Final Consultancy Report, by Ophélie Ratel – December 2020

Implementation of a method and calculation of ecological indicators to assess the potential for natural regeneration in La Selva, Costa Rica.

Introduction

General context

In a global context where forest landscapes are increasingly degraded, natural regeneration has established itself as one of the relevant approaches to restore and reforest these degraded landscapes (Chazdon & Guariguata, 2016). Natural regeneration (or secondary succession) of tropical forests occurs naturally on degraded or deforested lands after abandonment of land uses such as agriculture or pasture for cattle production. Natural regeneration allows the recovery of many ecosystem services (pollination, seed dispersal, carbon storage, etc.) to gradually reach pre-disturbance level (or close-by) in terms of composition, structure and function (Guariguata & Ostertag, 2001). However the recovery of ecosystem services depends of many factors acting at two different scales. At a local scale, i.e. within forest site, natural regeneration success is strongly influenced by many factors such as climate, soils characteristics, repeated stand-level disturbances, prior land use, surrounding vegetation, and the regional species pool (Chazdon, 2014). At the landscape-level, i.e. within landscape surrounding forest site, natural regeneration success is influenced by close proximity to large forests patches, soil quality and seed dispersing fauna have a high importance (Pereira *et al.*, 2013 ; de Rezende *et al.*, 2015 ; Sloan & Sayer, 2015 ; Martínez-Ramos *et al.*, 2016). Chazdon & Guariguata presented a methodological approach for large-scale natural regeneration restoration and suggested indicators that can be used *"to predict the capacity for natural regeneration within degraded or deforested tropical forest landscapes"* (Chazdon & Guariguata, 2016). There are both internal (within local site) and external indicators (within surrounding landscape) (Table 1). In Costa Rica there are studies that focused on certain ecosystem services (carbon stock, water quality) to evaluate the success of tropical forest restoration by natural regeneration in Costa Rica (Calvo-Alvarado *et al.*, 2009 ; Gilman *et al.*, 2016 ; Locatelli *et al.*, 2014). These studies did not take into consideration landscape indicators and did not generate any practical tool to predict the potential for natural forest regeneration. Here, we aim at taking into consideration both local and landscape indicators and designing a tool able to evaluate the natural regeneration recovery success illustrated by an ecosystem service (forest primary production) which will be evaluated by several variables of structure and composition. This work will be carried out in the San Juan La Selva Biological Corridor in Costa Rica (Figure 1).

Indicator	Internal	External
Presence of topsoil and soil organic matter	X	
Soil seed bank	X	
Presence of rootstocks	X	
Abundance and cover of shrubs	X	X
Abundance of remnant trees	X	X
Abundance of animal-dispersed trees	X	X
Living fences/hedgerows	X	X
Local avian abundance and diversity	X	X
Local mammal frugivore abundance and diversity	X	X
Remnant forest patches within 100 m		X
Riparian vegetation within 100 m		X
Large forest remnants or reserves within 200 m		X
Regional avian abundance and diversity		X
Regional mammal abundance and diversity		X

Table 1. Internal (local scale) and external (landscape scale) indicators suggested by Chazdon and Guariguata (2016) to predict natural regeneration potential in deforested and degraded tropical forest landscapes.

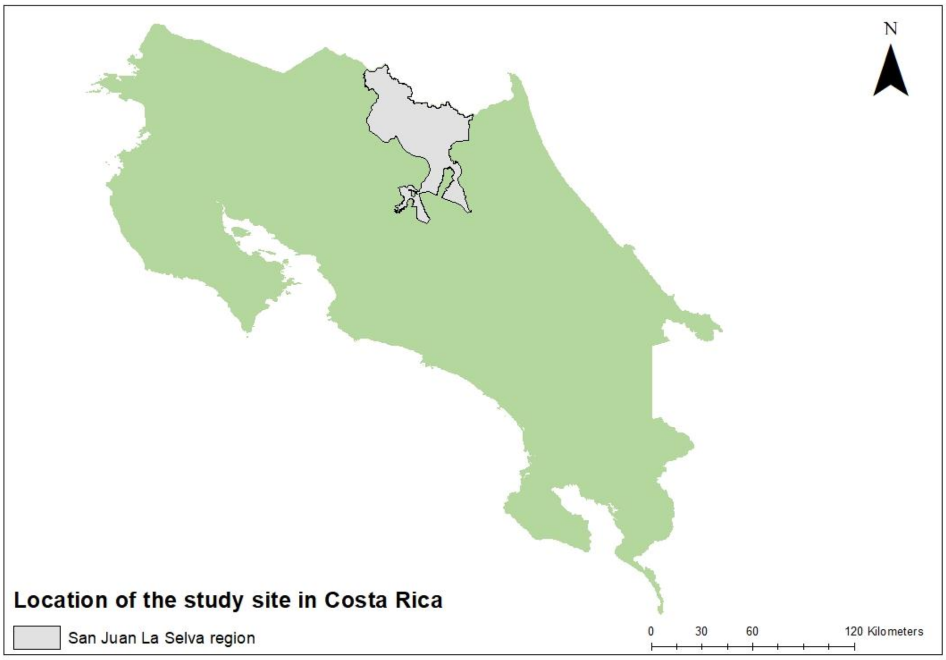

Figure 1. Location of San Juan La Selva Biological Corridor, Costa Rica.

Objective

The objective of this work is to express the quantity of biomass recovered over time in primary exploited and secondary forest plots located in La Selva, by including internal and external co-variables (landscape, climate, topography, soil). To achieve this objective, we will first gather the knowledge we have on land use dynamics in the study landscape (forest inventories, land use data, time series) in order to build ecological indicators of natural regeneration. At local scale, we will use environmental and geographical factors (DEM, soil properties, climate and slope) as we don't have all data necessary to build all internal indicators suggested by Chazdon & Guariguata, such as seed bank or abundance of remnant trees (Chazdon & Guariguata, 2016). At regional scale, i.e. within surrounding landscape, we will calculate spatial landscape metrics derived from land use time series and climate data. These metrics will be indicators of composition and configuration of the landscape. Then we will create a statistical model to express the quantity of biomass recovered over time in primary exploited and secondary forest plots, by including the co-variables selected. We choose to develop our model in a Bayesian framework, as it is particularly adapted when a low amount of data is available. Moreover, the addition of information that could be described as "non-pure data" or "priors" makes sure that our predictions are within the range of acceptable values given our prior knowledge on similar processes, and are thus especially important when data is scarce. Bayesian approach allows a rigorous estimation of parameters correlation and uncertainty.

Hypothesis

i. Landscape structure (configuration and composition) have an impact on the regeneration potential of forests (proximity to crops or to old-growth forest patches).
ii. The more complex the structure of the landscape (high level of heterogeneity), the more negatively it influences the rate of forest regeneration.
iii. The increase in the number of interfaces between forests and intensive agriculture reduces the regeneration potential of forests.
iv. The presence of large patches of forest near the plots studied will have a positive effect on the regeneration of the plots.

Material and method

Study site

The San Juan La Selva Biological Corridor, hereafter called "La Selva", is located in the northern zone of Costa Rica, in the provinces of Heredia and Alajuela, between the cantons of Sarapiqui and San Carlos. La Selva is covering an area of 244 618 ha with a wide altitudinal range, from 30 to 3000 m above sea level, ascending from the plains of San Carlos to the summits of the Central Volcanic Range. Looking at the land use map of La Selva, we can see that the landscape is dominated by mainly highly fragmented mature forest with some secondary forest, pastures and pineapple crops in the centre of the study area (Figure 2). La Selva was created in 2001, to maintain biological connectivity between larges patches of continuous forest in the protected areas of southeastern Nicaragua, the San Juan River, the system of protected areas of the Northern Arenal Huetar Conservation Area (ACAHN) and the Central Volcanic Cordillera Conservation Area (ACCVC) in Costa Rica. It is now part of the *Alianza Cinco Grandes Bosques de Mesoamérica* (the Five Great Forests of Mesoamerica Alliance). In La Selva, CATIE (*Centro Agronómico Tropical de Investigación y Enseñanza*) has established permanent plots in different types of forest systems: primary, production and secondary, in continuous or more fragmented matrices. These data will be used as the basis for calculating indicators to assess the regeneration potential of the forests of La Selva.

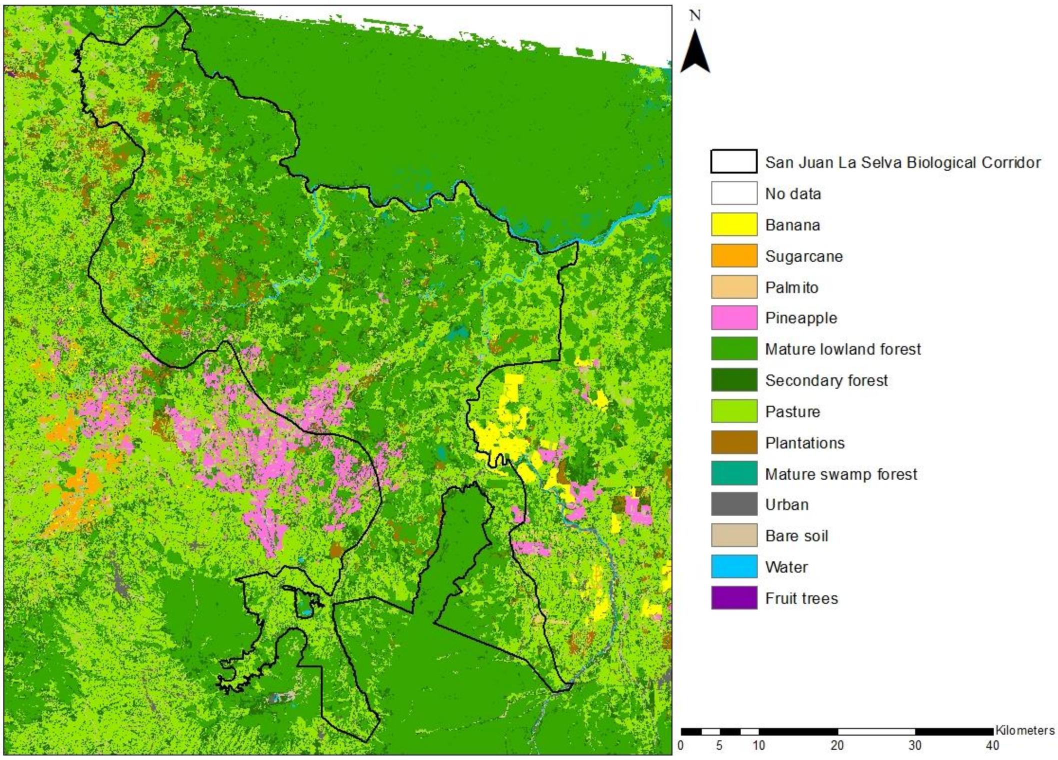

Figure 2. Land use map of the study area in 2011. Land cover data are from (Fagan *et al.*, 2016).

Forest plots data

For this analysis, 47 permanent forest plots located in La Selva, from three institutions, were retained to assess the potential of forest natural regeneration (Figure 3). There are 4 plots of secondary forest and 43 plots of exploited primary forest. We also used data of 49 primary forest plots as reference values (Table 2).

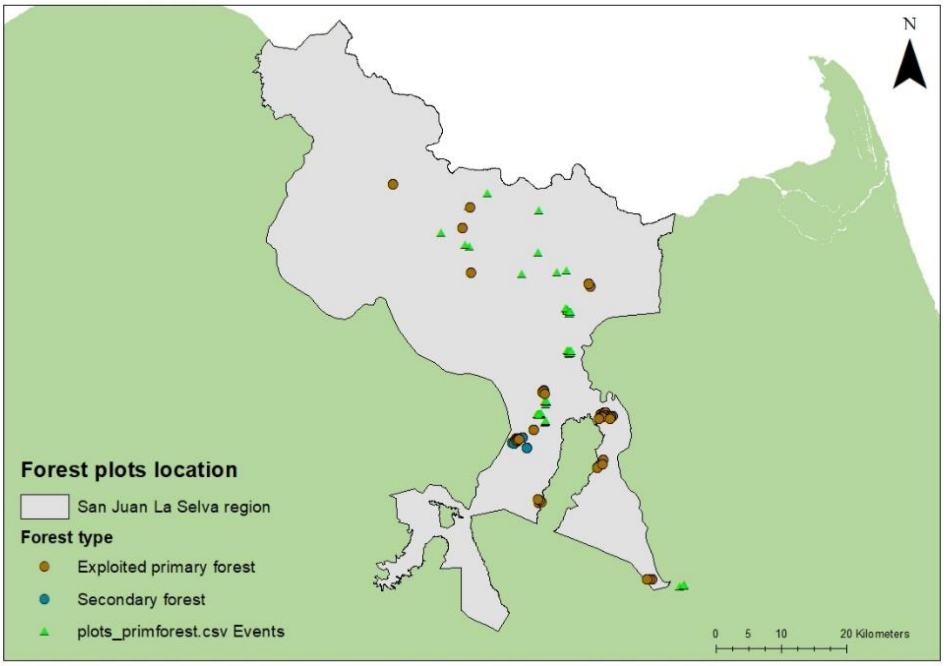

Figure 3: Location of the plots of secondary and exploited forest studied and the primary forests control plots.

Institution	Forest type	Treatment	Plots number	Area (ha)
CATIE	Primary exploited forest	Exploited with silvicultural	9	1
	Secondary forest	Harvested and abandoned	4	1.16 to 1.6
	Primary forest	None	49	0.2 and 1
CODEFORSA	Primary exploited forest	Exploited	3	1
FUNDECOR	Primary exploited forest	Exploited	30 1	0.3 1

Table 2. Plots description

For all these 47 plots, inventories over almost 30 years (from 1987 to 2017) are available with date of first exploitation for exploited forests and year of deforestation for secondary forests, surface area, treatment, and trees inventories with taxonomy, diameter at breast height (DBH) and tree height (H). Above-ground Biomass (AGB in Mg/ha) was estimated using the *computeAGB* function from the BIOMASS package in Rstudio software (R Studio, 2019). This function uses the pantropical equation of Chave et al. (2014) which uses tree wood density (WD), DBH and height as follow:

$$AGB = 0.0673 * (WD * H * D^2)^{0.976}$$ (Chave *et al.*, 2014)

The *getWoodDensity* function of the BIOMASS package was used to estimate wood density values per tree (WD). The estimation is made using the taxonomy of the trees and the global wood density database (Chave *et al.*, 2006 ; Réjou-Méchain *et al.*, 2017). It returns a value at species level (g/m3) representing the dry mass divided by the dry volume. For trees that were not identified at the species level, the function averages wood density values per higher taxonomic level (genus) or assigns average values per plot. An average biomass value per plot and per hectare was established.

Land use maps

Three land use classifications were available at different dates, from 1986 to 2013 (Table 3). For this work, the land use classification made by Fagan et al was chosen, as there are 5 different dates with an accurate classification (Fagan *et al.*, 2013). The Sesnie classification was used as information to estimate which type of forest is present in each plot (Sesnie, 2006). SINAC land use map of 2013 was used to upload Fagan's more recent map (2011) so we get a 2013 land use map similar to the other ones (Pedroni *et al.*, 2015). We also used 2017 land use data from CATIE to create a 2017 land use map for La Selva. Thus, we have a land use time series with 7 dates: 1986, 1996, 2001, 2005, 2011, 2013 and 2017.

Bibliographic reference	**Classification year**	**Classes number**	**Characteristics**
(Sesnie, 2006)	2001	32	Accurate classes for forests based on dominant species
(Fagan *et al.*, 2013)	1986, 1996, 2001, 2005, 2011	13	Distinction between different crops and tree plantations types
(Pedroni *et al.*, 2015) (SINAC)	Every 5 years from 1986 to 2013	9	Classes are less specific (permanent or annual cultures, presence of an "other land uses" class)

Table 3. Land use classifications available in the literature and their characteristics.

Soil, climatic and topographic data

To test the importance of climatic factors on biomass productivity, the average annual rainfall and temperature of all the plots were considered. These variables were obtained from the Chelsa database (*Climatologies at high resolution for the earth's land Surface areas*) (Karger *et al.*, 2017), through interpolation with the location coordinates of the plots using the Rstudio software (R Studio, 2019). In addition, soil factors such as soil fertility characteristics were obtained from the database of the *Center for Agronomic Research* (CIA) of the University of Costa Rica. Climatic Deficit Water (CWD) was also retrieved for each plot, based on the allometric equations of Chave et al (Chave *et al.*, 2014). We also had access to DEM (Digital Elevation Model) for Costa Rica at 30 meters of resolution, from SRTM (*Shuttle Radar Topography Mission*). Slope parameter (in degrees) was derived from this raster.

Landscape metrics

Landscape metrics were calculated using land use classification map with landscape ecology *Chloé* software (Boussard & Baudry, 2014). First of all, the optimal size of the sliding window that will be passed over the land use map must be calculated. To do this, we calculate the Shannon Heterogeneity Index (SHDI) both for randomly taken points in the landscape and for known points (our plots) in windows of variable scale (from 100m to 3 km). The average inflection curve representing the Shannon index versus window size is used to define the optimal window size (Figure 4). The index increases before reaching a saturation plateau. This plateau indicates that no more new elements or structures are captured by the study window. The window size just before reaching this plateau (1500m) can therefore be selected for metric calculation.

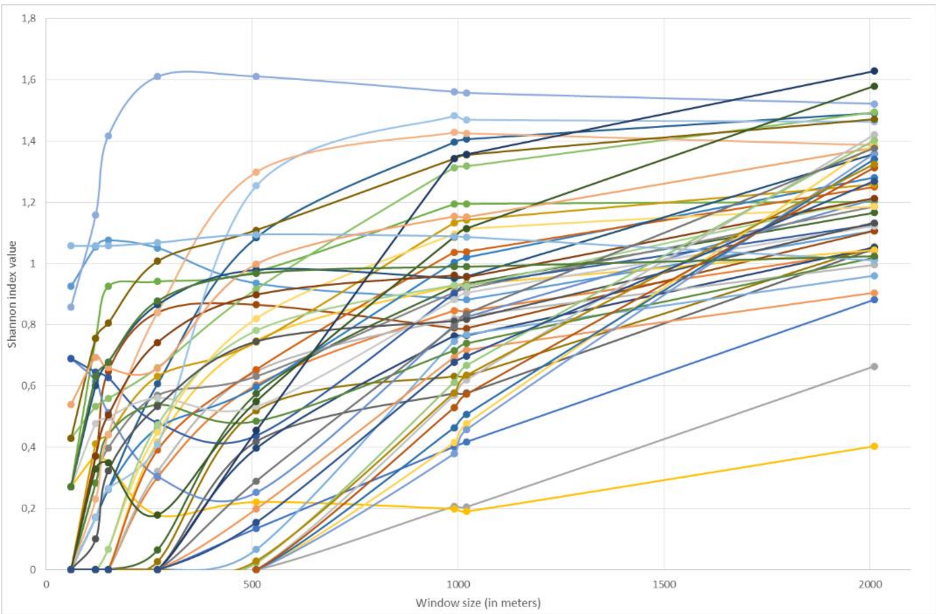

Figure 4: blbaddk

In order to calculate the landscape metrics, the previously established land use map was reclassified. An intensive agriculture class includes both banana and pineapple crops, and a forest class includes both primary and secondary forests (Figure 5). This transformation supports the hypothesis that two agricultural land uses, although different, will have the same effect on the structure of the landscape. For the forest class, the two types of forest have been grouped together because in the model the dynamics of both secondary and primary exploited forest plots are studied.

The metrics are then calculated in each plot. We took into consideration the date of the latest inventory corresponding to one of the land use maps. For example, if the last inventory in one of the plot was in 2012, landscape metrics were calculated using the 2011 land use map. A number of landscape metrics have been calculated: the interface proportions between non-homogeneous land use couples (*e.g. pNC1-3*), the Shannon Heterogeneity Metric (*SHDI*), the areas of the largest patch of a given land use lying within the sliding window (*e.g. LPI.class_3*).

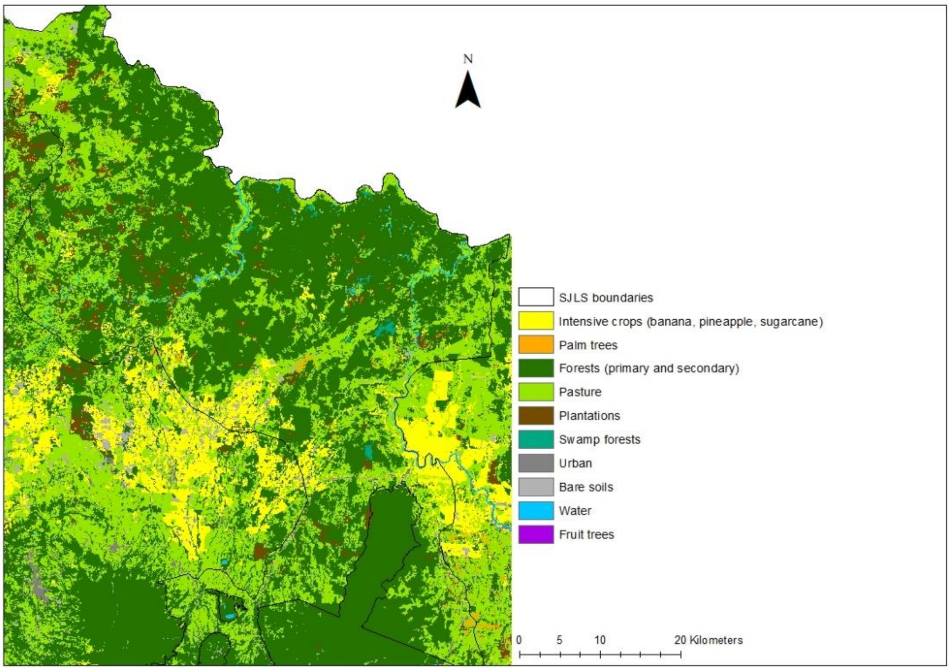

Figure 5: Land use classification (here in 2017) used for landscape metrics calculation.

Statistical analysis

Implementation of the model was done using R Studio and Stan package (Stan Development Team, 2020). Calibration was carried out using Stan's programming language (Carpenter *et al.*, 2017), and was developed in Rstudio (R Studio, 2019). The model was built following a three-parameter exponential function:

$$predAGB_{p,c}max = AGBmax * \left(1 - e^{-\beta_p * (t_c + t0_p)^{\theta}}\right) \quad \textbf{(1)}$$

With p the plot, c the census; $predAGB_{p,c}max$ is the predicted biomass in plot p at census c; $t_c > 0$ the recovery time, i.e. the time since the disturbance (deforestation or logging); $t0_p$ is the initial recovery time; *AGBmax* is the maximum attainable biomass; β_p is the recovery rate to reach AGBmax and θ the shape parameter: when $\theta > 1$ the function is sigmoid.

This type of equation was chosen based on the following criteria:

a. The function only takes positive values (no negative biomass);
b. A saturation of total biomass recovery (the recovering forest cannot accumulate biomass forever);
c. A null biomass at t = 0 (in the case of secondary forests);
d. A flexible function that can take a sigmoid shape.

This last criterion was chosen because the analysis of the dynamics of the observed data showed that the plots seemed to follow a sigmoid growth pattern, with a rather slow start of biomass recovery, then an increase in the recovery rate and finally the arrival at a saturation threshold. This equation therefore seemed to us the most appropriate for predicting biomass recovery in the plots studied (Figure 6).

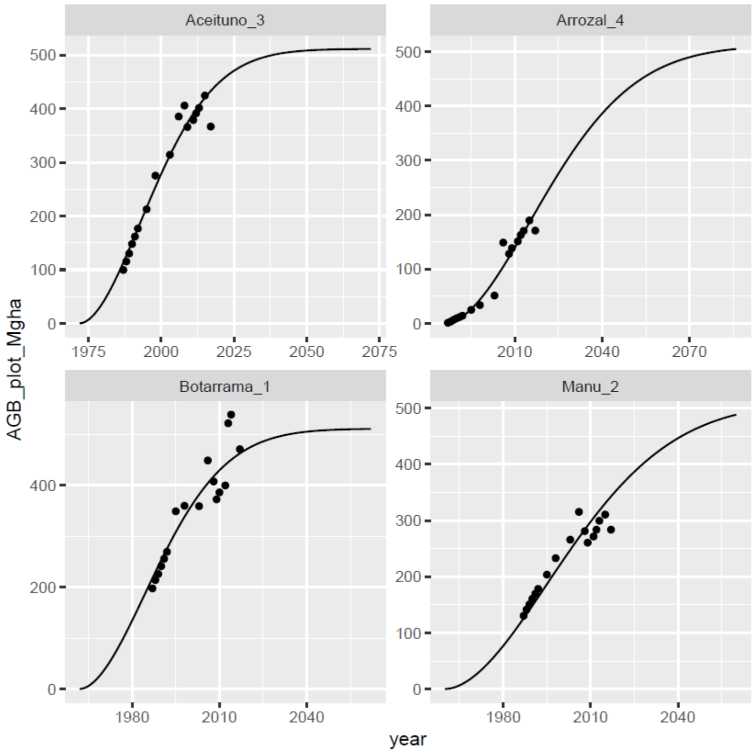

Figure 6: Prediction curve following an exponential function with three parameters. Biomass recovery in secondary forest plots according to time (black dots).

The several steps to build the model are:

i. Describe every input data as vectors

- Plots number [P] and inventories number [N];
- Exploited forest plots [L] and primary forest plots, used as reference plots [M];
- Year of inventory [year];
- Year of disturbance (deforestation or first exploitation) [dist];
- AGB value per plot [AGB];
- Mean AGB value in primary forest plots, used as reference for *AGBmax* [AGB_I];
- Co-variables [covar].

ii. Describe each parameter of the exponential function

- *AGBmax* is the maximum potentially attainable biomass;
- β_p is the recovery rate of plot *p*. In order to facilitate the interpretation of the results, we have deduced from β the parameter *tm*, which corresponds to the time needed to recover 50% of *AGBmax*. β and *tm* are linked by the following equation:

$$1/2 * AGBmax = AGBmax * (1 - e^{-\beta * tm^{\theta}})$$

$$\Leftrightarrow 1/2 = 1 - e^{-\beta * tm^{\theta}}$$

$$\Leftrightarrow (\log 1/2) = -\beta * tm^{\theta}$$

$$\Leftrightarrow \log 2 = \beta * tm^{\theta}$$

$$\Leftrightarrow tm = ({}^{\log 2}/_{\beta})^{\frac{1}{\theta}} \text{ And } \beta = {}^{\log 2}/_{tm^{\theta}} \quad \textbf{(2)}$$

- We added a random plot effect on parameter tm, as well the fixed effect of co-variables. All co-variables where centred and scaled, and their effect is quantified by parameters lambda (see below);
- One parameter *lambda* was estimated for every co-variable added (*e.g. lambda1* with *covar1*, etc.). Because all co-variables were centred and scaled, the values of lambdas can be compared to estimate the relative effect of co-variables on biomass recovery rates;
- θ is the parameter which give the sigmoid shape to the function, when $\theta > 1$;
- $t0_p$ is the initial recovery time, defined for each plot *p*: it is set to zero for secondary forests (that start with a null biomass) and takes positive values for logged forests.

iii. Model estimation

The likelihood of observations was defined as follows:

$$obsAGB_{p,c} \sim N(predAGB_{p,c}, \sigma^2) \quad \textbf{(3)}$$

Where $obsAGB_{p,c}$ is the estimated AGB in plot p at census *c*; $predAGB_{p,c}$ is the predicted AGB as defined in equation **(1)**; σ is the standard deviation.

We then added priors on the following parameters: the priori on *AGBmax* is a normal distribution with a mean value of 300 Mg/ha and a standard deviation of 200 Mg/ha. These values were chosen according to prior literature and expert knowledge (Finegan *et al.*, 2015 ; Rozendaal & Chazdon, 2015). *AGBmax* represents a potential maximum biomass and can therefore take on high values compared to what is observed in situ. We also took into consideration AGB data available in primary forest plots, which have a mean AGB value around 282 Mg/ha. Parameter *tm* follows a normal distribution of mean 40 years and standard deviation 20 years, as already seen in previous studies (Rozendaal & Chazdon, 2015).

iv. Variable selection

Given the quantity of variables available, several selection steps were carried out in order to keep only the most relevant ones. A matrix of correlation with all covariables was first carried out, and showed high levels of correlation between some of the variables, especially between landscape metrics (Figure 7). For example, the percentage of pixel couples forest-forest (*pNC-3.3*) is strongly positively correlated with the surface of the biggest forest patch (*LPI.class_3*), whereas it is strongly negatively correlated to the biggest agriculture patch surface (*LPI.class_1*), the percentage of pixel couples crops-forest (*pNC-1.3*) and the Shannon heterogeneity index (*SHDI*). Within the environmental covariables, elevation is highly correlated to mean precipitation level (*ppm_plot*) and mean temperature (*temp_plot*), which are negatively related between them. Percentage of organic carbon (*perCO*) and organic matter (*perMO*) are completely positively correlated. Effective cation exchange capacity (*ECEC*) is positively correlated to both *perCO* and *perMO*, but also to mean precipitation and to forest-related landscape metrics. The percentage of sand (*persand*) is very negatively correlated with both the percentage of clay (perclay) and the percentage of slime (perslime).

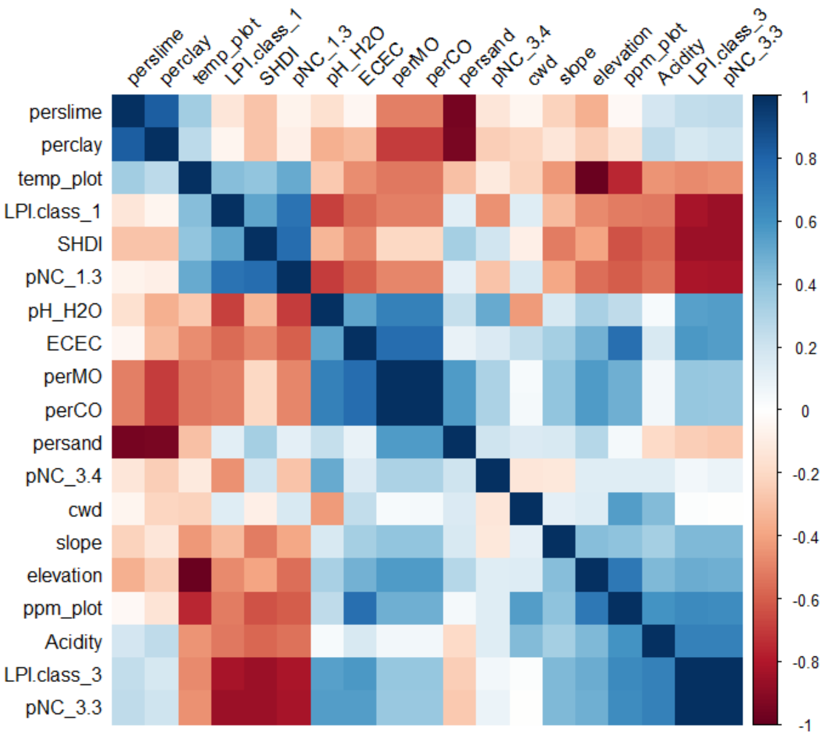

Figure 7: Correlation matrix between all environmental and landscape metrics.

This first stage of selection allowed us to set aside certain variables. With the remaining variables, we looked after the main factors influencing the biomass recovery rates. To do so, we used the maximum-likelihood values of parameter *tm* for each plot. We then related these values to the pre-set variables selection in a general linear model framework, applying a forward variable selection procedure based on the AIC criterion. We added variables to the model one at a time. At each step, each variable that is not already in the model is tested for inclusion in the model. The most significant of these variables is added to the Bayesian model, so long as its AIC decrease. It resulted in a list of 7 co-variables (Table 4).

Variable code	Description	Range values in the plot	Units
elevation	Plot elevation	[26 ; 532]	In meters (m)
slope	Slope	[0 ; 9]	In degrees
ECEC	Effective Cation Exchange Capacity	[4 ; 7.25]	In cmol/kg
perMO	Percentage of Organic Matter in soil first horizon	[2.5 ; 7]	In %
Acidity	Acidity level in soil first horizon	[1.5 ; 2.4]	None
SHDI	Shannon's heterogeneity index	[0.05 ; 1.25]	None
pNC-1.3	Percentage of pixel interface crops-forest	[0 ; 6]	In %

Table 4: Names and description of the co-variables included in the model.

Perspectives

In the light of these first results, landscape structure and configuration seems to have a relative effect on biomass recovery time, but more investigations are needed to better understand and estimate the extent to which these variables impact biomass recovery, by testing the significance of these effects for example.

More information on plots history and successive treatments would be required to better encompass forest dynamics in these plots.

This Bayesian approach makes it possible to predict the potential for biomass recovery from relatively little data, and to see which parameters influence this dynamic.

For the continuation and end of this work, the selection of variables will be refined in order to integrate into the model the most relevant parameters to best explain the biomass recovery capacity. The interpretation of the results will also be continued in order to clearly answer the initial questions.

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