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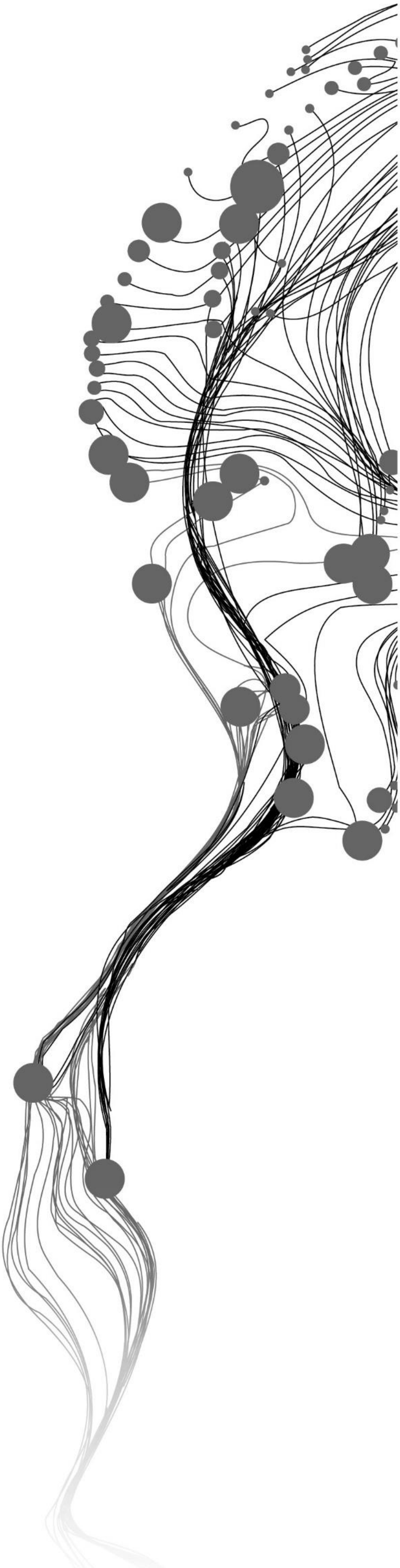

Exploring relationships between armed-conflict and deforestation in the Colombian Amazon

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Enschede, The Netherlands, February, 2018

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-Information Science and Earth Observation.
Specialization: Natural Resource Management

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ABSTRACT

The Amazon rainforest, located in South America, is the largest contiguous rainforest on the earth, despite its importance, deforestation rates remain high. Colombia, that comprises part of the Amazon, recently concluded a peace agreement to end an armed-conflict of more than 50 years. The effects of the reduction of armed-conflict on the deforestation of this portion of the Amazon are not yet explored. The aim of this study was to analyse the effect of the armed-conflict as a driver of deforestation in the Colombian Amazon and to forecast the deforestation in a post-conflict scenario. Analyses where carried out for two spatial extents, first, an analysis of the entire area, second, and analysis of the area most severely affected by deforestation (frontier zone). The results indicate that conflict is not the main driver of deforestation, however, it is a factor that can alter the rates of deforestation. The main identified drivers of deforestation for the study area were road infrastructure and population density. The effect of the armed conflict on deforestation varies depending on the area studied, showing that at the Amazon level the conflict increased deforestation, nevertheless, at the frontier zone level, the armed conflict reduced deforestation. A post-conflict scenario was evaluated, as general conclusion, the deforestation risk is likely to increase in the areas commonly affected by deforestation if the armed-conflict events drop.

Keywords: Colombia, Amazon, armed-conflict, deforestation, post-conflict.

ACKNOWLEDGEMENTS

I would like to express my gratitude to my supervisors Dr. Thomas A. Groen and Dr. Louise Willemen, their valuable contributions, constructive criticism, patience and encouragement made possible the completion of this MSc. Thesis. Additional thanks to Henk Kloosterman for his advice and ideas to develop the research proposal, and to Andreea Nowak for her valuable inputs on this manuscript.

I also want to thank to the UTS-ITC Excellence Scholarship programme for providing part of the financial support required to accomplish this graduate programme.

My gratitude to my former institution CIAT, particularly to my colleagues of the Terra-i project. Special thanks to Louis Reymondin and Alejandro Coca for their contributions and ideas that certainly enriched this research.

I would like to thank to my family and friends for their constant support, essential to complete this journey. All this effort was encouraged by the memory of my parents, relatives and friends, my source of inspiration.

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1. INTRODUCTION

1.1. Background

Forests are one of the most valuable natural resources. They play a key role in human well-being, as they provide different types of ecosystem services, such as climate and freshwater regulation, provision of biodiversity habitat and goods for humans (DESA, 2016; FAO, 2016).

Tropical forests haven the most biodiverse ecosystems on earth, rainforests and tropical seasonal forests compose this complex biome. Rainforests constitute roughly 86% of the tropical forest biome and are predominantly located close to the equator (Holzman, 2008). The Amazon, located in South America, is the largest contiguous rainforest on the earth, in 2001 it covered approximately 5.4 million km^2. Consequently, the Amazon plays a major role in earth system functioning (Malhi et al., 2007).

Globally, the forested area was reduced by about 39.99 million km^2 between 1990 and 2015 (FAO, 2016). Based on analyses of the Global Forest Change dataset of Hansen et al. (2013), the Amazon forest lost 282.500 square kilometres (km^2) between 2001 and 2013. Unsurprisingly, the reported average deforestation rate in this area was 18.100 km^2 per year between 1988 and 2006, with a decreasing trend from 2004 to 2012 (CIAT, 2017; Hansen et al., 2013; RAISG, 2012).

The Amazon rainforest is shared by nine countries: 60% lies in Brazil, 13% in Peru, 10% in Colombia; Venezuela, Ecuador, Bolivia, Guyana, Suriname and French Guiana share the remaining 37%. The Colombian part of the Amazon stretches over 457.200 km^2, an area which represents 40% of the country's territory (Eden, 1990).

In tropical countries, the most commonly identified drivers of deforestation at national level are population density, economic development and agricultural activity (Leblois et al., 2017). In the case of the Amazon, deforestation is specifically linked to infrastructure development, cattle ranching, industrial agricultural expansion, and logging (Malhi et al., 2007; Rosa; et al., 2013).

In the Colombian Amazon, the three main indirect factors driving the deforestation process since the late 1980s have been: landless peasants migration, illicit crop cultivation, and the presence of rebel groups and associated armed conflict (Etter et al., 2006a). Research results by Armenteras et al. (2006) suggest that deforestation rates in some highly populated areas of the Colombian Amazon are higher (up to 3.73% per year) than deforestation rates reported for other areas of the Amazon in countries such as Brazil (1-2%) (Müller et al., 2016).

The migration of peasants into the Amazon territories has caused unplanned colonization of the region. Conflicts of earlier decades, related to land tenure in the Andean regions resulted in the expansion of the agricultural frontier in the south-eastern rainforest of Colombia (Rodríguez, 2014). Migration motivated by the illegal coca economy, the hope to possess a piece of land to improve their economic situation drove peasants to settle in the Amazon region (Etter et al., 2006a).

The establishment of illicit crops is considered a relevant factor in the deforestation process. Coca (*Erythroxylum coca*) is the most widely cultivated species for narcotics production in Colombia (Álvarez, 2003; Dávalos et al., 2011; UNODC, 2017). The illicit coca cultivation have fuelled the armed conflict in the country for more than three decades (Álvarez, 2003; Collier et al., 2003; Dávalos et al., 2011). According to UNODC (2017), in 2016, the Amazonas Department hosted 86 ha of coca crops, however, neighbourhood areas belonging to the Amazon biome (see figure 1), such as Putumayo-Caquetá, and Meta-Guaviare harboured around 34.000 and 12.000 ha respectively representing roughly 32% of the total area cultivated with coca in Colombia. An increase in the area cultivated with coca in Colombia has also been reported in the last census executed by UNDOC (2017).

Coca establishment has been catalogued as a driver of deforestation in different studies. These describe three ways in which illicit crop establishment acts as an indirect driver of deforestation. First, the farmers that move away due to conflict associated to drug trafficking which promotes deforestation in other areas. Second, high incomes derived from coca crops lead to the increase of illegal and legal crop areas. Third, law enforcement forces farmers to move, encouraging deforestation (Álvarez, 2003; Armenteras et al., 2006; Dávalos et al., 2011; Messina and Delamater, 2006). In that sense, it is relevant to evaluate how the establishment of illicit crops may directly and/or indirectly affect the forest loss in the study area.

Another process influencing deforestation is armed conflict. Research has revealed that a great part of the world's armed conflicts occur in tropical forests (Baumann and Kuemmerle, 2016; Butsic et al., 2015). Although there have been many efforts to monitor deforestation, few researchers have explored the links between armed conflicts, natural resources and forest loss dynamics (Hanson et al., 2009; Ordway, 2015). Harmful indirect impacts on biodiversity and nature often occur when natural areas are left unprotected, when these become a shelter for troops or a resource to support the combat, or when these are directly affected by conflict (Ordway, 2015).

But there are also areas rich in biodiversity that are not being altered by conflict (but rather benefit from it), especially in instances of land abandonment and population displacement, or when economic activities become too risky to be taken up or continued (Baumann and Kuemmerle, 2016; Gorsevski et al., 2013; Ordway, 2015; Rustad et al., 2008). Such situations occurred in Rwanda, where the armed conflict led to thousands of rural inhabitants migrating to settlements, thus redistributing pressure on forests (Ordway, 2015) or in Congo, where reduced mining activities due to war had lessened the pressure over forests (Butsic et al., 2015).

Another important aspect when it comes to the relationship between armed conflict and deforestation is the fact that these effects (positive or negative) depend on the temporal scale of the armed conflict; more specifically, forest resources are affected in a different way in a conflict setting, compared to a post-conflict setting. For example, in the post-conflict[1] period, Rwanda experienced increased trends in forest loss outside protected areas, while deforestation trends within protected areas were decreasing. During the conflict, the massive migration led to a concentration of the population in refugee settlements, where deforestation rates increased mainly due to fuelwood harvesting (Ordway, 2015). Another relevant example can be found in the Republic of South Sudan. Despite conflict-related migrations occurring on the Sudan-Uganda border, mixed impacts on the forest were observed; some forest areas experienced recovery due to massive emigration, while others displayed forest loss as results of concentration of migrants (Gorsevski et al., 2013).

[1] Post-conflict is when the armed-conflict situation ends as result of a formal surrender, a negotiated cessation of hostilities and/ or a peace talks followed by a peace treaty (Brown et al., 2011).

The conflict in the Democratic Republic of Congo (DRC) unveiled potential risks for forests in post-conflict settings. Post-war economic recovery also implies resuming logging activities, rehabilitation of infrastructures, demographic growth, new mining activities, an increase of demand from the urban centres (Debroux et al., 2007). In DRC, this also meant a reduction of pressure on forests in the areas abandoned by displaced population in the county (Sierra et al., 2017). This shows once more that post-war scenarios are diverse and different outcomes related to deforestation can be observed.

In Colombia, an internal armed conflict (hereafter: armed conflict)[2] has been active for more than 50 years, being an important driver of deforestation in the country, as previous research has shown (Fergusson et al., 2014; Morales, 2017). In the country's Amazon region in particular, the armed conflict has taken place in the forests of north and central Guaviare, Caquetá, and northern Putumayo river basins, as well as in the foothills of the east Andes and the Serranía de la Macarena (see figure 1) (Álvarez, 2003).

While relationships between conflict variables and deforestation in Colombia seem more relevant in the grassland biomes, areas with more deforestation are the Caquetá moist forests and the northern Andean montane forests (Sanchez-Cuervo et al., 2012). Previous research on the relationships between forests and conflict in Colombia reference the inequality in land tenure and other social issues as one of the root causes of the armed conflict and highlight its possible link with deforestation (Castro-Nunez et al., 2017; Ibañez and Vélez, 2007; Sanchez-Cuervo et al., 2012).

Even though relationships between conflict and forests have been explored in Colombia, there are no studies yet that assess and try to forecast the future of forest loss and forest conservation risks under post-conflict settings. Considering the peace agreement recently signed by the Colombian government and the Revolutionary Armed Forces of Colombia (Fuerzas Armadas Revolucionarias de Colombia [FARC]), as the biggest armed group in the country, as well as the ongoing peace negotiations with the National Liberation Army (Ejercito de Liberación Nacional [ELN]), Concerns have been raised within the scientific community and the civil society regarding the potential negative or positive outcome that this new post-conflict scenario represents for the conservation of forests in Colombia (Álvarez, 2001; Baptiste et al., 2017; Morales, 2017).

As links between conflict and deforestation are not yet totally clear, sudden changes in political situations (such as the agreement to end the conflict) imply modifications in land use and land cover dynamics (Baptiste et al., 2017; Baumann and Kuemmerle, 2016; Sierra et al., 2017). Colombia as a mega-biodiverse country is assumed to safeguard key biodiversity areas from environmental damage, this not only for the pure biodiversity legacy but because adequate resource management can aid the peacebuilding process which at early stages seems to be weak. Baptiste et al (2017).

To conclude, zero-deforestation commitments in the UNFCCC Paris agreement has been signed by the Colombian government (United Nations Framefork Convention On Climate Change, 2015). For that purpose, informative tools as the one that will be proposed by this research are essential to a regional understanding of underlying factors that cause forest loss and their relationships with the armed-conflict, thus, enabling local governments and relevant stakeholders to shape policies and actions that mitigate negative consequences or boost positive outcomes that a post-conflict era may have on the deforestation process, hence, enhancing ecosystem resilience and contributing to mitigate climate change.

[2] For the sake of this study armed conflict follow the definition of the Uppsala Conflict Data Program (UCDP) available at: http://www.pcr.uu.se/research/ucdp/definitions/

1.2. Research objectives

The aim of this study is to analyse the effect of the armed-conflict as a driver of deforestation in the Colombian Amazon and to forecast the deforestation in the post-conflict settings.

Specific Objectives

1. To analyse differences in deforestation rates from 2001 – 2015 for conflict and non-conflict areas.

2. To identify the most relevant explanatory variables to model deforestation in conflict and post-conflict settings.

3. To forecast the deforestation process for the Colombian Amazon in post-conflict settings.

Research Questions

1. Are there differences in deforestation rates for conflict and non-conflict areas?

2. What are the main i) biophysical ii) socio-economic and iii) armed conflict-related variables that influence deforestation in the study area?

3. What is likely to be the rate and spatial distribution of deforestation in the upcoming post-conflict era in the Colombian Amazon?

2. MATERIALS AND METHODS

2.1. Study Area

The study area is the Colombian Amazon in South America, located between 5º0'N and 4º14'N, and between 77º40' and 66º50'W (figure 1). The area extends over 483.000 km² and comprises of six administrative departments (Amazonas, Caquetá, Guainía, Guaviare, Putumayo, and Vaupes) and part of other five departments (Cauca, Huila, Meta, Nariño, and Vichada). There are 98 municipalities in the study area, with a population density that ranges between 0 and 23 persons per hectare (Lloyd et al., 2017).

The definition of the Amazon used for this research was the proposed by RAISG (2012), in this delimitation ecological, environmental and social criteria are considered, consequently, the area differs from the Amazon river basin or the biome definition (Maretti et al., 2014).

The Amazon is the largest region of Colombia as well as the least transformed one. This area is mainly covered by tropical forests, but also contains wetlands, dry savannas and montane forests (Eden, 1990; Sanchez-Cuervo et al., 2012). The annual precipitation of the area ranges between 1000 and 5000 mm. High levels of precipitation are observed in the Andes foothills as well as in the eastern part of the country, while the central section of the Colombian Amazon receives low rainfall amounts per year (Fick and Hijmans, 2017). The elevation ranges from 0 m.a.s.l. in the lowlands to 4000 m.a.s.l. in the Andes mountains (USGS, 2015).

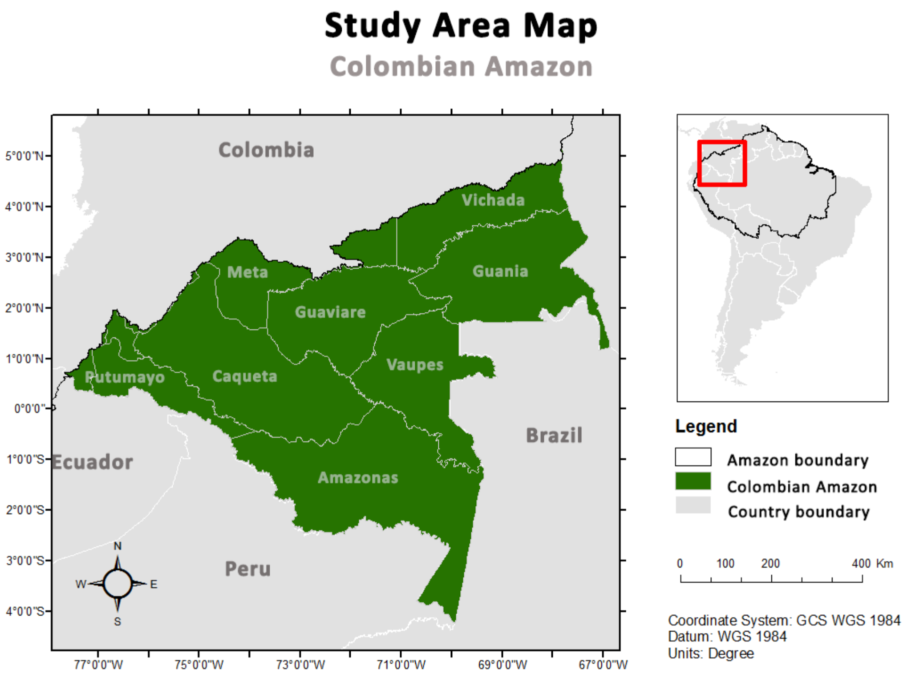

Figure 1. Map of the study area including the extent the Colombian Amazon and the Departmental divisions. The inset shows the extension of the entire Amazon Rainforest and its location in South America.

Common economic activities in the region are the agricultural production and the cattle ranching. This has become the predominant economic activity in the departments of Caquetá and Guaviare. Furthermore, oil and gold extraction take place in some areas of the Putumayo. Great part of the population is settled in the north west of the region, Department's capitals such as Florencia in Caquetá and San Jose del Guaviare in Guaviare witness accelerated population growth. The distribution of the population is around 50% rural and 50% percent urban. Some areas of the Amazon have been controlled by different armed groups by decades. Consequently, violence associated to drug trafficking and armed conflict has been constant in the region (Arcila, 2010).

2.2. Overview of the methods

To achieve the objectives of this research, different methods and approaches were employed. First, exploratory data analyses were used to portray the deforestation rates and its relationships with the armed-conflict. For that purpose, spatially explicit data was employed. To characterize the deforestation, data derived from satellite imagery were used, while to depict the armed-conflict data from specialized databases were used, attempting to use, in both cases, the most detailed spatial datasets available.

The second step was to identify the variables that best explain the deforestation process. To do so, previous studies on deforestation completed in the study area were consulted, and key variables were identified. Subsequently, correlation tests were performed between these and with the deforestation data.

Covariates that showed very poor or no relationship with deforestation data at early stage of the analysis were discarded. Finally, a check for multicollinearity was performed using the Variation Inflation Factor (VIF) as reference.

The remaining variables were proposed in the creation of two Logistic Regression Models (LRM). One for the entire Amazon area, and another one for the 20 municipalities with higher deforestation rates (referred hereafter as the frontier zone). These two approaches were proposed to depict differences that might be product of the scale of the study area. Additionally, for each of the spatial extents considered, a random sample set was generated with the objective of reducing spatial autocorrelation.

The next step was to refine the group of explanatory variables to be included in the LRMs. This was achieved with the implementation of a bootstrapping of stepwise regressions. This process was intended to: i) aid the identification of the most significant explanatory variables, and later ii) to assess the sensitivity of the model to the sample selection.

Heeding the analysis of the bootstrapping, the LRM parameters were estimated. Additionally, a non-conflict scenario was explored through reducing the effects of conflict variables. Subsequently, for each extent, deforestation probabilities were calculated and translated to probability maps using the fitted models. In parallel, probabilities were calculated for the non-conflict scenario for the Amazon and the frontier zone. Finally, the performance of the proposed models was evaluated using ROC curves and Kappa statistics.

2.3. Datasets

2.3.1. Deforestation

The dependent variable for the regression model was deforestation data, the dataset used was the Global Forest Change (GFC) version 1.3 (Hansen et al., 2013). This dataset offers information on forest loss at 30m spatial resolution on an annual basis, covering the period 2001 – 2015. It provides data on forest change at the global level with accuracies above 80%. The dataset is derived from Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery; the classification of the imagery was implemented using images taken in the growing season. Finally, forest loss was defined as the replacement of forest to other land covers.

2.3.2. Explanatory variables

Deforestation processes are driven in different ways and at different levels. Direct drivers are those that alter the land cover (i.e. agriculture frontier expansion), on the other hand, underlying factors are indirect drivers that may affect the deforestation process (i.e. increased prices of timber)(Geist and Lambin, 2001). Based on previous studies performed in Colombia (Armenteras et al., 2013a; Etter et al., 2006a, 2006b; Etter and McAlpine, 2007; González et al., 2011), a list of possible predictors was defined. These include variables on conflict, accessibility, biophysical conditions, policy, demography and land cover. Table 1 explains in detail the variables and datasets that were considered in this study, the maps of the variables used is presented in the appendix 1.

2.3.2.1. Conflict drivers

Armed conflict-related events reported in the Uppsala Conflict Data Program (UDCP) refer to violent actions associated to a war or armed conflict. This database, used in this current research, collects detailed data on armed conflicts worldwide, including information on the date of the event, actors taking part, source of information, location, and number of casualties (UCDP, 2016).

The dataset on forced migration victims used in this study refers to the number of victims of forced displacement aggregated at municipal level. The dataset was compiled from different government institutions and reported to the Single Victims Register (RUV Spanish acronym) and includes the number of people received and expelled per municipality and the year of the report (Unidad para la Atención y Reparación Integral a las Víctimas, 2017).

The dataset on events related to antipersonnel landmines includes information on detonated artefacts, detected artefacts, victims of explosions, location and date of the incident. The information is compiled from reports of different government institutions and reported by the Directorate for Integral Action against Antipersonnel Mines (AICMA, Spanish acronym) (AICMA, 2017).

Illicit coca crops data is produced by the UNDOC SIMCI project in association with the Colombian government. The analysis of satellite imagery and field work results in the annual report of areas planted with coca in the Colombian territory. The data used in this study was the areas reported coca aggregated by municipality, available at the Observatory of Drugs of Colombia (ODC, Spanish acronym) (ODC, 2017; UNODC, 2017).

2.3.2.2. Other drivers

Accessibility drivers included the road and river network available in OpenStreetMaps (OSM) (Contributors OpenStreetMaps, 2017). These open source datasets have been built from volunteering and crowd-sourcing efforts. The quality of these datasets is constantly under scrutiny by the scientific community and by private users, however, it has been widely used an accepted as a valid source of geographic information for various applications including research.

The human settlements dataset was also included in the accessibility category. The dataset was made available by the National Administrative Department of Statistics (DANE, Spanish acronym) and downloaded from its data portal (DANE, 2015). This dataset includes the names and coordinates of 6939 human settlements in the national territory.

Biophysical data included two variables. The first one was altitude from a Digital Elevation Model (DEM). This dataset was derived from the Shuttle Radar Topography Mission (SRTM) aboard the space shuttle Endeavour launched in 2000. The specific product used in this case was the SRTM 1 Arc-Second Global (USGS, 2015). The second biophysical variable was precipitation, which was obtained from the WorldClim bioclimatic variables, a dataset of spatially interpolated climatic data constructed using the best performing regional models and variables at global scale (Fick and Hijmans, 2017). The specific variable used was BIO12, which contains the average annual precipitation.

Protected areas and land property distribution were included as variables related to policy. The protected areas datasets were obtained as polygons from the environmental information system of Colombia (SIAC, Spanish acronym) (Sistemas de Información Ambiental de Colombia, 2017). The Gini index of land measures land distribution in relation to total population of a territory (IGAC, 2012).

Population density was included as demographic variable. The Worldpop dataset is a high resolution raster of population density that integrates census, satellite and GIS data, providing detailed population counts for the years 2010, 2013 and 2015 (Lloyd et al., 2017).

2.3.3. Data processing

As the available datasets differ in spatial units - some of them are aggregated by municipality, -some others are raster based (see table 1) -, a series of conversions were necessary to obtain a homogeneous and consistent dataset suitable to fit a deforestation model.

To start, all the explanatory variables were converted to raster format and resampled to 1km cell size., which is the spatial resolution of the coarsest dataset that was used (in this case the climatic data). Data on forest cover were resampled using majority filter; hence, each class (forest, non-forest and deforested) was extracted as binary maps. Slope data were calculated from a 30m digital elevation model, subsequently, altitude and slope were resampled to 1km by capturing the mean of all the 30m pixels inside each 1km pixel. Population data was averaged (2010, 2013, 2015), and subsequently resampled to 1km adding all the values of 100m pixels inside each 1km pixel.

Data available as linear vectors (such as roads, rivers and forest edges) and point datasets (i.e. armed-conflict related events, human settlements, landmines) were converted to maps of Euclidian distances. Those are commonly used as proxies to explain deforestation (Lambin et al., 2001; Mayfield et al., 2017; Veldkamp and Lambin, 2001).

2.3.4. Creation of a sample set of the deforestation and its explanatory variables

To reduce spatial autocorrelation, two random samples of the response and explanatory variables were generated. One for the entire Amazon and one for the frontier zone. Each sample set was composed by 10.000 points. This is equivalent to 1.74 and 12.7% of the total pixels conforming the Amazon and the frontier zone respectively. The distribution of the sample was 99% non-deforested 1% deforested in the case of the Amazon. The distribution of the frontier zone sample set was 5% deforested – 95% non-deforested.

To favour the accurate diagnosis of model performance, the complete sample set was divided in a training dataset, equivalent to 70% of the total samples, and a test dataset corresponding to the remaining 30% points (Kuhn and Johnson, 2013). The full sample set of the Amazon, composed by 10000 observations, was used to calculate the VIF.

The two training datasets, composed of 7000 observations each (Amazon and frontier), were used in the bootstrapping process, as well as to fit the LRMs of deforestation. Finally, the test datasets, composed of 3000 observations each, were used to evaluate the performance of the Amazon and frontier zone models.

Table 1. Explanatory variables, sources, and datasets to include in the model.

Category	**Variable**	**Source**	**Name**	**Information**	**Resolution /scale**	**Format**	**Period**
Conflict	Armed conflict events	UCDP	UCDP Georeferenced Event Dataset (GED) Global version 17.1 (2016)	coordinates, number, date	NA	table	2001 -2015
	Forced migration	RUV	Displaced people per municipality	number, municipality	NA	table	2001-2015
	Coca crops	UNODC	Illicit crops census	Areas	NA	table	2001-2015
	Landmines	AICMA	Landmine incidents	Coordinates, date	NA	table	2001-2015
Accessibility	Road Network	OSM	Road network	Roads	multiple	shp	2016
	River network	OSM	Rivers	Rivers	multiple	shp	2016
	Towns	DANE	Human settlements	coordinates	1:100000	shp	2015
Biophysical	Elevation	METI, NASA	ASTER GDEM	DEM	30m	raster	2001
	Slope	METI, NASA	ASTER GDEM	Calculated from DEM	30m	raster	2001
	Precipitation	Bioclim	Average annual precipitation BIO 12	precipitation	1km	raster	1970-2000
Policy	Protected areas	SPNN	Protected areas	Areas	1:100000	shp	2015
	Inequality	IGAC	Gini of land	Gini index/municipality	NA	table	2001-2015
Demographic	Population	Worldpop	Persons per hectare	Population density	100m	raster	2010,2013, 2015

2.4. Exploring the relations between armed conflict and deforestation

2.4.1. Definition of spatial units of the study, conflict and non-conflict areas

To address the links between conflict and deforestation rates, two spatial units were considered: i) municipalities and ii) Thiessen polygons of human settlements. The advantage of using municipalities as study units is that many of the conflict datasets available have information at this level; the drawback of this approach is that the relatively large mean size of the municipalities in this region of Colombia, which is above 4.900 km^2. To address the large size of the municipalities, spatial data on human settlements was used to subdivide the area in Thiessen polygons created from human settlements; thus, the units of analysis were smaller and at the same time related to the populated areas.

To determine whether the armed conflict has influenced the deforestation rates in the Colombian Amazon or not, the study area was characterised in relation to the presence or absence of armed conflict events, recorded in the conflict dataset from the Uppsala Conflict data Program (UCDP, 2016). Although there are other datasets related to conflict such as coca plantations, forced migration and antipersonnel landmines, these were not considered at this stage. To summarize, municipalities and Thiessen polygons where no conflict-related events occurred, were flagged as non-conflict, and areas where armed conflict events occurred, were flagged as conflict areas.

2.4.2. Differences in deforestation rates in conflict and non-conflict areas

Deforestation rates were calculated at municipality level, and Thiessen polygons level, using the next formula:

DR = DA/FA*100

Where DR is deforestation rate (%), DA is the deforested area in the period 2001 - 2015 and FA is the Total Forested Area in 2000. This calculation assumes no variations in annual deforestation rates, as it calculates the overall rate for the entire period.

Results of deforestation rates in conflict and non-conflict were tested for normality using the Shapiro-Wilk W normality test (Shapiro and Wilk, 1965). Subsequently, to assess differences between conflict and non-conflict areas, t-test (Student, 1908) and Kruskal Wallis (Kruskal and Wallis, 1952) non-parametric test were applied for normally and non-normally distributed observations respectively.

2.5. Relationships between conflict variables and forest loss

Relations between three indicators of conflict were investigated: i) armed conflicts and landmines ii) coca plantation and iii) forced migration.

First, links between conflict and deforestation were explored by evaluating spatial relationships between the land cover and armed conflict events. Euclidean distance maps were computed from the armed conflict related events dataset, presence of landmine incidents and human settlements. Later, the areas were classified into 9 distance categories a priori (0-5, 5-10, 10-20, 20-30, 30-40, 40-50, 50-100, 100-200, 200-300 and >300 km). Subsequently, a spatial histogram for the land cover map was derived using these distance categories. This procedure was repeated for the distance to landmine-related events, as well as for the human settlements dataset; the last one was used to test if human settlements have similar effects on the deforestation.

Second, the relationship between deforestation rates and victims of forced migration was explored. To test this variable, two datasets were analysed; on the first place, the number of expelled people per municipality was contrasted with the deforestation rates; on the second place, the number of incoming victims (of forced migration) in each municipality was compared with the deforestation rate.

The third conflict indicator in the case of Colombia is the presence of illicit coca plantations. To explore the relationships between illicit coca crops and deforestation rates, the density of area cultivated with illicit coca crops per municipality was calculated as follows:

$$CR = CA/MA*100$$

Where: CR is the percentage of the area planted with coca in each municipality, CA is the average of the 2001-2015 annual coca area in hectares, and MA is the municipality area in hectares.

2.6. Relevance of variables to explain deforestation and models sensitivity

The assessment of the explanatory variables was done in three steps:

First, multicollinearity tests were performed. Collinearity refers to the correlation between covariates. It constitutes a risk to the suitable and effective estimation of the relationships between the response and the explanatory variables used in regression models. High correlation often leads to high variances and low statistical significance (Farrar and Glauber, 1967; Jou et al., 2014; Zuur et al., 2010). The Variance Inflation Factor (VIF) was used as indicator of correlation between the various explanatory variables. A threshold of VIF >= 4 was used to select variables to remove (Zuur et al., 2010).

Second, bootstrapping procedures were performed to generate two sequences of 100 stepwise regressions each. The first one used the training sample set of the Amazon, the second one used the training set of the frontier zone. The bootstrapping consisted of a random selection with replacement (Efron and Tibshirani, 1997). This process was programmed using a custom function in Rstudio (RStudio Team, 2016).

To analyse these results, bar plots were produced for the Amazon as well as for the frontier zone, these evidenced: a) the number of times that the variable was included in the regression model, b) the number of times that the variable was included but was not significant, c) number of times that the variable was significant at $\alpha = 0.05$ and d) the number of times that the variable was significant at $\alpha = 0.01$.

The third step, was to refine the selection of explanatory variables using as criteria the results of the stepwise regressions in the bootstrapping. For that purpose, only variables that were significant at $\alpha <= 0.05$ at least in 50% of the stepwise regressions were included.

Finally, to test the sensitivity of the models to the sample selection, deforestation probabilities were calculated. Hence, for each stepwise regression model in the bootstrapping, a map of deforestation probability was produced. Then, the standard deviation of the resultant maps was computed.

2.7. Exploring the effect of a reduction on conflict-related variables

For each case (Amazon and frontier zone), and using the glm function in R (RStudio Team, 2016), a Logistic Regression Model was fitted. Using the binary deforestation data as response variable, and the set of relevant explanatory variables. The model was fitted using the training sample set equivalent to 7000 points.

To create a non-conflict scenario, deforestation explanatory variables linked to the armed-conflict were reduced to simulate a reduced conflict scenario. To achieve this, the conflict variables included as proxies (distance to armed-conflict related events and distance to landmine related events) were transformed as follows:

To ensure that the effects of the conflict proxies were minimized, the maximum value of each distance map (landmines and armed conflict events) was applied to the correspondent conflict event proxies. Moreover, the areas planted with illegal coca crops were reduced to 0. Although, the land inequality index may be related to the conflict, it was not modified, since it is a condition that might not change as result of the peace agreement.

The performance of the models was tested using Receiver Operating Characteristic (ROC) and AUC, furthermore, Kappa statistics were calculated. Finally, based on the models fitted, probability maps of deforestation were produced, for the conflict and non-conflict situation, as well as, for the Colombian Amazon and the frontier zone, using the package PresenceAbsence in R (Freeman and Moisen, 2008).

3. RESULTS

3.1. The spatial unit approach

In Colombia, the municipality is the second administrative level; this division is often related to the amount of the population settled in specific areas. The study area shows smaller divisions in areas with higher population density, such as the Amazon piedmont located in the north-west (Figure 2a). Municipalities with low population densities are also higher in size, compared to municipalities with higher population density. This is an important factor when analysing deforestation, since the deforestation rates are calculated based on the remaining forest area and the size of the municipality.

When the study area is divided in Thiessen polygons using as reference the human settlements, the units become smaller. Thus, the number of resulting polygons is greater when compared with de municipality divisions. Furthermore, the concentration of human settlements is more evident in the north-west of the Amazon (figure 2). Thus, the analysis of deforestation based on Thyessen polygons depict deforested areas associated to specific human settlements.

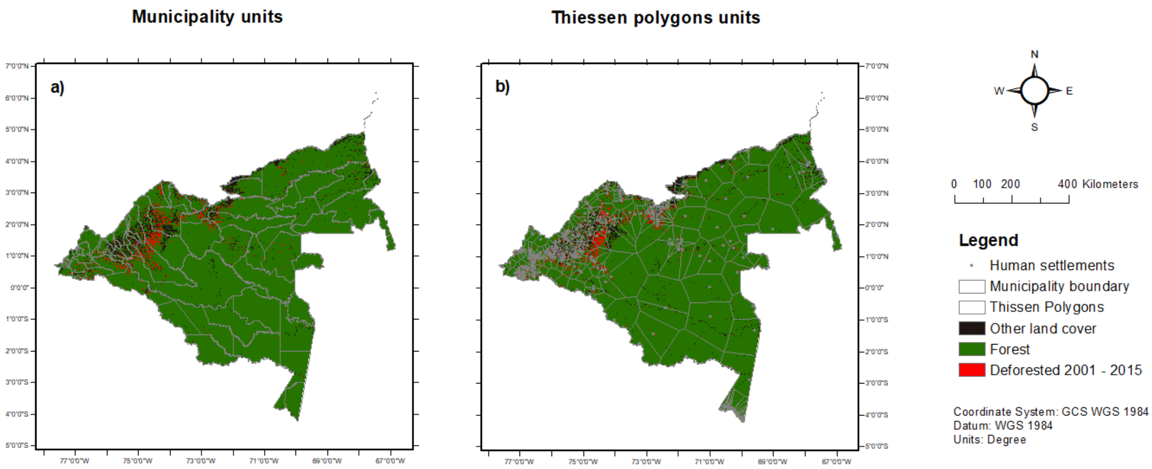

Figure 2. Division of the study area for the exploration of relationships between conflict deforestation a) at the municipality level, b) at Thiessen polygons level.

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Deforested areas are clustered around the north-west of the Amazon. Generally, these areas overlap with the areas that show high densities of human settlements. These areas are known as a colonization front, resulting from the expansion of the agricultural frontier (figure 3).

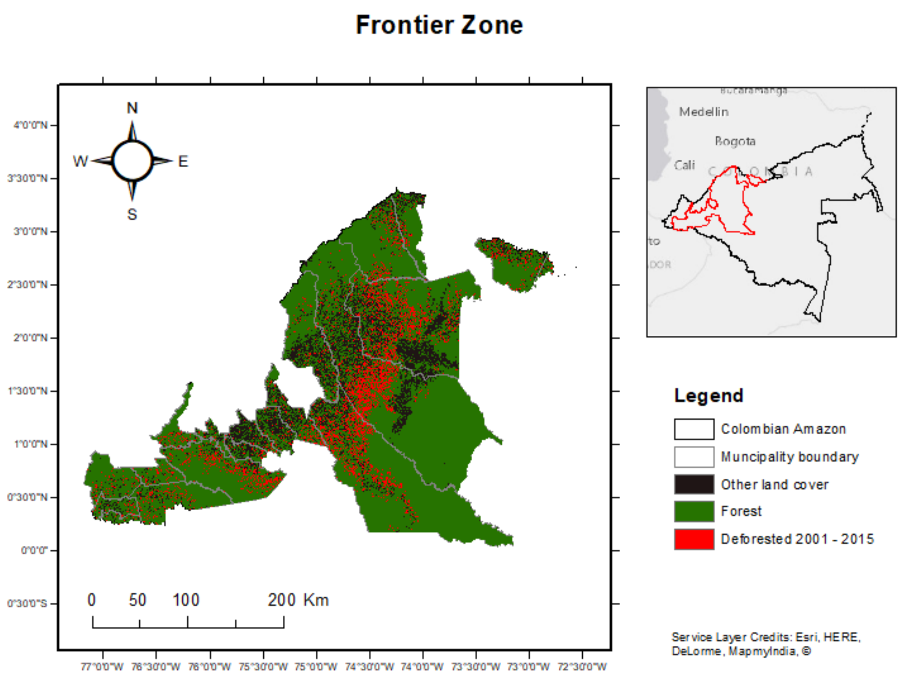

Figure 3. Administrative division at the municipality level including the municipalities with higher deforestation rate (frontier zone).

3.2. Areas of conflict and non-conflict

The municipalities and Thiessen polygons were classified in accordance to the presence or absence of any armed-conflict related event. The conflict – non-conflict classification of municipalities and Thiessen polygons is presented in the figure 4.

The analysis shows that armed-conflict related events occur more often in populated areas, as also found by Baumann and Kuemmerle (2016). In addition, areas with low accessibility or dense forests such as those in the Brazil-Peru-Colombia border (south and south-east) seems to have reduced presence of armed-conflict events.

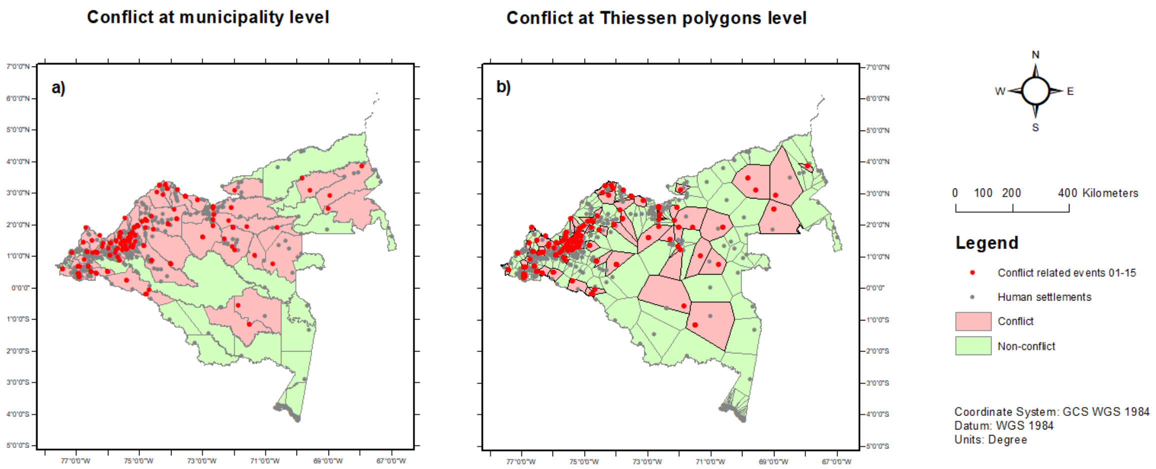

Figure 4. Map of conflict and non-conflict affected municipalities a) at municipality level b) at Thiessen polygons level.

3.2.1. Differences in deforestation rates in areas with and without presence of armed conflict events.

The annual average of deforested area was approximately 0.18% for the entire Amazon. The total forest lost in the study area between 2001 and 2015 represents 2.54% of the total forest in 2000. this is equivalent to approximately 115,000 km2 (figure 2). The average annual deforestation rate per municipality was 0.74%. The most deforested areas were observed in the municipalities of San Vicente del Caguán, Cartagena del Chairá y La Macarena with 149,000, 147,700, and 125,500 ha, respectively. Higher deforestation rates were observed in the La Macarena, Solita, Montañita and El Paraiso, with around 18% of the forest lost in each municipality, in the period 2001-2015. This translates into an annual average forest loss of approximately 1.28%.

The normality tests for deforestation rates in conflict and non-conflict municipalities and Thiessen polygons resulted in p-values < 0.001, meaning that deforestation rates of municipalities and of Thiessen polygons are not normally distributed. Therefore, the differences in deforestation rates between conflict and non-conflict areas were evaluated using Kruskal-Wallis test. For the municipalities, the results showed p-values <0.001, meaning statistically significant differences between deforestation rates in conflict and non-conflict municipalities. By contrast, results for the Thiessen polygons showed no difference in deforestation rates between conflict and non-conflict areas.

In conclusion, there were significantly higher deforestation rates (Kruskal-Wallis test; $P<0.01$) in municipalities affected by armed conflict, compared to municipalities that were not affected by armed conflict. However, these differences disappeared when the comparison was based on Thiessen polygons (Figure 5).

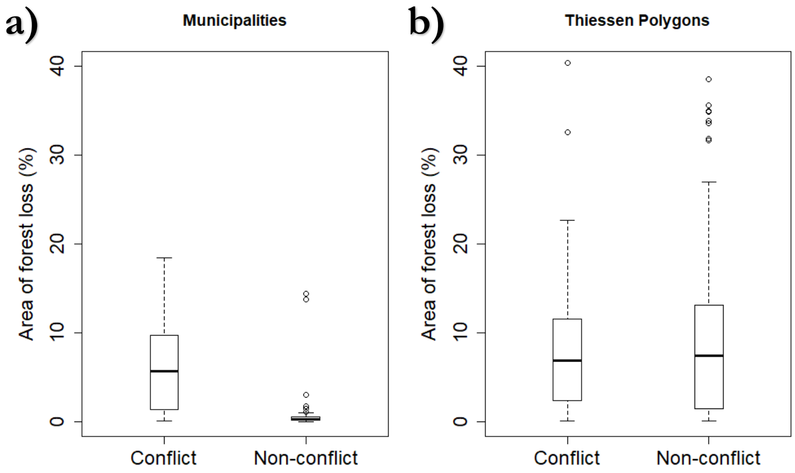

Figure 5. Boxplots of the deforestation rates in conflict and non-conflict a) municipalities b) Thiessen polygons.

3.3. Relationships between conflict variables and deforestation

3.3.1. Armed-conflict related events and landmines

The analysis of deforestation for the entire Amazon showed that the deforestation rate declines as the distance from conflict related event increases (figure 6a). A similar behaviour was observed for the landmines (figure 6b). Additionally, the analysis of human settlements shows a comparable trend (figure 6c). At this point, it is rather complex to differentiate the individual effects of each of these two conflict variables on the deforestation rate.

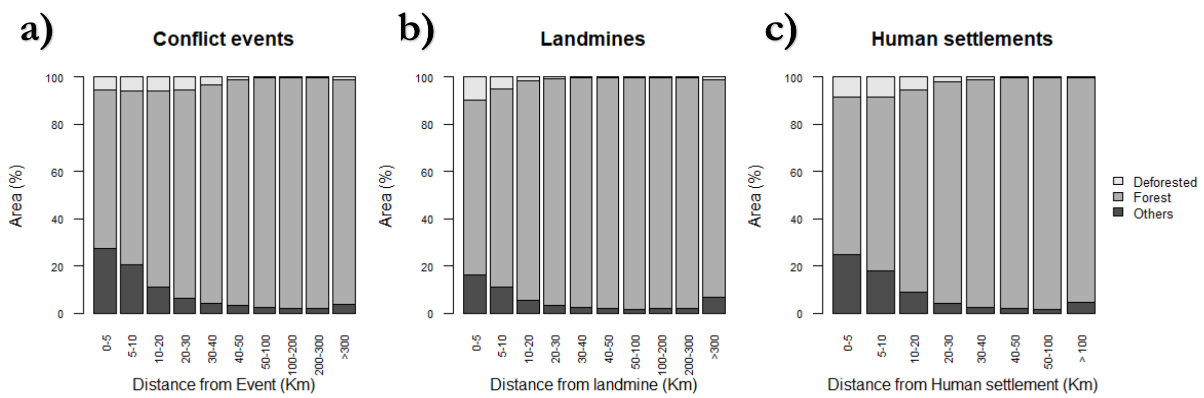

Figure 6. Distribution of Forest, non-forest, and deforestation in relation proximity to: a) conflict events, b) Landmines, c) Human Settlements[3]

[3] Distance categorization of human settlements has less classes because on distances >100 km the only landcover is forest.

3.3.2. Coca plantations

The study of data on coca cultivated areas showed a Pearson's correlation of 0.40 between the percentages of municipality areas planted with coca crops and the deforestation rate per municipality (figure 7). Since coca planted areas are, in general, small in relation to the municipality area, the data was transformed - only for visualization purposes - using the natural logarithm of the values. This enhanced the visibility of the relationship in the plot. The average area of coca cultivated in the municipalities of the region is 424.15 hectares. Thus, the mean area occupied by this illicit crop is around 0.086 % of the mean municipality area.

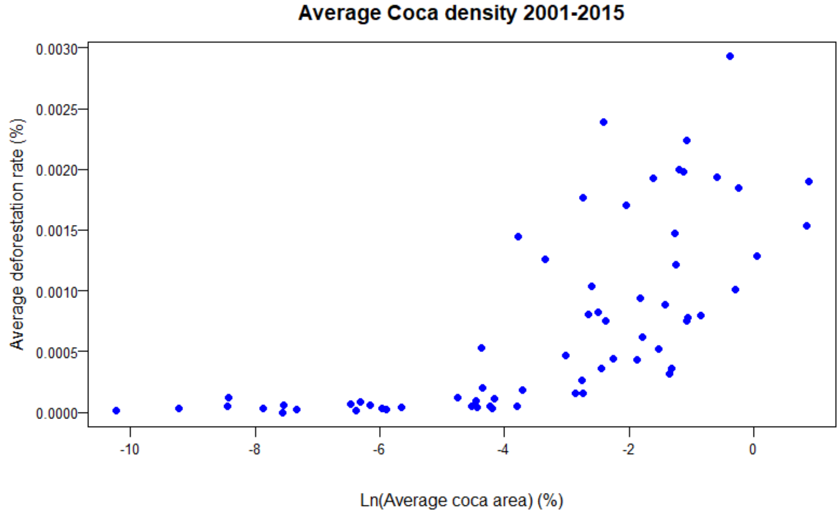

Figure 7. Scatterplot showing the correlation between deforestation rate and of density of coca plantations per municipality.

3.3.3. Forced migration

The Pearson correlation test between rates of deforestation and the expelled people per municipality was 0.54, while the correlation of deforestation with received people per municipality was 0.03. This means that incoming victims of displacement per municipality do not explain deforestation. However, people expelled out of the municipality (forced to migrate) has a moderate correlation to the deforestation process. Figure 8 shows how deforestation rates correlate to forced migration.

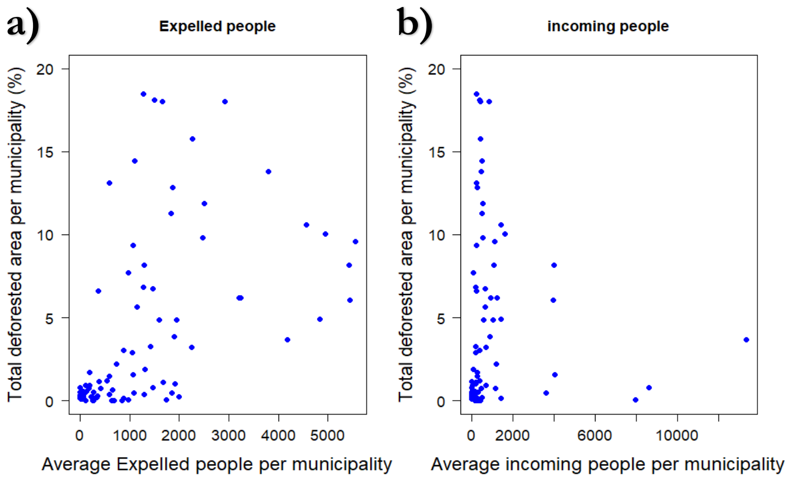

Figure 8. Relationship between forced migration and deforestation a) expelled people, b) incoming people

3.4. Selection of most relevant variables to explain deforestation

3.4.1. Multicollinearity test

Results of the multicollinearity test show that all the variables tested showed Variance Inflation Factors (VIF) lower than 4. This indicates that possible multicollinearity problems are not present between covariates, consequently they are fit to be included in the stepwise regression.

Table 2. Variation Inflation Factor (VIF) of the explanatory variables

Variable	VIF
Mean elevation	3.22
Mean slope	2.73
Distance to roads	1.92
Distance to settlements	1.87
Land inequality	1.6
Distance to armed-conflict events	1.48
Distance to landmines	1.40
Protected areas	1.39
Average annual precipitation	1.38
Coca density	1.14
Distance to forest edge	1.11
Mean population (2010-2013)	1.07
Distance to rivers	1.07

3.4.2. Most relevant explanatory variables

The training datasets used to perform the bootstrapping procedures had the following characteristics:
The distribution of the deforestation observations in the Amazon training sample set was 1 % of deforested observations and 99% non-deforestation observations. The training sample set of the frontier zone showed a distribution of the observations of 5.5% of deforestation, compared to 94.5% non-deforestation observations.

Based on the Amazon training dataset, the bootstrapping for the Amazon (figure 9) shows that distance to roads is the variable that has more power to explain deforestation, followed by distance to antipersonnel landmines, average annual precipitation, average population density, distance to armed conflict events, distance to forest edge, land inequality, distance to human settlements and annual average precipitation.

On the other hand, distance to rivers, distance to forest edge, coca density, protected areas and slope did not fulfil the selection threshold (at least 50% p-value < 0.05). Therefore, these were not considered for the final Amazon model.

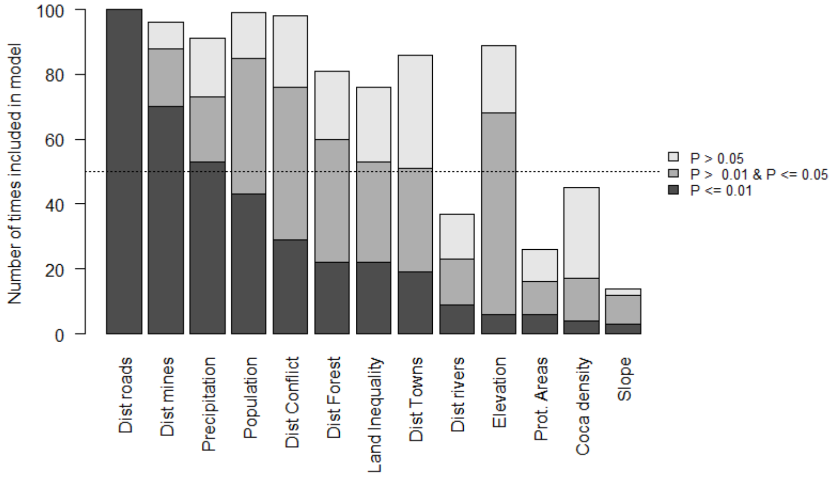

Figure 9. Number of times a variable was retained in a stepwise model for the Amazon during the bootstrapping routine in combination with the level of significance (grey scales). The dashed line indicates the 50% threshold used to filter covariates.

Based on the frontier zone training dataset, the bootstrapping for the frontier zone (figure 10) shows a generalized increase in the significance of variables, compared to the Amazon model. Variables such as average population density, distance to roads, distance to rivers, distance to human settlements, distance to forest edge, elevation, coca density, average annual precipitation and distance to armed conflict events displayed p-values lower than 0.01 in most of the cases. Land inequality, slope, protected areas and distance to antipersonnel landmines were not consistently included in the stepwise models, as they did not fulfil the 50% threshold condition set previously.

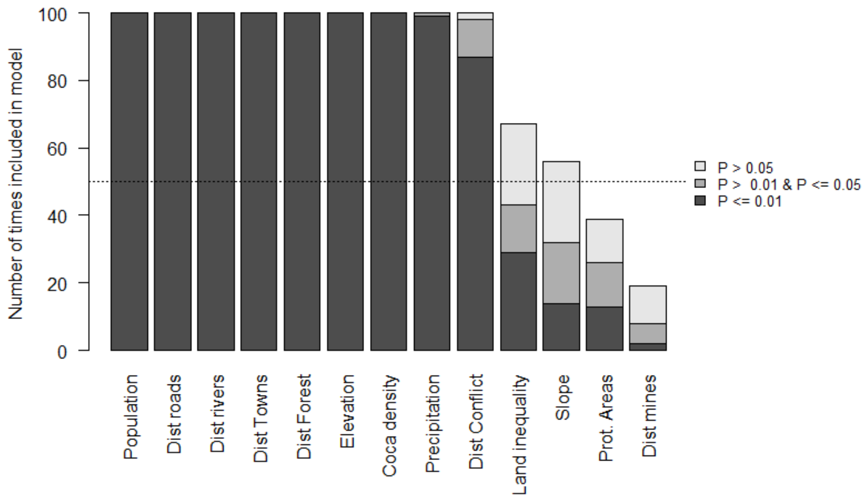

Figure 10. Number of times a variable was retained in a stepwise model for the frontier zone during the bootstrapping routine in combination with the level of significance (grey scales). The dashed line indicates the 50% threshold used to filter covariates.

There are several differences between the Amazon and the frontier model bootstrapping stepwise regressions results. In first place, the number of variables with high significance (p-value < 0.01) is greater in the frontier zone models. The second difference is that, while one of the most relevant variables for the Amazon case is distance to landmines, this variable seems to be not relevant for the frontier zone. By contrast, distance to rivers seems very relevant for the frontier case, but not for the Amazon case. Finally, coca density seems to be relevant only in the frontier zone case.

3.4.3. Sensitivity of the deforestation models associated to the training set

The bootstrapping presented in previous sections was also used at this stage to test model robustness. The standard deviation map of the Amazon (figure 11a), product of the stepwise regressions, shows that, for the case of the Amazon model, high variability is expected in areas in the south-western part of La Macarena, east of San Vicente del Caguán, central and south west of Puerto Rico, the central part San Jose del Guaviare, central part of Mapiripan and south of la Uribe (figure 11b). Overall the areas with low predicted deforestation probabilities seems to be more robust, than the areas where deforestation probabilities are high. In conclusion, the predictions of the Amazon model for these areas are most sensitive to the sample used and need to be interpreted with caution.

On the other hand, the standard deviation map of the frontier zone (figure 11c), shows high variability in the south east of La Macarena, central San Vicente del Caguán, as well as the south of Cartagena del Chairá. Therefore, deforestation predictions of the frontier zone model, for these areas, may present uncertainties.

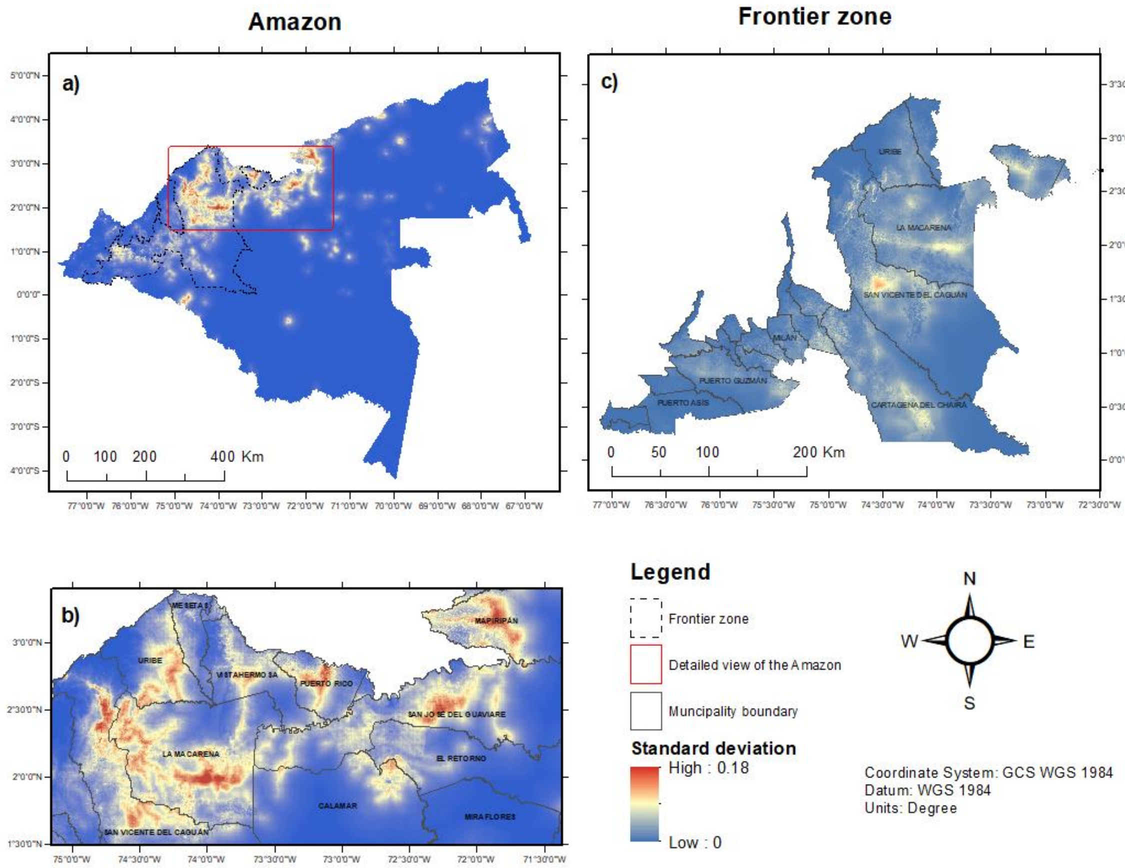

Figure 11. Standard Deviation maps calculated from 100 stepwise regressions. a) Amazon b) hotspots Amazon c) Frontier zone

3.5. Amazon and frontier zone models of deforestation

3.5.1. Significance of explanatory variables in the deforestation models

Using the best explanatory variables selected from the bootstrapping, two Logistic Regression Models (LRMs) were fitted (table 3), one for each study extent (Amazon and frontier zone). Later, those models were applied for a non-conflict scenario. In the case of the Amazon, the most significant covariates (p-value < 0.01) in the LRM were: distance to roads, distance to antipersonnel landmines, average population density and average annual precipitation. Other important variables (p-value < 0.05) were elevation, land inequality, distance to armed conflict events and distance to human settlements. Finally, distance to forest edge showed less significance (p-value < 0.1).

On the other hand, the model estimates for the frontier zone (table 3) show that all the variables were highly significant (p-value < 0.01), however distance to armed conflict events showed a positive sign, opposite effect compared to the Amazon model.

Table 3. Regression results for deforestation explanatory variables of the Amazon and frontier zone models.

	Amazon			**Frontier**		
Variables	Estimate	Pr(>|z|)	Sign	Estimate	Pr(>|z|)	Sign
Distance to roads	< 0,001	**< 0,001**	-	< 0,001	**< 0,001**	-
Distance to landmines	< 0,001	**0,005**	-	n.a	n.a	n.a
Average population density	-0,144	**0,007**	-	-0,098	**< 0,001**	-
Average annual precipitation	-0,001	**0,008**	-	-0,001	**< 0,001**	-
Elevation	-0,002	**0,025**	-	-0,004	**< 0,001**	-
Land inequality	1,743	**0,029**	-	n.a	n.a	n.a
Distance to armed conflict	< 0,001	**0,032**	-	< 0,001	**< 0,001**	+
Distance to human settlements	< 0,001	**0,034**	-	< 0,001	**< 0,001**	-
Distance to forest edge	-0,001	0,056	-	-0,001	**< 0,001**	-
Distance to rivers	n.a	n.a	n.a	< 0,001	**< 0,001**	
Coca	n.a	n.a	n.a	-1,295	**< 0,001**	-
Constant	1,962	0,129	+	0,581	0,026	

3.5.2. Predictions of deforestation for the scenarios

The estimated probability of deforestation for the entire Amazon in the conflict scenario (figure 12a) suggests higher probabilities of deforestation in the north and north west of the Amazon, specifically in Caquetá, Guaviare and south of Meta departments. Low deforestation probabilities are mostly clustered in areas of reduced accessibility. Incidentally, municipalities commonly affected with deforestation and with high populations show higher probabilities than those less populated.

The map of deforestation predictions for the non-conflict scenario of Amazon model (figure 12b), shows high deforestation probabilities in similar areas as the conflict scenario. However, in the colonization front, deforestation probabilities seem to be consistently lower than in the conflict scenario. For the non-conflict scenario, new deforestation risks are predicted for areas in the north of Guaviare and around Leticia, in the southern part. Similarly, deforestation risks increase in low accessible areas that have been previously deforested.

The deforestation predictions for the frontier case show that, in the conflict scenario (figure 12c), deforestation probabilities range between 0 to 0.18. These are high in the central areas of La Macarena and San Vicente del Caguán, as well as in the south of Cartagena del Chairá. On the other hand, the non-conflict scenario for the frontier zone (figure 12d), shows probabilities between 0 and 0.99. High probabilities are widespread in all the municipalities.

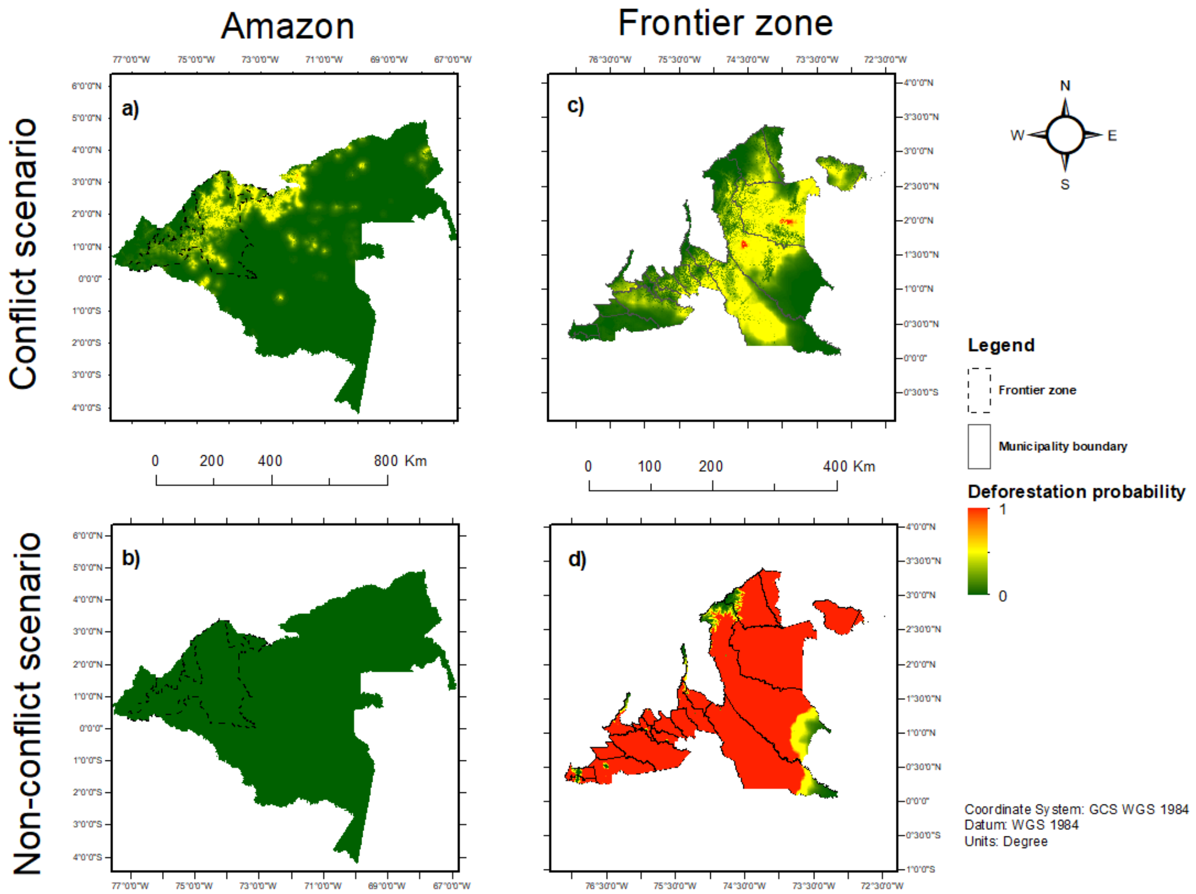

Figure 12. Deforestation probability maps. a) Amazon, conflict scenario. b) Amazon, non-conflict scenario. c) frontier zone, conflict scenario. d) frontier zone, non-conflict scenario.

3.6. Performance of the deforestation models

Performance of the models seems satisfactory given relatively high ROC curves. The Amazon model showed an Area Under the Curve (AUC) of 0.91 (figure 13a), while the AUC of the frontier zone model was 0.83 (figure 13b).

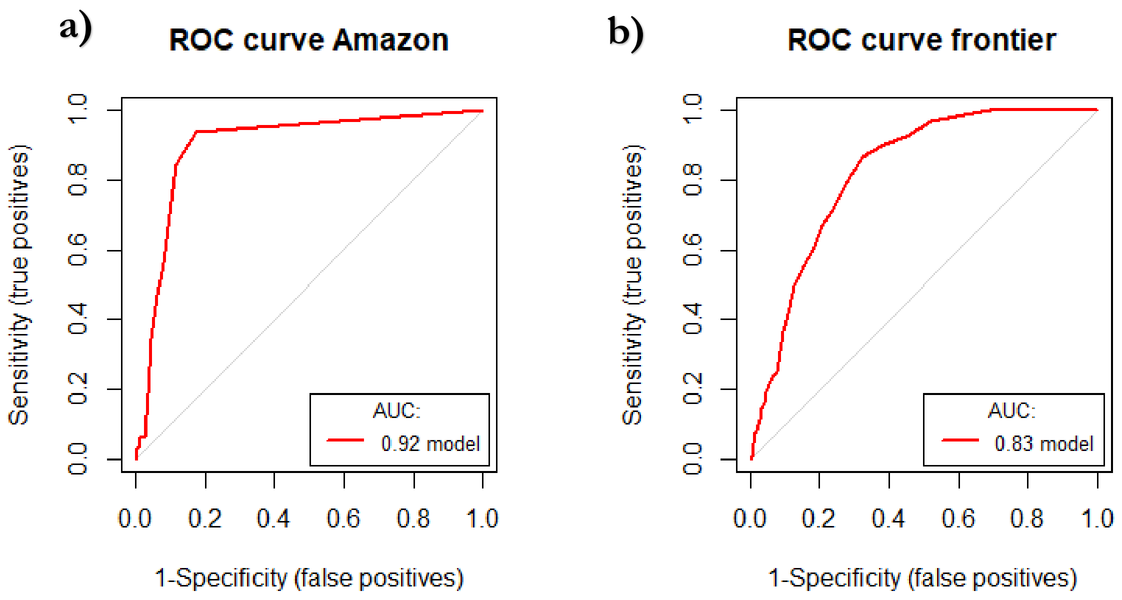

Figure 13. ROC and AUC for the deforestation models. a) Amazon b) frontier zone.

The Amazon model display a maximum kappa threshold of 0.04 (figure 14a). This means that according to the model in the conflict scenario, nearly 58000 km^2, or roughly 10% of the Colombian Amazon forest would be at risk of deforestation. On the other hand, the Amazon model suggests that 0% of the area is under risk of deforestation in the non-conflict scenario. It is important to highlight that deforestation probabilities cannot be directly translated in to allocated deforestation.

The crossing point of specificity and sensitivity suggest a similar threshold to the maximum kappa value. Therefore, selecting the sensitivity-specificity crossing point as threshold would yield similar areas as those predicted with the maximum kappa.

The frontier zone model (figure 14 b) shows a maximum kappa threshold of 0.12, which can be translated as nearly 12000 km^2, an area equivalent to approximately 15% of the frontier zone. For the non-conflict scenario, roughly 73000 km^2, or 93% of the frontier area is under deforestation risk, according to the model.

In both models, the range of high kappa values is reduced, this is associated to the unbalanced samples used to build the models.

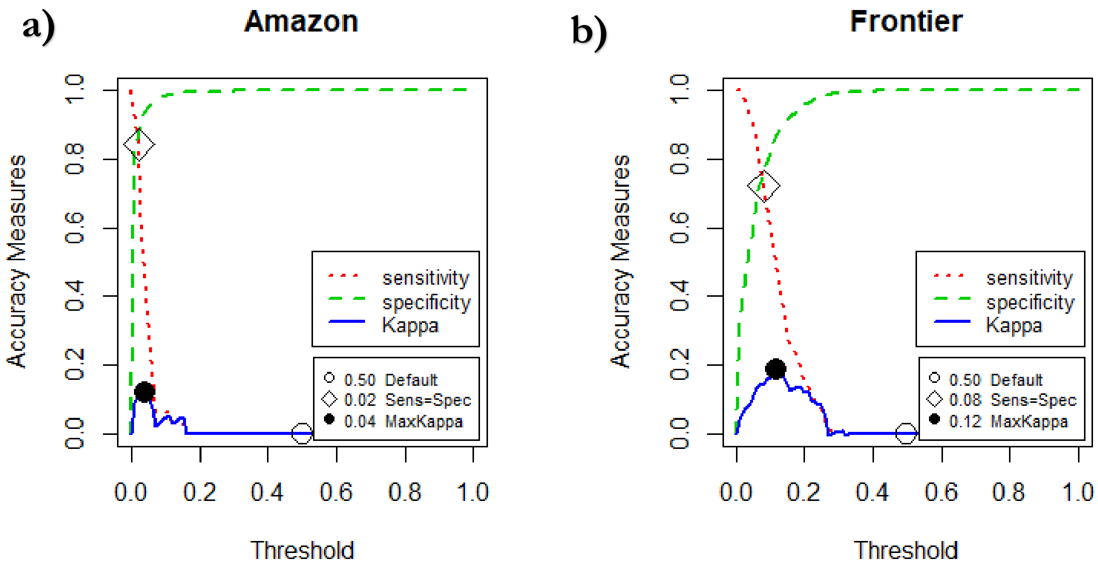

Figure 14. Kappa maximization curve a) Amazon model b) Frontier zone model

4. DISCUSSION

The results of this research contribute to the understanding of links between armed-conflict and deforestation in the Colombian Amazon. Even though previous studies have proposed deforestation models (Armenteras et al., 2006; Dávalos et al., 2011; Etter and McAlpine, 2007), this is the first predictive model that includes the effects of armed-conflict, including a scenario of reduced conflict. This research assesses how a reduction of armed conflict-related events associated to the peace accord would affect the loss of Amazon rainforest in Colombia. As general outcome of this study, the relevance of armed conflict variables to explain deforestation was evaluated. Findings indicate that, i) conflict is not the main driver of deforestation ii) the effect of conflict on deforestation, depend on the scale of the study (Amazon and frontier zone). Thus, showing negative effects in areas most affected by deforestation, but increase at the general scale.

4.1. Are deforestation rates in the Colombian Amazon higher in conflict or non-conflict areas?

The first objective of the research was to analyse differences in deforestation rates for conflict and non-conflict areas. The classification of areas in relation to the presence or absence of conflict allowed us to compare the deforestation rates accordingly. The analyses suggested that the units of study might yield different results. For example, the difference in deforestation rates between the conflict and non-conflict areas is clear when the unit of analysis is the municipality. However, when analysed based on Thiessen polygons, the data does not indicate clear differences between these two situations. This might be related to the distribution of conflict across the study area. Since armed conflict events are mostly clustered around highly populated areas, and incidentally, those areas are more accessible. Therefore, the observed differences might be the result of low accessibility, rather than a result of the conflict. On the other hand, when the area is divided according to human settlements, the classification of conflict and non-conflict seems to be more detailed. Therefore, the accessibility differences between conflict and non-conflict areas are less evident. Additionally, in the case of the Thiessen polygons, the population density is distributed among units. Thus, the effect of population density on deforestation is less clear.

It was also observed that armed conflict events are in general clustered around human settlements, which is in line with previous findings (Baumann and Kuemmerle, 2016). The large size of municipalities in the study area, obstructs the accurate characterization of conflict and non-conflict zones. The Thiessen polygons correct this problem, since the divisions were smaller compared to municipalities and these were based on human settlements which indirectly link them to the armed conflict.

One of the initial expectations of this study was that conflict areas show lower deforestation rates than non-conflict ones. The findings suggest that this is not the general rule in the Amazon. Álvarez (2003) reported that the so-called 'gunpoint' conservation was protecting forests in areas such as La Macarena as they were used as hideaways by rebel troops. Nonetheless, at the same time the promotion of grassland establishment, as means of land appropriation, was commonly encouraged by illegal armed groups. La Macarena and San Vicente del Caguán are examples of municipalities regularly controlled by the FARC and, at the same time, largely affected by deforestation (Álvarez, 2003; Etter et al., 2006a).

Similar deforestation rates in conflict and non-conflict areas were found. This might be due to the indirect effect of conflict on the deforestation process. Previous studies in Congo revealed that annual rates of deforestation in primary forests during the war time were more than double than those in the post-war time (Butsic et al., 2015; Nackoney et al., 2014). During that same conflict, people moved into the forests to escape of the war which resulted in high population pressures inside the primary forests. Similarly, in the Caucasus, forests disturbance rates were higher during the war than in the post-war period, however is relevant to mention that compared to other land covers, forests were the less transformed (Baumann et al., 2015). These cases do not reflect the Colombian situation, where most of the displaced victims migrate to urban centres, and the abandoned land is seized by illegal groups (Ibañez and Vélez, 2007).

In Rwanda, the differences in the deforestation rates during armed conflict and post conflict were little (Ordway, 2015). The patterns of forest loss in relation to distance to conflict events, or conflict affected settlements, in Rwanda, coincide with the Colombian Amazon. In both cases, areas closer to armed conflict events or human settlements present higher deforestation, and as the distance increases the deforestation decreases.

4.2. What can explain deforestation in key areas in the Colombian Amazon?

The second objective of this research was oriented towards the elucidation of relationships between deforestation drivers - including conflict - and the deforestation process. Our results suggest that the main drivers of deforestation are road infrastructure and population density (table 3). At the same time, armed conflict variables, such as armed conflict events and distance to antipersonnel landmines, partially explain deforestation in combination with other factors.

Road infrastructure has been widely documented as a driver of deforestation. More than 50% of deforestation in the Amazon takes place within 50 kilometres of a road (Barber et al., 2014; Baumann and Kuemmerle, 2016; Geist and Lambin, 2001; Nepstad et al., 2001; Reymondin et al., 2014; Veldkamp and Lambin, 2001). Our results are in line with such findings. Nonetheless, they oppose to some of the previous studies of the area that suggest that rivers play a more important role than road infraestructure (Armenteras et al., 2006; Etter et al., 2006b). A key discussion point is the difference between road dataset used in each case. Although the official road network dataset is available on IGAC geoportal, it only includes the primary roads and it is outdated. On the other hand, the OSM road dataset, used in the present study, includes an updated and more detailed inventory of roads. Consequently, the increased number of roads included in the present study may increase the understanding of links between road infrastructure and deforestation.

Distance to rivers has been previously identified as a deforestation proxy in the Amazon (Barber et al., 2014; Geist and Lambin, 2001; Nepstad et al., 2001). The findings of this study illustrate that those are more important at the frontier zone than at the Amazon level. Unexpectedly, the sign of the relationship between these variables is positive, which suggest that, the farther away from rivers, the higher the deforestation rate. These contrasts with previous results that indicate that deforestation is worsened in proximity to rivers (Armenteras et al., 2006; Etter et al., 2006b). A possible explanation for this result is that the area where deforestation prevails coincides with an area where highest distance to rivers exist. Besides, the conclusions in the previous studies were based on deforestation and landscape patterns, which differ from the approach of the present study. Or in other case of Etter et al (2006b), the rivers dataset only included navigable river network which is less dense than the complete river network of OSM.

Human settlements trigger deforestation processes as well. Accessibility increased by road infrastructure expansion results in the establishment of settlements and colonization fronts (Geist and Lambin, 2001; Lambin et al., 2001). In the Colombian Amazon, the establishment of new settlements occurred in previous decades (Rodríguez, 2014). Nevertheless, nowadays deforestation is associated with the expansion of the agricultural frontier (Armenteras et al., 2013a, 2013b; Dávalos et al., 2014). Results of the present research indicate that population density is an important driver of deforestation. The results concur with other findings for this region (Armenteras et al., 2006; Sanchez-Cuervo et al., 2012). Thus, the relationships between high population densities and high deforestation rates seem to be relevant on the study area.

The results of this research indicate that the inequality in land distribution is relevant only at the Amazon level. A possible explanation is that in the Amazon areas the most equally distributed land (pristine forest owned by the state) overlaps with areas of no deforestation. On other hand, areas where land is less equally distributed, generally overlap with deforested areas. This contrast makes it relevant at the Amazon level. In the case of the frontier zone all the area shares similar values of land inequality, which prevents the identification of clear relationships between the land inequality and the deforestation. In conclusion, the inequality in land distribution is not explaining de deforestation, this is similar to results of Castro-Nunez et al (2017) where the authors point land inequality as a less relevant factor of deforestation for this area of the country.

In the case of biophysical variables, we observed that lowlands are more susceptible to be deforested. Although slope had been mentioned as a relevant factor to consider in the deforestation process (Armenteras et al., 2013a; Etter and McAlpine, 2007), it seems that, for our study area, the slope variable is not relevant. In the study area, the deforestation takes place in flat areas, but the non-deforested areas are also abundant in areas of reduced slope. Therefore, the model is unable to associate the slope with the deforestation only. Precipitation was significant in both models, since the distribution of deforested areas occurs at the same precipitation ranges (1500-2500 mm).

Protected areas have been acknowledged as an effective policy measure to reduce forest loss (Dávalos et al., 2016; Leblois et al., 2017; Leisher et al., 2013). In this research, we also tested the associations between protected areas and deforestation. The results suggest that protected areas have no influence on the deforestation process, similar results were obtained by Armenteras et al (2006). These outcomes contradicts results by Etter et al (2006b) and from Dávalos et al (2011). The difference may be rooted in the protected areas considered in each case. While in previous studies natural parks and IUCN protected areas were considered, the present study considers all types of legally protected areas including natural parks and areas defined as protected by laws of forest protection at national and regional levels. The Colombian Amazon is considered a forest reserve, which, in theory, is protected by law; nevertheless, most of the deforestation takes place inside this protected area. Law enforcement is applied with more rigor in natural parks.

From the conflict variables, different relationships between distance to armed conflict-related events at the Amazon level and the frontier zone were observed. At the Amazon level, the closer the armed conflict event, the higher the deforestation, while at the frontier zone, results show the opposite. At the Amazon level, this might be the result of the links between conflict and population. Thus, areas with high population densities present also high number of conflict, and at the same time more deforestation. When the distance to the conflict increases, the population density and de deforestation also decrease. By contrast in the frontier zone the behaviour is different since deforestation seem to prevail in areas relatively distant to armed conflict events. This could be an example of how the conflict reduced the pressure on forests.

Distance to landmines is relevant at the Amazon level but not at the frontier zone. Presence of landmines may become a risk to agricultural activities, therefore, deforestation is expected to stay far away from landmine areas (Baumann and Kuemmerle, 2016). Our results show that, indeed, the deforested areas prevail in areas far from landmines. However, the presence of landmines may serve as indicator of areas under armed conflict. Unfortunately, landmines-related events were not considered in the initial classification of conflict and non-conflict areas. The effect of landmines has not been studied in detail, therefore, further research in this regard is recommended.

Even though the use of casualties as conflict variable was not tested, due to multicollinearity issues with the armed-conflict events (the events are the same, but they fluctuate on number of casualties). Previous literature indicated no difference in model results, when the number of victims was used instead of armed conflict events (Butsic et al., 2015).

Surprisingly, the density of coca plantations did not show any significant effect on deforestation at the Amazon level. While some of the previous studies also agree with such findings (Armenteras et al., 2013a), others (not focused particularly in the Colombia Amazon) did find associations between the two phenomena (Dávalos et al., 2011). One reason for this could be the type of data used in this analysis, since it was aggregated by municipality and, as we previously discussed, large extents tend to cover the singularities present on the ground. By contrast, at the frontier zone, the density of coca plantations appears to impact the deforestation process. In the case of Colombia, the role of forests as resources to maintain the armed conflict is secondary. Drug trafficking, illegal mining and land grabbing, provide higher revenues than those derived from forests products (Álvarez, 2003; Fergusson et al., 2014; Ibañez and Vélez, 2007; Idrobo et al., 2014). It has been reported that drug trafficking is linked to deforestation in Central America. Where different forest are cleared to launder illegal profits (McSweeney et al., 2014). This may apply to the Colombian context, thus, explaining why illicit coca crop density may have impacts on deforestation rates in the frontier area. In summary, the expansion of the grasslands in the north-western Amazon is not related to the increase in beef or agricultural production or fuelwood harvesting, but driven by the increased value of the cleared land (Dávalos et al., 2014; McAlpine et al., 2009).

To conclude, armed conflict is a complex phenomenon that is attached to social and institutional contexts (Castro-Nunez et al., 2017). Despite the impacts of armed conflict on human development, there are still gaps in the measurement of armed violence. Although some indicators have been proposed (Geneva Declaration Secretariat, 2008), these might be subject to deliberation. This condition must be considered in the interpretation of the present research results.

4.3. Are deforestation rates likely to change in the future, following the peace accord?

Deforestation risk maps at the Amazon level indicated higher deforestation risks in the conflict than in the non-conflict scenario. These results might be product of difficulties of the Amazon model to depict specific relationships of conflict with deforestation. The large size of the Amazon area is linked to high spatial variability in the factors that explain deforestation, for this reason, a general model might fail to depict those details.

By contrast, at the frontier zone level, the results indicate that conflict decreases deforestation, and a reduction of the conflict would increase the deforestation risk. Those results are not surprising, since our initial expectation was that the end of the conflict may result in higher forest threats (Álvarez, 2001; Baptiste et al., 2017; Debroux et al., 2007; Sierra et al., 2017).

Even if the overall performance of the models is good (AUCs > 0.8), a careful examination is necessary to interpret the result of the models. The standard deviation maps, derived from the bootstrapping of stepwise regressions indicate that, there are areas where the deforestation risks predictions are less reliable. This is due to the sensitivity of the model to the sample set variations. Incidentally, the random sample used to create the models is composed 99% of non-deforestation events, which makes the prediction of deforestation less accurate. Since, the probability of deforestation differs of the allocated deforestation, an allocation process would help to prioritize areas based on realistic expected deforestation rates.

To conclude, a reasonable interpretation of the model could be that, at the Amazon level, the deforestation may decline in a non-conflict scenario, but in the frontier zone the deforestation is expected to increase.

The assumption of the non-conflict scenario was the reduction of armed conflict events, as well as the reduction of landmines incidents, and a reduction of 100% of areas cultivated with coca. However, the model did not include secondary effects of the peace accord, such as change in population densities, or increased accessibility by improvements of road infrastructure, that certainly would trigger deforestation risks.

As results suggest, relevance of road accessibility and population is higher than relevance of armed conflict variables. In consequence, an evaluation of a scenario where changes in road infrastructure and population density associated to reduction of the armed conflict are considered, would be valuable to increase the understanding of possible effects of the peace accord on forest loss.

Nowadays, the national government is making efforts to improve the accessibility to remote areas around the country, including road projects in the Amazon area, specifically in Putumayo, Caquetá and Guaviare (INVIAS, 2016). These development plans need to contemplate the role of new, or better roads on the increase of deforestation, thus adopting the necessary measures that benefit isolated communities while avoiding the depletion of forest resources.

Benefits derived from the peace agreement go beyond the reduction of related armed conflict events. Expectations include the increase of economic activities in areas affected by the armed conflict. Those imply the reactivation and promotion of investments in agriculture, tourism, mining and rural enterprises at small, as well as, at large scales (Morales, 2017). Thus, estimations of new settlers attracted by the new economic opportunities are key to improve the understanding of the future of key natural resources in this area of the country.

5. CONCLUSIONS

Deforestation is a complex phenomenon that has different drivers. The results of this study show the spatio-temporal specificity of the deforestation process, as well as the variability of the factors linked to forest loss.

Differences in deforestation between conflict and non-conflict areas depend on various factors. The indicators used and the the division of the area of study are factors that influence the conflict categorization. As shown in this research, the use of administrative divisions might not be the best approach to explore relationships of phenomena that are not strictly linked to political divisions of the territory. The results also show how the extent of the study area might influence the results of a study, to the point of obtaining contradictory results.

The results of this research confirm that, although deforestation and conflict take place in similar areas of the Colombian Amazon, the effects of conflict on deforestation are not easy to identify. There are numerous variables related to the armed conflict, which, if taken individually, do not show clear relationships with the deforestation process. As previous research suggests, when those variables are studied together, their effects might be more easily identified (Harwell, 2010; Ordway, 2015).

The quality of data used in the predictive model influences the accuracy of the results. Consequently, the availability of spatially-disaggregated and up-to-date datasets is a key step to improve forecasting actions. The accurate identification of factors affecting deforestation is essential for designing strategies to mitigate the problem.

In the case of the Colombian Amazon, rivers were spotted as main drivers of deforestation. These results suggest that roads are also a relevant driver to consider. Additionally, population density influences the deforestation process. This calls for attention on the need of effective land administration systems. As suggested by Todorovski (2016), efficient land administration is a key process that needs to be addressed in early stages of the post-conflict. This goes in hand with effective protection of natural areas and primary forest. The efforts should go beyond the definition of protection laws. The enforcement of the protection laws should be a priority.

Even though the reduction of conflict may result in increased risk of forest loss, it also represents a key moment for conservation planning (Butsic et al., 2015). The post-conflict scenario opens the possibility to include sustainable development objectives in the socio-economic development agenda.

As deforestation data of the Colombian Amazon in post conflict settings is still reduced, different approaches are needed to forecast the effects of the reduction of armed conflict events. For instance, Reymondin et al (2014) proposed a methodology to use experiences from similar contextual characteristics to fill the data gaps. Thus, the experience of other comparable cases where post-conflict has already taken place could be useful to forecast more accurately the Colombian post-conflict scenario.

Another option to explore, with the objective of improving the results of this study, could be the use of near real time forest loss data. Products such as Terra-i (Reymondin et al., 2012), FORMA (Hammer et al., 2007) and GLAD (Hansen et al., 2016) provide valuable up to date data on forest loss that is useful to develop a more realistic post-conflict scenario.

LIST OF REFERENCES

AICMA, 2017. Víctimas de Minas Antipersonal [WWW Document]. URL http://www.accioncontraminas.gov.co/estadisticas/Paginas/victimas-minas-antipersonal.aspx (accessed 12.8.17).

Álvarez, M.D., 2003. Forests in the Time of Violence. J. Sustain. For. 16, 47–68. https://doi.org/10.1300/J091v16n03_03

Álvarez, M.D., 2001. Could peace be worse than war for Colombia's forests? Environmentalist 21, 305–315.

Arcila, O.H., 2010. La Amazonia colombiana urbanizada Un análisis de sus asentamientos humanos. Instituto Amazónico de Investigaciones Científicas- Sinchi.

Armenteras, D., Cabrera, E., Rodríguez, N., Retana, J., 2013a. National and regional determinants of tropical deforestation in Colombia. Reg. Environ. Chang. 1181–1193. https://doi.org/10.1007/s10113-013-0433-7

Armenteras, D., Rodríguez, N., Retana, J., 2013b. Landscape Dynamics in Northwestern Amazonia: An Assessment of Pastures, Fire and Illicit Crops as Drivers of Tropical Deforestation. https://doi.org/10.1371/journal.pone.0054310

Armenteras, D., Rudas, G., Rodriguez, N., Sua, S., Romero, M., 2006. Patterns and causes of deforestation in the Colombian Amazon. Ecol. Indic. 6, 353–368. https://doi.org/10.1016/j.ecolind.2005.03.014

Baptiste, B., Pinedo-Vasquez, M., Gutierrez-Velez, V.H., Andrade, G.I., Vieira, P., Estupiñán-Suárez, L.M., Londoño, M.C., Laurance, W., Lee, T.M., 2017. Greening peace in Colombia. Nat. Ecol. Evol. 1, 102. https://doi.org/10.1038/s41559-017-0102

Barber, C.P., Cochrane, M.A., Souza, C.M., Laurance, W.F., 2014. Roads, deforestation, and the mitigating effect of protected areas in the Amazon. Biol. Conserv. 177, 203–209. https://doi.org/10.1016/j.biocon.2014.07.004

Baumann, M., Kuemmerle, T., 2016. The impacts of warfare and armed conflict on land systems. J. Land Use Sci. 11, 672–688. https://doi.org/10.1080/1747423X.2016.1241317

Baumann, M., Radeloff, V.C., Avedian, V., Kuemmerle, T., 2015. Land-use change in the Caucasus during and after the Nagorno-Karabakh conflict. Reg. Environ. Chang. 15, 1703–1716. https://doi.org/10.1007/s10113-014-0728-3

Brown, G., Langer, A., Stewart, F., Stewart Is Professor, F., 2011. A Typology of Post-Conflict Environments (No. 1).

Butsic, V., Baumann, M., Shortland, A., Walker, S., Kuemmerle, T., 2015. Conservation and conflict in the Democratic Republic of Congo: The impacts of warfare, mining, and protected areas on deforestation. BIOC 191, 266–273. https://doi.org/10.1016/j.biocon.2015.06.037

Castro-Nunez, A., Mertz, O., Buritica, A., Sosa, C.C., Lee, S.T., 2017. Land related grievances shape tropical forest-cover in areas affected by armed-conflict. Appl. Geogr. 85, 39–50. https://doi.org/10.1016/j.apgeog.2017.05.007

CIAT, 2017. Terra-i Visualisation tool [WWW Document]. URL http://www.terra-i.org/terra-i/data/data-statistics.html (accessed 6.1.17).

Collier, P., Elliot, V., Hoeffler, A., Reynal-Querol, M., Sambanis, N., 2003. Breaking the Conflict trap Civil war an development policy. Washington.

Contributors OpenStreetMaps, 2017. OpenStreetMaps [WWW Document]. URL https://planet.osm.org

DANE, 2015. Geoportal DANE - Consulta colaborativa de centros poblados y veredas (beta) [WWW Document]. URL https://geoportal.dane.gov.co/v2/index.php?page=elementoConsultaDivipola (accessed 12.8.17).

Dávalos, L.M., Bejarano, A.C., Hall, M.A., Correa, H.L., Corthals, A., Espejo, O.J., 2011. Forests and Drugs: Coca-Driven Deforestation in Tropical Biodiversity Hotspots. Environ. Sci. Technol. Sci. Technol 45, 1219–1227. https://doi.org/10.1021/es102373d

Dávalos, L.M., Holmes, J.S., Rodríguez, N., Armenteras, D., 2014. Demand for beef is unrelated to pasture expansion in northwestern Amazonia. Biol. Conserv. 170, 64–73. https://doi.org/10.1016/j.biocon.2013.12.018

Dávalos, L.M., Sanchez, K.M., Armenteras, D., 2016. Deforestation and Coca Cultivation Rooted in Twentieth-Century Development Projects. Forum Biosci. Biosci. 974, 974–982. https://doi.org/10.1093/biosci/biw118

Debroux, L., Hart, Karsenty, T., Topa, A., 2007. Forests in Post-Conflict Democratic Republic of Congo Analysis of a Priority Agenda. CIFOR, Jakarta.
DESA, 2016. The Sustainable Development Goals Report 2016, 2nd ed, The Sustainable Development Goals Report. United Nations, New York. https://doi.org/10.18356/3405d09f-en
Eden, M., 1990. Amazonia, Ecology and Land Management in. Belhaven press, London.
Efron, B., Tibshirani, R., 1997. Improvements on Cross-Validation: The .632 + Bootstrap Method. J. Am. Stat. Assoc. 438, 548–560.
Etter, A., McAlpine, C.A., 2007. Modeling Unplanned Land Cover Change across Scales, in: Aspinall, R.J., Hill, M.J. (Eds.), Land Use Change Science, Policy and Management. London, p. 178. https://doi.org/https://doi.org/10.1201/9781420042979
Etter, A., Mcalpine, C., Phinn, S., Pullar, D., Possingham, H., 2006a. Unplanned land clearing of Colombian rainforests: Spreading like disease? Landsc. Urban Plan. 77, 240–254. https://doi.org/10.1016/j.landurbplan.2005.03.002
Etter, A., McAlpine, C., Wilson, K., Phinn, S., Possingham, H., 2006b. Regional patterns of agricultural land use and deforestation in Colombia. Agric. Ecosyst. Environ. 114, 369–386. https://doi.org/10.1016/j.agee.2005.11.013
FAO, 2016. The Global Forest Resources Assessment 2015, 2nd ed. Food and Agriculture Organization of The United Nations, Rome.
Farrar, D.E., Glauber, R.R., 1967. Multicollinearity in Regression Analysis: The Problem Revisited. Source Rev. Econ. Stat. 49, 92–107.
Fergusson, L., Romero, D., Vargas, J.F., 2014. The Environmental Impact Of Civil Conflict: The Deforestation Effect Of Paramilitary Expansion In Colombia The Deforestation.
Fick, S.E., Hijmans, R.J., 2017. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. Int. J. Climatol. Int. J. Clim. 37, 4302–4315. https://doi.org/10.1002/joc.5086
Freeman, E.A., Moisen, G., 2008. PresenceAbsence: An R Package for Presence Absence Analysis. J. Stat. Softw. 23, 1–31. https://doi.org/10.18637/jss.v023.i11
Geist, H.J., Lambin, E.F., 2001. What Drives Tropical Deforestation? Louvain-la-Neuve.
Geneva Declaration Secretariat, 2008. How to Measure and Monitor AV? - Geneva Declaration [WWW Document]. URL http://www.genevadeclaration.org/measurability/how-to-measure-and-monitor-armed-violence.html (accessed 10.8.17).
González, J.., Etter, A.A., Sarmiento, A.H., Orrego, S.A., Ramírez, C., Cabrera, E., Vargas, D., Galindo, G., García, M.C., Ordoñez, M.F., 2011. Análisis de tendencias y patrones espaciales de deforestación en Colombia. Instituto de Hidrología, Meteorología y Estudios Ambientales-IDEAM, Bogotá D.C., Colombia.
Gorsevski, V., Geores, M., Kasischke, E., 2013. Human dimensions of land use and land cover change related to civil unrest in the Imatong Mountains of South Sudan. Appl. Geogr. 38, 64–75. https://doi.org/10.1016/j.apgeog.2012.11.019
Hammer, D., Kraft, R., Wheeler, D., 2007. FORMA: Forest Monitoring for Action—Rapid Indentification of Pan-tropical Deforestation Using Moderate-Resolution Remotely Sensed Data. Washington D.C .
Hansen, M., Krylov, A., Alexandra, T., Potapov, P., Turubanova, S., Bryan, Z., Suspense, I., Belinda, M., Stolle, F., Moore, R., 2016. Humid tropical forest disturbance alerts using Landsat data. Environ. Res. Lett. 11, 1–12.
Hansen, M.C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S.A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S.J., Loveland, T.R., Kommareddy, A., Egorov, A., Chini, L., Justice, C.O., Townshend, J.R.G., 2013. High-Resolution Global Maps of 21st-Century Forest Cover Change. Science (80-.). 342, 850–853. https://doi.org/10.1126/science.1244693
Hanson, T., Brooks, T.M., Da Fonseca, G.A.B., Hoffmann, M., Lamoreux, J.F., MacHlis, G., Mittermeier, C.G., Mittermeier, R.A., Pilgrim, J.D., 2009. Warfare in biodiversity hotspots. Conserv. Biol. 23, 578–587. https://doi.org/10.1111/j.1523-1739.2009.01166.x
Harwell, E., 2010. Forests in Fragile and Conflict-Affected States. Washington DC.
Holzman, B.A., 2008. Tropical forest biomes. Greenwood Press, Westport.
Ibañez, A.M., Vélez, C.E., 2007. Civil Conflict and Forced Migration: The Micro Determinants and Welfare Losses of Displacement in Colombia. World Dev. 36, 659–676. https://doi.org/10.1016/j.worlddev.2007.04.013
Idrobo, N., Mejía, D., Tribin, A.M., 2014. Illegal Gold Mining and Violence in Colombia. Peace Econ. Peace Sci. Public Pol. 20, 83–11.

IGAC, 2012. Atlas de la Distribución de la Propiedad Rural en Colombia. Instituto Geográfico Agustín Codazzi , Bogotá D.C.
INVIAS, 2016. Vias para la Equidad [WWW Document]. URL https://www.invias.gov.co/index.php/archivo-y-documentos/programa-estrategico-de-obra-publica/3809-programa-estrategico-de-obra-publica-presentacion/file (accessed 2.7.18).
Jou, Y.-J., Chien-Chia, ·, Huang, L., Cho, H.-J., Jou, Y.-J., Huang, C.-C.L., Cho, H.-J., 2014. A VIF-based optimization model to alleviate collinearity problems in multiple linear regression. Comput Stat 29, 1515–1541. https://doi.org/10.1007/s00180-014-0504-3
Kruskal, W.H., Wallis, W.A., 1952. Use of ranks in one criterion variance analysis. J. Am. Stat. Assoc. 47, 583–621.
Kuhn, M., Johnson, K., 2013. Applied Predictive Modeling. Springer Science & Business Media, New York. https://doi.org/10.1007/978-1-4614-6849-3
Lambin, E.F., Turner, B.L., Geist, H.J., Agbola, S.B., Angelsen, A., Bruce, J.W., Coomes, O.T., Dirzo, R., U Unther Fischer, G., Folke, C., George, P.S., Homewood, K., Imbernon, J., Leemans, R., Li, X., Moran, E.F., Mortimore, M., Ramakrishnan, P.S., Richards, J.F., Sk, H., Steffen, W., Stone, G.D., Svedin, U., Veldkamp, T.A., Vogel, C., Xu, J., 2001. The causes of land-use and land-cover change: moving beyond the myths. Glob. Environ. Chang. 11, 261–269.
Leblois, A., Damette, O., Wolfersberger, J., 2017. What has Driven Deforestation in Developing Countries Since the 2000s? Evidence from New Remote-Sensing Data. World Dev. 92, 82–102. https://doi.org/10.1016/j.worlddev.2016.11.012
Leisher, C., Touval, J., Hess, S., Boucher, T., Reymondin, L., 2013. Land and Forest Degradation inside Protected Areas in Latin America. Diversity 5, 779–795. https://doi.org/10.3390/d5040779
Lloyd, C.T., Sorichetta, A., Tatem, A.J., 2017. High resolution global gridded data for use in population studies. Sci. DATA. https://doi.org/10.1038/sdata.2017.1
Malhi, Y., Roberts, T., Betts, R.A., Killeen, T.J., Li, W., A., N.C., 2007. Climate Change, Deforestation, and the Fate of the Amazon. Scienceexpress. https://doi.org/10.1126/science.1146961
Maretti, C.C., Riveros, S., Hofstede, J.C., Oliveira, R., Charity, D., Granizo, S., Alvarez, T., Valdujo, C., Thompson, C., 2014. STATE Of ThE AMAZON Ecological Representation in Protected Areas and Indigenous Territories. Gland, Switzerland.
Mayfield, H., Smith, C., Gallagher, M., Hockings, M., 2017. Use of freely available datasets and machine learning methods in predicting deforestation. Environ. Model. Softw. 87, 17–28. https://doi.org/10.1016/j.envsoft.2016.10.006
McAlpine, C.A., Etter, A., Fearnside, P.M., Seabrook, L., Laurance, W.F., 2009. Increasing world consumption of beef as a driver of regional and global change: A call for policy action based on evidence from Queensland (Australia), Colombia and Brazil. Glob. Environ. Chang. 19, 21–33. https://doi.org/10.1016/j.gloenvcha.2008.10.008
McSweeney, K., Nielsen, E.A., Taylor, M.J., Wrathall, D.J., Pearson, Z., Wang, O., Plumb, S.T., 2014. Drug Policy as Conservation Policy: Narco-Deforestation. Science (80-.). 343, 489–490. https://doi.org/10.1126/science.1244082
Messina, J.P., Delamater, P.L., 2006. Defoliation and the war on drugs in Putumayo, Colombia. Int. J. Remote Sens. 27, 121–128. https://doi.org/10.1080/01431160500293708
Morales, L., 2017. Peace and Environmental Protection in Colombia: Proposals for Sustainable Rural Development.
Müller, H., Griffiths, P., Hostert, P., 2016. Long-term deforestation dynamics in the Brazilian Amazon—Uncovering historic frontier development along the Cuiabá–Santarém highway. Int. J. Appl. Earth Obs. Geoinf. 44, 61–69. https://doi.org/10.1016/J.JAG.2015.07.005
Nackoney, J., Molinario, G., Potapov, P., Turubanova, S., Hansen, M.C., Furuichi, T., 2014. Impacts of civil conflict on primary forest habitat in northern Democratic Republic of the Congo, 1990â€“2010. Biol. Conserv. 170, 321–328. https://doi.org/10.1016/j.biocon.2013.12.033
Nepstad, D., Carvalho, G., Cristina Barros, A., Alencar, A., Äo Paulo Capobianco, J., Bishop, J., Moutinho, P., Lefebvre, P., Lopes Silva Jr, U., Prins, E., 2001. Road paving, fire regime feedbacks, and the future of Amazon forests 154, 395–407.
ODC, 2017. SIDCO: Cultivos Ilícitos por municipio [WWW Document]. Obs. Drog. Colomb. URL http://www.odc.gov.co/sidco/oferta/cultivos-ilicitos/departamento-municipio (accessed 12.8.17).
Ordway, E.M., 2015. Political shifts and changing forests: Effects of armed conflict on forest conservation in Rwanda. Glob. Ecol. Conserv. 3, 448–460. https://doi.org/10.1016/j.gecco.2015.01.013
RAISG, 2012. Amazonia under pressure [WWW Document]. URL

https://www.amazoniasocioambiental.org/wp-content/uploads/2017/01/Amazonia_bajo_presion.pdf (accessed 8.8.17).
Reymondin, L., Coca, A., Arango, D., Jarvis, A., Navarrete, C., Suding, P.H., Watkins, G., 2014. Potential Impact of Road Projects on Habitat Loss and Greenhouse Gas Emissions in Guyana from 2012 to 2022. Washington.
Reymondin, L., Jarvis, A., Perez-Uribe, A., Touval, J., Argote, K., Coca-Castro, A., Rebetez, J., Guevara, E., Mulligan, M., 2012. A methodology for near real-time monitoring of habitat change at continental scales using MODIS-NDVI and TRMM [WWW Document]. URL http://www.terra-i.org/dam/jcr:508a0e27-3c91-4022-93dd-81cf3fe31f42/Terra-i Method.pdf (accessed 10.8.17).
Rodríguez, F., 2014. Colonización y poblamiento del piedemonte amazónico en el Caquetá. El Doncello 1918 -1972. Pontificia Universidad Javeriana.
Rosa, I., Purves, D., Souza, C., Ewers, R., 2013. Predictive Modelling of Contagious Deforestation in the Brazilian Amazon. PLoS One 8, e77231. https://doi.org/10.1371/journal.pone.0077231
RStudio Team, 2016. RStudio: Integrated Development for R.
Rustad, S., Rød, J.K., Larsen, W., Gleditsch, N.P., 2008. Foliage and fighting: Forest resources and the onset, duration, and location of civil war. Polit. Geogr. 27, 761–782. https://doi.org/10.1016/j.polgeo.2008.09.004
Sanchez-Cuervo, A.M., Aide, T.M., Clark, M.L., Etter, A., 2012. Land Cover Change in Colombia: Surprising Forest Recovery Trends between 2001 and 2010. PLoS One 7. https://doi.org/10.1371/journal.pone.0043943
Shapiro, S.S., Wilk, M.B., 1965. Biometrika Trust An Analysis of Variance Test for Normality (Complete Samples). Source Biometrika Biometrika Trust 52, 591–611.
Sierra, C.A., Mahecha, M., Poveda, G., Álvarez-Dávila, E., Gutierrez-Velez, V.H., Reu, B., Feilhauer, H., Anáya, J., Armenteras, D., Benavides, A.M., Buendia, C., Duque, Á., Estupiñan-Suarez, L.M., González, C., Gonzalez-Caro, S., Jimenez, R., Kraemer, G., Londoño, M.C., Orrego, S.A., Posada, J.M., Ruiz-Carrascal, D., Skowronek, S., 2017. Monitoring ecological change during rapid socio-economic and political transitions: Colombian ecosystems in the post-conflict era. Environ. Sci. Policy 76, 40–49. https://doi.org/10.1016/j.envsci.2017.06.011
Sistemas de Información Ambiental de Colombia, 2017. Catálogo de mapas [WWW Document]. URL http://www.siac.gov.co/catalogo-de-mapas (accessed 7.22.17).
Student, 1908. The Probable Error of a Mean. Biometrika VI.
Todorovski, D., 2016. Post-conflict land administration, facilitator of post-conflict state building. University of Twente, Enschede, The Nederlands. https://doi.org/10.3990/1.9789036540421
UCDP, 2016. UCDP - Uppsala Conflict Data Program [WWW Document]. URL http://ucdp.uu.se/#country/100 (accessed 4.8.17).
Unidad para la Atención y Reparación Integral a las Víctimas, R., 2017. Registro Único de Víctimas (RUV) | RNI - Red Nacional de Información [WWW Document]. URL https://rni.unidadvictimas.gov.co/RUV (accessed 12.8.17).
United Nations Framefork Convention On Climate Change, 2015. Intended Nationally Determined Contributions: Colombia.
UNODC, 2017. Monitoreo de territorios afectados por cultivos ilicitos 2016. UNODC, Bogotá D.C.
USGS, 2015. Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global | The Long Term Archive [WWW Document]. URL https://lta.cr.usgs.gov/SRTM1Arc (accessed 12.7.17).
Veldkamp, A., Lambin, E.F., 2001. Predicting land-use change. Agric. Ecosyst. Environ. 85, 1–6.
Zuur, A.F., Ieno, E.N., Elphick, C.S., 2010. A protocol for data exploration to avoid common statistical problems. Methods Ecol. Evol. 1, 3–14. https://doi.org/10.1111/j.2041-210X.2009.00001.x

APPENDIXES

APPENDIX 1 – Maps of explanatory variables of deforestation