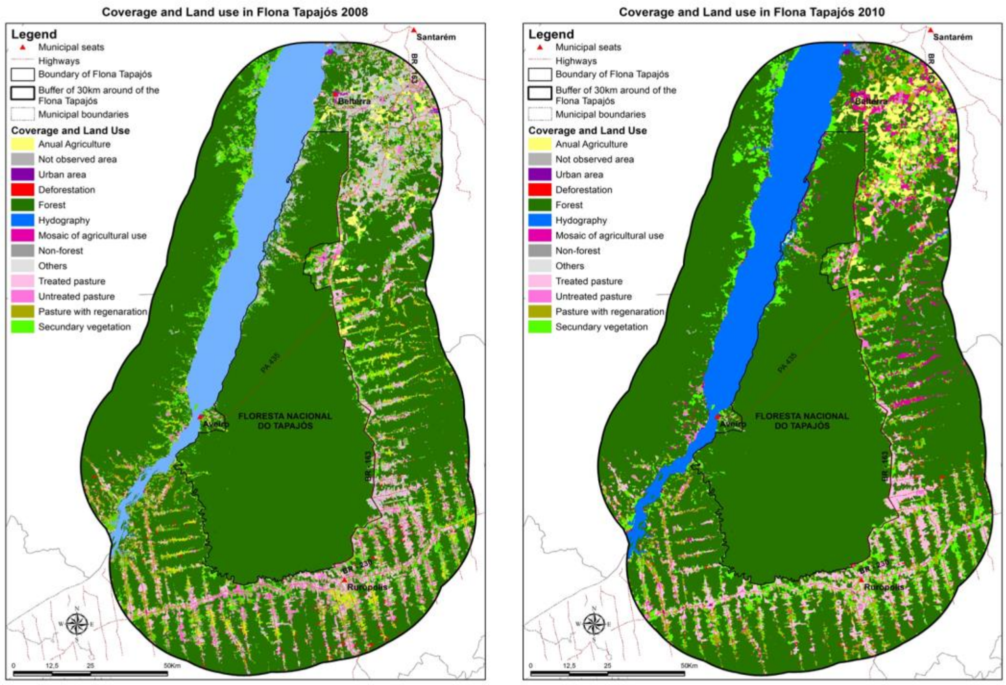


Figure 27. Land use and land cover in FLONA and surroundings for the years 2008 and 2010.

Table 4. Transition rates of land use change between 2008 and 2010.

From 2008	To 2010	Rate transition
Forest	Secondary vegetation	0.061961755593901
forest	Regeneration pastor	0.0184949631591879
forest	Agriculture annual	0.00302662309971166
forest	Agriculture	0.0835660889432377
forest	Desflorestation	0.00386727329038769
forest	Urban area	0.000541197978297481
Secondary vegetation	Regeneration pastor	0.0356298766931367
Secondary vegetation	Agriculture annual	0.00514844282102459
Secondary vegetation	Agriculture	0.110663576022181
Secondary vegetation	Desflorestation	0.00639032111695159
Secondary vegetation	Urban area	0.000364701101397326
Secondary vegetation	Secondary vegetation	0.0856104611524721
Secondary vegetation	Agriculture annual	0.00828356377321443
Secondary vegetation	Agriculture	0.122501295372113
Secondary vegetation	Desflorestation	0.00807903133436963
Secondary vegetation	Urban area	0.000177261446998827
Agriculture annual	Secondary vegetation	0.0788474702843985

Agriculture annual	Regeneration pastor	0.0201423029850437
Agriculture annual	Agriculture	0.132885265625324
agriculture	Secondary vegetation	0.10514611182469
agriculture	Regeneration pastor	0.0322118651874434
agriculture	Agriculture annual	0.00314940375112758
agriculture	Desflorestation	0.0067620062327604
agriculture	Urban area	0.000444079833561312
Desflorestation	Secondary vegetation	0.08279176201373
Desflorestation	Regeneration pastor	0.0473836765827612
Desflorestation	Agriculture	0.0984591914569031
Desflorestation	Urban area	0.000427154843630816

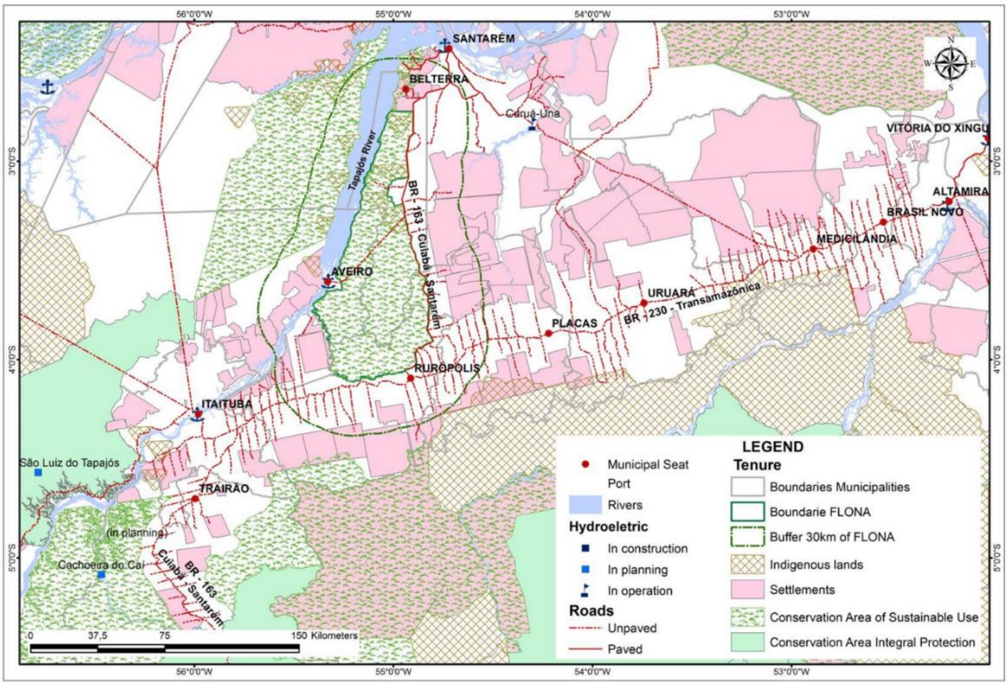


Figure 28. Context of infrastructure and tenure that show the pressure to deforestation on the FLONA surroundings.

Conclusions

We conclude that the emancipation of the São Jorge Community entails a further loss in the total area of FLONA for 18 years scenario, therefore leading to a threat for this Conservation Unit. In addition, it is recommended that it is recommended to the agency responsible for the management of conservation units that should have a more strict access control to the Tapajos River.

Acknowledgements

The authors would like to acknowledge their appreciation for EMBRAPA and thank the ROBIN Project for the new challenges.

3.2.5. Future scenarios for the north of Amapá State considering REDD+ as a conservation tool[8]

Introduction

Forests are vital to life on Earth at all scales, including for the development of economic activities. However, they have a limited capacity for the production of renewable resources (e.g. fibre and fruits) and ecosystem services (e.g. water and air purification), which have only recently begun to receive attention by governments and scientists. The ecosystem services provided by forests are important for ecosystem maintenance, and support, protect or affect the activities and human well-being. Much of the forests in the north region of Eastern Amazon, especially in the State of Amapá, are under some type of protection, being one of the most pristine areas of the Amazon.

These forests may be threatened by being in an area of the border with French Guiana, where the current political development of the State is being targeted, resulting in actions that modify the current scenario and pressure on natural resources in the region. The main threats are the paving of the highway BR-156, the implementation of the binational bridge over the river Oiapoque, and the expansion of agriculture, livestock and gold mining activities.

In this sense, this study assessed how the provision and maintenance of ecosystem services such as carbon stocks, provision of water and maintenance of biodiversity can contribute to local and regional sustainable development aimed at improving the quality of life in the northern area of Amapá State border with French Guiana. This study allowed creating development scenarios for the northern region of Amapá to 2030. These results contribute to the discussion of a policy to subsidize programs aiming at reduction of emissions from deforestation and degradation (REDD) and payment for ecosystem services (PES) implementation, by defining priority areas in the border region between Amapá and French Guiana.

Materials and methods

This study was conducted in the northern region of the State of Amapá (02°24'32 'and 04°01'12' North and 51°38'59 'and 52°00'04' 'W) across the municipalities of Calçoene and Oiapoque (Figure 29). This area lays within the Guyana Shield, which is characterized by a low population density, difficulty access to remote forest areas

[8] Sotta, E.D.; Guadalupe, V.; de Aguiar, L.J.G.; dos Santos, V.F.; Martorano, L.G. (2015)

and for being a geological and biological unit where high levels of endemism and biodiversity exists (Gond, et al., 2011; Hollowell & Reynolds, 2005).

Then, three future scenarios of deforestation were modelled considering different levels of forest governance (Table 5). Further was estimated the opportunity cost of avoiding forest conversion using information of the net present value (NPV) of four land use activities, namely, forest, cattle ranching, and gold mining, and the average carbon stock values of these land use categories. This latter data was associated with a land use transition matrix and further processed using the REDD Abacus SP software. The output is the graphical representation of the differences derived from the returns of the forest and those land uses that will replace it, with differences in carbon stocks of the emissions avoided by not converting the forest to other uses.

Additionally, three opportunity cost scenarios were modelled to which a sensitivity analysis was done and, based on these results, scenarios were simulated using the REDD Abacus SP software.

Table 5. Scenario's definition for modelling future deforestation

Scenario A: Historical facts endure in time (Historical projection)	**Scenario B:** Weak governance and quick expansion of socio-economic activities (Pessimistic)	**Scenario C:** Strong governance and implementation of PES-REDD+ program (Optimistic)
• Slash and burn activities persist. • Non sustainable productive systems. • Land speculation. • Cattle ranching concentration in the north zone and agriculture in the south zone. • No restoration of gold mining areas.	• Total paving of BR-156 and opening of the bi-national bridge. • Expansion and improvement of rural roads. • Higher agriculture production with no improvement of the production systems. • Low productivity cattle ranching persists. • No control and monitoring system.	• Consolidated Amapá State Forest (FLOTA) with limits recognized by producers. • Sustainable productive systems implemented in settlements and indigenous territories. • Production diversification. • Progressive reduction of deforestation by the implementation of REDD+PES that avoid deforestation.

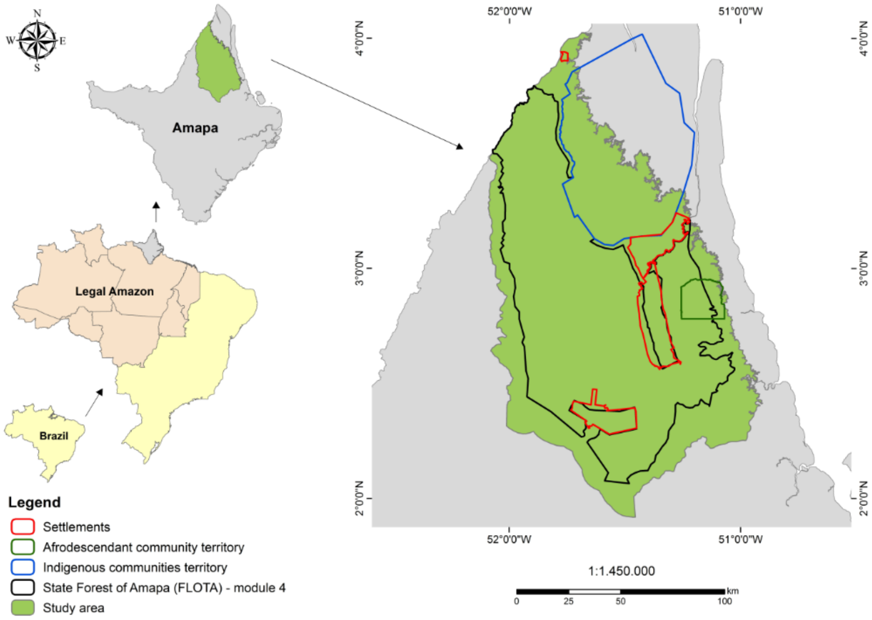


Figure 29. Study area (Data source: INCRA 2010).

Results and discussion

The cumulative reduction of forest cover in 2030 was higher in the pessimistic scenario compared to the other two simulated scenarios (Figure 30 and Figure 31). In the optimistic scenario, we observed a clear effect in reducing deforestation by implementing a program of PES-REDD+, which results in a level of deforestation close to the historical projection.

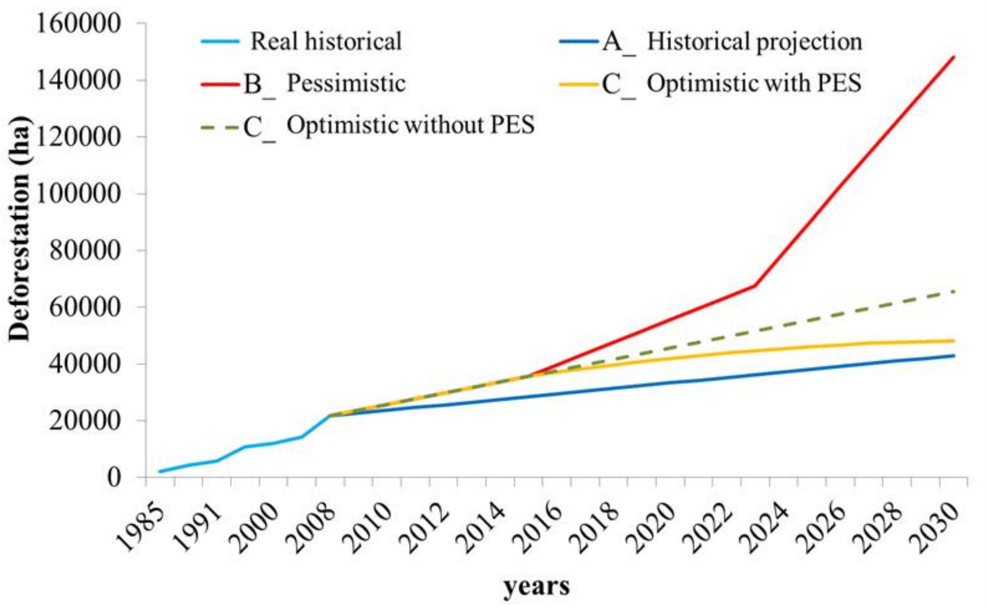


Figure 30. Real history of deforestation from 1985 to 2008 and projected deforestation for 22 simulated years (2008-2030) according to the assumptions of the three scenarios: baseline (A), pessimistic (B) and optimistic (C).

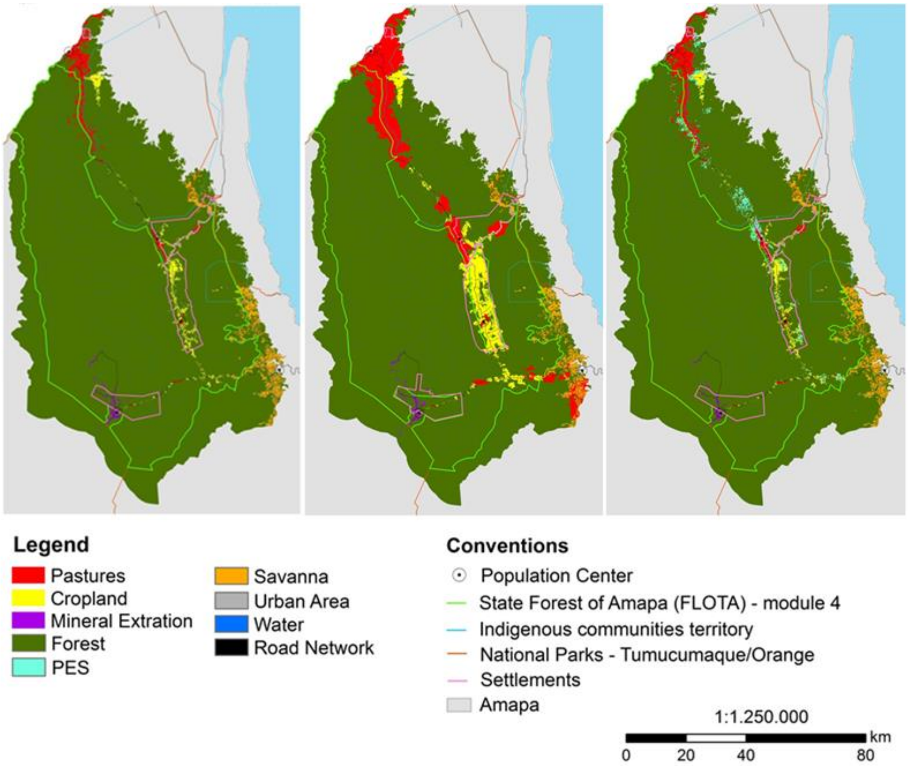


Figure 31. Spatial representation of future development scenarios: baseline (A), pessimistic (B) and optimistic (C).

The opportunity cost of avoiding the conversion of land use at the current per ton of carbon price (R$ 14.6/tCO2e = $ 7.5/tCO2e) varied between R$ 3.00/tCO2e and R$ 2410.00/tCO2e, corresponding to a potential annual reduction of emissions between 0.14 and 0.02 tCO2e per hectare (Figure 32).

Thus, the largest potential abatement of emissions derives from avoiding forest conversion to cattle ranching activities (0.14 tCO2e.ha-1.year-1) at a cost of R$ 3.00/tCO2e.

Included variations in profitability (NPV) of land uses associated with the three scenarios of deforestation, livestock continue to be the most attractive activity for the implementation of a REDD + project. In modelling the opportunity cost in terms of the three scenarios of deforestation, we found that the pastures activities remain as the most attractive activity for developing REDD+ projects, with an average cost of R$ 4.93 ± 2.73/tCO2e for the three scenarios, at the Acurrent average price per ton of carbon. This shows the potential of establishing a program of payment for environmental services with small cattle ranching producers who practice a low-productivity activity.

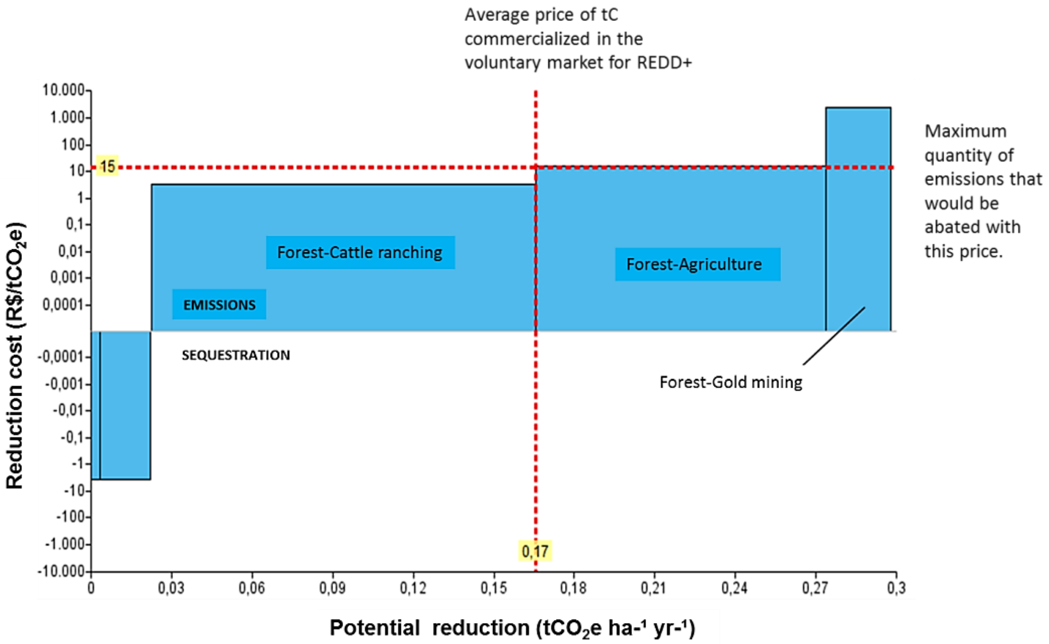


Figure 32. Curve of opportunity cost and emission reduction. The red dotted line parallel to the horizontal axis represents the average price per ton sold in the voluntary carbon market for REDD+ projects developed with VCS methodology, while the line parallel to the vertical axis represents the maximum amount of emissions that would be abated at that price.

Conclusions

The high interest of the state government for opening the binational bridge Brazil - French Guiana, as well as and the completion of the paving of the main highway that runs through the state from North to South (BR-156) that will connect the North with the most populated cities Santana and Macapá and with their port and airport infrastructure, respectively. These constitute real threats to the maintenance of forests, above all, for the implementation of REDD + and of its expected additional ecological benefits (i.e. biodiversity and ecosystem services conservation) in the northern region of the state, due to loss of competitiveness of forest land against an increased opportunity cost.

The balance between the implementation of conservation policies and economic development will give the state alternatives for successfully implement REDD + mechanism. However, this success will depend on strengthening of institutional capacities and land regularization measures, which will provide the necessary information to the construction of the policies and the REDD+ strategy of the state. Many steps have been taken in this direction and this study can contribute to the process, providing various elements to support the construction of such a policy, especially for the construction of its baseline.

Acknowledgements

The authors would like to thank all the collaborator of the REDD+FLOTA project, the financial support of CNPq (550467/2010-6) and EMBRAPA (SEG: 03.09.01.029.00) and also acknowledge ROBIN Project for the new challenges.

4. Continental analysis[9]

4.1. Introduction

As mentioned in the introduction, the aim of the WP 1.2.3 is to model the dose response relations between land-use change and climate change, and the biodiversity, ecosystem integrity and ecosystem services indicators. The change in land use will be considered as the dose having an effect on carbon emissions, biodiversity and ecosystem integrity and services (response). For this purpose, in a first step the extension of land that has changed its use has been determined. Then the effect of this land use change on the carbon emissions, the biodiversity and on the ecosystem services and integrity has been assessed.

4.2. Land use change

The FAO dataset is a dataset developed by the FAO for the Global Remote Sensing Survey. It covers the whole world with a grid with a latitude range between 75 degrees North/South. At every latitude and longitude degree intersection a 10x10 km area is sampled. The information contained in the original dataset for each tile is:

- Tile area
- Forest coverage in 1990, 2000 and 2005
- Water coverage in 1990, 2000 and 2005
- Other coverage in 1990, 2000 and 2005
- Forest gain, forest loss and net forest change between 1990 and 2000 and between 2000 and 2005. Absolute and percentage values.

In the original dataset, each tile was an individual shapefile divided in polygons, where each polygon shows where there has been a change in land use (Figure 33).

[9] This section summarises the research of Garcia Esteban, M. (2015)

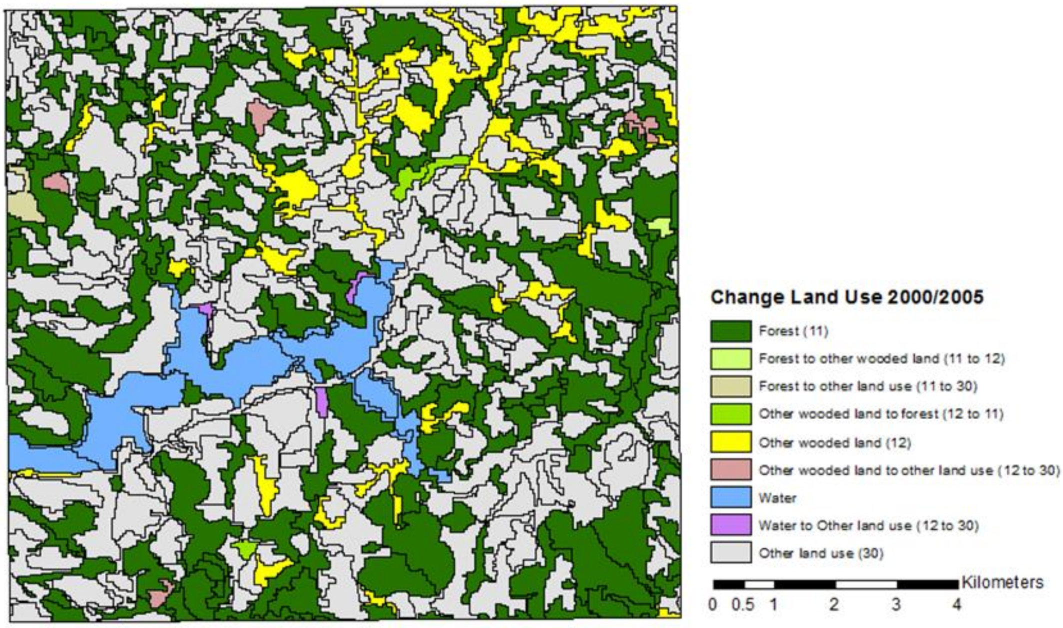


Figure 33. Change in land use from 2000 to 2005 for FAO tile located in the intersection of the parallel 25S and the meridian W050.

Using the FAO dataset, the land use area change was calculated by comparing the extensions of forest for 1990 and 2000.

Dataset production

The first step to produce a dataset showing the changes in forest cover in Latin America[10] is to merge all the 1617 files that cover it. Afterwards, the different polygons contained in each of the tiles are merged so as to get the area of forest gain, forest loss, forest no change and other change (Figure 34).

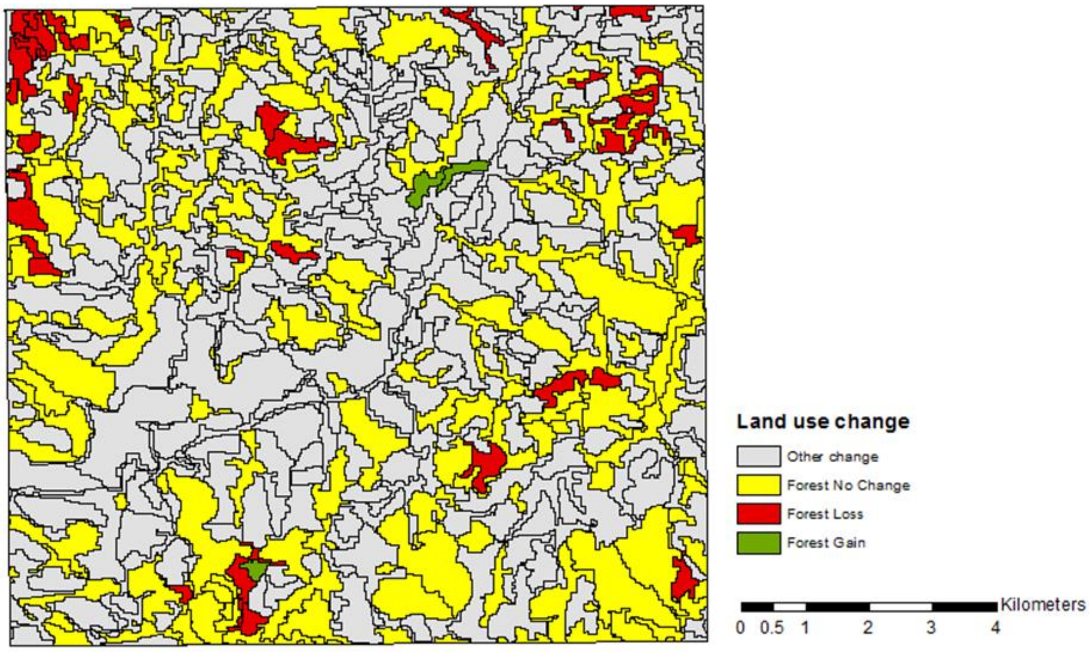


Figure 34. Land use change between 2000 and 2005 - Forest oriented.

The extension of the different land use changes is saved as an attribute. After this step, each tile contains information of the total area covered by the tile, the area of forest gained and lost between 1990 and 2000, the area of forest non-changed between 1990 and 2000 and the area with other land use class. The area gained and the area lost between 1990 and 2000 represent respectively, the gross forest area loss and gain (Figure 35).

[10] Latin America in this study consists of the countries: Argentina, Chile, Bolivia, Paraguay, Uruguay, Peru, Brazil, Ecuador, Colombia, Venezuela, Guyana, Surinam, French Guiana, Panama, Costa Rica, Nicaragua, El Salvador, Honduras, Mexico and Cuba.

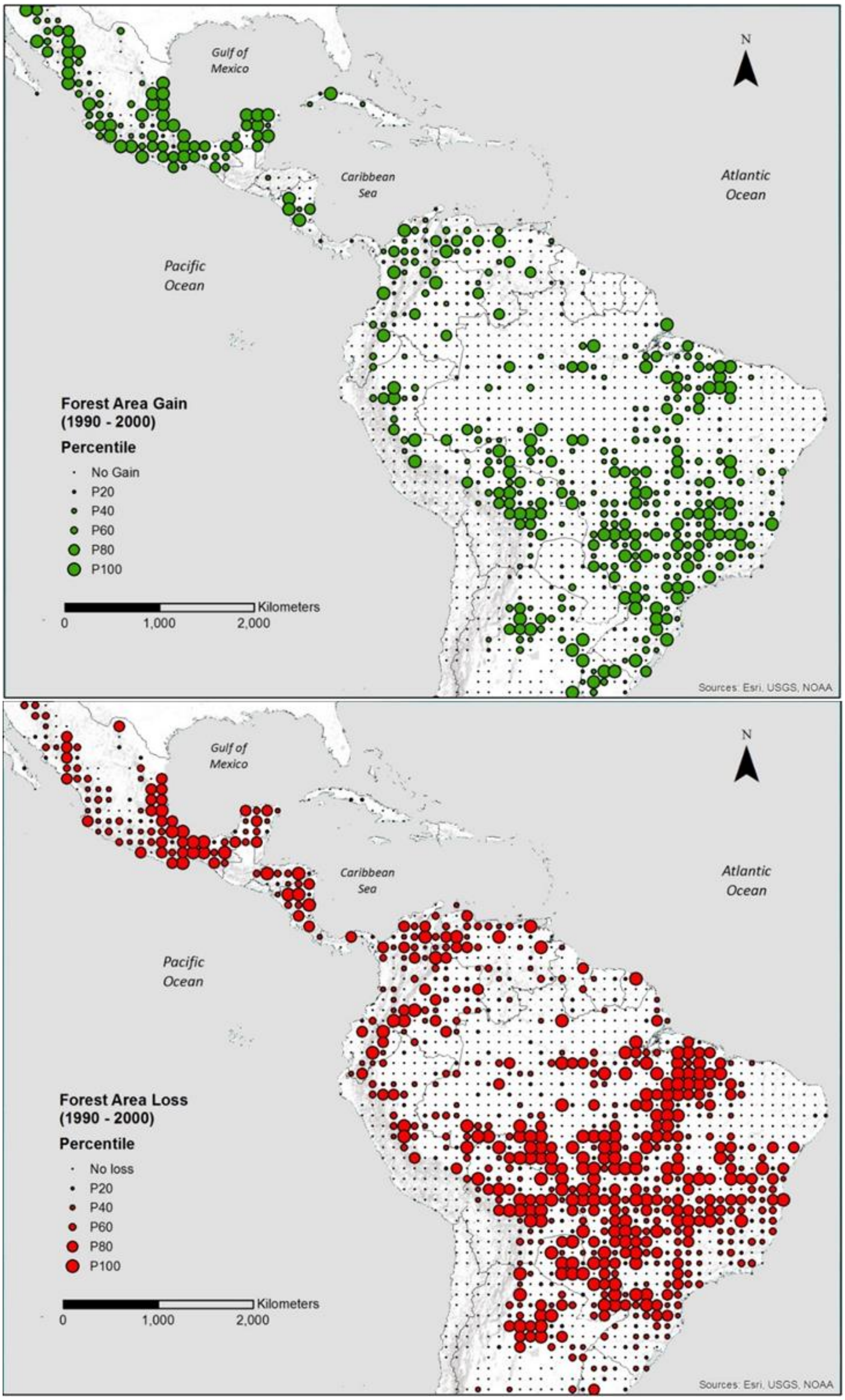


Figure 35. Above: Forest area gain 1990-2000. Below: Forest area loss 1990-2000. The values are expressed in 20% percentiles (20% of the total number of observations).

4.3. Land use change and carbon emission

The relation between land use change and carbon emissions was based on the combination of the forest area lost and the biomass accumulated in that area. Considering the carbon stocked in the biomass as the 50% of the total biomass (Saatchi, Harris et al. 2011, Timothy, Sandra et al. 2014), this total biomass was calculated by combining the above and below ground biomass (Saatchi, Harris et al. 2011):

$$C_{cont} = 0.5 * (Biomass + 0.489 * Biomass^{0.89})$$

where C_{cont} stands for carbon emissions and Biomass for the above ground biomass. Since the biomass distribution (tC/ha) can be spatially related to the forest coverage (ha), it is possible to calculate the carbon emitted from deforestation as:

$$C_{em} = C_{cont} * \Delta AF_{90-00}$$

where C_{em} stands for carbon emissions and ΔAF_{90-00} for the forest area variation between 1990 and 2000. The biomass values were extracted from a previously produced biomass dataset (Ge, Avitabile et al. 2014). The results would be the net emissions for the considered area (Figure 36).

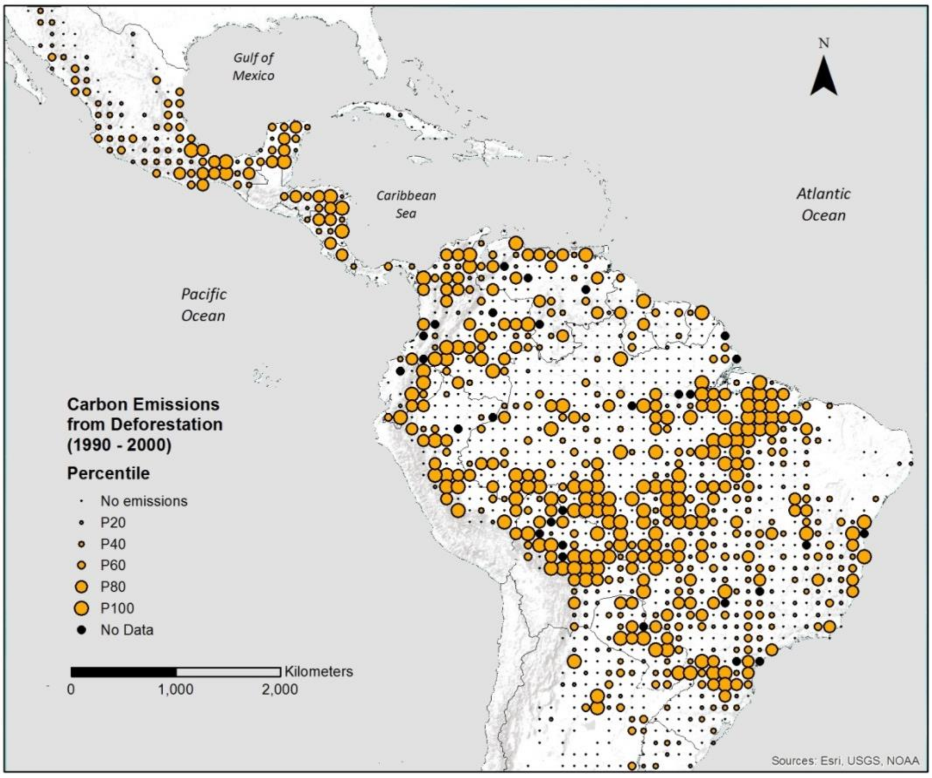


Figure 36. Carbon emissions due to deforestation between 1990 and 2000 for the 10 km FAO tiles. The values of emissions are expressed in 20% percentiles (20% of the total number of observations).

4.4. Land use change and impacts on biodiversity

The analysis of the impacts of land use change on biodiversity was assessed separately for tree species and animal species.

4.4.1. Effect of land use change on Tree Biodiversity

The analysis of the effects of deforestation on tree biodiversity is based on a dataset of 58 forest sites throughout Latin America where tree species were recorded between 2000 and 2010 (Figure 37). The dataset comes from Poorter et al (2015) and contains information about the site name, country, number of 1 ha plots, number of 0.1 ha plots, minimum stem diameter considered, plot size, length and width of the plots, plot size (ha), annual rainfall, cation exchange capacity and site average for aboveground biomass, rarefied species richness and average tree diameter. The rarefied tree species range for these points go from 0 to 42 species per 50 tree stems.

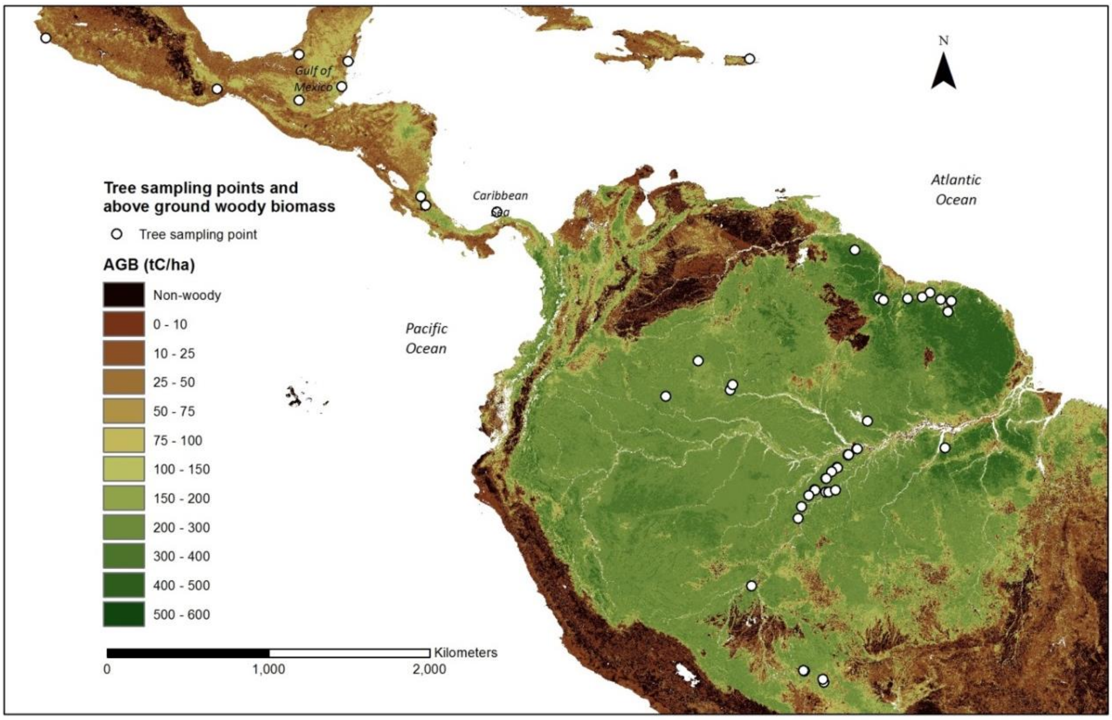


Figure 37. Sampling points for tree biodiversity (white points). Background: biomass map[11].

[11] From: New pan-tropical forest biomass map at 1 km res. (Avitabile et al., in prep.; Ge et al., 2014)

These biodiversity points were used as the response factor in a regression model, where the biodiversity value for that point was related to several explanatory factors, expected to have influence on the biodiversity value. Up to 31 factors related to the climate, productivity, biodiversity and ecosystem dynamics. From these factors, some were significant for explaining the biodiversity distribution. The selection of factors was based on minimising the unexplained variability by removing the factors that were not independently or globally significant. The final model was used for calculating the biodiversity value for the different locations of the FAO tiles.

In order to be able to compare and/or combine the datasets, these were reprojected to WGS84 and cropped to the extension of the smaller dataset (phenology) and resampled to 0.05º. Next to that the temperature data was grouped in minimum, maximum and average temperatures.

Tree biodiversity distribution modelling

Since the aim was to study the effect of land use change on biodiversity for the FAO tiles with forest presence, the point information was used to model tree biodiversity distribution for the whole of Latin America. However, this modelling was carried out for areas within similar ecozones to increase data accuracy. The tree biodiversity distribution was modelled using all the available explanatory factors (31 factors). Using these factors as inputs, the biodiversity values of the tree dataset were modelled for the location of the 58 points. These values were extracted for each point by using the tool Raster to Point in ArcGIS. These points were analysed in R and used to fit a linear regression model where the tree biodiversity distribution was the result of summing up the factors (xi) times their respective coefficients (βk).

$$TreeBD = \beta_0 + \beta_1 * x_{i1} + \beta_2 * x_{i2} + \beta_3 * x_{i3} + \cdots + \beta_K * x_{iK} + U_i$$

By analysing the different input factors and discarding those that were not independently or globally significant, 6 factors were identified as statistically significant, explaining 56.81% (Adjusted R2) of the tree biodiversity distribution with a RMSE of 3.91(Figure 38). The relevant parameters were: amphibians, plant biodiversity, Hants NDVI dynamics, minimum precipitation for 2008 and the absolute average and maximum temperatures for the year 2005, 2006 and 2007 (

Table 6).

Table 6. Significant factors for the linear model.

Amphibians	Plants Biodiversity	Hants NDVI dynamics
Rain maximum 2008	Temp avg (05, 06, 07)	Temp max (05, 06, 07)

All of these factors are independently significant (t-test) at a level α<0.01. As part of the model (F-test), all the factors except "temperature average" are significant at a level α<0.01. The reason for the low value for "temperature average" could be its correlation with "temperature maximum" (-0.87). When removed from the model, the adjusted R2 goes down to 45.05% and only "plant biodiversity", "Hants NDVI dynamics" and "temperature minimum" remain individually significant (α<0.05). The resulting values and their differences with the original values can be seen in Figure 38.

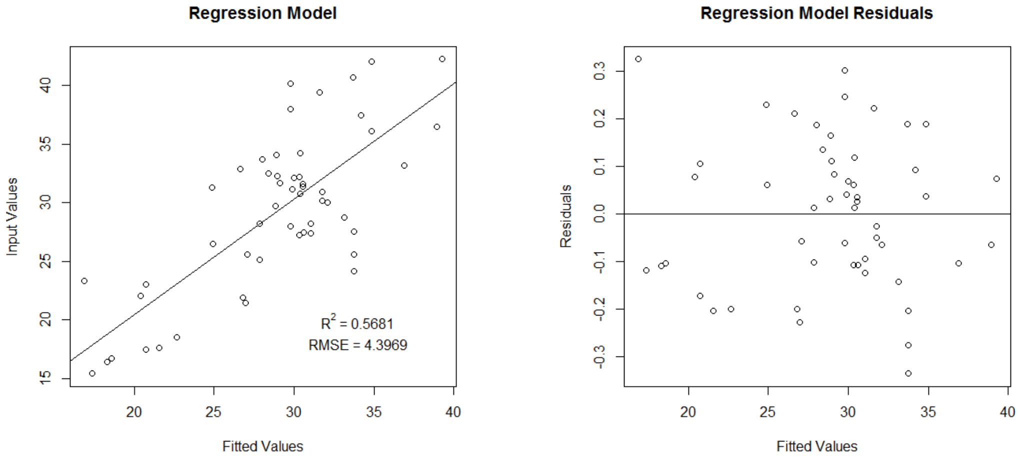


Figure 38. Left - Modelled values for tree biodiversity vs. original values. Right - Differences between modelled values for tree biodiversity and original values. The horizontal line shows the mean of the residuals.

Mapping model results

Using the regression model, tree biodiversity was calculated for the area of Latin America covered by the input datasets. The extension for which the biodiversity could be calculated was restricted by the smallest explanatory input raster (Hants NDVI dynamics). The results can be seen in Figure 39 and Figure 40.

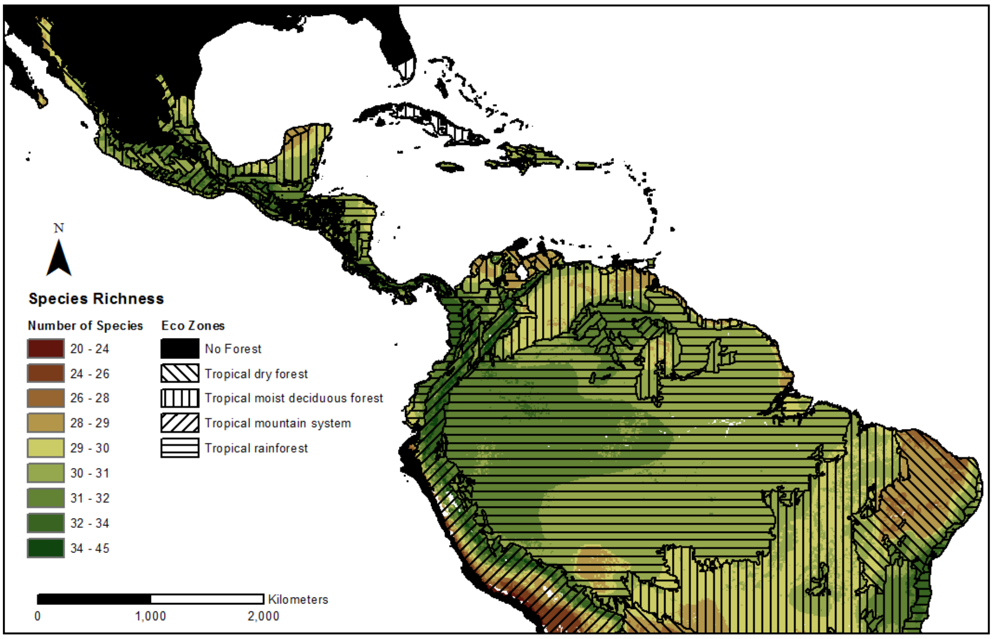


Figure 39. Result of modelling the rarefied tree species richness (number of species per 50 stems) based on the tree sampling points. Only for forest eco-zones (tropical rain forest, tropical moist deciduous forest and tropical dry forest).

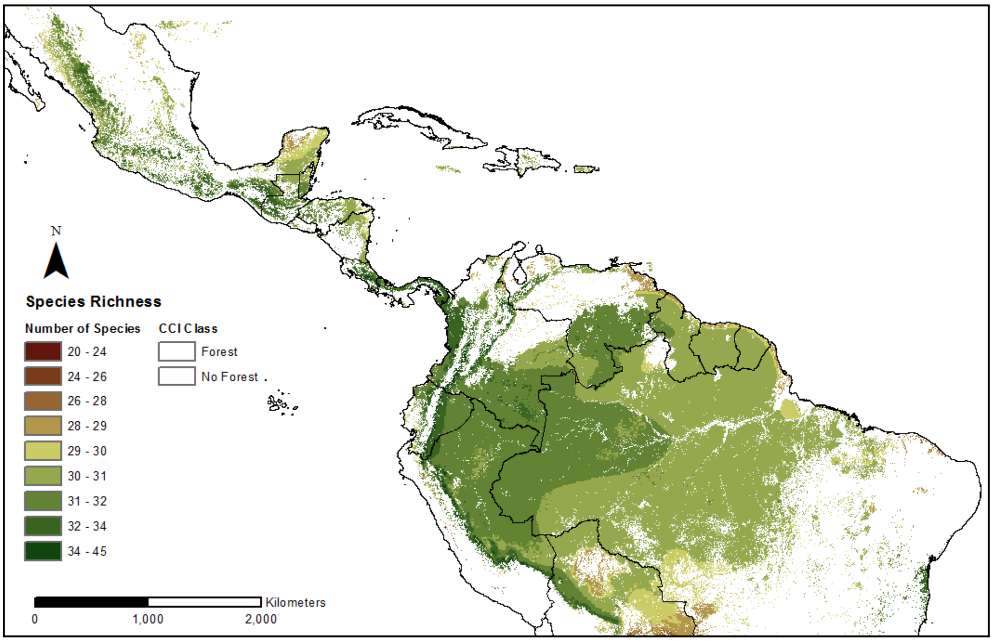


Figure 40. Result of modelling the rarefied tree species richness (number of species per 50 stems) based on the tree sampling points. Only for CCI classes forest (evergreen and deciduous forest).

Tree biodiversity in FAO Tiles

By linking the biodiversity information to the FAO tiles, it become possible to compare biodiversity value versus land use for a specific place. Therefore, the FAO tiles were updated with the modelled biodiversity values assuming that, even though the model uses datasets from 2000-2010, the variables would be similar for 2000. First, the raster for the modelled tree biodiversity was aggregated for the coverage of the tiles by means of zonal statistics. Afterwards, the FAO tiles were converted to points and the points updated with the aggregated raster value. Finally, the attribute table for the points was merged to the attribute table for the FAO tiles, using the tile ID as matching criteria. The calculated value for the tree biodiversity was related to the forest coverage, obtaining then a Species Richness Index:

$$SRI = \widehat{SR}_{00} * forest_{00}$$

where SRI stands for species richness index [No. Spp], SR_{00} for the modelled tree biodiversity for 2000 (No. Spp/ha) and $forestloss_{00}$ for the forest area lost between 1990 and 2000 (ha). The resulting values can be seen in Figure 41, where the values have been grouped in 20% percentiles. Each percentile represents 20% of the observations. These percentiles show where the impact of the deforestation on the tree biodiversity is expected to be bigger due to either a high deforested area or to a high tree biodiversity.

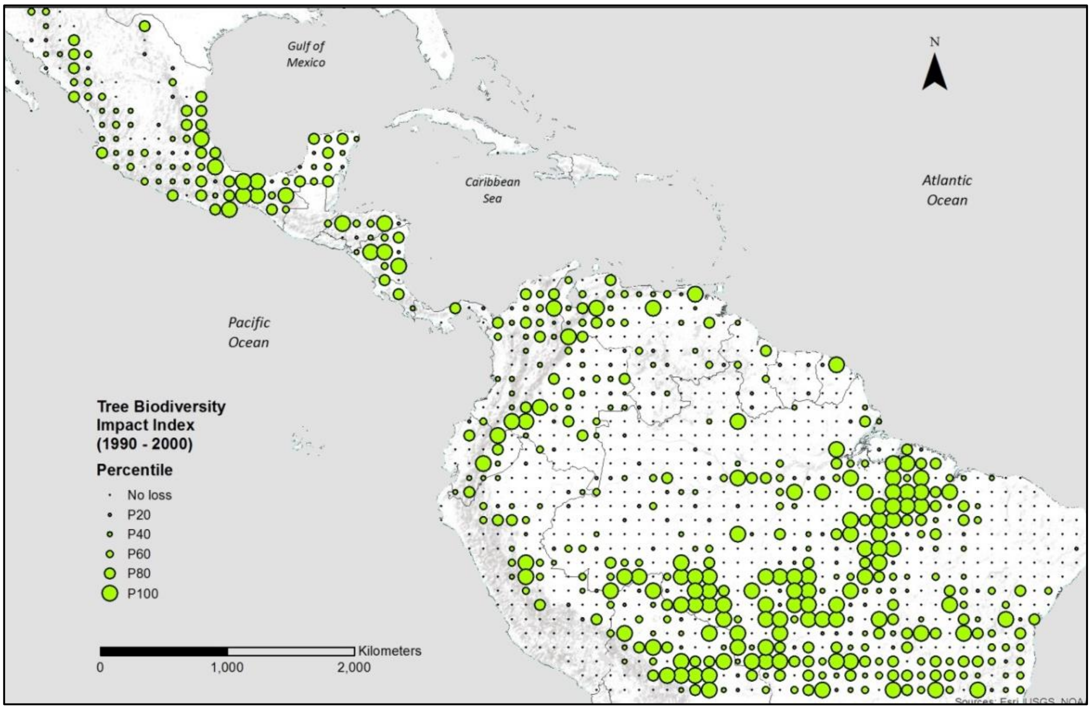


Figure 41. Circles showing the impact of forest loss on tree biodiversity. The values are expressed in 20% percentiles (20% of the total number of observations).

Biodiversity vs. carbon stock

When comparing per tile the number of species versus the carbon stock, it can be seen in Figure 42-left that there is no strong relation between these two variables (R2adj=0.10). However, when the comparison is between the species richness and the carbon stock, it can be seen in Figure 42-right that the higher values for species richness are related to higher values of carbon stock (R2adj=0.52).

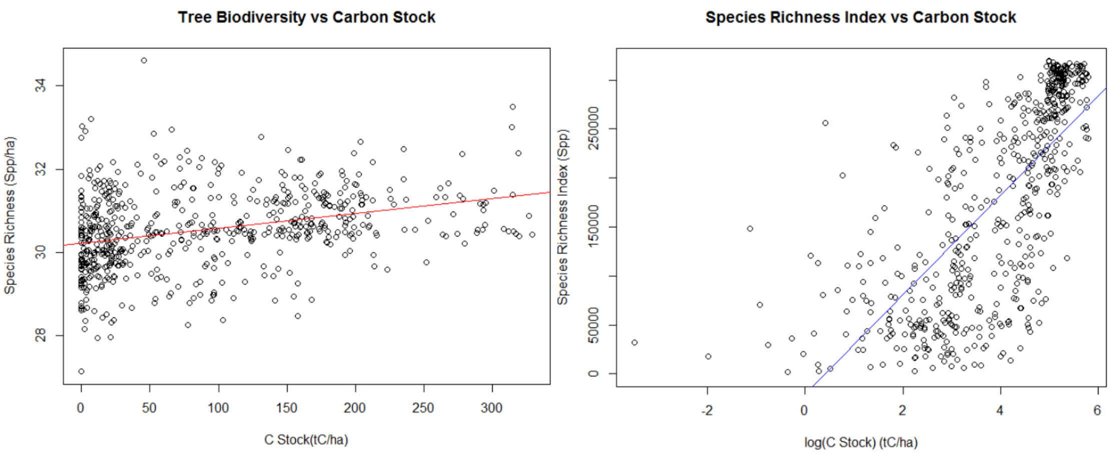


Figure 42. Left: Number of tree species vs. carbon stock (R2adj=0.10). Right: Species richness index vs. log(carbon stock) (R2adj=0.52).

Effects of deforestation on the animal biodiversity

The analysis of the effects of deforestation on the animal biodiversity followed similar steps as the ones used in the calculation of the effects of deforestation on the tree biodiversity. One of the differences was the inclusion of the perimeters of the different land use class. This was done to take into account the forest fragmentation, aware of its effect on some species.

4.4.2. Effect of land use change on Animal Biodiversity

In the case of animal biodiversity, the starting point is the calculation of the total animal biodiversity for the area of interest. The input datasets were biodiversity maps available online[12] and based on scientific publications (Jenkins, Pimm et al. 2013, Pimm, Jenkins et al. 2014). The complete shapefile datasets are available at the IUCN Red List of Threatened Species[13]. The datasets describe the global biodiversity distribution of the classes: birds, mammals and amphibians (Figure 43).

[12] http://www.biodiversitymapping.org/
[13] http://www.iucnredlist.org/technical-documents/spatial-data

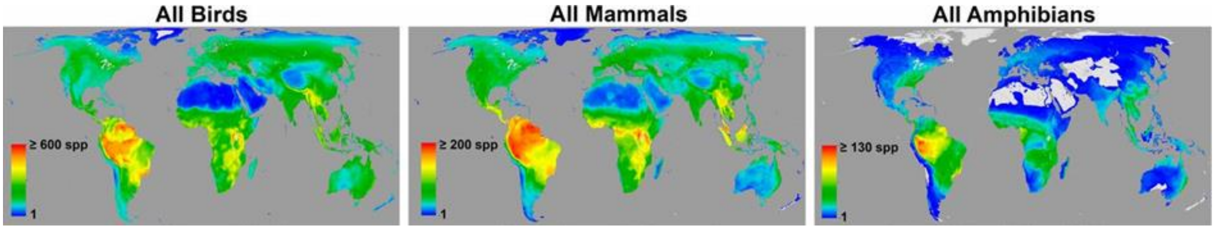


Figure 43. Birds, mammals and amphibians biodiversity values.

The animal biodiversity values for the FAO tiles were calculated based on the combination of the three input datasets, assuming that they would represent the biodiversity value for the year 2000 (values in the datasets are from different years). Afterwards, the animal biodiversity for 2000 for the FAO tiles was modelled based on the eco-zone, the forest area and the forest perimeter:

$$AnimalBD00_i = \beta_0 + \beta_1 \cdot EZ_i + \beta_2 \cdot Area_{00,i} + \beta_3 \cdot Perim_{00,i}$$

where $AnimalBD00_i$ stands for the number of animal species for the FAO tile i for the year 2000, EZ_i stands for the eco-zone value for the FAO tile i, $Area_{00,i}$ stands for the forest coverage in 2000 for the FAO tile i and $Perim_{00,i}$ stands for the forest perimeter in 2000 for the FAO tile i. The βj are the coefficients associated to the different model variables. The different eco-zones were given numbers based on the AGB values given in Saatchi et al., (2011) for that eco-zone. The highest eco-zone value stands for the eco-zone class with the highest AGB value.

Direct analysis of the data returns an adjusted-R2 of 0.5598, explaining 55.98% of the animal biodiversity distribution for 2000 (Figure 44). The regressor explaining the highest variability is the ecozone, being responsible for 53.24% of the variability. The area explains 0.98% of the variability and the perimeter the 1.87%.

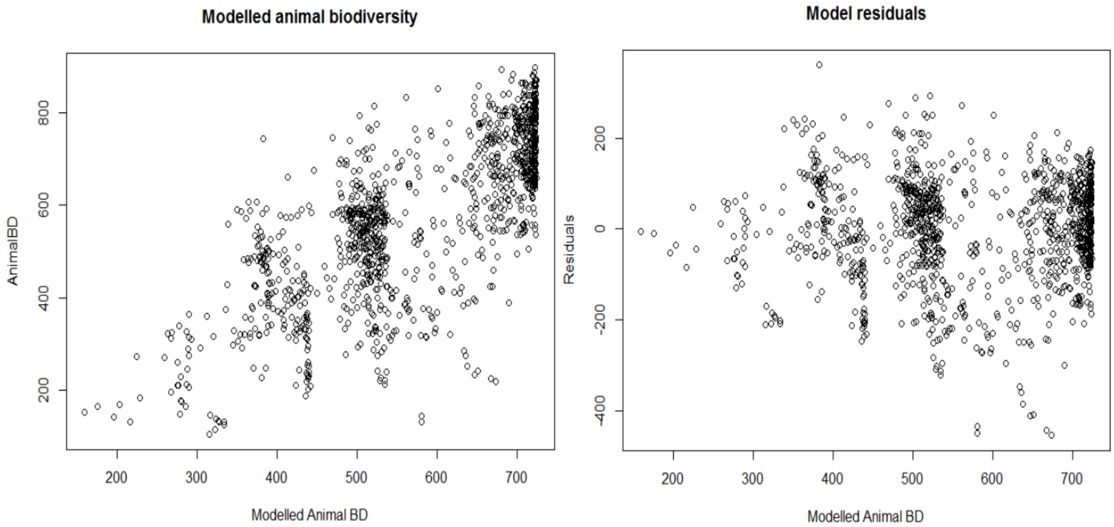


Figure 44. Left: plot of input values vs. modelled values. Right: plot of residuals distribution.

The animal biodiversity values for 1990 were calculated using the regression equation and replacing there the original values for the forest values 1990 for area, perimeter and perimeter. The difference between the calculated biodiversity values for 1990 and 2000 represent the variation in biodiversity for that period:

$$\Delta AnimalBD_{9000} = AnimalBD_{00} - AnimalBD_{90}$$

where $\Delta AnimalBD_{9000}$ stands for the difference in animal biodiversity between 1990 and 2000, $AnimalBD_{00}$ for the animal biodiversity for 2000 and $AnimalBD_{90}$ for the animal biodiversity for 1990.

This calculation assumed that the ecozone did not change for the considered period, relating the change in biodiversity, exclusively to the forest coverage and the fragmentation degree. For some areas where the forest area increased, the model predicts an increase in biodiversity. Since which might not sound logical and were therefore neglected. In Figure 45 the areas where the model shows a loss in animal biodiversity between 1990 and 2000 are presented.

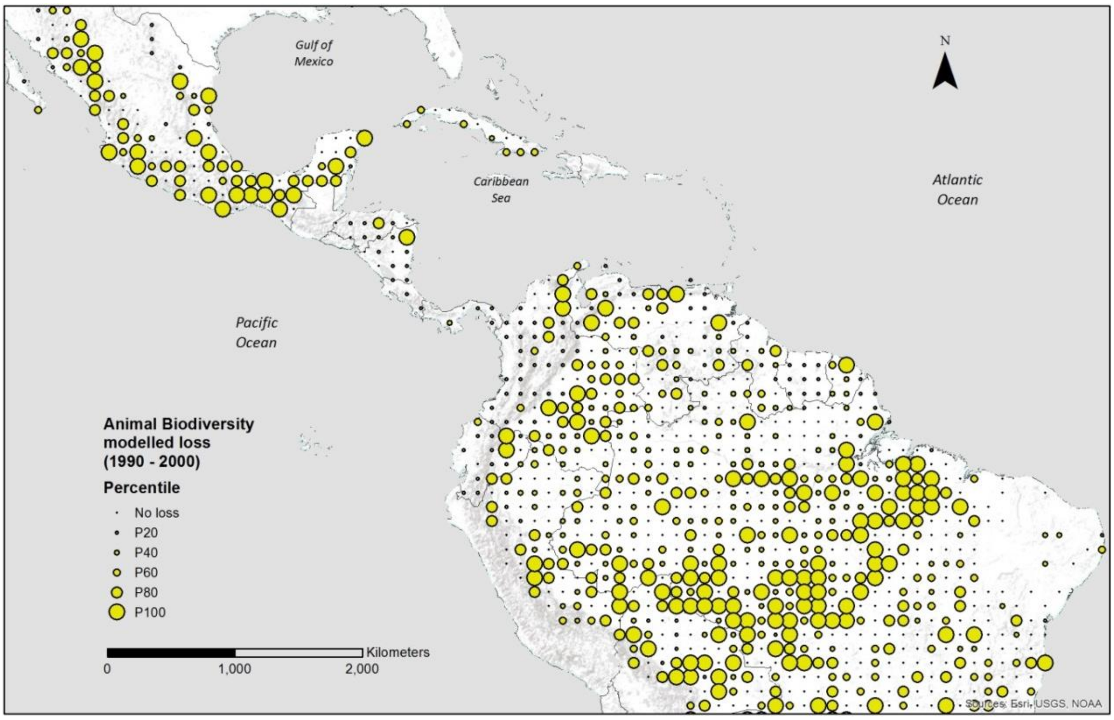


Figure 45. Animal biodiversity loss in number of species between 1990 and 2000. The values are expressed in 20% percentiles (20% of the total number of observations).

4.5. Land use change and ecosystem services

Introduction

Carbon sequestration takes place when vegetation grows, locking atmospheric carbon as part of its structure. Great part of this carbon sequestration takes part in secondary forest. The distribution of this carbon sequestration capacity has been modelled for a time lapse of 20 years[14] and can be seen in Figure 46.

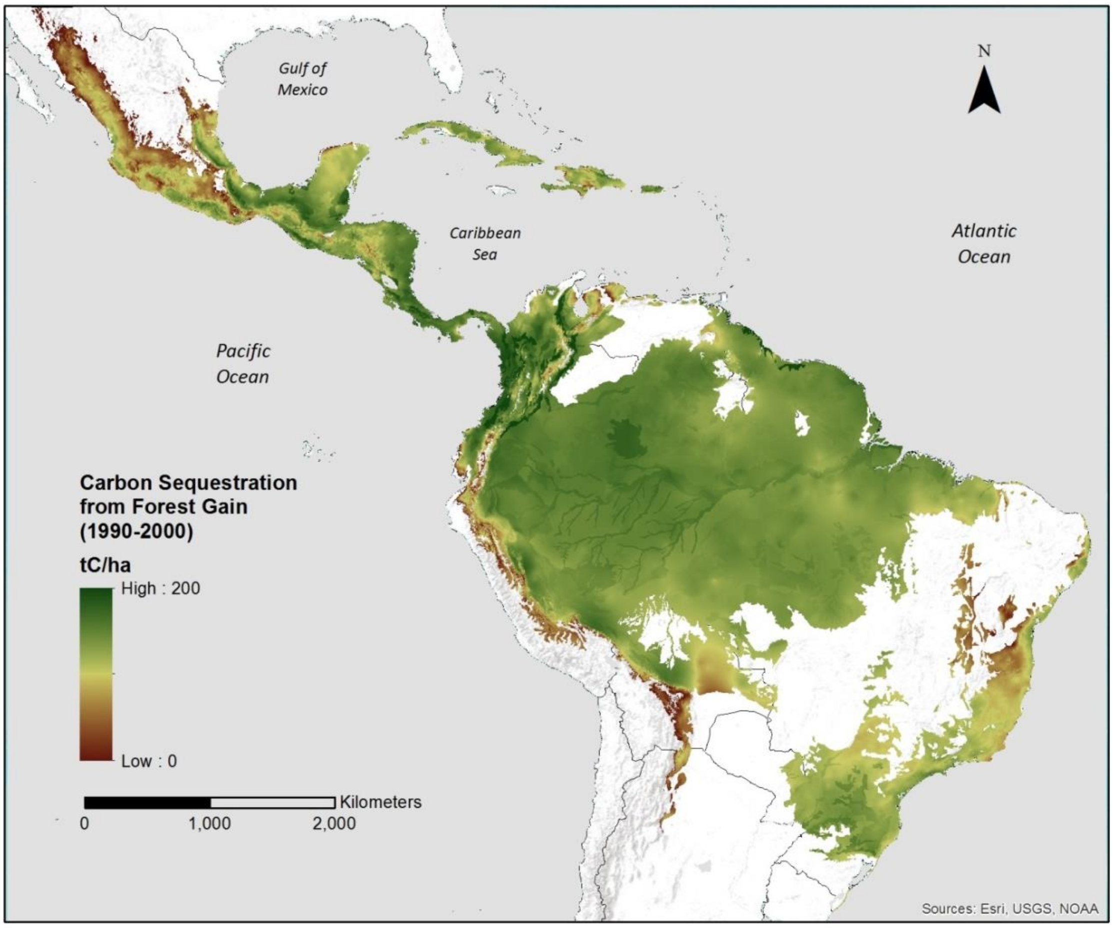


Figure 46. Carbon sequestration capacity in secondary forests in 20 years.

A high value for carbon sequestration in one area indicates a high capacity of the forest for recovering its initial biomass. It also indicates that the impact of deforestation in that area is lower than in others with lower carbon sequestration values.

[14] In preparation to be published as Poorter, L., Bongers, F, et al. (2015). Biomass resilience of Neotropical secondary forests

Carbon sequestered between 1990 and 2000

The value of the carbon sequestration (tC/ha) can be linked to the forest area (ha) in order to derive the amount of carbon sequestered (tC) for the considered period (1990-2000). The amount of carbon sequestered would be:

$$Csequestered = ForestGain_{9000} * Cseq_{20yr}$$

where Def_{Seq} stands for deforestation versus carbon sequestration, $ForestGain_{9000}$ for the forest loss between 1990 and 2000, and $Cseq_{20yr}$ for the carbon sequestration in 20 years (Figure 47).

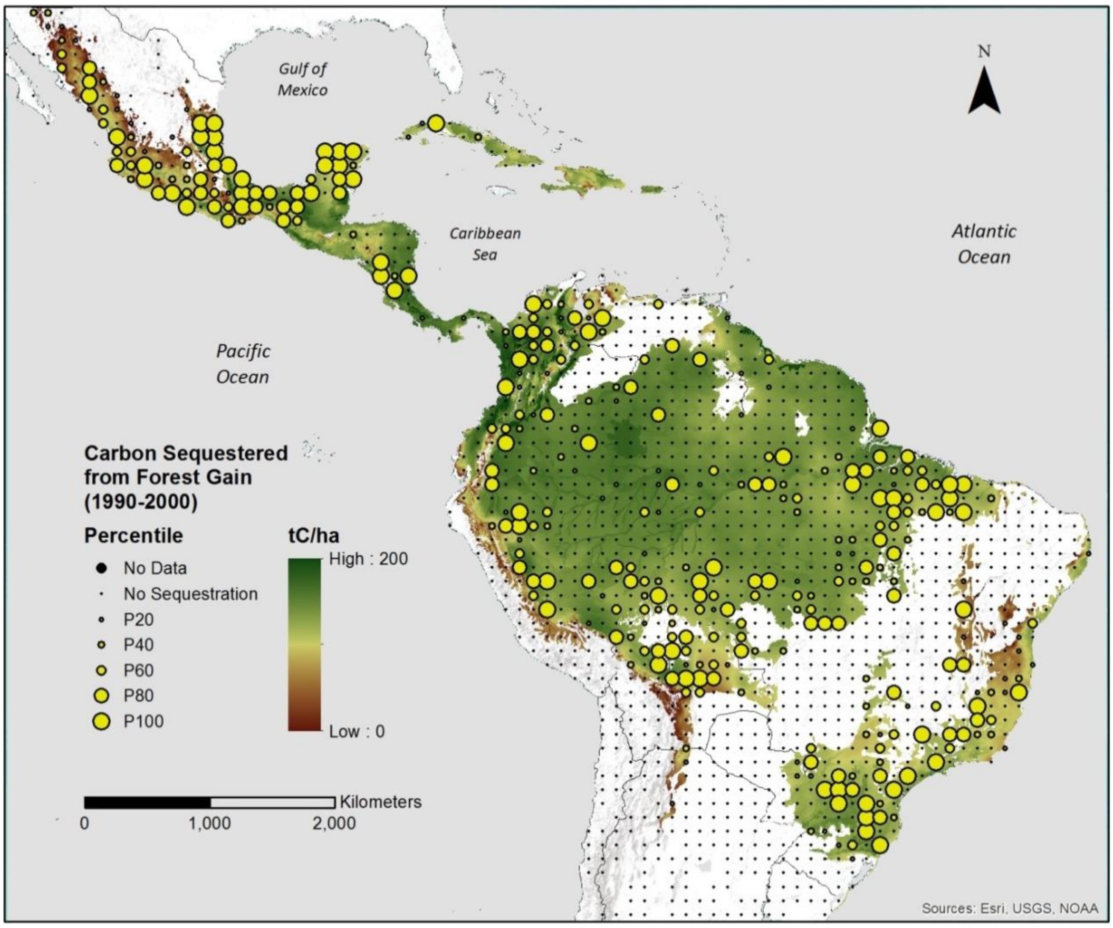


Figure 47. Carbon sequestered from 1990 to 2000 due to forest gain for the considered 10x10 km FAO tile. The values are expressed in 20% percentiles (20% of the total number of observations).

5. Implications for mitigation activities and REDD+[15]

Introduction

Forests can both emit and capture greenhouse gasses depending on whether deforestation or regrowth is taking place. Aware of this role of forests in terms of greenhouse gases and their link to climate change, the UN joint efforts in 2005 in a project to reduce emissions from deforestation (RED). Two years later, in 2007, the project broadened its aim of Reducing Emissions from Deforestation by including reduction of emissions from forest Degradation (REDD) and accounting for additional climate mitigation activities in the forest sector in developing countries (REDD+). This mitigation activities relate to the role of conservation, sustainable management of forests and enhancement of forest carbon stocks. In 2013 the Warsaw Framework for REDD+ was adopted even though it was not completely clear regarding the definitions of forests, deforestation, drivers or activities. (Hargita, Günter et al., Weatherley-Singh and Gupta 2015) The lack of clarity was due to a lack of agreement in terms of the national priorities and capacities and it was left to the different countries to determine the Intended Nationally Determined Contributions (INDCs) to the project (Swick 2014).

Strong political momentum from REDD+ (COP 21) and SDGs

Currently, tropical countries are getting involved and engage in upcoming climate agreement, resulting in 39 countries having included REDD+ in their INDCs (Figure 48). In addition the Sustainable Development Goal 15.2 for 2020 are becoming prominent: promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally. So there is strong momentum for tropical country engagement in upcoming climate agreement (REDD+ and SDGs).

While the focus remains on carbon and GHG for REDD+, the sustainable development goals and the findings of ROBIN once again highlight that REDD+ implementation has to consider biodiversity beyond being just a safeguard and co-benefit.

[15] Section prepared by Martin Herold. (WU)

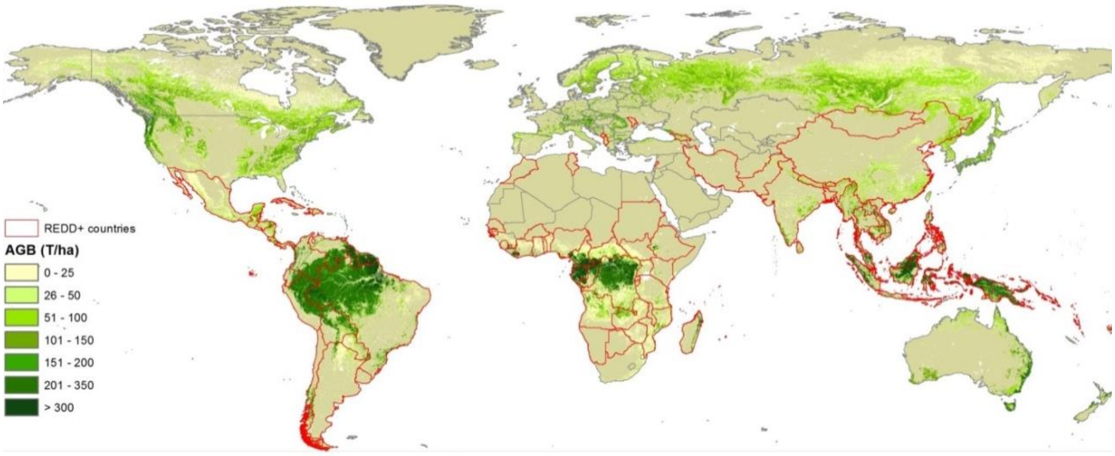


Figure 48. Distribution of aboveground forest biomass and countries (red boundaries) actively involved in REDD+.

Tropical forests offer up to 25% of mitigation potential

The net emissions due to forest loss represent 8% of the global greenhouse gas emissions, where the gross emissions make up for 16-19% of the global emissions. On the other hand, growing forest can remove 8-11% of global emissions. For mitigation purposes it is important to consider the forest as sink and source and so its potential would be around 25% of total greenhouse gas emissions (Figure 49, Goodman and Herold, 2014 and related blog).

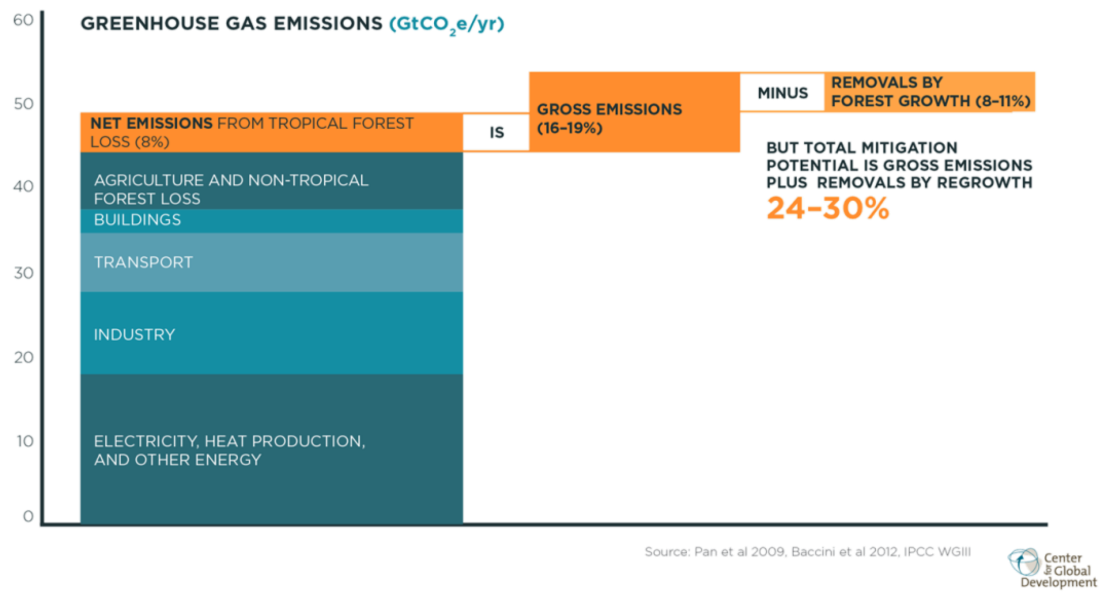
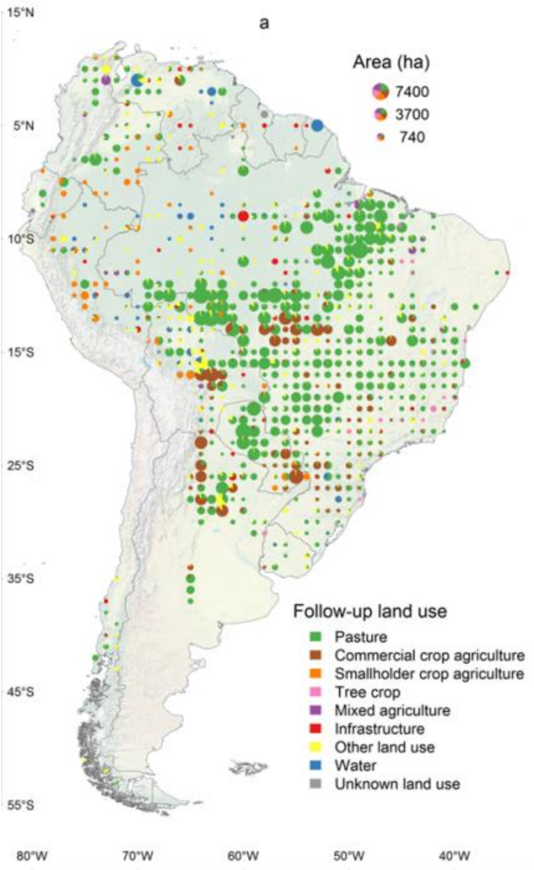


Figure 49. Forest mitigation potential (See also: Goodman and Herold, 2014 and related blog).

Forests as a key part of climate-smart development in the tropics

The drivers for deforestation may vary among different regions. In order to find out the drivers leading to deforestation in South America, a global forest remote sensing survey (FAO) was analysed (Figure 50 left). From this analysis it was concluded that agriculture is responsible of almost 90% of the total deforestation (Figure 50 right). It is because of this that for reducing emissions from deforestation and forest degradation, forests have to be taken into account in the development of smart agriculture and development strategies. This includes efforts to foster sustainable supply chains, coherent multi-sector policies on the national (i.e. between forest and agriculture sector), and the development and implementation of landscape-scale solutions to land use that consider multiple objectives related to climate change mitigation, adaptation and food security.



Follow-up land use	Area (10^3 ha)	%
Mixed agriculture	505	0.8
Smallholder crop agriculture	1557	2.4
Commercial crop agriculture	8448	13.2
Tree crops	263	0.4
Pasture	46347	72.1
Agriculture	**57121**	**88.9**
Infrastructure	1029	1.6
Other land use	4168	6.5
Water	1802	2.8
Unknown	124	0.2
Other	**7123**	**11.1**
Total	64243	100

Figure 50. Result of assessing land use following deforestation as part of the global forest remote sensing survey (1990-2005). Left: map with spatial distribution of changes and drivers. Right: Area change vs. drivers. Niki de Sy, WU.

Reducing carbon emissions also preserves biodiversity but magnitude varies regionally

When reducing emissions from deforestation, forest-related biodiversity is preserved (Figure 51). The figure emphasizes a series of important comparisons:

- The deforestation patterns (1990-2000) highlight the arc of deforestation in South America.
- This pattern is somewhat correlated with those carbon emissions with Amazon forests having higher emission factors due to higher carbon stocks.
- Deforestation area, carbon emissions and impacts on forest species diversity are correlated (especially carbon density and rarefied species richness) but there are regional differences.
- The impacts on animal diversity seem to have a somewhat different pattern (i.e. higher impact in Meso-America and in Western part of the Amazon).

These results show that REDD+ could provide biodiversity as co-benefits but that regional pattern should be taken into account.

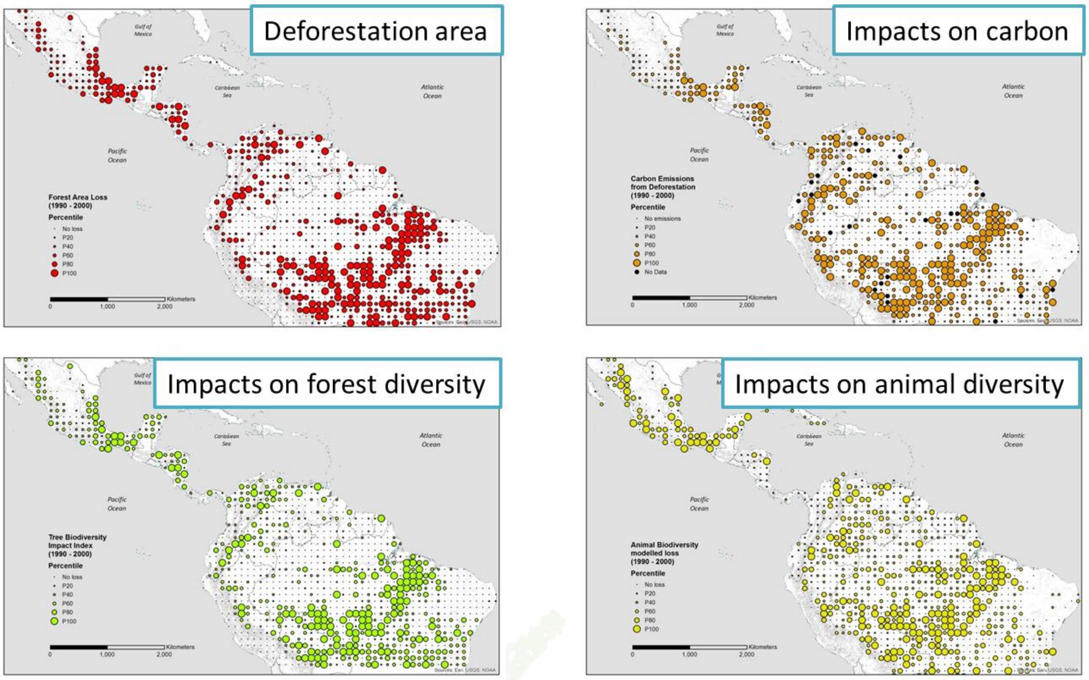


Figure 51. Comparing spatial patterns of deforestation (1990-2000 using FAO FRA RSS data), carbon emission from deforestation (impacts on carbon stocks), with those to deforestation-related changes in tree diversity (rarefied species richness)

and on animal diversity. The values are expressed in 20% percentiles (20% of the total number of observations).

Biodiversity as key for forest resilience to climate change and reducing risk of reversals

Next to that, biodiversity fosters forest resilience to climate change by giving functionality to the forest. As a result, the risk of reversals or "failure" or REDD+ activities are reduced. So even if REDD+ activities are successful the need to have resilient forests is important to preserve them in the long-term under changing climate conditions. In this sense biodiversity is a safeguard for REDD+.

Enhancing forest (carbon stocks) requires functioning forest ecosystems (requirement)

When considering the mitigation potential of the forest sink in the tropics, it is important to realize that this is a term that has not been researched enough in terms of quality and quantity. The ROBIN project has made important contributions in better clarifying:

- The importance of various forest types (i.e. managed/degraded forests, secondary forests, and new forests/reforestation) to be able to provide a large and so far unquantified sink.
- The effective sequestration of carbon in re-growing forests is very much related to biodiversity and the functioning of the forest ecosystem.

New data and impact for national and sub-national strategies and implementation

REDD+ as discussed under the UNFCCC will always have limitations in terms of how to consider biodiversity in implementation, since international fail to be completely sufficient, clear and specific to regional situations. Thus, the key for integration between climate change objectives and those related to other conventions (i.e. UNCBD) will have to happen on the national and sub-national level. The ROBIN project has provided important new data and concepts to better include biodiversity concerns in the climate change mitigation activities and it is important that these findings have an impact on country specific strategies and how and where REDD+ activities can include issues on carbon, biodiversity, resilience and functioning of forest ecosystems in an integrated way. Figure 52 shows conceptually and how this could be done.

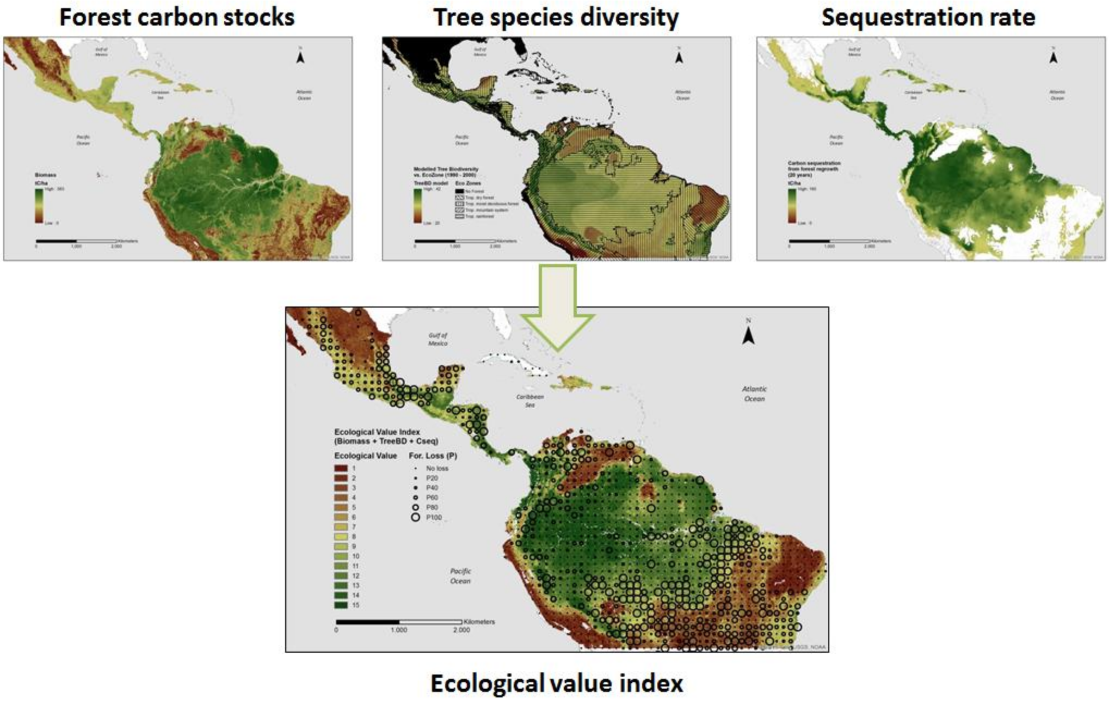


Figure 52. Ecological value as a function of the forest carbon stocks (biomass), the tree species diversity (forest biodiversity) and the sequestration rate (forest resilience).

REDD+ in terms of carbon performance may target areas with high carbon stocks in order to reduce emissions and preserve forests. It may further consider the distribution of tree diversity to look at areas of both high-carbon and high-biodiversity value or the other way around. Particularly when considering the forest carbon sink, the aspects of carbon sequestration potential and the ability of forests to recover after disturbances become of high-relevance. With a smart integration of ground-observations and remote sensing data, these maps can now be created with higher confidence and can provide a basis for targeting implementation. The presented results clearly highlight that there is a strong gradient between the Eastern Amazon and the Arc of deforestation, and the western and north-western Amazon. This gradient does not show in the carbon stock data alone and emphasizes the importance of such data and analysis to be taken into account for the planning and implementation of REDD+ mitigation options.

6. References

ASTER GDEM, 2009. Global digital elevation model ASTER. These data are distributed by the Land Processes Distributed Active Archive Center (LP DAAC), located at the U.S. Geological Survey (USGS) Center for Earth Resources Observation and Science (EROS) http://LPDAAC.usgs.gov.

Baccini, A., Friedl, M., Woodcock, C. & Warbington, R. Forest biomass estimation over regional scales using multisource data. Geophysical Research Letters 31, L10501 (2004).

Batista, V.H.S.; Martorano, L.G.; Silva, G.M.da; Moraes, J.R.C. Dinâmica de ações antrópicas para apontar evidências da contribuição socioeconômica e ambiental da flona tapajós aos municípios em seu entorno. In: CONGRESSO BRASILEIRO DE AGROMETEOROLOGIA, 09, 2013, Belém. Anais...Belém, 2013. 5p.

Bienert, A., S. Scheller, E. Keane, F. Mohan, and C. Nugent. 2007. “Tree Detection and Diameter Estimations by Analysis of Forest Terrestrial Laserscanner Point Clouds.” In ISPRS Commission III Workshop, 50–55. Espoo, Finland. http://www.dresden-uni.com/die_tu_dresden/fakultaeten/fakultaet_forst_geo_und_hydrowissenschaften/fachrichtung_geowissenschaften/ipf/photogrammetrie/publikationen/pubdocs/2007/2007_Bienert_Helsinki2007.pdf.

Brasil. Presidência da República. Plano Amazônia Sustentável: diretrizes para o desenvolvimento sustentável da Amazônia Brasileira / Presidência da República. – Brasília: MMA, 2008. 112 p

Buntime W. Operations for learning with graphical models. Journal of Artificial Intelligence Research, 2:159–225, 1994.

Calders, K., G. Newnham, A. Burt, S. Murphy, P. Raumonen, M. Herold, D. Culvenor, et al. 2015. “Nondestructive Estimates of above-Ground Biomass Using Terrestrial Laser Scanning.” Edited by Sean McMahon. Methods in Ecology and Evolution 6 (November): 198–208. doi:10.1111/2041-210X.12301.

Castro, E., Monteiro, R., Castro, C. P.. Dinâmica de atores, uso da terra e desmatamento na Rodovia Cuiabá- Santarém. Belém: NAEA, 2004.

CGEE. (2011). REDD in Brazil: A focus on the Amazon. Principles, criteria, and institutional structures for a national program for Reducing Emissions from Deforestation and Forest Degradation – REDD. Brasilia, DF. Brazil.

Christophe, E., Inglada, J. & Giros, A. (2008) Orfeo Toolbox : A Complete Solution for Mapping From High Resolution Satellite Images. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences., 37, 1263–1268.

Díaz-Maeda, P., 2015. Zonas de vida de Holdridge de Mexico. CONABIO, Mexico City, Mexico.

Equihua Zamora, M., García Alaniz, N., Pérez-Maqueo, O., Badillo Benítez, G., Kolb, M., Schmidt, M., Equihua Benítez, J., Maeda, P., 2014. Integridad ecológica como indicador de la calidad ambiental, in: Gonzalez-Zuarth, C., Vallarino, A., Low-Pfeng, A., J. C. Pérez (Eds.), Bioindicadores: Guardianes de Nuestro Futuro Ecológico. Ecosur, INECC, Mexico.

Ge, Y., V. Avitabile, G. B. Heuvelink, J. Wang and M. Herold (2014). "Fusion of pan-tropical biomass maps using weighted averaging andregional calibration data." International Journal of Applied Earth Observation and Geoinformation 31(1): 13-24.

Gebhardt, S., Wehrmann, T., Muñoz Ruiz, M.A., Maeda, P., Bishop, J., Schramm, M., Kopeinig, R., Cartus O., Kellndorfer, J., Ressl, R., Santos, L.A. y Schmidt, M. 2014. MAD-MEX: Automatic Wall-to-Wall Land Cover Monitoring for the Mexican REDD-MRV Program Using All Landsat Data. Remote Sensing, 6(5):3923–3943. doi:10.3390/rs6053923

González-Abraham, C.E., Escurra, E., Garcillán, P.P., Ortega-Rubio, A., Kolb, M., Bezaury-Creel, J.E., 2015. The Human Footprint in Mexico: Physical Geography and Historical Legacies. PLOS ONE 10 (3): 1-17.

Hargita, Y., S. Günter and M. Köthke "Brazil submitted the first REDD+ reference level to the UNFCCC—Implications regarding climate effectiveness and cost-efficiency." Land Use Policy.

Harja, D., Dewi, S., van Noordwijk, M., Ekadinata, A., & Rahmanulloh, A. (2011). REDD Abacus SP. User Manual and Software. World Agroforestry Centre (ICRAF), Bogor, Indonesia.

Holling, C. S. 1973. Resilience and stability of ecological systems. Annual Review of Ecological Systems 4:1–23.

Holling, C. S. 1996. Engineering resilience versus ecological resilience. In P. C. Schulze, editor. Engineering within ecological constraints. National Academy Press, Washington, D.C., USA.

Holopainen, M., M. Vastaranta, and V. Kankare. 2011. “Biomass Estimation of Individual Trees Using Stem and Crown Diameter TLS Measurements.” International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVIII (August): 29–31.

Hosoi, F., Y. Nakai, and K. Omasa. 2013. “3-D Voxel-Based Solid Modeling of a Broad-Leaved Tree for Accurate Volume Estimation Using Portable Scanning Lidar.” ISPRS Journal of Photogrammetry and Remote Sensing 82 (August). International Society for Photogrammetry and Remote Sensing, Inc. (ISPRS): 41–48. doi:10.1016/j.isprsjprs.2013.04.011.

Holling, C. S. 2001. Understanding the Complexity of Economic, Ecological, and Social Systems. Ecosystems 4:390–405.

IBGE. Rio de Janeiro, 2012. Disponível em: <http:www.sidra.ibge.gov.br>.

Ives, A. R, Carpenter S. R 2007. Stability and diversity of ecosystems. Science 317: 58–62.

Jenkins, C. N., S. L. Pimm and L. N. Joppa (2013). "Global patterns of terrestrial vertebrate diversity and conservation." Proceedings of the National Academy of Sciences 110(28): E2602-E2610.

Kankare, V., M. Holopainen, M. Vastaranta, E. Puttonen, X. Yu, J. Hyyppä, M. Vaaja, and P. Alho. 2013. “Individual Tree Biomass Estimation Using Terrestrial Laser

Scanning." ISPRS Journal of Photogrammetry and Remote Sensing 75 (January). International Society for Photogrammetry and Remote Sensing, Inc. (ISPRS): 64–75. doi:10.1016/j.isprsjprs.2012.10.003.

Kay, J. J. 1991. A nonequilibrium thermodynamic framework for discussing ecosystem integrity. Environmental Management 15: 483–495.

Kolb, M. 2009. Reporte técnico de los modelos prototipo de impactos a la biodiversidad mexicana, mexbio. CONABIO, México.

Kolb, M., Equihua,M., Schmidt, M,. García, N., Verboom,, J. Diaz Maeda, P., Equihua, J., Maqueo, O., Peña Claros, M., Dutrieux, L. Arets, E. (2013). Dose-response relationships. Public report D1.2.1 from the EC ROBIN project.

Kolb, M. Parr, T., Equihua, J., Equihua, M., Pérez-Maqueo, O., Díaz, P., Schmidt, M., García Alaníz, N., Simões, N., Ferraz, R., Peña Claros, M., Verweij, P. (2014). Changes in indicators of biodiversity associated with land use change and degradation. Public report D1.2.2 from the EC ROBIN project.

Lindley, D. V. (1972). Bayesian Statistics, a Review. Philadelphia, PA: SIAM. [A sharp comprehensive review of the whole subject up to the 1970's, emphasizing its internal consistency].

Martorano, L. G., Nechet, D., Pereira, L. C. 1993. Tipologia climática do Estado do Pará: adaptação do método de Köppen. Boletim de Geografia Teorética, v. 23, p. 45-46.

MacArthur, R.H. & MacArthur, J. (1961) On bird species diversity. Ecology, 42, 594–598.

Manuel-Navarrete, D. and Kay, J. J. 2004. Ecological integrity discourses: linking ecology with cultural transformation. Human Ecology Review 11:215–229.

Matsushita, B., Yang, W., Chen, J., Onda, Y. & Qiu, G. (2007) Sensitivity of the Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) to Topographic Effects: A Case Study in High-density Cypress Forest. Sensors, 7, 2636–2651.

Mu, Q., F. A. Heinsch, M. Zhao, and S. W. Running (2007b), Development of a global evapotranspiration algorithm based on MODIS and global meteorology data, Remote Sens. Environ., 111, 519–536, doi:10.1016/j.rse.2007.04.015.

Nascimento NCC. Cenários de uso da terra nas mesobacias hidrográficas dos Igarapés Timboteua e Buiuna, Pará. Brasil. Thesis (Msc). Mestrado em Gestão de Recursos Naturais e Desenvolvimento Local na Amazônia. Núcleo de Meio Ambiente. Universidade Federal do Pará. 2011.

Nepstad, D., Stickler, C. M., Filho, B. S., & Merry, F. (2008). Interactions among Amazon land use, forests and climate: prospects for a near-term forest tipping point. Philos Trans R Soc Lond B Biol Sci, 363 (1498), 1737-1746.

Ogaya, R., Barbeta, A., Başnou, C. & Peñuelas, J. (2014) Satellite data as indicators of tree biomass growth and forest dieback in a Mediterranean holm oak forest. Annals of Forest Science, 72, 1–10.

Pagiola, S., & Bosquet, B. (2009). Estimating the costs of REDD at the country level. Munich Personal RePEc Archive (MPRA Paper No. 18062, posted 26), 23.

Pfeifer, N., B.H. Gorte, and D. Winterhalder. 2004. “Automatic Reconstruction of Single Trees from Terrestrial Laser Scanner Data.” International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences 35. Istambul, Turkey. http://218.196.194.5/portal/wenxian/gis article/533.pdf.

Pimm, S. L., C. N. Jenkins, R. Abell, T. M. Brooks, J. L. Gittleman, L. N. Joppa, P. H. Raven, C. M. Roberts and J. O. Sexton (2014). "The biodiversity of species and their rates of extinction, distribution, and protection." Science 344(6187): 1246752.

Raumonen, P., M. Kaasalainen, M. Åkerblom, S. Kaasalainen, H. Kaartinen, M. Vastaranta, M.Holopainen, M. Disney, and P. Lewis. 2013. “Fast Automatic Precision Tree Models from Terrestrial Laser Scanner Data.” Remote Sensing 5 (2): 491–520. doi:10.3390/rs5020491.

Raumonen, P., S. Kaasalainen, M. Kaasalainen, and H. Kaartinen. 2011. “Approximation of Volume and Branch Size Distribution of Trees from Laser Scanner Data.” International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences XXXVIII (1): 1–6.

Regier, H. 1995. Ecosystem Integrity in a Context of Ecostudies as Related to the Great Lakes Region. P. 88–101 In: Westra, L. and Lemons, J. (eds). Perspectives on Ecological Integrity SE - 7. Springer Netherlands.

Saatchi, S. S., N. L. Harris, S. Brown, M. Lefsky, E. T. Mitchard, W. Salas, B. R. Zutta, W. Buermann, S. L. Lewis and S. Hagen (2011). "Benchmark map of forest carbon stocks in tropical regions across three continents." Proceedings of the National Academy of Sciences 108(24): 9899-9904.

Saleska, S.R., Didan, K., Huete, A.R. & Rocha, H.R. (2007) BREVIA Amazon Forests Green-Up During 2005 Drought. Science, 318, 2007–2007.

Sims, D. a., Rahman, A.F., Cordova, V.D., El-Masri, B.Z., Baldocchi, D.D., Flanagan, L.B., Goldstein, A.H., Hollinger, D.Y., Misson, L., Monson, R.K., Oechel, W.C., Schmid, H.P., Wofsy, S.C. & Xu, L. (2006) On the use of MODIS EVI to assess gross primary productivity of North American ecosystems. Journal of Geophysical Research: Biogeosciences, 111, 1–16.

Soares-Filho, B., Nepstad, D. C., Curran, L. M., Cerqueira, G. C., Garcia, R. A., Ramos, C. A., Voll, E., McDonald, A., Lefebvre, P., & Schlesinger, P. (2006). Modelling conservation in the Amazon basin. Nature, 440 (7083), 520-523.

Stickler, C. M., Nepstad, D. C., Coe, M. T., McGrath, D. G., Rodrigues, H. O., Walker, W. S., Soares, B. S., & Davidson, E. A. (2009). The potential ecological costs and cobenefits of REDD: a critical review and case study from the Amazon region. Global Change Biology, 15 (12), 2803-2824.

Suomalainen, J., N. Anders, S. Iqbal, G. Roerink, J. Franke, P. Wenting, D. Hünniger, H. Bartholomeus, R. Becker, and L. Kooistra. 2014. “A Lightweight Hyperspectral Mapping System and Photogrammetric Processing Chain for Unmanned Aerial Vehicles.” Remote Sensing 6: 1–26. doi:10.3390/rs60x000x.

Swick, S. (2014). "INDCs, REDD+, And The Alphabet Soup Of COP 20." Retrieved 27/10/2015, 2015, from http://www.ecosystemmarketplace.com/articles/indcs-redd-alphabet-soup-cop-20/.

The Orfeo Toolbox Cookbok (2015) https://www.orfeotoolbox.org/packages/OTBCookBook.pdf

Timothy, R. H. P., B. Sandra and M. C. Felipe (2014). "Carbon emissions from tropical forest degradation caused by logging." Environmental Research Letters 9(3): 034017.

TOPODATA. 2014. Banco de Dados Geomorfométricos do Brasil, In: http://www.dsr.inpe.br/topodata/ Taxas de desmatamento da Amazônia Legal. Monitoramento da Floresta Amazônica Brasileira por Satélite. INPE. 2014. Disponível em: http://www.obt.inpe.br/prodes/index.php.

Weatherley-Singh, J. and A. Gupta (2015). "Drivers of deforestation and REDD+ benefit-sharing: A meta-analysis of the (missing) link." Environmental Science & Policy 54: 97-105.

White, D., & Minang, P. (2011). Estimating the Opportunity Costs of REDD+: A training manual. (Version 1.3 ed.). Forest Carbon Partnership Facility (FCPF)/World Bank Institute (WBI)/Consultative Group on International Agricultural Research (CGIAR). , Washington, DC. USA.

Wood, E.M., Pidgeon, A.M., Radeloff, V.C. & Keuler, N.S. (2012) Image texture as a remotely sensed measure of vegetation structure. Remote Sensing of Environment, 121, 516–526.

Yanai, A. M., Fearnside, P. M., GRAÇA, P. M. L. d. A., & NOGUEIRA, E. M. (2012). Avoided deforestation in Brazilian Amazonia: Simulating the effect of the Juma Sustainable Development Reserve. Forest Ecology and Management, 282 (0), 78-91.

Zuur, A.F., Ieno, E.N. & Elphick, C.S. (2010) A protocol for data exploration to avoid common statistical problems. Methods in Ecology and Evolution, 1, 3–14.