EXAMINING THE POTENTIAL OF USING REMOTELY SENSED FIRES AND SOCIO-ECONOMIC VARIABLES TO DETECT COCA CULTIVATION IN FOREST AREAS IN COLOMBIA

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ABSTRACT

Fires in forest areas have been considered an important threat to the Andean Region and the Amazon rainforest. On many occasions the occurrence of fire is human induced. In Colombia, fire is used to expand the agricultural frontier (including illicit crops) which results in the conversion of virgin forests for cattle ranching. Given the importance of avoiding deforestation and to control coca expansion, this research has two main objectives which are: 1) To understand the relationship between fires and deforestation, coca and deforestation and hence the relationship between coca and fires; 2) To examine the potential of using remotely sensed fires and socioeconomic variables (inhabitants in rural areas, basic unsatisfied needs and expulsion) to predict the occurrence of new coca fields in forest areas in Colombia and to build a model which uses relationships between coca increment which is defined as part of this research as the sum of the increase in the area of coca cultivation between the subsequent and previous years calculated for each consecutive pair of years for the period 2000 - 2010, fires in the forest and socioeconomic variables. The analysis was assessed over a ten year period (2000-2010) at a municipality level in two areas with high coca dynamics (Central Region and Putumayo – Caquetá) by means of Pearson correlations and three different models – a Linear Probability model, a Logit model and a Probit model. The results of the analysis showed that there is a positive relationship between fire and deforestation. Although in general the correlation between coca and deforestation is positive, it differs at the municipality level depending upon the coca dynamics and the quantity of forest cover. The results of applying the Logit and Probit models showed that fire and expulsion can be used as indicators to highlight coca expansion in forest areas.

ZUSAMMENFASUNG

Waldfeuer werden als eine ernsthafte Bedrohung des Andischen Waldes und des Regenwaldes im Amazonas angesehen. In vielen Faellen is das Aufreten von Waldfeuern vom Menschen verursacht. In Kolumbien wir Feuer dazu genutzt um die Landwirtschaftlichen Flaechen (die illegalen Pflanzen inbegriffen) auszuweiten. Diesse Expansion fuehrt zum Konvertieren von Urwald zu Gebieten von Viehhaltung. Aufgrund der Wichtigkeit das Abholzen vom Urwald zu stoppen und die Expasion von Koka einzudaemmen hat diese Forschungsarbeit zwei Hauptziele: 1) Das Bessere Verstehen der Beziehung zwischen Feuer und Entwaldung, Koka Anbau und Entwaldung und daraus resultierend zwischen dem Anbau von Coca und dem Auftreten von Feuer. 2) Zu untersuchen ob das Auftreten von Feuer welche mit Satellitenbildern identifiziert werden koennen und weiteren sozio-oekonomischen Variablen (wie die Einwohnerzahl in laendlichen Gebieten, eine nicht ausreichende Grundversorgung und Vertreibung) einen Hinweis auf das Vorkommen von Kokaanbau geben kann. Weiterhin hat diese Arbeit zum Ziel, ein Model zu erstellen welches die Korrelation zwischen Koka inkrement, Waldfeuer und Sozio-oekonomische Variablen nutzt.

Die Analyse wurde in einer Periode von 10 Jahren auf der Flaecheneinheit einer Gemeinde in zwei Gebieten (Central Region and Putumayo – Caquetá) hoher Kokadynamik durechgefuehrt. Mit Hilfe der Pearson Korrelationskoeffizienten und 3 verschiedenen Modellen – lineare Wahrscheinlichkeit, einem Logit und einem Probit Model. Die Ergebnisse zeigen dass eine positive Korrelation zwischen Feuer und Entwaldung besteht. Auch ist die Korrelation zwischen Entwaldung und Koka generell positv, jedoch variiert sie in Abhangigkeit von der Kokadynamik und der Groesse des Waldes in der jeweiligen Gemeinde. Das Resultat des Logit und Probit models zeigt auf, dass Feuer und Information ueber die Anzahl der Vertriebenen dazu benutzt werden kann um Gebiete zu identifizieren wo moeglicherweise eine Expansion von Koka stattfinden wird.

Introduction

Colombia has been the biggest coca producer in the world for many years. In the last 10 years, in particular, the government has tried to control the expansion of coca through eradication and aerial spraying. However, as a result of these measures, coca has expanded to new zones in a more surreptitious manner. Since coca is illicit, people try to hide the coca crops in forest areas (Dávalos et al., 2011) and fire is used as a management tool to clear the area in order to colonize new areas where forest exists.

Given the importance of the conservation of forests and the control of coca by the Colombian government, as a first objective, this research focuses on understanding the relationship between fires and deforestation, coca and deforestation and hence the relationship between coca and fires. The second objective of the thesis is to examine the potential of using remotely sensed fires and socioeconomic variables (inhabitants in rural areas, basic unsatisfied needs and expulsion) to predict new coca fields in forest areas in Colombia and to build a model which uses relationships between coca increment, the occurrence of forest fires and socioeconomic variables.

The thesis is divided into five chapters which include: a literature review, a description of the study site and methods, the results, a discussion and the conclusions from this research.

Chapter 1 contains a literature review which is composed of a brief history of coca followed by a description of the role of coca in Colombia. Subsequently, the relationship between coca, fires and deforestation is described. The chapter finishes with a short introduction on the Integrated Illicit Crops Monitoring System (SIMCI) in Colombia.

Chapter 2 describes the study site and the methods used. The study areas were chosen with the help of SIMCI project staff. The criteria which were used to determine the selection of the study area are also described in detail.

The GIS package ArcGIS 10 (produced by the company ESRI- http://www.esri.com/software/arcgis) was used to carry out the digital spatial analyses. The Pearson Correlation was undertaken using SPSS (http://www-

01.ibm.com/software/de/analytics/spss/). The multiple regression model was built using the eViews package (www.eviews.com/home.html).

The methods therefore involved an analysis of the amount of fire in forest areas having spatial coincide with coca increment in forest areas. Additionally, the relationships between coca increment and deforestation and fire and deforestation were analysed. Finally, a model was built in order to understand if it was possible to use detected fire in forest areas and socio-economic variables to highlight new coca plantations in forest areas.

Chapter 3 presents the results. These include an examination of the density of fires per municipality and all of the statistical analysis undertaken on the data such as correlations between the variables as well as a description of the statistical models developed.

Chapter 4 discusses the results in light of the different datasets used and compares the dynamics of fire and coca in different municipalities. In addition, the different models are compared.

Finally, Chapter 5 presents the conclusions which highlight the most relevant findings and provide recommendations for further analysis.

It is important to note that there are new coca data available for the year 2011 which were not included in the analysis as these data were not available when the research was carried out.

1. LITERATURE REVIEW

1.1 History of Coca.

The Coca plant is a native species found along the Andes, from Colombia to Argentina, although mainly in Peru, Bolivia and Colombia (Plowman, 1985). Its cultivation dates back to 700 BC (Catalayud and Gonzàlez, 2003). It has been chewed for at least 5000 years for many purposes and is used as a stimulant. It is a traditional medicine and it is traded in the religion. It is important to highlight that there is a considerable difference between the use of coca for cultural proposes and the use of coca for producing cocaine hydrochloride (Matteuchi et al., 2011).

There are two main species of coca in South America which are *Erythroxylum coca* (Lam). and *E. novogranatense* (Morris). They have similar characteristics; the difference is in the concentration of alkaloid (Plowman, 1985).

The chewing of coca by indigenous and rural people in the Andean Region is important because it helps to increase the energy and strength when working in hard conditions. Other important use of coca is as a medicine; in this case it can be used as an infusion as well. Among the illnesses that can be treated and which can potentially be cured with coca are indigestion, cramps, diarrhea and soroche (Plowman, 1985) as well as illnesses affecting the nervous system (Grinspoon and Bakalar, 1981).

Coca became famous in Europe and the United States (US) in the 19th century due to these medicinal properties for curing a variety of illnesses. Several doctors from different parts of Europe prescribed it for diverse reasons. By the end of the 19th century, Sigmund Freud in his paper “On Coca” recommended to use coca or cocaine to treat physical affections known as neurasthenia. Afterwards it was used as an anesthetic for different types of surgery such as rhinology, gynecology, urology and others (Grinspoon and Bakalar, 1981).

In that period doctors also started to recommend coca to help people with an addiction to morphine, but the psychiatrist Albrecht Erlenmeyer began to observe symptoms related to the abuse of cocaine and started to warn people about its effects. Subsequently, there was a division between people who defended coca, and who realized that the effects of coca were completely different to the that of chemical cocaine, and the people who were simply against it (Grinspoon and Bakalar, 1981).

By the end of the 1920s cocaine was declared to be an illicit drug and many US states created Acts to prohibit its use (Grinspoon and Bakalar, 1981, Das, 1993). In other countries such as the United Kingdom, cocaine was added to the list of narcotics to be forbidden in The Dangerous Drug Act of 1920 (Berridge, 1980).

In 1997, the United Nations created the Office for Drug Control and Crime Prevention, which in 2002, was renamed to the United Nations Office on Drugs and Crime (UNODC) (United Nations General Assembly, 1997). There are three conventions which guide the UNODC programs which are: the Single Convention on Narcotic Drugs of 1961 (United Nations, 1961); the Convention on Psychotropic Substances of 1971 (United Nations, 1971); and the United Nations Convention against Illicit Traffic in Narcotic Drugs and Psychotropic Substances of 1988 (United Nations, 1988).

1.2 Coca in Colombia.

Colombia is located in the northern part of South America; it has two coasts: the Pacific and the Caribbean. The territory consists of 45% of mountainous regions and the rest is plain terrain. Colombia has six natural regions which are the Andean region, the Caribbean littoral, the Pacific region, the Orinoquian region, the Amazonian Region and the Insular Region (Armenteras-Pascual et al., 2011)

Coca has a traditional history in the Andean region including in Colombia. Its cultivation as an illicit drug began in the 1980s and the 1990s in response to the control activities to stop cultivation of coca in Peru and Bolivia and as a consequence of the collapse of the trade agreement on coffee, which produced a serious economic crisis. At the beginning Colombia imported the coca base from Peru and Bolivia, transformed it and exported it as cocaine to the United States. Due to the high revenues, the business expanded and Colombia became a producer of coca leaves (Diaz and Sanchez, 2004).

In the 1980s, the expansion of coca was huge, covering more than 10.000 hectares in the Putumayo and the regions around it (Bagley, 1985). During this decade, Colombia became the largest producer of coca in the world and powerful drug cartels started to evolve (Thoumi, 2002). Since then, Colombia has remained the biggest exporter of coca. As a result, the country has experienced a great deal of violence due to the conflicts between the cartels and the state (Vargas, 2004).

One of the most important contributors to the prevalence and large expansion of coca was the presence of illicit armed groups such as FARC (Revolutionary Armed Forces of Colombia) as well as paramilitaries. These groups took a number of regions under control, offering opportunities, education and solving social problems for the local population. In return, people had to plant coca and to support the coca trade (Vargas, 2004). However, the government is to blame for this situation because it has abandoned development in rural areas in Colombia (Pérez, 2012).

It is common to find coca crops in places with high poverty and high rates of illiteracy (Pérez, 2012). In addition, it can be associated with local factors that are a function of specific social, economic, environmental, and institutional conditions (Rincon, 2010). Coca regions tend to have similar environmental and socio-economic conditions, although these conditions are not exclusively associated to the coca crop. However, there are a group of common conditions that are only present in coca regions. Namely, high levels of Rural Unsatisfied Needs, low levels of GDP per capita, high levels of forced displacement and homicides, low road density, presence of illegal groups and high percentage of forest areas (Rincon, 2010).

Because of the long history of drugs in Colombia, the government created a program to eradicate illicit crops using aerial spraying. This program was implemented since there are places that are difficult to reach by land or water and also because of the unexpected growth of coca in different areas such as forest. Although the reduction of coca in some areas has been significant due to manual eradication and aerial spraying, it can now be found in places where it did not exist before (Pérez, 2012).

Furthermore, a bilateral agreement between Colombia and the US called Plan Colombia was developed in order to end drug trafficking into the US and to promote peace and economic development in Colombia (Veillete, 2005). The agreement was signed in 1999 and is currently still in force (www.mindefensa.gov.co, 2012).

The expansion of areas cultivated with coca did not just occur in Colombia but also in Peru and Bolivia as a result of the international demand for psychoactive substances. In addition, coca generates high returns due to its illegality. Consequently, if coca decreased in Colombia, it would simply increase in Peru and Bolivia in order to satisfy the market (Pérez, 2012). Accordingly, coca is not just a national but also an international issue. This is the case not just because the US and Europe are the biggest coca consumers, but also because they are involved in the coca traffic chain (Vargas, 2004).

1.3 Coca, fires and deforestation.

The human demands for timber, food, oil palm plantations as well as coca are increasing the pressure on natural resources. These human needs are impacting on land use, and hence on deforestation. The coca business is one of the factors having a negative impact on natural resources in Colombia.

The sequence of a coca crop usually starts with the clearing of forest (primary or secondary), removing the bulk material and subsequent burning. After that, cultivation starts. For instance, for one or two years rice is planted, and then for one or two years cassava and maize together. Afterwards coca is planted, using in the first year cassava as shade, and then coca and citrus are mixed. At the end of the cycle (20 years), the coca plants are eliminated and the citrus remains. In addition, coca plantations are found mainly in mountainous areas which imply high drainage, with clay – loam soils rich in nutrients (Matteucci et al, 2011). It is important to note that the crop sequence can change by crop type used and based on the duration of the cycle.

The impacts of coca on deforestation in Colombia and its surrounding countries have been analyzed by many authors. In a study by Dourojeanni (1992), the impact of coca on deforestation and erosion was analyzed in the Amazon region of Peru. It is argued that coca cultivation has the strongest impact on deforestation and is usually found together with banana, corn and other kinds of plantations. In Peru, coca was responsible for 10% of the total deforestation in the twentieth century. Moreover, coca causes depletion of nutrients in the soil. Coca is cultivated in humid zones, subtropical forest and extremely subtropical humid forest. Some negative ecological impacts attributed to coca crops are the methods or techniques used to grow it. One of the strongest impacts is the need to clear the forest in order to grow the coca crop.

Another important study was carried out by Viña et al. (2004) on the analysis of deforestation rates and patterns along the Colombian and Ecuadorian border during a 23 year period (1973 – 1996). It was found that Colombia had higher annual rates of deforestation than Ecuador with values of 43% and 22%, respectively. The study concluded that this might have been due to the colonization pressure and intensification of illicit coca crops.

In a study by Armenteras et al. (2006) about 'Patterns and causes of deforestation in the Colombian Amazon', it was concluded that deforestation patterns of unplanned colonization follows the river courses in Amazonia. Moreover, they used indicators of human influence such as demographic pressures, the quality of life and economic indicators to determine the impact on deforestation. They found that population density had a strong impact on deforestation. In areas with high population density, the deforestation rates were 3.73% and 0.97% (in Alto Putumayo and Macarena respectively), while in relatively unpopulated areas, the rates were below 0.31%.The main factors associated with these changes were oil extraction, deforestation, cattle ranching or illicit cropping.

Alvarez (2002) made a spatially explicit analysis relating illicit crops and forest areas. She found that the south of the Andes region has the highest conservation priority, but the area is affected by illicit crops. In addition, the largest forested areas affected by illicit crops were in the Amazonia. However, the Amazonas has high biodiversity and furthermore, it has a high impact on the global water cycle and on the regional climate for regulating eco system services. Thus areas of high biodiversity are clearly being threatened by the planting of illicit crops.

In Colombia between 2001 and 2008, coca has been responsible for the deforestation of 110.026 ha of primary forest. In 2001, 97% of coca cultivation was present in areas with warm humid to very humid climate. Of this, 49% was found in high plains with slopes of less than 50%, around 21% was found in alluvial plains with slopes of less than 7% and the rest 8% was found in fluvial – colluvial foot hills with slopes of less than 12% (Rincon, 2010). For the year 2008, similar patterns could be found. However, a decrease of coca crops in warm humid and very humid climate was observed.

The census made by SIMCI in 2010 showed that 18% of new coca cultivation was occurring in primary forest that had still been intact in the year 2009. 222.639 hectares of all the coca that was planted between 2001 and 2010 was found in areas where previously a native forest existed. In addition, since 2006, there has been a tendency to plant coca in forest areas. In 2010, 35% of all coca planted caused deforestation (UNODC, 2011a).

Armenteras-Pascual et al. (2011) made a characterization of fires and the spatial interaction pattern with climate and vegetation in Colombia using monthly time series of rainfall, burned area and an active fire product between December 2000 and 2009. The kind of vegetation most affected in terms of burned area by fire was grassland follow by secondary vegetation, pasture and forest. Between the submontane and lowland Andes and the Amazon, many active fires have been detected. This may have been due to an increase in colonist population, small farms, grazing and livestock production and illicit crop production.

The study of Rincon (2010) aimed at defining the local conditions that characterize the areas associated with municipalities in which coca in Colombia is grown and how these conditions increase deforestation caused by the coca crops. A statistical analysis was made using bivariate Local Indicators of Spatial Association (LISA). The result showed that primary forest, the presence of illicit armed groups, road density and the municipal development index of the rural unsatisfied needs have the highest correlations with coca.

Armenteras and Retana (2012) showed that although fires depend a lot on drought conditions, humans can modify the fire patterns in specific conditions due to the demand for agricultural land and timber products, and in many cases, illicit crops play an important role especially in remote areas. This means that fires do not always depend on climatic conditions but also on land use practices by humans.

1.4 Monitoring system of illicit crops in Colombia – the SIMCI project

The SIMCI project was initiated with the support of the UNODC in 1999 in order to monitor the dynamics of illicit crops in Colombia, mainly coca. Since 2001, the annual census of illicit crops for the whole of Colombia has been undertaken and published (UNODC, 2011a).

The measurement of the extension of coca crops is made using satellite technology, aerial photographs and field verification (UNODC, 2011a). This process is similar to the one used in Bolivia and Peru. The main satellite images used for the identification process are LANDSAT, ASTER and SPOT in Colombia (Biesimci, 2012), Ikonos, WorldView and RapidEye in Bolivia (UNODC, 2012) and SPOT and ASTER in Perú (UNODC, 2008).

In general the methodology to detect coca crops is the same in the three countries. After the acquisition of the images, there is a pre-processing including radiometric improvement, geo-referencing and minimization of areas without information (mainly in Colombia). Subsequently, the visual interpretation of the images is done based on over flights and aerial photographs. Moreover, there is verification on the field (UNODC, 2008, UNODC, 2011, UNODC 2012).

Within the project, a thematic identification of the land use and vegetation is made. The different land cover categories in the images are classified in order to identify and visually detect where coca areas could occur in the future. The categories are primary forest and tropical jungle, secondary forest, scrubs, water, pasture, illicit crops and others. Figure 1 shows an example of the interpretation of the images (Biesimci, 2012)

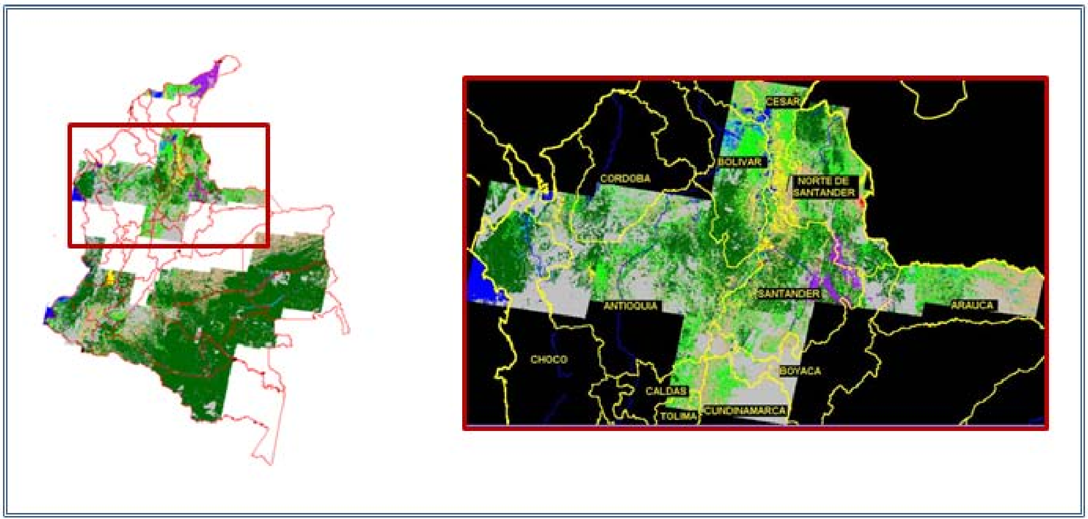


Figure 1. Cover Mosaic – Interpretation 2001.

Source: SIMCI-UNODC. Online.

Afterwards, the visual interpretation of coca areas is made based on satellite images and factors as such texture, form and pattern. Moreover, the aerial photographs taken by the Anti-Narcotics Police (DIRAN) are used to help in the visual interpretation (Biesimci, 2012).

Figure 2 shows an example of the coca areas interpreted. Green areas with green boundaries represent coca cultivation and red areas represent forest cover.

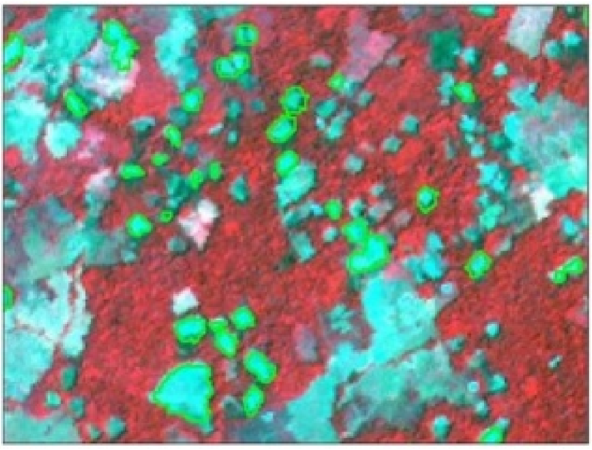


Figure 2. Coca areas interpreted in an ASTER image. (Coca areas are in green).

Source: SIMCI - UNODC. Online.

Once the interpretation of the images is completed, flights over the suspected areas are undertaken for verification in the field in order to improve and correct the preliminary interpretation. At the end, quality control and corrections due to cloud cover are made (Biesimci, 2012).

Coca census in Colombia.

The area planted with coca by 2010 was 62.000 hectares. This area has been adjusted for the presence of small fields (< 0.25 Ha). The area without this adjustment is 57.000 hectares. This means that the estimation contains 4,908 hectares of small plots (UNODC, 2011a).

Regarding the dynamics of coca between 2001 and 2010, there are two important aspects; one of them is the decline in the size of the coca field and the second one is the stability of the coca fields. Despite a reduction in the area planted with coca, the areas with higher concentration have remained stable since 2001 (UNODC, 2011).

Between 2001 and 2004 at a national level, the area under coca cultivation decreased, between 2005 and 2007 it showed a small increase, and between 2008 and 2010, coca cultivation decreased again (see Figure 3)(UNODC, 2011a).

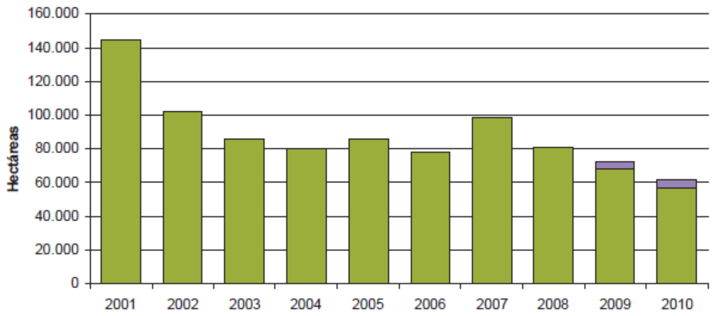


Figure 3. Coca cultivation in Colombia 2001 – 2010.

Source: UNODC. 2011.

The census in 2010 shows the presence of coca in 23 of the 32 departments in Colombia, where most of the cultivated area with coca is concentrated in the following departments: Nariño, Cauca, Guaviare, Antioquia, Putumayo, Córdoba, Bolivar and Chocó (Figure 4) (UNODC, 2011).

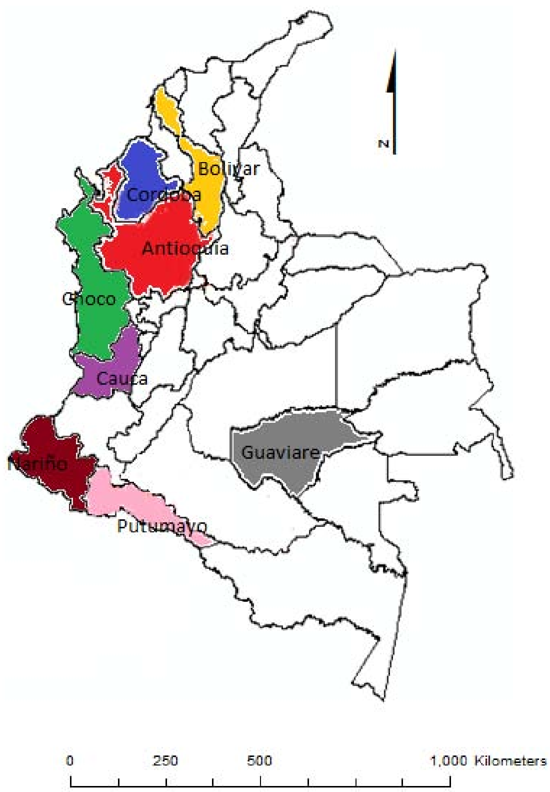


Figure 4. Departments with the highest coca cultivation in Colombia 2010.

Regarding coca dynamics since 2001, one of the most important factors is that growers are reducing the size of the coca field. This is being done in order to make it difficult to identify and to control coca by the government. Another important factor is that there are specific zones in Colombia where the cultivation is permanent (UNODC, 2011). Table 1 shows the regional distribution of coca cultivation since 2001.

Table 1. Regional distribution of coca cultivation since 2001.

Region	Total		Unaffected Area 2008 - 2010		Permanent Affected Area 2001-2010		Affected Area since 2008		Intermittently Affected Area 2001 -2010	
	km²	%	km²	%	km²	%	km²	%	km²	%
Amazonas	27.125	10,0	8.025	3,0	1.225	0,5	5.475	2,0	12.400	4,6
Central	54.275	20,0	19.950	7,3	5.450	2,0	5.275	1,9	23.600	8,7
Sierra Nevada	4.700	1,7	1.725	0,6	475	0,2	750	0,3	1.750	0,6
Meta -Guaviare	51.925	19,1	18.225	6,7	13.075	4,8	1.750	0,6	18.875	6,9
Norte de Santander	11.750	4,3	4.250	1,6	1.200	0,4	1.125	0,4	5.175	1,9
Orinoquía	29.425	10,8	10.050	3,7	2.575	0,9	2.325	0,9	14.475	5,3
Pacífico	45.675	16,8	4.725	1,7	6.525	2,4	9.725	3,6	24.700	9,1
Putumayo-Caquetá	46.825	17,2	12.375	4,6	12.700	4,7	1.925	0,7	19.825	7,3
Total	**271.700**	**100**	**79.325**	**29,2**	**43.225**	**15,91**	**28.350**	**10,4**	**120.800**	**44,5**

Source: UNODC. 2011

2. RESEARCH SITE AND METHODS

2.1 Research Site

The study area corresponds to two different regions in Colombia which are the Central Region, and Putumayo – Caquetá. These regions are specifically defined by SIMCI for the annual coca census, which do not correspond to other geographic or political boundaries.

2.1.1 Central Region

The Central Region is composed of nine departments which are Bolivar, Cesar, Santander, Norte de Santander, Boyacá, Cundinamarca, Caldas, Antioquia and Cordoba. Cesar and Caldas are not included in the analysis because the data were not provided by UNODC.

The Central Region covers different ecosystems. The crops found in 2010 are just 2 km away from the ones found in 2001, meaning that new crops are found close to the established areas The expansion is taking place in the direction of the mountains as well as within this zone.

In 2000 the areas with large coca cultivations were Norte de Santander and the south part of Bolivar. Five years later the expansion of coca took place in Antioquia, and more recently, Norte de Santander has seen a reduction in coca areas (UNODC, 2011b). Figure 5 shows a map of the dynamics of coca for this region between 2001 and 2010.

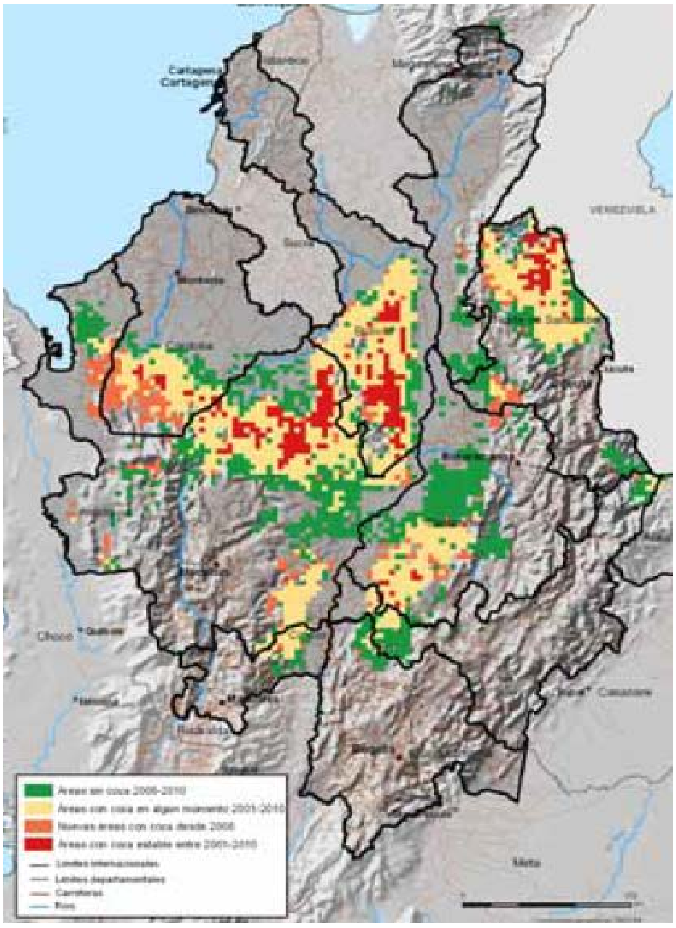


Figure 5. Coca dynamics in Central Region 2001-2010.

Source: (UNODC, 2011b) – Conventions: Green: Area with coca 2008-2010. Yellow: Areas with coca at least once in 2001-2010. Red. Estable coca areas in 2001-2010. Orange: Coca areas 2008.

Below is a table with a short description of the most relevant aspects of each department and its municipalities. The table includes boundaries, physical structure, climate and coca dynamics.

Figure 6 show the maps per department with the municipalities where coca has been cultivated over the last ten years where the red shaded areas are those municipalities with particularly high coca dynamics.

Table 2. Description of the most relevant aspects per department – Central Region

Department	Location	Extention	Boundaries	Physical Structure	Climate	Coca dynamics (2000 - 2010)
Antioquia	Northwestern part of Colombia	62.839 km²	The Caribbean Sea, Sucre, Bolívar and Córdoba in the north, Santander and Boyacá in the west, Caldas and Risaralda in the south and Chocó in the east.	Highlands, regional escarpments and canyons. 60% of the total area is mountainous terrain and 40% is flat plains and alluvial valleys. 69% of the territory is suitable for forest, it only covers 39% of this area where the rest is agricultural land use including illicit crops.	Temperatures in some places of 13°C and 28°C in other places. The annual values of precipitation vary between 1500 and 4000mm.	50 out of 125 municipalities have evidence of coca cultivation. Municipalities such as Anorí, Briceño, Cáceres, El Bagre, Ituango, Nechí, Remedios, Segovia, Taraza, Valdivia and Zaragoza have cultivated coca each year since 2001.
Boyacá	Central eastern part of Colombia	23.189 km²	Santander, Norte de Santander and part of Venezuela in the north, in the south with Cundinamarca and a small part of Meta, in the east with Arauca and Casanare and with Arauca and Casanare in the west.	Mountainous areas, highlands, piedmonts and plains.	Rainy tropical climatewith high temperatures and high precipitation most of the year, dry climate with high temperatures and low precipitation and mountain climate.	12 municipalities out of 123 had evidence of coca cultivation. Otanche and Puerto Boyacá are the municipalities with the largest coca plantations where 93% of coca cultivation was concentrated in these municipalities in 2010. The average size of the coca plot was 0.87 hectares in 2010.
Bolivar	Northern part of Colombia	26.392 km²	The Caribbean Sea and Jamaica in the north, in the west by the departments of Atlántico, César, Magdalena and Santander, in the east by the departments of Sucre, Cordoba and Antioquia and by Antioquia again in the south.	Two important mountain areas which are *Montes de María* and *Serranía de San Lucas*. There are three important savannas and mangrove areas located in the bays of this department.	Temperature between 26 and 30°C and precipitation between 800mm and 2800mm per year	15 municipalities where during the period 2001-2010 coca plantations could be found, the majority of cultivated areas are concentrated in: Cantagallo, Montecristo, San Pablo, Santa Rosa del Sur and Simití. the average size of the coca plot was 0.75 hectares in 2010.
Cordoba	Northwestern part of Colombia	23.980 km²	Sucre and the Caribbean Sea in the north, Antioquia and the Caribbean Sea in the east, Bolivar, Sucre and Antioquia in the south	From south to north, the western Cordillera forms a mountainous region with undulations and gullies. The Paramillo Natural Park is situated in the south of this region and it is home to the biggest concentration of native flora and fauna in Latin América.	The climate of Córdoba varies from 28°C in the coast to 18°C in the mountains. The precipitation in the coastal areas is 800mm per year while 3000mm per year falls in the mountains.	5 out of 28 municipalities contained evidence of coca plantations: La Apartada, Montelíbano, Valencia, Puerto Libertador and Tierralta. In the last three municipalities coca has been present for this entire time period. Moreover, 64% of coca was concentrated in Tierralta in 2010. The average size of the coca plot was 0.70 hectares in 2010.
Cundinamarca	Central eastern part of Colombia	24.210 km²	Boyacá in the north, Huila in the south, Tolima and Caldas in the west and Meta in the east.	There lowlands next to the Magdalena River are characterized by being warm and dry. Through the middle of the department passes the Eastern Cordillera and the piedmont is found on the eastern part of the region.	The temperature varies from 12°C to 24°C	4 municipalities out of 118 showed evidence of coca cultivation, which were: Caparrí, Paime, Topaipí and Yacopí. Coca has been present in Yacopí in all years except 2009. Moreover, 97% of coca cultivation was concentrated in this municipality in 2010. The average size of the coca plot was 0.72 hectares in 2010.
Santander	Central eastern part of Colombia	30.537 km²	Cesar and Norte de Santander in the north, Boyacá in the south and east and with the Magdalena River in the west	The *Valley of Magdalena Medio* is characterized by an uneven flat area, on the banks of *Magdalena River*, where jungle vegetation is predominant and part of the equatorial forest can be found here. Eastern Cordillera.has steep slopes reaching up to 3000m. In addition Santander has dry terraces and the *Chicamocha Canyon* which are also part of this varied landscape.	The average temperature varies from 32°C in some places to 7°C in the moorlands. The precipitation can reach from 500 to 3800 mm per year	26 municipalities out of 87 had evidence of coca cultivation. The municipalities with the presence of coca during this time period were Bolívar, Cimitarra, La Belleza, Landazuri, and Sucre where 55% of coca was concentrated in Bolívar, Cimitarra and Sucre in 2010. The average size of the coca plot increased from 0.67 hectares to 0.91 hectares.

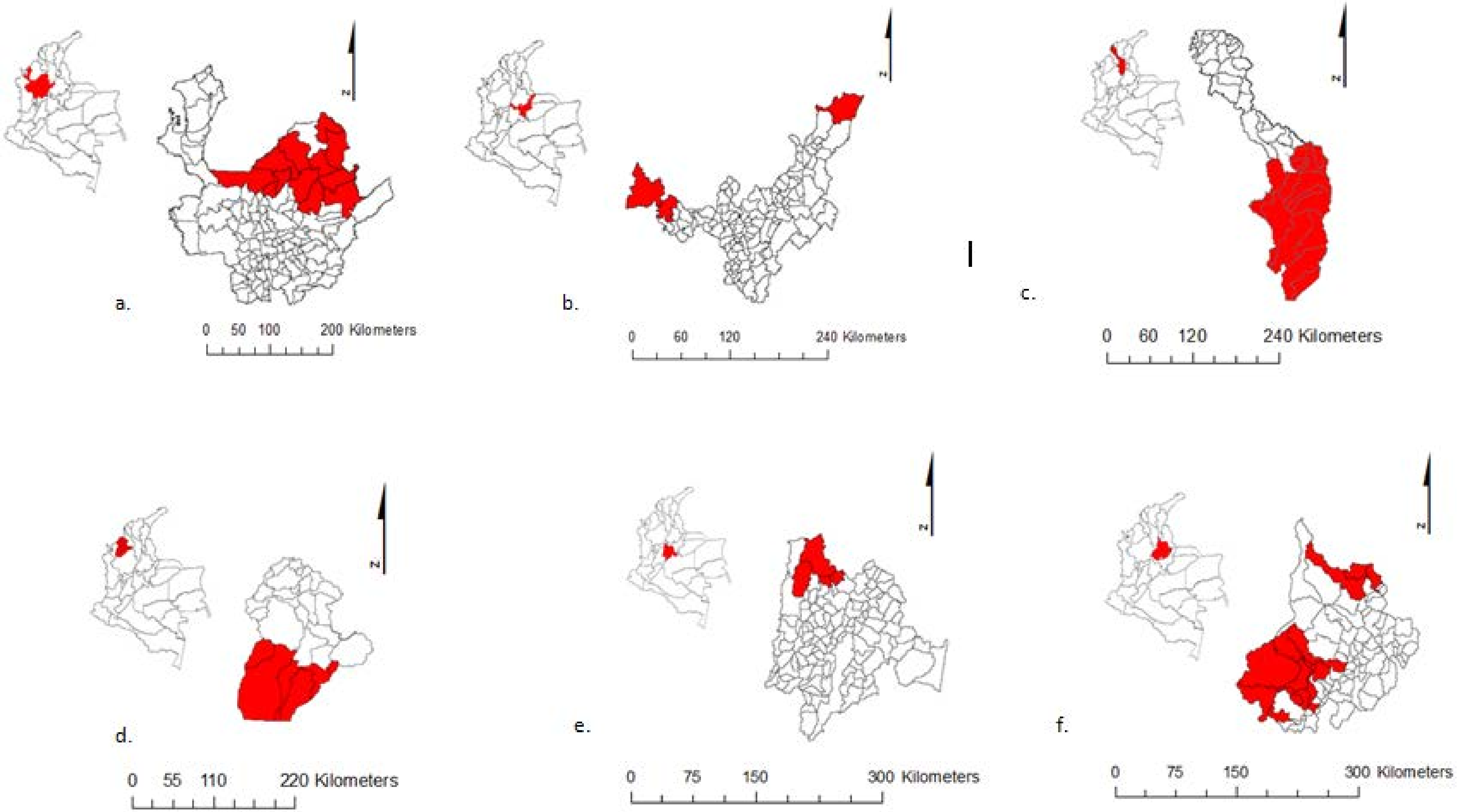


Figure 6. Municipalities with high coca dynamics 2000 – 2010. a. Antioquia. b. Bolívar. c. Boyacá. d. Córdoba. e. Cundinamarca. f. Santander.

Red shaded areas are those municipalities with particularly high coca dynamics.

2.1.2 Putumayo – Caquetá

Putumayo – Caquetá is one of the most stable coca regions in Colombia. New plots of coca are found at a distance of 2 km from the old plots, meaning that the expansion of coca is happening around a central nucleus. Moreover, the density of the cultivation has decreased significantly during the last 10 years, especially in Valle del Gamúez, San Miguel and Cartagena del Chaira (UNODC, 2011b).

In this region 27% is a stable coca area, 42% shows evidence of coca cultivation during some of the years between 2001 and 2010, and 28% of the area has been not affected since 2008 (UNODC, 2011b). Figure 6 shows a map representing the dynamics of coca for this region between 2001 and 2010.

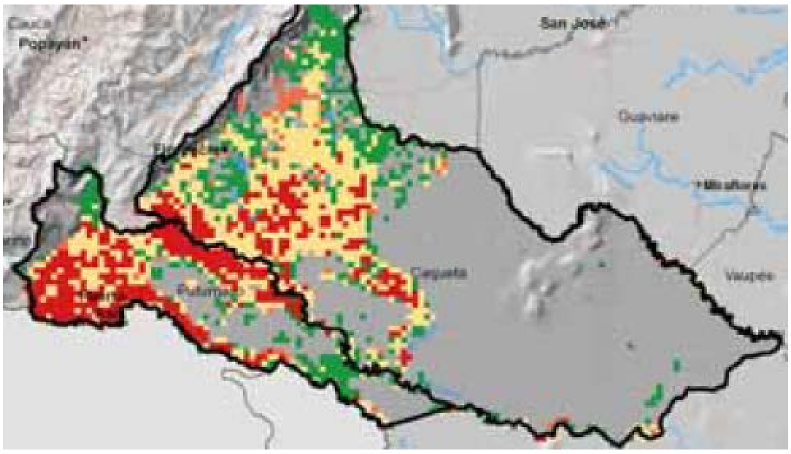


Figure 7. Coca dynamics Putumayo - Caquetá 2001-2010.

Source: (UNODC, 2011b) - Green: Area with coca 2008-2010. Yellow: Areas with coca at least once in 2001-2010. Red. Stable coca areas in 2001-2010. Orange: Coca areas 2008.

As with the Central Region, the table below provides a short description of the most relevant aspects of Putumayo, Caquetá and its municipalities.

Figure 8 show the maps per department with the municipalities where coca has been cultivated over the last ten years where the red shaded areas are those municipalities with particularly high coca dynamics.

Table 3. Description of the most relevant aspects per department – Putumayo – Caquetá

Department	Location	Extention	Boundaries	Physical Structure	Climate	Coca dynamics (2000 - 2010)
Putumayo	Southern part of Colombia	24.884 km²	In the north by the departments of Nariño and Cauca and Caquetá River, in the east by Caquetá, in the south by Amazonas and Putumayo and the San Miguel River and in the west by Nariño.	There are two important morphological regions: the eastern flank of the Andes and the Amazonian plain.	In the mountainous region the precipitation reaches between 2300 and 3500 mm. The plain is characterized by high temperatures, i.e. 27°C, with an average yearly precipitation of 3900mm. The relative humidity can reach 80%.	10 municipalities out of 13 have shown evidence of coca crops. With the exception of El Colón, Santiago, San Francisco and Sibundoy, all municipalities have had the presence of coca during this time period. The main concentration, i.e. 67% of the area, was cultivated with coca in the year 2010 in Puerto Asis, Puerto Guzman and Puerto Leguízamo.
Caquetá	Southern part of Colombia	88.985 km²	In the north by the departments of Meta and Guaviare, in the south by Putumayo and Amazonas, in the east by Vaupés and Amazonas and in the west by Huila and Cauca.	There are three natural regions which are the eastern flank of the Andes, the piedmont and the Amazon plain	Three specific climate regions can be found in Caquetá. The first comprises the Cordillera area under 1500m and the piedmont where the precipitation reaches 5000mm. The second comprises the intermediate band where the precipitation is between 3000mm and 4000mm. The third corresponds to the Amazon plain where the precipitation average is less than 3000mm. The average temperature is 27°C	All municipalities of Caquetá have shown evidence coca cultivation, with the exception of Florencia. Cartagena del Chaira, San Vicente del Caguán and Solano are the municipalities with the majority of the coca cultivation in this department

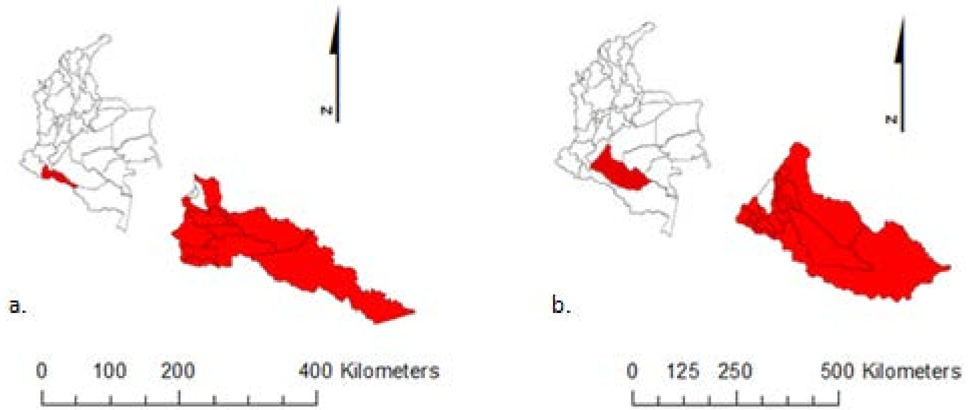


Figure 8. Municipalities with high coca dynamics 2000 – 2010. a. Putumayo. b. Caquetá.Red shaded areas are those municipalities with particularly high coca dynamics.

2.2 Methods

Figure 9 shows the data sources used in this research. There were four main sources of data: the coca census from 2000 to 2010; maps of forest cover in 2000; data on fire occurrence between 2000 and 2010; and socio-economic data. Each of these data sources is now described in more detail in the sections that follow.

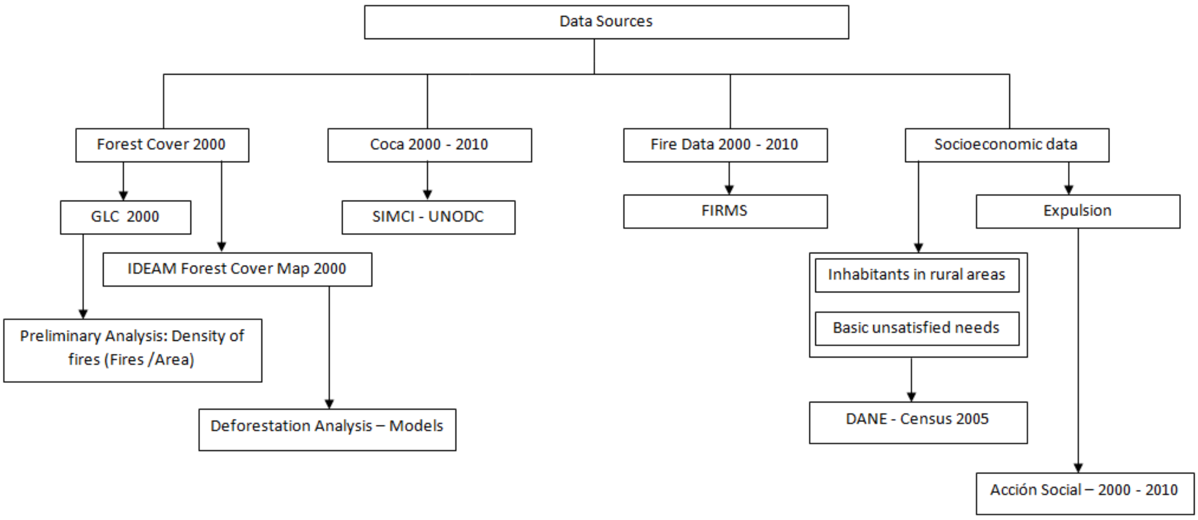


Figure 9 . Data sources used for the research

2.2.1 Forest Data

Two forest cover maps were used. The first is the Global Land Cover 2000 (GLC-2000) product, which contains a number of classes for forest cover (Bartholomé et al, 2005). This product is at 1km resolution at the equator. The second product used was a forest cover dataset for the year 2000 at a finer resolution of 30m. This latter product was obtained from a project entitled 'Scientific and institutional capacity building to support Reducing Emissions from Deforestation and Degradation (REDD)' in Colombia, which was carried out by the Institute of Hydrology, Meteorology and the Environment (IDEAM - Instituto de Hidrología, Meteorología y Estudios Ambientales de Colombia).

These two different forest cover datasets were used in order to understand if the relationship between the variables changes depending upon the resolution of the maps used, i.e. the coarse resolution of GLC-2000 compared to the finer resolution found in the forest cover data from the IDEAM). Figure 10 shows the forest cover map obtained from IDEAM.

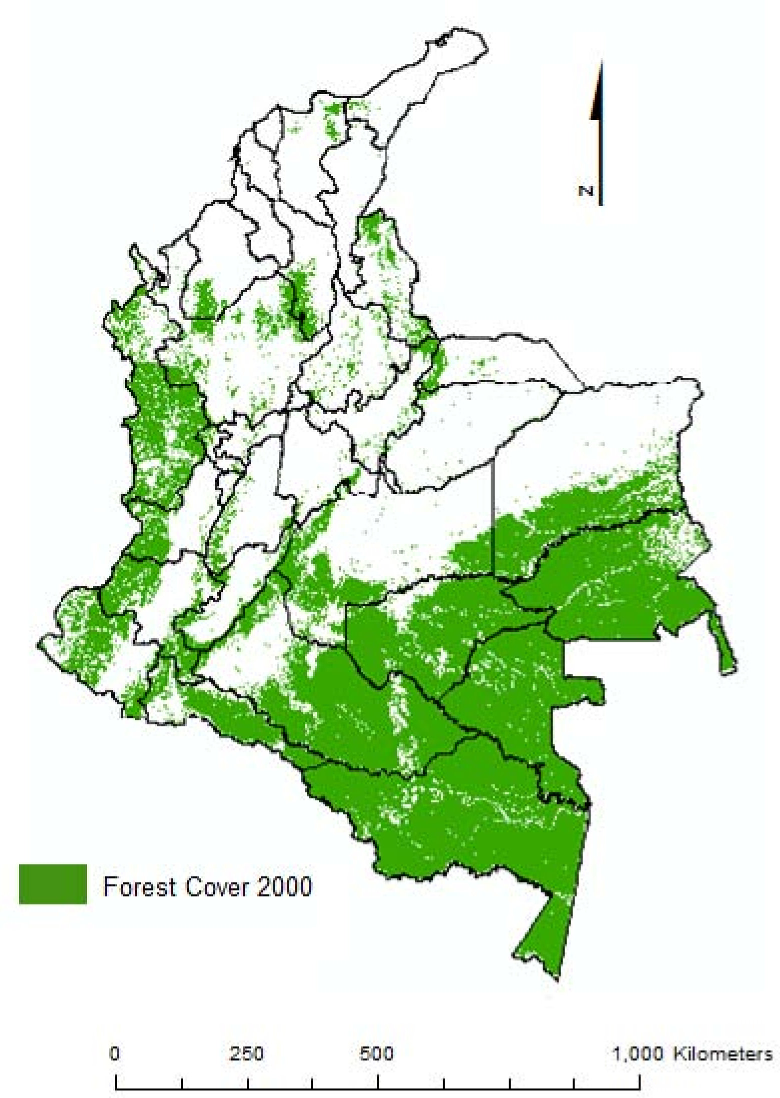


Figure 10. Map of forest cover 2000 - IDEAM

2.2.2 Coca Data

The coca datasets were obtained from the UNODC Colombia under the SIMCI project. The coca data are expressed as area in hectares for each 1 km grid cell as a raster layer provided for the two regions of the study area. Raster data layers were available as a time series from 2000 to 2010. In addition, the data layers contain information regarding the municipality to which each 1km grid cell belongs.

They provided the data as an Excel file of the following form: Latitude, longitude, area under coca cultivation per year in hectares and municipality. The coordinates were provided regular grid spacing so it was necessary to first create a point file in ArcGis. From these points a raster grid was created at a 1 km resolution. This was repeated foe each year and for both regions.

Figure 11 shows a map of the municipalities under study and the areas where coca plantations are located in 2009.

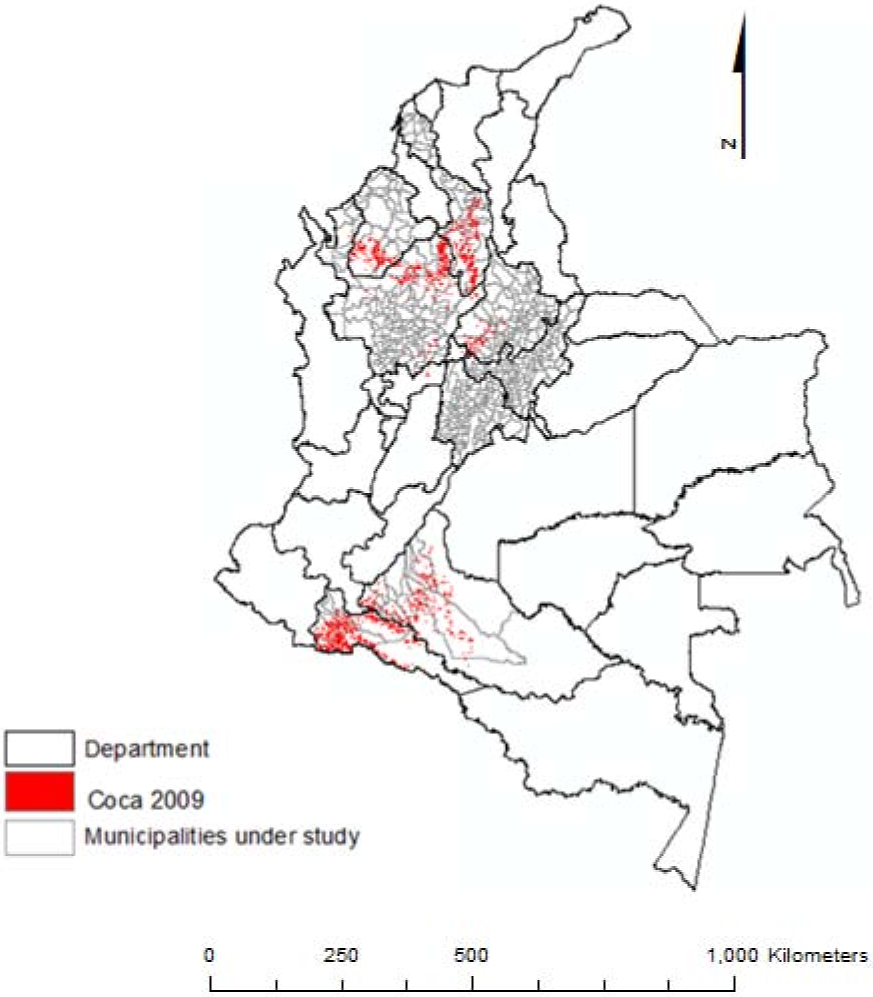


Figure 11. Coca 2009 in regions under study with municipal boundaries.

Source: Based on data from SIMCI - UNODC.

2.2.3 Fire data

Fire data were obtained from the MODIS active fire product, which detects fires in a 1km pixel as the satellite passes over the area (Giglio et al., 2003). The data were downloaded from the Fire Information for Resource Management System (FIRMS) funded by NASA (http://firefly.geog.umd.edu/firms/, 2011). This system delivers near real-time information and allows fire hotspots to be displayed as detected by the MODIS Rapid Response System (Davies et al., 2009). The dataset covers the years 2000 – 2010. The number of forest fires per municipality was computed for only those areas where there is forest cover (see Figure 12).

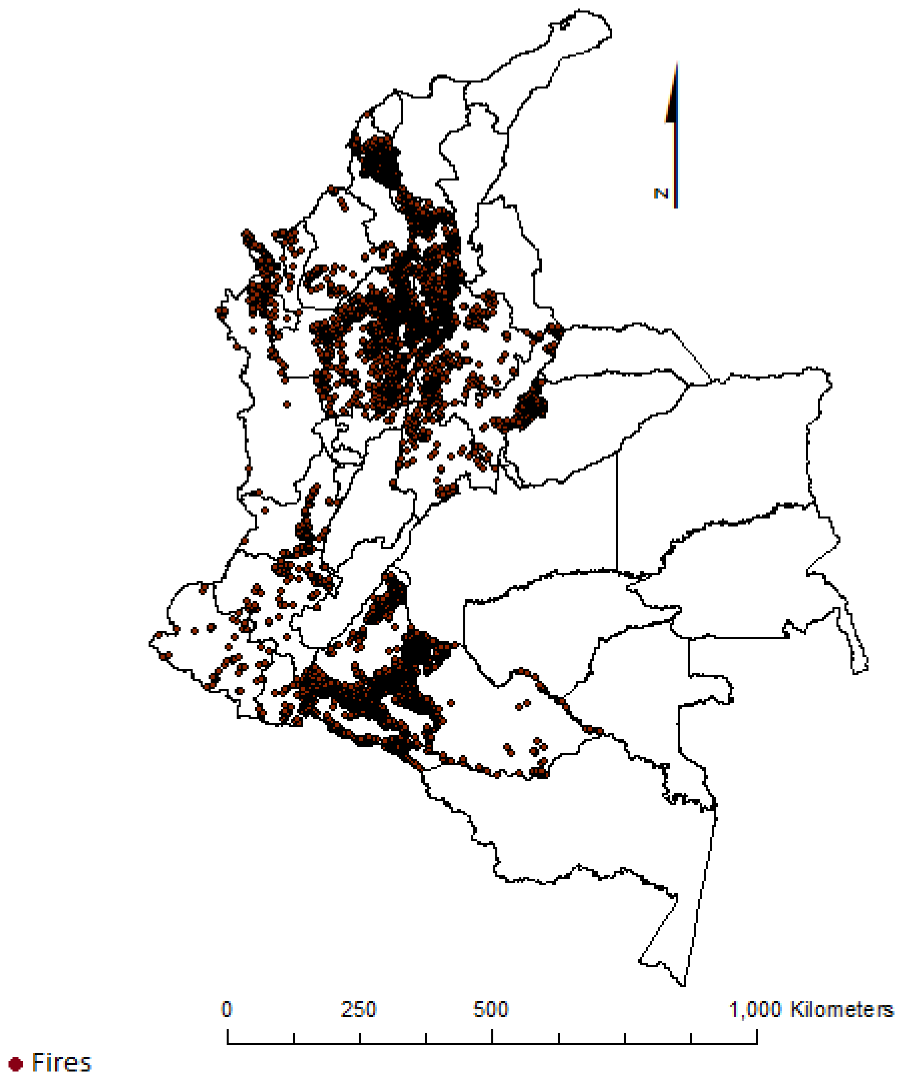


Figure 12. Fires in the municipalities under study 2000 - 2010.

Source: Base on data from FIRMS.

2.2.4 Coca Increment

The coca increment is defined as part of this research as the sum of the increase in the area of coca cultivation between the subsequent and previous years, calculated for each consecutive pair of years for the period 2000 – 2010 for each 1 km grid cell as shown in Equation 1:

Coca Increment = *Pos_value*(*Coca 2001 – Coca 2000*) + *Pos_value* (*Coca 2002 – Coca 2001*) + *Pos_value* (*Coca 2003 – Coca 2002*) +….+ *Pos_value* (*Coca 2010 – Coca 2009*)
Coca Increment *›0*
with
Pos_value ›0*, positive values after the subtraction for each consecutive pair of years*

(1)

Only the positive values or increases in coca are considered when the current years coca grid is substrated from the previous one, since the analysis focuses only on coca increment to determine if the increment of coca is related to fires occurring in forest areas. Consequently, the decreases in coca or stable coca 1km girds are not important for the analysis.

The figures below show an example in order to clarify the calculation of coca increment.

The first step was to calculate the change of coca plantations for the period 2000 – 2001 subtracting coca 2001 – coca 2000 for each 1 km grid. Then, coca increment for the period 2001 – 2000 was calculated in the same way (Figure 13).

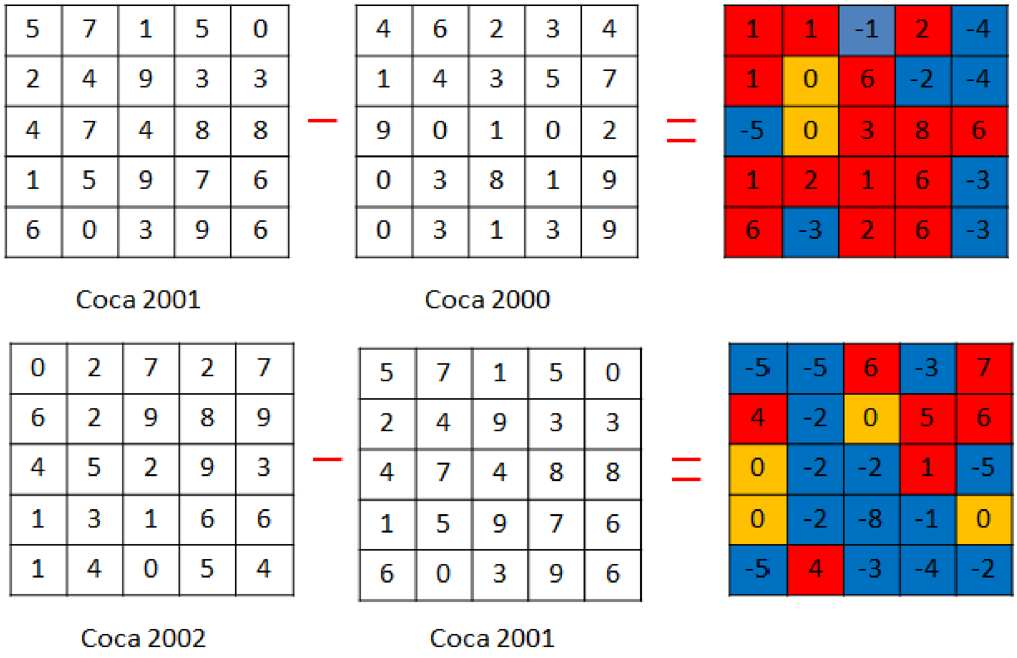


Figure 13. Representation of change of coca plantations for the period 2000-2001-2002

Only the positive values after the subtraction for each consecutive pairs of years were taken into account (Figure 14).

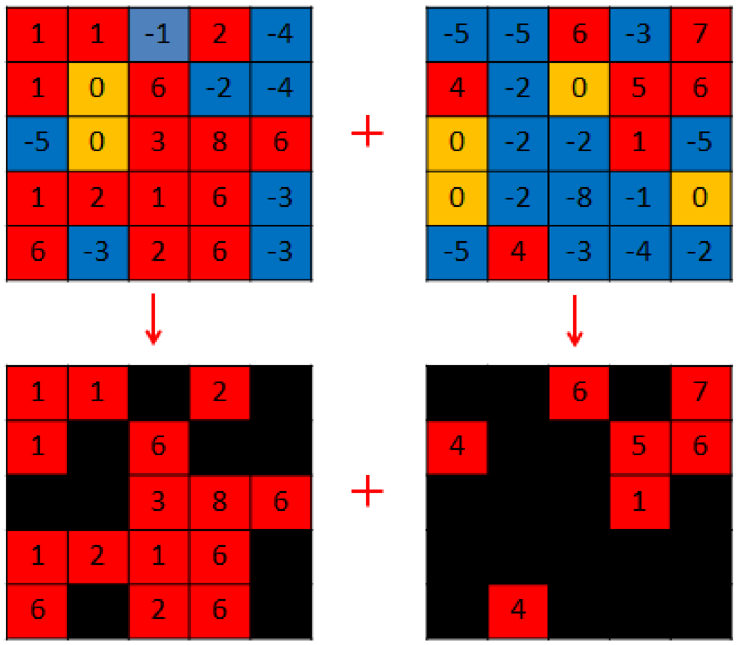


Figure 14. Representation of positive values after the subtraction

Coca increment is the result of the sum of the positive values after the subtraction for each consecutive pairs of years (Figure 15)

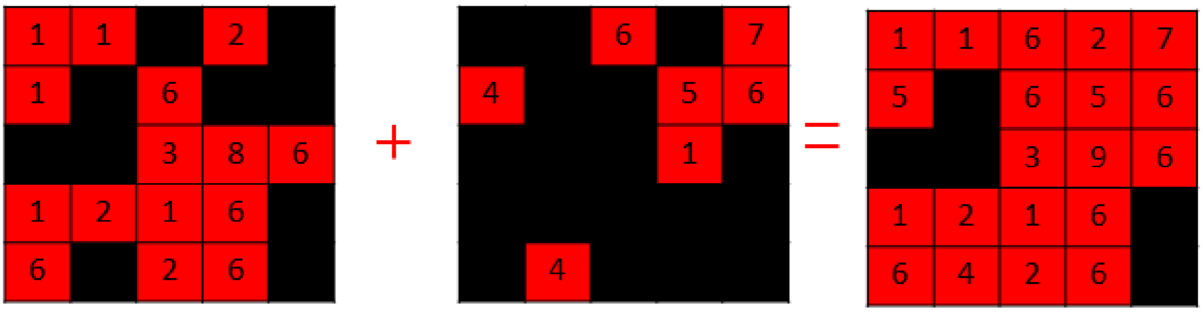


Figure 15. Representation of coca increment

The layer containing the coca increment was then clipped with the layers on forest cover to obtain the coca increment in forest areas as shown in Figure 16.

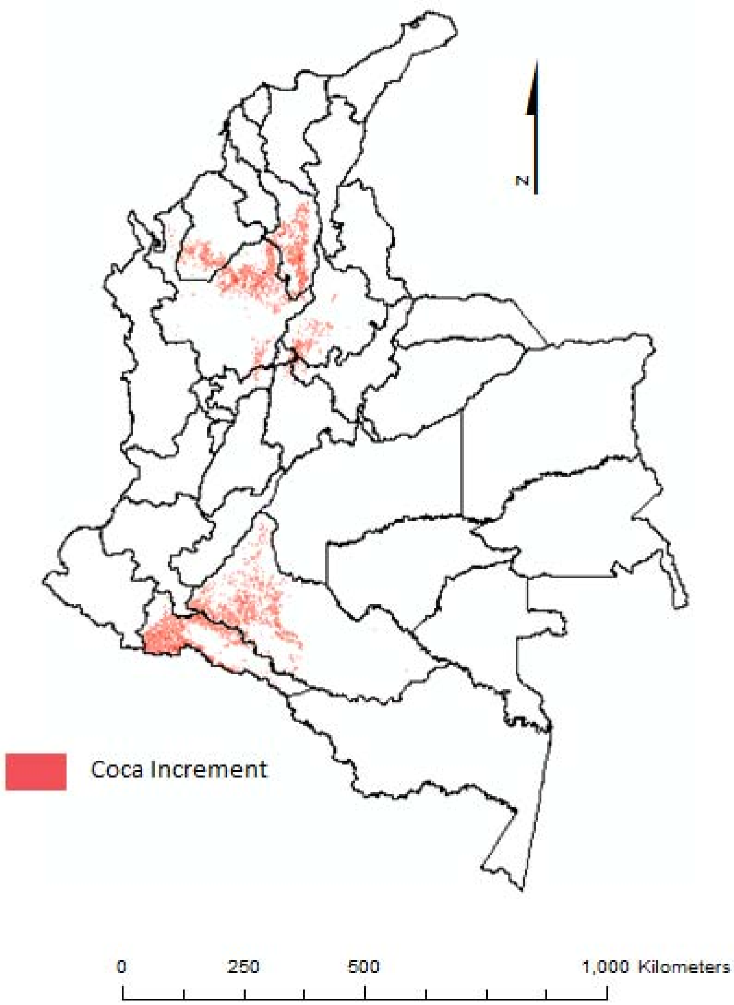


Figure 16 . Coca increment period 2001 – 2010.

Source: Based on data from SIMCI - UNODC

2.2.5 Forest Fires

To obtain the forest fires from the FIRMS dataset (which includes fires for all areas globally), it was necessary to use a land cover map of Colombia which was reclassified as forest, non forest in order to extract fire data only in forest areas. Two different forest maps of Colombia were used.

After the identification of forest cover in Colombia for the year 2000, the number of fires in forest areas per municipality was computed by combining the forest and fire dataset. Figure 17 shows an example of fires on a forest cover map.

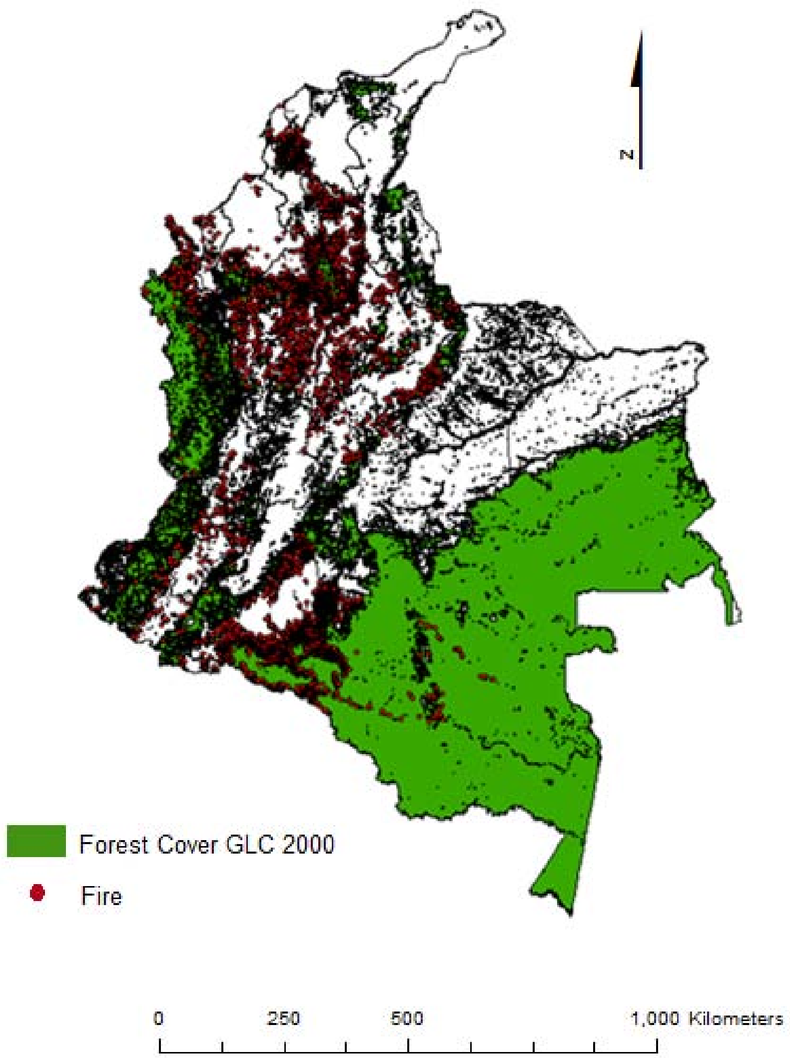


Figure 17. Fires in forest areas 2000 - 2010.

Source: Based on data from GLC2000 and FIRMS.

2.2.6 Calculation of density of fires per municipality area

The number of fires per municipality was computed in order to determine whether fires are associated with different coca related classes. Three classes were defined within the each municipality. The first class was the density of fires per area of coca increment, the second class was the density of fires per non-coca area and the third class represents the density of fires in stable or decreasing coca areas. It is essential to clarify that these areas do not represent the real area of coca increment, non coca or stable or decreasing coca areas but it represents the total area of the entire 1km grid affected by the increment, the grids not affected by coca and the grids affected by stable or decreasing coca (see Figure 18).

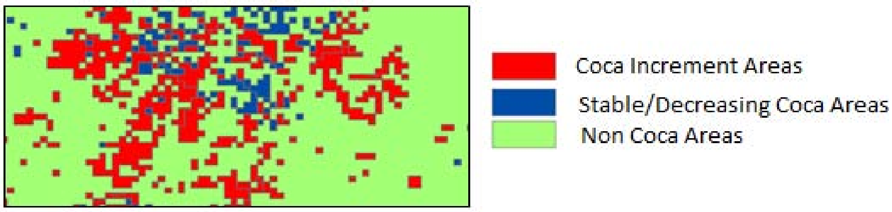


Figure 18. Areas Classification

Density of fires means the number of fires in the forest divided by the corresponding area calculated as shown below:

$$Density = \frac{\# Fires}{Area\ (km^2)} \tag{2}$$

For this part of the analysis the land cover map used was the GLC-2000.

2.2.7 Coca increment, fires and deforestation

The aim of this part of the study is to analyze the relationship between forest fires and coca increment in forest areas. A model was developed in order to tests whether detected fires can be used as an indicator of new coca areas in the forest. Moreover, an analysis of coca increment and deforestation was undertaken.

To develop such a model (see section 2.3.2), the forest cover map of 2000 for Colombia (IDEAM) was used. In order to make the deforestation analysis, two forests cover change maps were used, one from the year 2000 and the other one from the year 2005.

A map of forest cover change 2000 - 2005 for Colombia was obtained from IDEAM as part of the project entitled 'Scientific and institutional capacity building to support Reducing Emissions from Deforestation and Degradation (REDD) project in Colombia' as mentioned previously. The map of deforestation for the period 2005 – 2010 was generated based on the forest – non forest cover maps for the years 2005 and 2010.

Due to the fact that the information of fires and coca is available at a 1km resolution, the Colombian forest cover maps which were available at a resolution of 30m were resampled to the same 1 km resolution. The classification of the map shows forest areas, areas of deforestation, areas without information and the remaining areas, i.e. the 'Rest' class. The Rest class contains non forest vegetation classes and a small area of regeneration (Figure 19).

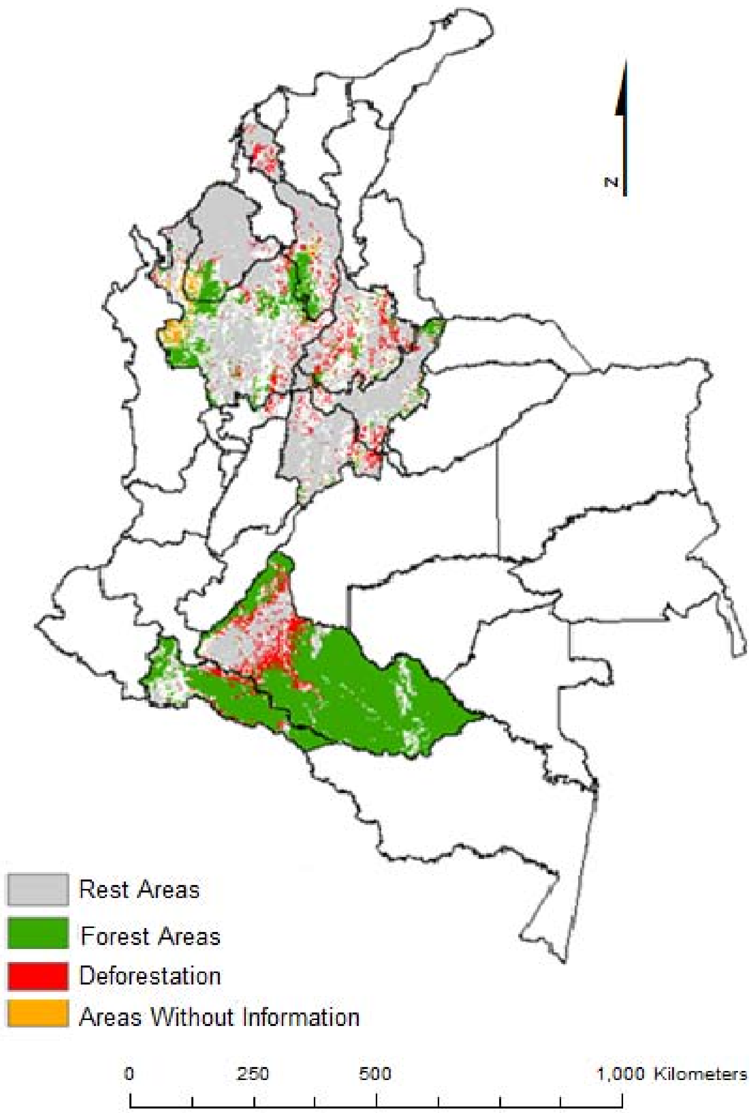


Figure 19. Map of cover change 2000 – 2005 (1Km)

Source: Based on Cabrera et al, IDEAM, 2011

A Pearson correlation analysis was then undertaken in order to determine the relationship between the coca increment and fires occurring in forest areas. Figure 20 shows a map relating coca increment and fires.

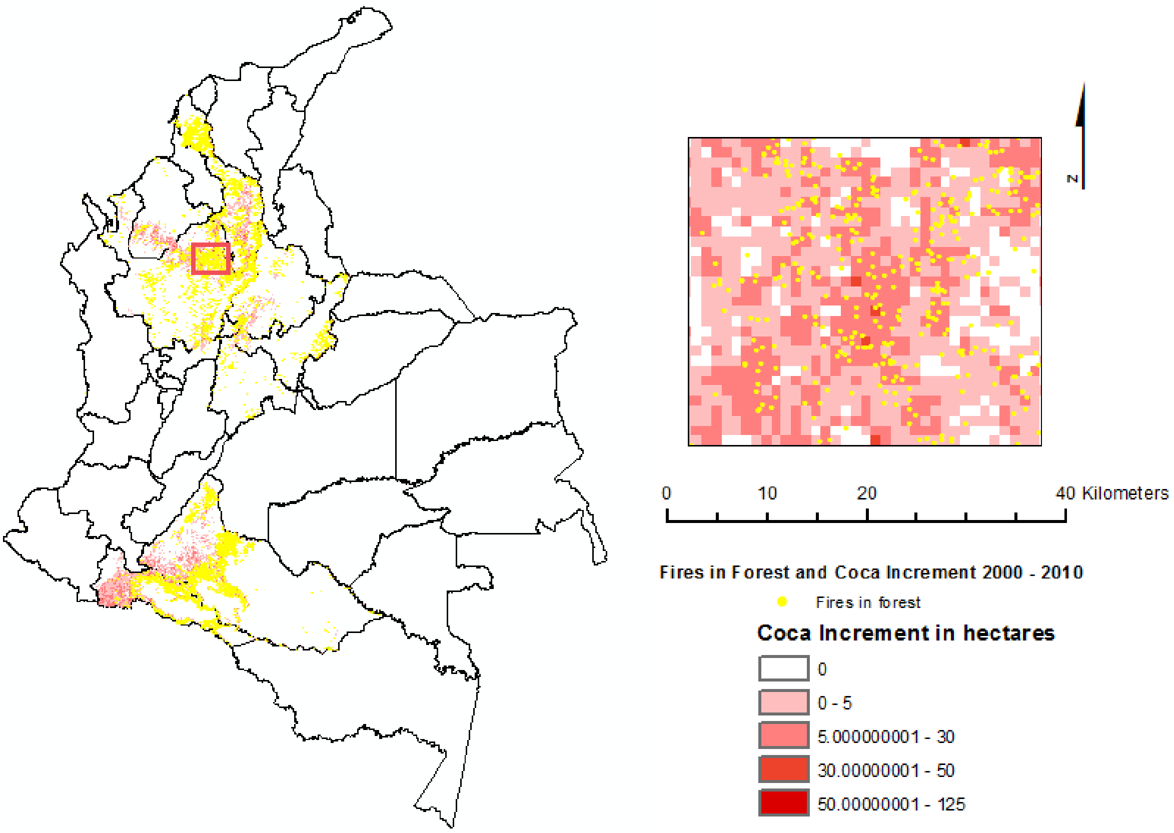


Figure 20. Fires and Coca Increment

In addition, a Pearson correlation analysis was undertaken relating fires and coca increment in deforestation areas per municipality in order to observe the impact of coca in forest areas. Figure 21shows an example of deforestation areas and coca in these areas of deforestation.

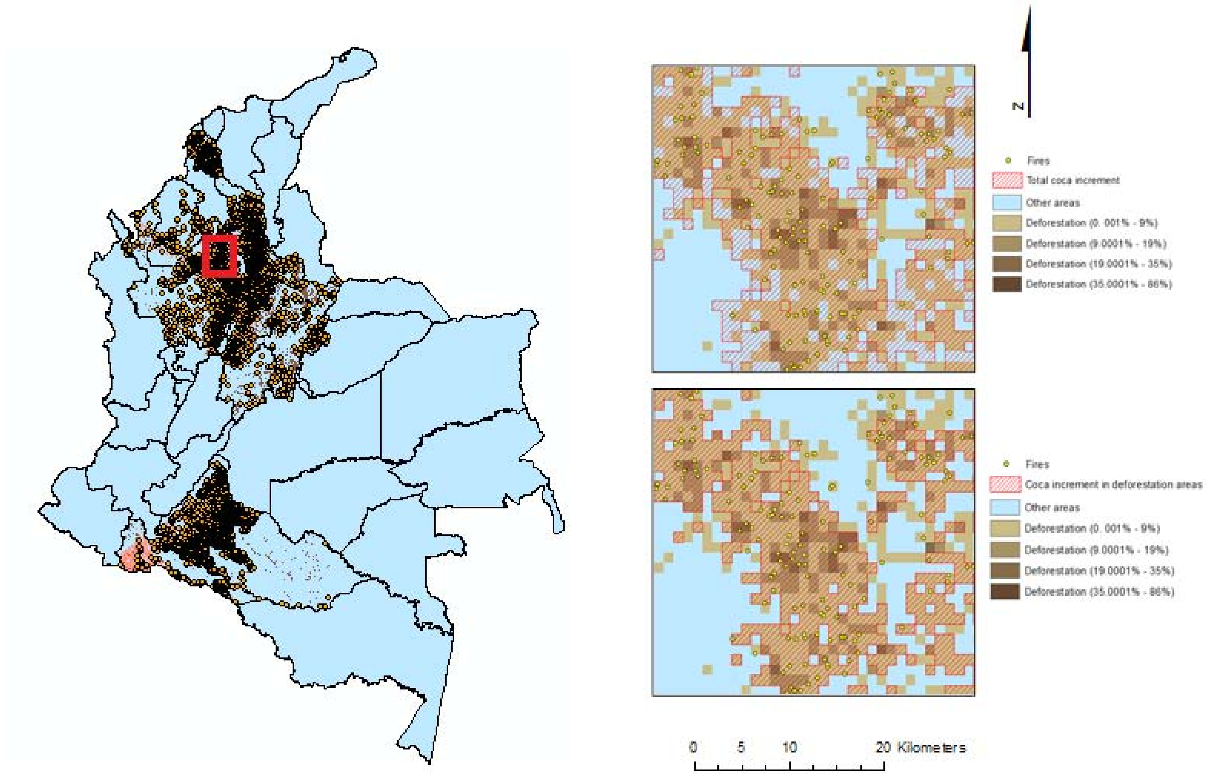


Figure 21. Fires - Coca increment - Deforestation

2.2.8 Socioeconomic data

Three socioeconomic datasets were taken into account for the analysis. The data are inhabitants in rural areas, unsatisfied basic needs and expulsion. The two first datasets were obtained from the National Department of Statistics – Colombia (DANE) from the census made in 2005. The last data were obtained from Social Action – Colombia (currently the Department for Social Prosperity – DPS) for every year for the period 2000 – 2010.

Inhabitants in rural areas refer to the number of people living outside of the urban areas (www.dane.gov.co, 2012).

Unsatisfied basic needs is an indicator of poverty. It determines if the basic needs of the population are covered based on some indicators such as inadequate housing, crowded housing, housing with inadequate services, housing with high economic dependence and housing with school age children who are not attending school (www.dane.gov.co, 2012).

Expulsion is a measure of forced displacement by violence. Expulsion many times takes place when illegal groups such as the FARC are present (www.dps.gov.co, 2012).

2.3 Statistical Analysis

The statistical analysis is divided into two parts. The first part aims to identify if there is a relationship between fire and deforestation and coca and deforestation based on Pearson Correlation. The second part aims to build a model in order to identify if fire in forest areas and socioeconomic variables (inhabitants in rural areas, unsatisfied basic needs and expulsion) can be used to highlight potential coca increment in forest areas.

2.3.1 Pearson Correlation

The relationship between fire and deforestation was analysed using Pearson correlation which is a measure of the strength of the linear dependence between two variables. This value can be between 0 (no correlation) and 1 (perfect correlation) (SPSS Tutorial). For example, Pearson correlation has been used to identify the relationship between socio-economic variables such as population density, population growth rate, extent of forest area, total land area and foreign exchange earned through the export of forest products and deforestation over 141 countries in different continents (Murali and Hedge, 1997).

Eva and Fritz (2003) used Pearson correlation to identify the relationship between forest fires and deforestation in South America. The fires were detected by the NOAA-AVHRR satellite. Deforestation data were obtained from a high resolution satellite (LANDSAT and SPOT) at 41 sites. The results showed that 25 sites had a significant correlation between forest fire counts and deforestation.

2.3.2 Building a model to establish a relationship between coca increment, fires and other socio-economic variables

Three different models were built to find out how forest fires and socio-economic data (inhabitants in rural areas, basic unsatisfied needs and expulsion) influence the coca increment.

The models used in this research were: a Linear Probability Model (LPM), a Logit model and a Probit model. These types of models have been used to relate deforestation to socio-economic variables as described in the studies below. For instance, the LPM and the Probit model were used in Costa Rica to determine the interactions of neighbours in areas affected by deforestation. The positive coefficients showed that neighboring deforestation raises the probability of deforestation (Robalino and Pfaff, 2011).

Furthermore, the Logit model had been used to model tropical deforestation in the southern Yucatán Peninsular Region. The model used inputs from satellite data, spatial environmental and socioeconomic data as explanatory variables to estimate the deforestation in the landscape (Geoghegan et al., 2001). In another study, a Logit model was used to measure the initial impacts of Mato Grosso's program for environmental control in Brazil on deforestation. The aim of the program was to introduce an innovative system to increase compliance with land use regulations (Chomitz and Wertz-Kanounnikoff, 2005).

Description of the model:

Only those municipalities with complete data for all variables were selected. This was necessary as not all municipalities recorded all the variables. Therefore, those municipalities which had missing values could not be used for the model.

- ***Sample:*** Cross-Sectional Data
- ***Cross-Sections:*** 526 Municipalities in Colombia
- ***Binary Dependent Variable:***
    - $\boldsymbol{coc\_pl_i}$: Increment in coca plantations
        - $coc\_pl_i = 1[coc\_pl_{i,2010} - coc\_pl_{i,2000} > 0]$
- ***Independent Variables:***
    - $\boldsymbol{fires_i}$: Total fires in forest areas between 2000 and 2010 (Sum)
    - $\boldsymbol{inhab_i}$: Total inhabitants in rural areas base on the data from the census 2005 (in log)
    - $\boldsymbol{needs_i}$: Basic unsatisfied needs base on the data from the census 2005 (given as a % of basic needs)
    - $\boldsymbol{expl_i}$: Total expulsion between 2000 and 2010 (in log)

Note: The data of Inhabitants in rural areas and Expulsion were transformed using logarithms to obtain a normal distribution.

1. *Linear Probability Model (LPM)*

Assumption: the response probability is linear in the parameters β_j for $j = 1,2,3,4.$. In the LPM, β_j measures the change in the probability of success when x_j increases by one unit, holding the other variable fixed:

$$\Delta P(coc\_pl_i = 1|\boldsymbol{x}) = \beta_j \Delta x_j \tag{3}$$

Model:

$$\boxed{coc\_pl_i = \beta_0 + \beta_1 fires_i + \beta_2 \log(inhab_i) + \beta_3 needs_i + \beta_4 \log(expl_i) + u_i} \tag{4}$$

The following assumption must be satisfied is the model is to be used:

1. The error term u has an expected value of zero given any values of the independent variables. In other words, $E(u|\boldsymbol{x}) = 0$, where $\boldsymbol{x}$ is shorthand for all the explanatory variables.

Goodness-of-fit measure

By using the original data (coc_pl_i) and the fitted values ($\widehat{coc\_pl_i}$) it was possible to obtain the proportion of overall correct predictions. Mathematically, $\widehat{coc\_pl_i} = 1$ if $G(\widehat{coc\_pl_i}) \geq \tilde{\alpha}$ and $\widehat{coc\_pl_i} = 0$ if $G(\widehat{coc\_pl_i}) \leq \tilde{\alpha}$, where $\tilde{\alpha}$ is the value of $\alpha \in (0,1)$ that maximizes the correctly predicted values and minimizes the erroneously predicted variables. After trial-and-error for the values $\alpha \in [0.1, 0.2, \ldots, 0.8, 0.9]$ it was found that $\tilde{\alpha} = 0.4$ maximizes the predicted value.

This measure turned into percentage is the ***percent correctly predicted (PCP)***, a widely used ***goodness-of-fit measure*** for binary dependent variables. PCP is the percentage of observations that are correctly predicted.

2. *Logit and Probit Models*

The LPM has certain drawbacks. One of the most important drawbacks is that for extreme values of the independent variables, the predicted value of the dependent variable will be either less than zero or greater than one, which is impossible for a probability. Logit and Probit models overcome the shortcomings of the LPM.

Model:

$$\boxed{\begin{aligned} P(coc\_pl_i = 1|\boldsymbol{x}) &= G(\beta_0 + \beta_1 fires_i + \beta_2 \log(inhab_i) + \beta_3 needs_i + \beta_4 \log(expl_i)) \\ &= G(\beta_0 + \boldsymbol{x\beta}) \end{aligned}}$$

(5)

Where G is a function taking stricter values between 0 and 1 for all real numbers. This ensures that the estimated response probabilities are strictly between zero and one.

<u>Logit Model:</u> G is the logistic function:

$$G(z) = \frac{\exp(z)}{1 + \exp(z)} = \Lambda(\mathrm{z})$$

(6)

This is the cumulative distribution function for a standard logistic random variable.

<u>Probit Model:</u> G is the standard cumulative distribution function (cdf), which is expressed as an integral:

$$G(z) = \Phi(z) \int_{-\infty}^{z} \phi(v) dv$$

(7)

Where $\phi(v)$ is the standard normal density

$$\phi(z) = (2\pi)^{-1/2} \exp(-\frac{z^2}{2})$$

(8)

Both variations of defining G are increasing functions.

Maximum Likelihood Estimation of Logit and Probit Models

The general theory of MLE for random samples implies that, under very general conditions, the MLE is consistent, asymptotically normal and asymptotically efficient, which means that it is the most precise estimator in large samples.

Interpreting the Logit and Probit Estimates

1. ***Goodness of fit – Percent correctly predicted***

We can use the original data (coc_pl_i) and the fitted values of the probit ($\dddot{coc}\_pl_\iota$) and logit models ($\widetilde{coc\_pl_\iota}$) to obtain the proportion of overall correct predictions. Mathematically, $\dddot{coc}\_pl_\iota = 1$ if $G(\hat{\beta}_0 + \boldsymbol{x}\widehat{\boldsymbol{\beta}}) \geq \alpha$ and $\dddot{coc}\_pl_\iota = 0$ if $G(\hat{\beta}_0 + \boldsymbol{x}\widehat{\boldsymbol{\beta}}) \leq \tilde{\alpha}$, where $\tilde{\alpha}$ is the value of $\alpha \in (0,1)$ that maximizes the correctly predicted values and minimizes the erroneously predicted variables.

Cross – validation and Bootstrapping

Cross – validation and Bootstrapping are both methods for estimating generalization error based on resampling. Bootstrapping is a nonparametric method which compute estimated standard errors, confidence intervals and hypothesis testing.

The 10 fold cross – validation method has the advantage that all observations are used for both training and validation, and each observation is used for validation exactly once. This leads to a more accurate way to measure how efficiently the algorithm has "learned" a concept, based on training set data (Payman et al, 2008).

Leave-one-out cross-validation (LOOCV) is a method where K equals the number of data and the model is tested in one observation (Payman et al, 2008).

2. ***Marginal effects***

A marginal effect is the effect created by engaging in an incremental change in behavior. The primary goal is to explain the marginal effects of $\boldsymbol{x}$ on $P(coc\_pl_i = 1|\boldsymbol{x})$.

There are different ways to calculate the scale factor. The most interesting one is the ***average partial effect (APE).***

In the Logit model:

$$g(z) = \frac{\exp(z)}{[1+\exp(z)]^2} \tag{9}$$

In the Probit model:

$$g(z) = \phi(z) = (2\pi)^{-1/2}\exp(-\frac{z^2}{2}) \tag{10}$$

3. RESULTS

The results of the study comprise three different types of analysis which are the density of fires per municipality grouped by department, a fire-deforestation analysis and three different models between coca increment, fires and other socioeconomic variables.

3.1 Density of fires per municipality area

The graphics below show the density of fires per municipalities within the department starting with the Central Zone and at the end Putumayo – Caquetá. The density of fires is defined here as the number of fires per municipality area. The data used for the graphics are shown in the Appendix.

3.1.1 Central Zone:

Antioquia: Figure 22 shows the density of fires per coca increment areas, stable and decresing coca areas and non coca areas per municipality. Most of the municipalities show higher density of fires in coca increment areas. The municipalities with the highest density of fires in coca increment areas are: Zaragoza, Maceo and Segovia. Arenal is the only municipality having the higher density of fires in stable and decreasing coca areas.

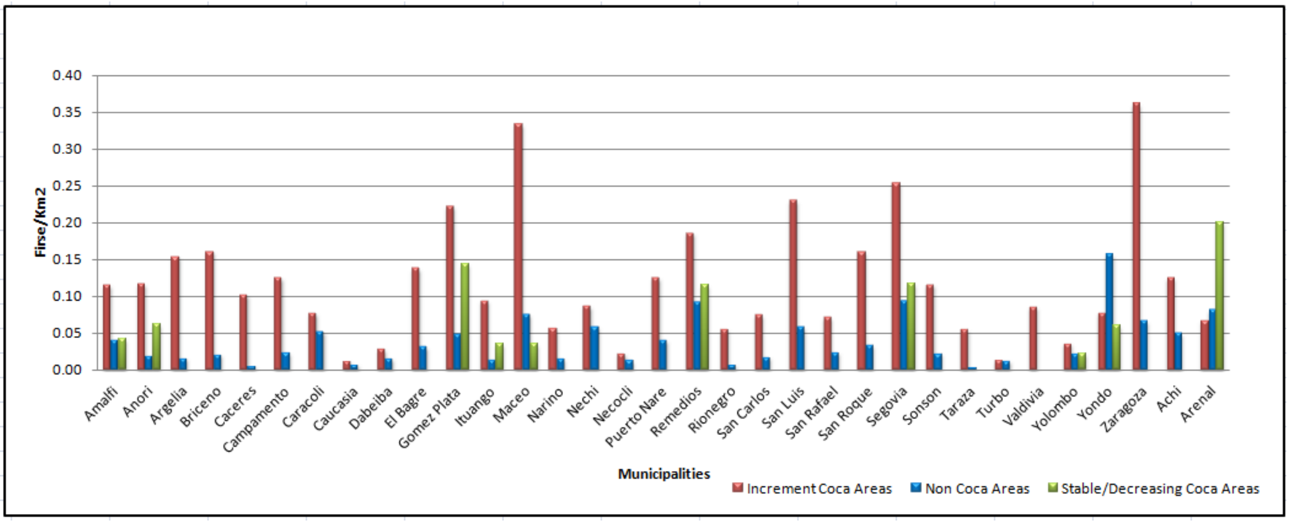


Figure 22. Density of fires – Antioquia.

Bolivar: (see Figure 23) Santa Rosa del Sur and San Pablo are the municipalities with the highest density of fires in coca increment areas (grids affected by coca increment).Out of the eleven municipalities showing fires in the increment areas, three of them show higher density of fires in these areas compared to non-coca areas and stable/decreasing coca areas.

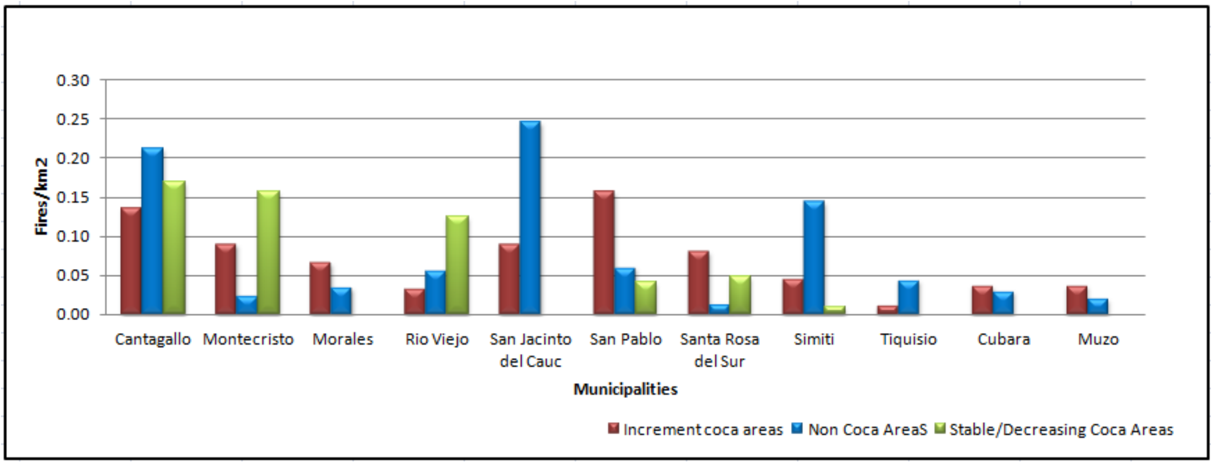


Figure 23. Density of fires – Bolivar

Boyaca: (see Figure 24) All municipalities showing fires in the increment coca areas have higher density in these areas compared to non-coca areas and stable/decreasing areas. Otanche and Puerto Boyacá have the highest density of fires in coca increment areas (grids affected by coca increment).

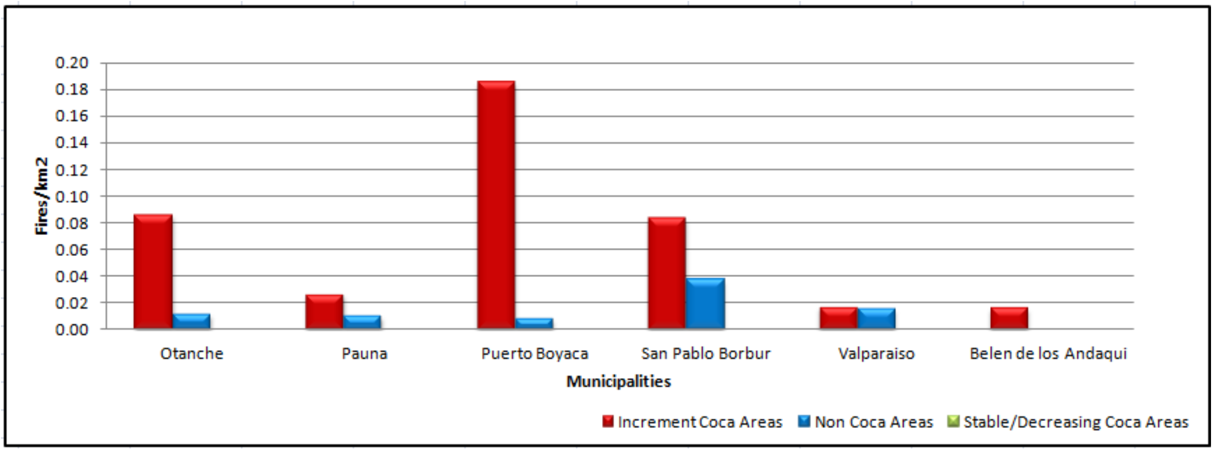


Figure 24. Density of fires – Boyacá

Cordoba: (see Figure 25) Out of the five municipalities showing coca increment, three of them show forest fires in the increment areas. In all three the density of fires is higher in these areas compared to non coca areas and stable/decreasing coca areas.

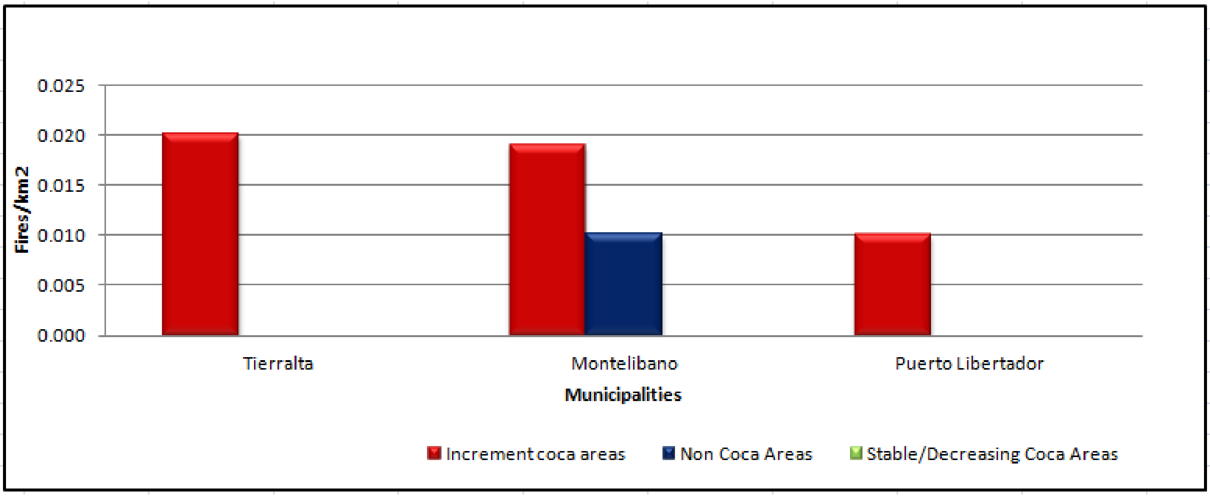


Figure 25. Density of fires – Cordoba

Cundinamarca: Out of the five municipalities showing coca increment, Yacopí is the only one with forest fires in the increment areas. In this municipality the density of fires is higher in this area compare to non coca areas and stable/decreasing coca areas.

Santander: (see Figure 26) The municipalities with the highest area (grids affected by coca increment) of coca increment in descending order are: Puerto Parra, La Belleza and Cimitarra. All municipalities showing fires in the increment coca areas have higher density of fires in these areas compared to non coca areas and stable/decreasing coca areas.

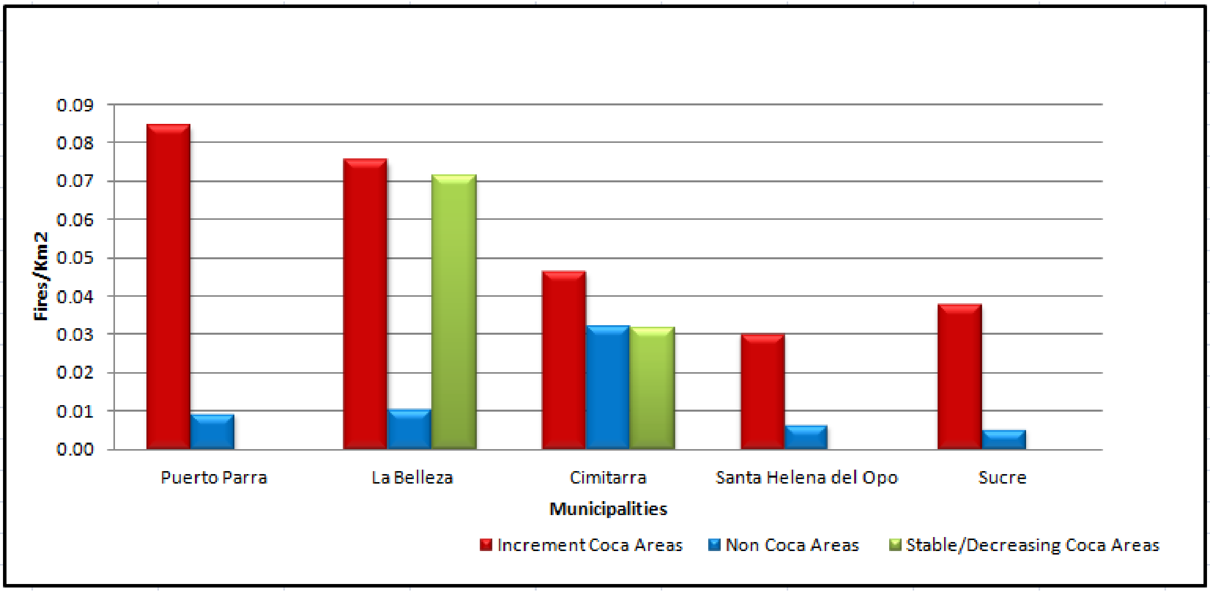


Figure 26. Density of fires – Santander

3.1.2 Putumayo – Caquetá

Caquetá: (see Figure 27) This department shows a different behavior compared to the other departments. San Vicente del Caguán and Solano show the highest density of fires in stable/decreasing coca areas. In this department there is not a specific pattern in the distribution of fires; some municipalities have the same density of fires in coca increment areas and in non coca areas.

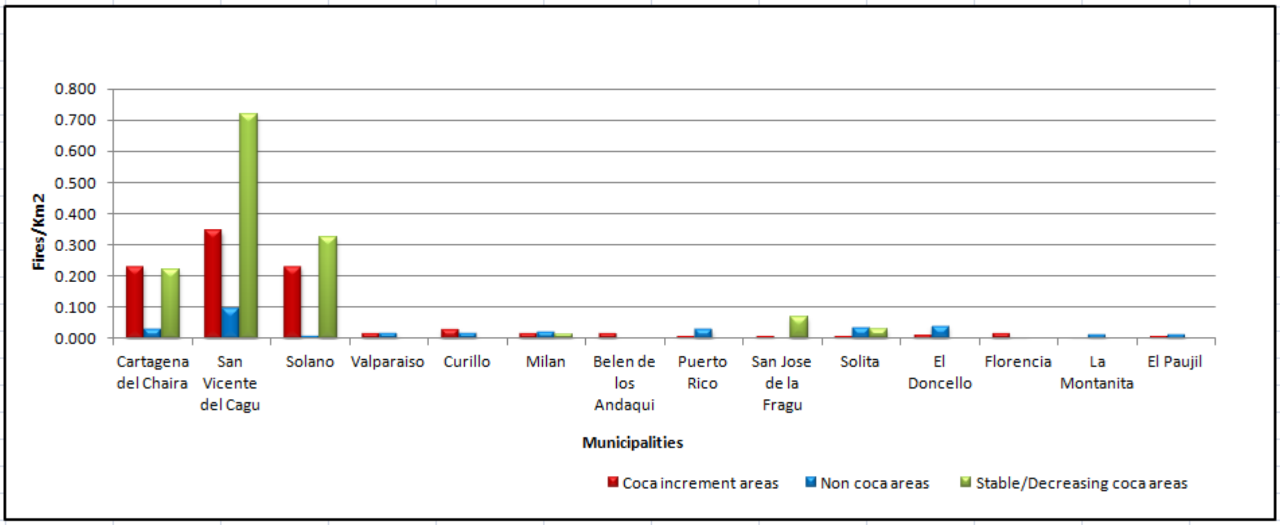


Figure 27. Density of fires – Caquetá

Putumayo: (see Figure 28) Puerto Leguizamo has the highest number of fires per square kilometer in coca increment areas followed by Puerto Guzman and San Francisco. In Puerto Guzman the density of fires in coca increment areas and stable/decreasing coca areas is equal. San Miguel and Mocoa have the highest density of fires in stable/decreasing coca areas. The rest of municipalities show highest density of fires in coca increment areas.

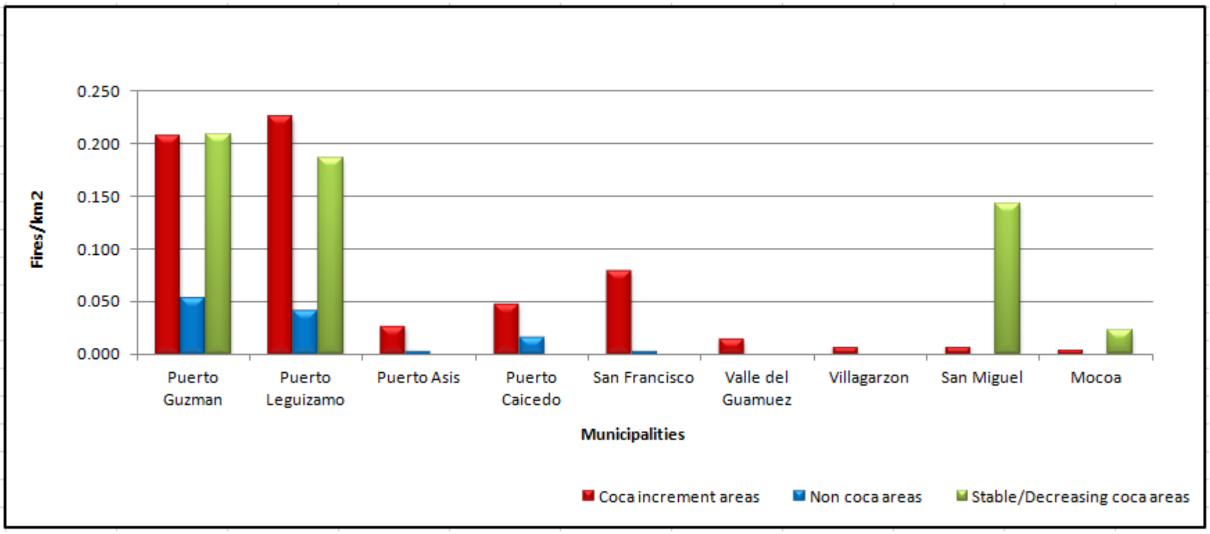


Figure 28. Density of fires – Putumayo

Figure 29 shows a classification of the municipalities depending on its density of fires. It can be observed that in the central region most of the municipalities have higher density of fires in coca increment areas (fires/km^2) than in non-coca increments. In Putumayo the situation is similar to the central region but Caquetá has a different behavior, showing the biggest municipalities with higher density of fires in the stable or decreasing coca areas.

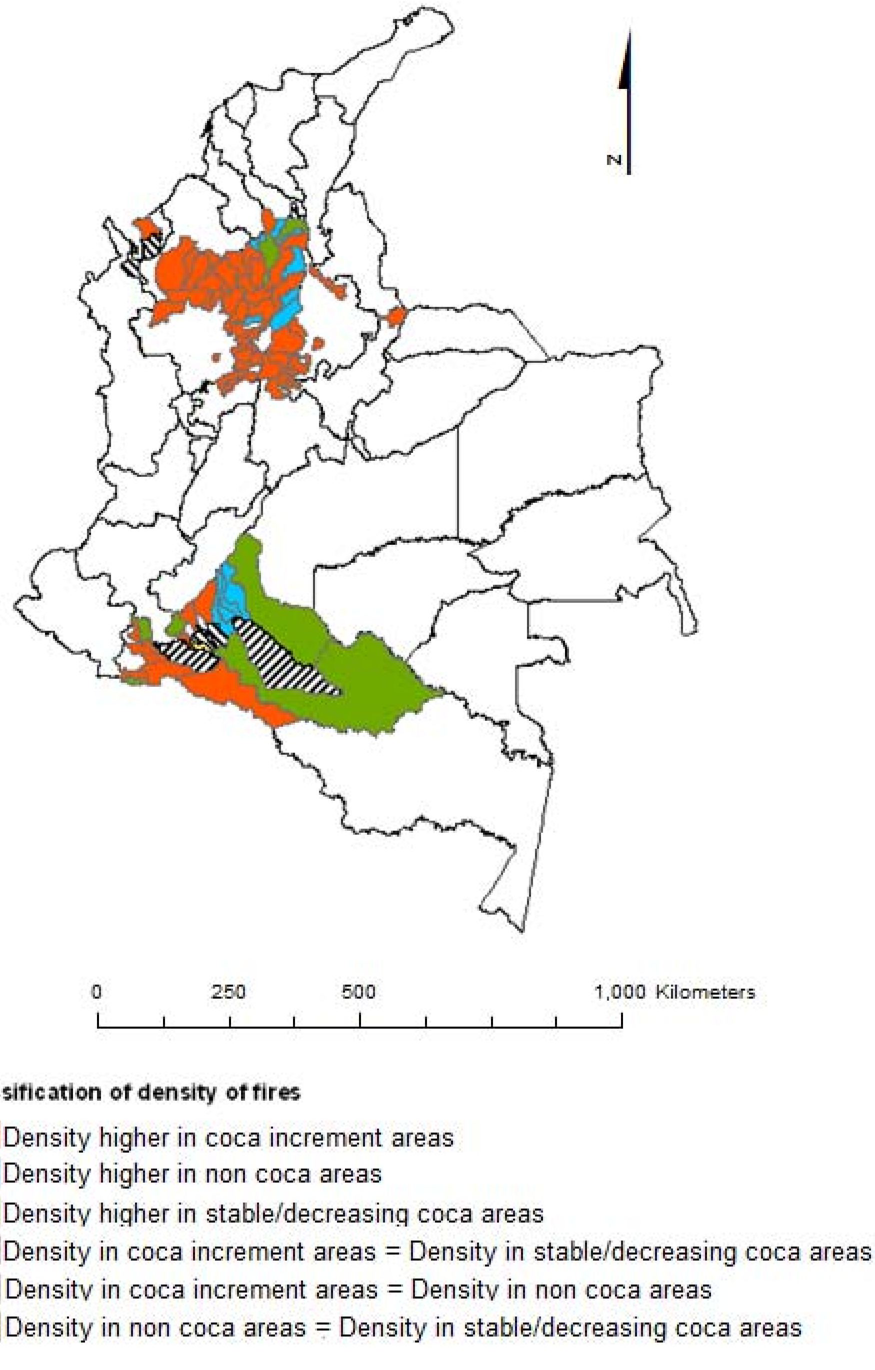


Figure 29. Density of fires classification

When comparing municipalities with forest fires in coca increment areas and municipalities without forest fires in coca increment areas at department level it can be seen that the major coca increment during the period (2000 – 2010) per department is found in the municipalities with forest fires in coca increment areas (see Appendix).

Table 4. Comparison between municipalities with and without forest fires in coca increment areas (2000 – 2010)

Department	Total Coca increment (ha)	Municipalities with fires in coca increment areas		Municipalities without fires in coca increment areas	
		Number	% of coca increment	Number	% of coca increment
Antioquia	32664.68	32	98.51	15	1.49
Bolivar	24528.43	12	98.09	3	1.91
Boyaca	1642.55	6	91.88	8	8.12
Cordoba	9185.79	3	99.41	2	0.59
Cundinamarca	387.80	1	72.96	4	27.04
Santander	5684.19	6	85.21	16	14.79
Caqueta	32909.56	14	97.89	2	2.11
Putumayo	51802.45	9	87.18	2	12.82

When undertaking the same comparison but using coca increment just in forest areas a similar situation is presented.

Table 5. Comparison between municipalities with and without forest fires in coca increment in forest areas (2000 – 2010)

Department	Total Coca increment in forest areas (ha)	Municipalities with fires in coca increment areas		Municipalities without fires in coca increment areas	
		Number	% of coca increment in forest areas	Number	% of coca increment in forest areas
Antioquia	14690.61	32	99.05	15	0.95
Bolivar	6756.04	12	100.00	3	0.00
Boyaca	973.72	6	93.43	8	6.57
Cordoba	1678.17	3	100.00	2	0.00
Cundinamarca	40.02	1	53.45	4	46.55
Santander	2482.08	6	92.34	16	7.664
Caqueta	10530.19	14	99.92	2	0.079
Putumayo	19416.12	9	93.73	2	6.272

3.2 Fires – Coca Increment - Deforestation

- ***Fires and Deforestation***

To better understand the relationship between fires and deforestation the Pearson Correlation Coefficient was used. There is a strong relationship between the number of fires and deforestation area (Pearson coefficient = 0.930 significance at 0.01 level).

- ***Coca Increment – Deforestation***

The maps below show how coca has influenced deforestation between 2000 and 2010 separate in two periods. The deforestation map was overlaid with the coca map and it was examined if the grid of coca increment was in a deforestation grid.

The map for the period 2000 to 2005 shows that in the majority of municipalities in Central Region and Putumayo - Caquetá coca may be associated between 0.01 and 20% of the total deforestation. Specifically in Putumayo in some municipalities coca is associated with 80% to 100% of the total deforestation (Figure 30).

The map for the period 2005 to 2010 shows that in the majority of municipalities in Central Region and Putumayo - Caquetá coca may be associated between 0.01 and 20% of the total deforestation as in the period before. The rate of coca associated to deforestation in Putumayo decreased compare to the period before (Figure 31).

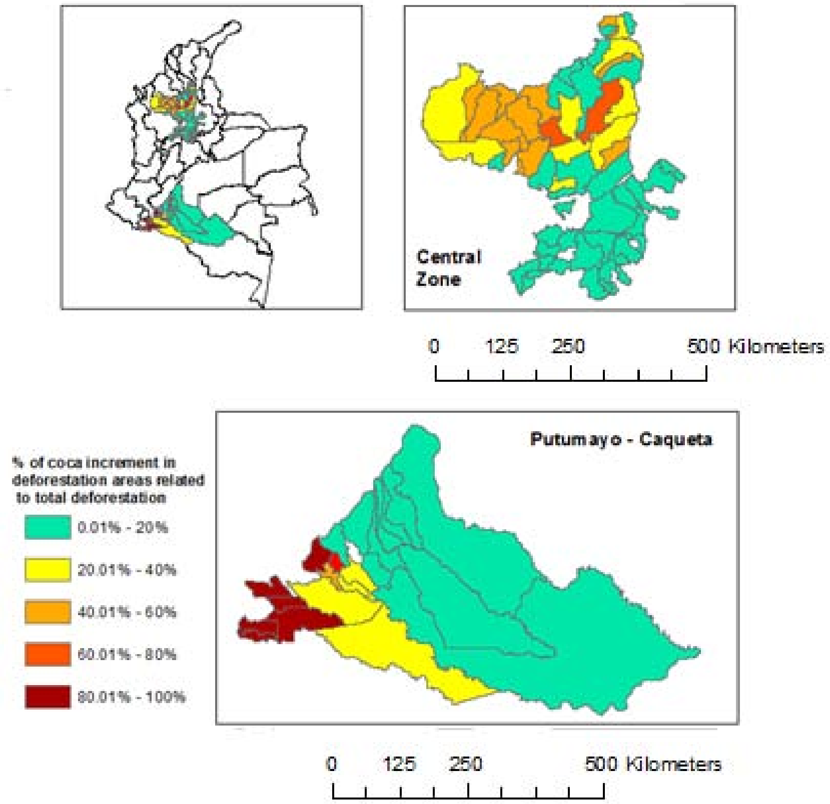


Figure 30. Coca and deforestation 2000 - 2005

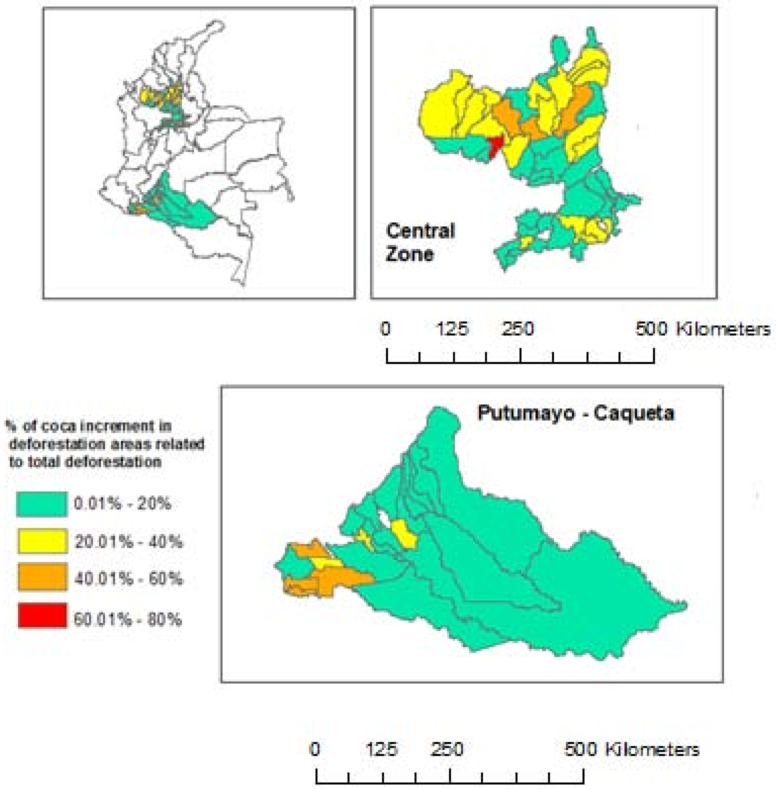


Figure 31. Coca and deforestation 2005 – 2010

The correlation between the coca increment and deforestation in the last ten years is highly significant at 0.01 level (Pearson coefficient = 0.729).

Although this study cannot show that coca is the independent variable and deforestation the dependent variable, there are many studies showing that expansion of cropped land, including coca plantation, is driving deforestation (Armenteas et al 2011).

3.3 Model Results

Table 6 shows the results of the three models

Table 6. LPM, Logit and Probit Estimates of Coca Plantations

Explanatory Variables	**LPM [(a)] (OLS)**		**Logit [(a)] (MLE)**		**Probit [(a)] (MLE)**	
Constant	-0.6477*[(b)]	[0.1540][(c)]	-9.1721*	[2.0628]	-4.4680 *	[1.0430]
Fires in forest	0.0004*	[0.0001]	0.4973*	[0.0739]	0.2788*	[0.0394]
(Log) Inhabitants in rural areas	0.0245	[0.0182]	0.1152	[0.2229]	0.0156	[0.1188]
Basic unsatisfied needs	0.0042*	[0.0008]	0.0288*	[0.0103]	0.0146*	[0.0055]
(Log) Expulsion	0.0650*	[0.0079]	0.5544*	[0.1188]	0.2926*	[0.0637]
Pseudo R-squared	0.2856 [(d)]		0.5802		0.5798	
Log-likelihood value	--		-101.0538		-101.1484	
Percent correctly predicted [(e)]	86.69		93.35		93.35	
F-statistic	52.08*		--		--	
LR-statistic	--		279.32*		279.13*	

Note: (a) The first column reports the coefficients′ estimates from the ***Linear Probability Model*** (**LPM**) calculated using OLS. The second and third column report the coefficients′ estimates obtained with the ***Logit*** and ***Probit*** models, respectively. Both of them were calculated using *maximum likelihood estimation (MLE).* (b) The star (*****) denotes coefficients′ estimates that are statistically significant at the 5% level. (c) The standard errors are displayed in brackets. (d) This is just the usual R-squared reported for OLS. (e) These were predicted using the threshold value 0.4 for all models.

Interpretation:

- R-squared: The proportion of the total variation in the dependent variable that is explained through the model.
- Pseudo R-squared: analog to the R-squared in linear regression models.

- Log-likelihood value: maximized value of log-likelihood function
- Percent correctly predicted: goodness of fit measure. Proportion of overall correct predictions turned into percentage based on fitted values and the threshold 0.4.
- F-statistic: tests
    - $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ is rejected. The explanatory variables are jointly significant
- LR-statistic: Analog for F test in linear model
    - $H_0: \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0$ is rejected. The explanatory variables are jointly significant

Table 7. Magnitude of the marginal effects of statistically significant explanatory variables (LPM, Logit and Probit Estimates)

Explanatory Variables	LPM [(a)] (OLS)	Logit [(b)] (MLE)	Probit [(c)] (MLE)
Constant	-0,6477	-2.2342	-1.6972
Fires in forest	0.0004	0.1211	0.1059
(Log) Inhabitants in rural areas	0,0245	0.0281	0.0059
Basic unsatisfied needs	0.0042	0.0070	0.0055
(Log) Expulsion	0.0650	0.1350	0.1111

Note: (a) The first column reports the coefficients´ estimates from the *Linear Probability Model* (**LPM**) calculated using OLS. (b) The second and third columns report the coefficients´ estimates obtained with the ***Logit*** and ***Probit*** models multiplied by the scale factors 0.2436 and 0.3799, respectively.

LPM Interpretation:

1. One more fire in forest increases the probability of the increment of coca plantations by 0.0004 ha when all the other variables are held fixed.
2. 1% of increase in the log of basic unsatisfied needs increases the probability of the increment of coca plantations by 0.0042 ha when all the other variables are held fixed.
3. 1% of increase in the log of expulsion increases the probability of the increment of coca plantations by 0.0650 ha when all the other variables are held fixed.

Logit Interpretation:

1. One more fire in forest increases the probability of the increment of coca plantations by 0.1211ha when all the other variables are held fixed. .
2. 1% of increase in the log of basic unsatisfied needs increases the probability of the increment of coca plantations by 0.0070 ha when all the other variables are held fixed.
3. 1% of increase in the log of expulsion increases the probability of the increment of coca plantations by 0.135 ha when all the other variables are held fixed.

Probit Interpretation:

1. One more fire in forest increases the probability of the increment of coca plantations by 0.1059 ha when all the other variables are held fixed.
2. 1% of increase in the log of basic unsatisfied needs increases the probability of the increment of coca plantations by 0.0055 ha when all the other variables are held fixed.
3. 1% of increase in the log of expulsion increases the probability of the increment of coca plantations by 0.1111ha when all the other variables are held fixed.

The coefficients of the Linear model show that this model is not appropriated to describe the data. In addition, partial effects are constant for all explanatory variables. Logit and Probit model give similar results although they assume different functions which are logistic distribution and normal distribution respectively. Despite, its similarity there is one advantage to choose the Logit model which is the simplicity of the equation compare to the equation to the Probit model.

The 10 fold out cross – validation method was used where the original population was divided in 10 groups. 9 of them are trained groups and 1 is used to evaluate the model. The mean corrected classified value is 0.92 meaning that the model is successful in 92% of the cases.
The leave - one - out cross validation method with 500 iterations was another method used in order to validate the model. In each one of the repetitions the proportion of the mean corrected classified values is around 0.93 which means the model is wrong approximately in just 7% of the cases. The proportion of the corrected classification values is showed in mean of corrected classified values because different iterations in each test have a correspondent proportion. The final result is the average of these proportions.

Below there is one example evaluating the change in the probability of coca increment when one additional fire around the existing plantation is registered in the municipality of Altos del Rosa (Bolivar). All the other factors have to be fixed.

The general equation is given by:

$$\begin{aligned}\Delta P(coc\_pl_i &= 1|\boldsymbol{x}) \\ &= G\big(\hat{\beta}_0 + \hat{\beta}_1(fires_i + 1) + \hat{\beta}_2\log(inhab_i) + \hat{\beta}_3 needs_i + \hat{\beta}_4\log(expl_i)\big) \\ &- G\big(\hat{\beta}_0 + \hat{\beta}_1 fires_i + \hat{\beta}_2\log(inhab_i) + \hat{\beta}_3 needs_i + \hat{\beta}_4\log(expl)\big)\end{aligned}$$

Based on the coefficients of the Logit Model the change in the probability is:

$$\Delta P(coc\_pl_{Altos\ del\ Rosa} = 1|\boldsymbol{x}) = 0.1103$$

This means that the probability of increment of coca plantations will increase from 0.0123 (i.e. fitted value of the Logit model with fires at its current level) to 0.1226 (i.e. fitted value of the logit model with one more fire). Although the increase of the probability is highly significant it is still below the critical threshold level (i.e. 0.4).

Figure 32 shows the municipalities with the probabilities based on the coefficients of the Logit Model.

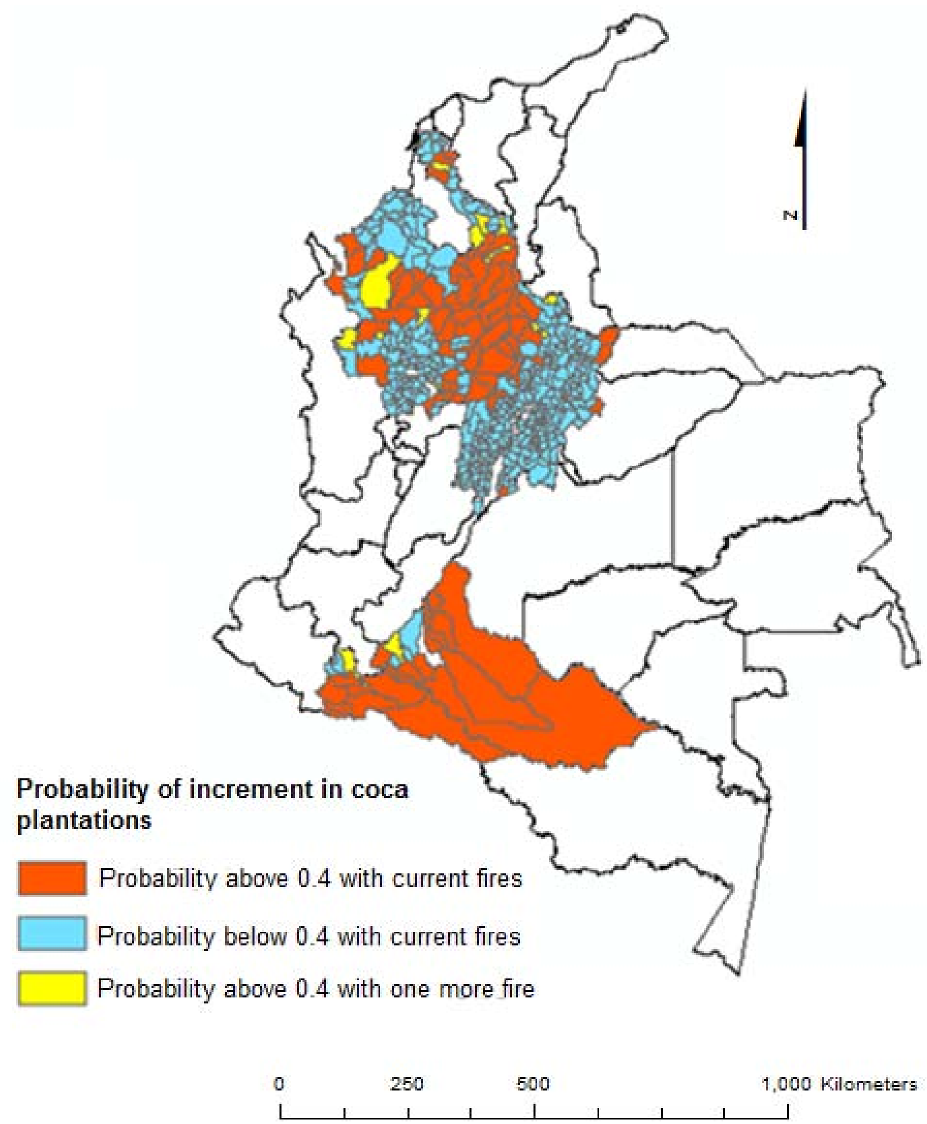


Figure 32. Probability of coca increment – Logit Model.

When there is one more fire fourteen municipalities move from below the threshold level of below 0.4 to above 0.4. Examples of these municipalities are Uramita (Antioquia), Tierralta (Córdoba), San Jacinto (Bolivar) and Muzo (Boyacá).

4. DISCUSSION

Coca in Colombia has a large history. Nevertheless, the degree of impact on forests has been different across the regions. There are innumerable factors contributing to deforestation such as agriculture, cattle ranching, population pressure and illicit crops. In most of the cases fire is used to open new areas for human activities (Silvestrini et al., 2010)

There are three important findings that can be drawn from this study. The first finding is that there is a certain relationship between coca increment and forest fires. The second finding is that if coca cultivation increases it is likely that this leads to deforestation (see Dávalos et al., 2011 and Armenteas et al., 2011). The third finding is that fires around established coca areas and the socio-economic variable expulsion can be used as an indicator of coca increment in forest areas.

The relationship between coca increment and fires in forest areas was analyzed using two different datasets. GLC 2000 (1 km resolution) and the forest cover map from Colombia for the year 2000 – IDEAM (30 m resolution). Both datasets show that there is a positive correlation between coca increment and fires in forest areas.

Whereas the correlation using GLC 2000 is 0.644, the correlation using the forest cover map from Colombia for the year 2000 made by IDEAM is 0.577. Interestingly when using the dataset with the higher resolution the correlation decreases. The reason might be that due to the lack of information in the satellite images used not all forest areas were covered by the IDEAM dataset.

The density of fires analysis per municipality (using GLC 2000) shows that fire is used to clear forest to grow coca. Even though in many cases the majority of fires occurs in areas where coca increment is found in some regions this is not the case. For instance, in Antioquia and Putumayo all municipalities have higher density of fires in coca increment areas compared to the other areas. In Bolivar and Caquetá there is not a particular pattern found which relates to the density of fires. This means that the density of fires per area varies among municipalities. The explanation can be that the quantity of new coca plantations is occurring with different degrees of concentration, For instance, coca plantations in Antioquia have increased significantly in the last years (UNODC, 2011a).

However, the major of coca increment in forest areas in all municipalities under study is spatially associated to fires. In addition, when the density of fires is higher in non coca increment areas or stable and decreasing coca areas the increment of coca has not been representative (has been low) during the whole period.

Analyzing the percentage of coca increment having a spatial relation with fires it can be said that (see Table 4) among the departments belonging to Central Region four of them show a higher percentage (more than 90%) of coca increment in areas where fires and coca increment are spatially related. Boyacá and Cundinamarca show a percentage of coca increment higher than 70%. Regarding the region Putumayo – Caqueta a similar pattern can be observed. The percentage of coca increment which are related to fires is higher than 97% and 87% respectevely.

Furthermore, in order to be more specific, when using coca increment just in forest areas a similar situation is presented (see Table 5). In all departments where coca increment in forest areas can be observed fire is used as a management tool. Comparing the municipalities with fires related to coca increment and municipalities without fires related to coca increment it becomes clear that 90% of this increment is related to fires in forest areas.

In Cundinamarca the situation is different. One municipality has 53.45% of the total coca increment in forest in this department with fires spatially related. The other four municipalities do not have fires related to coca increment and have 46.55% of the coca increment.

It is interesting to note from table 3 and table 4 (see section 3.1) that in most cases when there is coca increment this results in fire activities. So the relationship between fires and coca-increment works very well when coca is increasing. In brief, nearly in all cases when coca is increasing fires occur in the 10 year observation period, but the occurrence of fires does not always relate to coca increment. This is an important finding as this means that there are hardly any places where coca increment has not had an occurrence of fires. In nearly all coca increment grids fires can be found.

This may indicate that in these areas fire is an important tool to open new areas to grow coca. However, forest fire cannot be in all cases attributed to coca, although it influences strongly the expansion of the agricultural frontier (Armenteras and Retana, 2012). In some cases fire can be attributed to cattle ranching and the demand for timber (Armenteras et al., 2011).

In order to understand the sequence fire – deforestation - coca, the relationship between coca increment and deforestation and fire and deforestation was analyzed. Subsequently, the analysis between fire and coca increment was made.

There are numerous factors influencing the cultivation and enlargement of existing coca plantations which result in further deforestation such as eradication, armed conflict and the world demand for this illicit drug (Dávalos et al, 2011). These types of pressures provoke people to reallocate coca crops and these new locations in many cases are in forest areas.

The Pearson correlation between coca increment and deforestation for the period 2001 – 2010 shows a positive relationship (Pearson Coefficient = 0.729). The two periods included in the deforestation analysis (2000-2005 and 2006-2010 – IDEAM dataset) show that in general in the south part of the Central Region coca increment is associated with a percentage of deforestation less than 20% of the total deforestation. In the north part coca increment is associated between 20% and 60% of the total deforestation.

In Putumayo – Caquetá Region coca increment is associated in general with a percentage less or equal than 20% of the total deforestation in Caquetá for the whole period (2000-2005 and 2006-2010- IDEAM dataset). In Putumayo for the period 2000 -2005 coca increment is associated in some places with a percentage between 20% and 40% and more than 80%. For the period 2006 – 2010 coca increment is associated in general with a percentage less than 20%.

The coca increment deforestation analysis shows that coca has an influence on deforestation. However, the level of influence is different depending on the region and the quantity of forest cover.

Some municipalities belonging to the departments in the Central Region are located over the Andean Mountains. Putumayo and Caquetá are located in the Amazonian rainforest. As coca growers tend to hide the crops under the forest these regions are consequently highly vulnerable to degradation. In addition, the lack of governance, sufficient policing, population growth and armed conflicts increase the threat of coca expansion and subsequent deforestation in these regions.

In general new coca plantations and deforestation patterns show some relationship at department level, but at municipality level the influence varies depending on the area of the municipality and the area of forest cover. For instance, in Antioquia there are some municipalities such as Zaragoza, Anori, Cáceres and Taraza in which the percentage of deforestation that may be attributed to coca exceeds 50%, but in others such as Puerto Nare the association between the two variables is less than 1%. In Bolivar, in Santa Rosa del Sur the percentage of deforestation that may be attributed to coca exceeds 60% and in other municipalities exceeds 40%, but in San Jacinto del Cauca the percentage is less than 2%. In Boyacá and Santander the percentage of coca increment that can be associated to deforestation is less than 10%. In Cordoba the percentage of coca increment that can be associated to deforestation is less than 20%. In Cundinamarca this percentage is less that 2% (Figure 30 and Figure 31).

In the north of Putumayo in some municipalities coca may be associated with more than 80% of the deforestation. In the municipalities of Caquetá (as was mentioned above) deforestation attributed to coca is associated to 20%. The different coca dynamics in these regions can be associated to the different projects implemented by the government. For instance, the project called 'Milk for cocaine' backed by $5.3 million from the UN (http://www.economist.com/node/431804, UNODCCP, 2000) in San Vicente del Caguán its aimed at boosting dairy farming. In this municipality it is therefore unlikely that coca expansion and deforestation or coca and fires are related.

The Pearson correlation between fire and deforestation for the period 2000 – 2010 shows a strong positive relationship (Pearson Coefficient = 0.930). This indicates that as shown in previous studies (Eva and Fritz, 2003, Armenteras et al., 2006, Dávalos et al., 2009) there is a strong correlation between fires and deforestation. Assuming that in general almost all fires that occur in coca increment are anthropogenic, it can be said that climatic conditions are not the only variables determining the occurrence of fires. Human activities play an important role determining the pattern of fires as well (see also Armenteras and Retana, 2012).

Accordingly, if there are new expanding activities of coca growth into forest areas, deforestation can be linked to coca increment and population dynamics in coca-growing areas. (see also Dávalos et al., 2011) .

Since these correlations exist it was attempted in chapter 3 to build a model between forest fires, socio-economic variables and coca increment. The estimates from the three models are consistent with each other. In other words, the signs of the coefficients are the same across models and the same variables are statistically significant in each model.

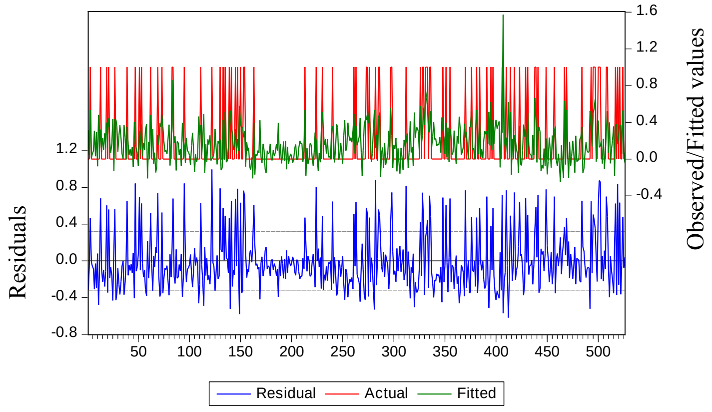
The Linear Probability Model has the advantage that is easy to interpret but it has the disadvantages that the predictions (fitted probabilities) can be less than zero or greater than one. In addition, a probability cannot be linearly related to the independent variables for all their possible values. In another words this means that the partial effect of any explanatory variable (appearing in level form) is constant. Instead the Logit and Probit Models imply diminishing magnitudes of the partial effects. With data for every other variable, it is possible to determine the increase in the probability of the existence of a new coca plantation is going from zero to one.

Logit and Probit are a link function of the linear regression models; as such the results are very similar (Train, 2007). So, it is no surprisingly that in this case the coefficients` estimates obtained are similar, for instance the coefficient for the explanatory variable fires in forest is 0.1211 and 0.1059 respectively.

It is important to highlight those municipalities where an increase of one fire would be reflected in moving from below to above the pre-established threshold ($\tilde{\alpha} = 0.4.$). Examples of this situation are Cicuco (Bolivar), Corcona (Antioquia), Betulia (Santander).

The Percent Correctly Predicted is a measure of the goodness of fit, has the disadvantage that treats in the same way different probabilities (Train, 2007). In this case PCP treats a probability of 0.41 equal as one probability of 0.99 despite the fact that a probability of 0.99 says much that one of 0.41.

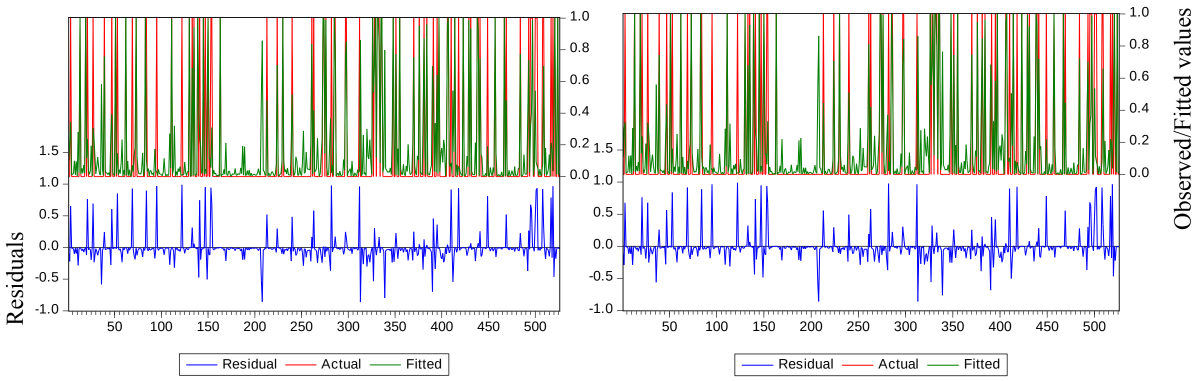
Comparing the graphs from the LPM, Logit and Probit, it can be observed that in the LPM model the actual and fitted values do not correspond to each other (Figure 33). Therefore, this model is not appropriate. In addition, the residual values show several outliers.



Municipalities

Figure 33. Fitted – Actual and Residual values LPM

Comparing Logit and Probit models it can be observed that the fitted values cover up the actual values. Additionally, the residuals have less outlier (Figure 34).



a. b.

Municipalities

Figure 34. Fitted – Actual and Residual values a. Logit b. Probit

5. CONCLUSIONS

This study demonstrates that in general fire is a widely used tool to grow coca crops in forest areas. However, it is not easy to always associate directly fires to coca because in some situations coca plantations can be a consequence of the agricultural expansion as is difficult to know which one is the first interest for the growers. For instance, the grower can think first in expanding the legal crops and afterwards see the possibility to grow coca at the same time or it can be the other way around. Nevertheless, the study makes clear that most of the new coca plantations are found in forest areas and that fire is associated with them.

In addition, the study shows that the correlation between fire and deforestation is high, supporting previous work on the possibility to use fire as an indicator of deforestation. Moreover, a high correlation was found between coca increment and deforestation as well. However, the impact of coca on the total deforestation per municipality differs as the increment of coca plantations depends on the different dynamics of each region.

The Logit and Probit models, show that in general fire data together with socio-economic variables can be used to highlight potential new coca crops in forest areas at the municipality level. The evaluation of the coefficients` estimates at each municipality gives as a result the prediction at municipality level.

In some municipalities the increase of one more fire is determining if the probability of a new coca plantation in forest areas is below or above the threshold, which means that having the current number of fires the probability is below 0.4 and when there is one more fire the probability is above 0.4.

Comparing the three socioeconomic factors used in the models, expulsion shows the highest probability of the occurrence of new coca plantation when all the other variables are held fixed. Nonetheless, in Colombia it is challenging to get up to date socioeconomic data.

Therefore, fire in forest areas can potentially be used as a first indicator of new coca plantations in forest. Due to the fact that fire data are easily available on the internet this offers interesting monitoring facilities at low costs as near real time information and can be downloaded for free on the internet.

However, this research also illustrates fire data from satellite imagery to determine new coca areas have to be used carefully due to the fact that errors can be found in the fire dataset, in the forest mask and in the census of coca areas. In addition, the method can work just in areas where the ignition is easy to happen.

Moreover, the study was carried out with a dataset of 10 years and shorter time periods could be examined in order to be able to detect potentially new coca evolving fields at an earlier stage.

The model was developed for Colombia where a very sophisticated analysis of LANDSAT type data, with subsequent aerial survey exists. However, the model could be used and applied in other countries where some potential new coca growing areas could be missed by the manual interpretation of satellite imagery to take place. Additionally the model could be applied in places where coca is currently increasing and where resources are limited in terms of carrying out satellite image interpretation and where cloud cover persists. Moreover the model could be used to complement existing surveys and to potentially detect coca expanding.

In the future the models developed can be extended to other variables to better understand coca dynamics, for instance, eradication, size of the fields and presence of illegal groups.

There are still many things to understand concerning the relation between fires and new coca plantations in forest areas and how this is related to deforestation, always subject to data availability.
The results have to be use carefully because there are many factors influencing both coca increment and fires in forest areas and in different regions they can be not be directly related. However, this study can potentially contribute to the prevention of the expansion of coca plantations in some forest areas.

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APPENDIX

Density of fires per municipality

Department	Municipio	Coca increment	Forest Fires Increment coca	Fires non coca	Fires rest coca	Area Coca Increment (km2)	Area non coca (km2)	Area Coca Rest (km2)	Fires increment/km2	Fires non coca/km2	Fires rest coca/km2	Sum Densities	Fires increment/km2 (%)	Fires non coca/km2 (%)	Fires rest coca/km2(%)	Classification
Antioquia	Amalfi	847.64	36.00	37.00	1.00	313.00	902.00	24.00	0.12	0.04	0.04	0.20	58.18	20.75	21.08	1
Antioquia	Anori	3200.91	90.00	12.00	1.00	771.00	632.00	16.00	0.12	0.02	0.06	0.20	58.89	9.58	31.53	1
Antioquia	Argelia	34.57	4.00	3.00	0.00	26.00	191.00	0.00	0.15	0.02	0.00	0.17	90.74	9.26	0.00	1
Antioquia	Briceno	406.39	18.00	6.00	0.00	112.00	286.00	2.00	0.16	0.02	0.00	0.18	88.45	11.55	0.00	1
Antioquia	Caceres	3208.93	68.00	7.00	0.00	667.00	1245.00	2.00	0.10	0.01	0.00	0.11	94.77	5.23	0.00	1
Antioquia	Campamento	81.21	4.00	3.00	0.00	32.00	131.00	6.00	0.13	0.02	0.00	0.15	84.52	15.48	0.00	1
Antioquia	Caracoli	23.54	1.00	12.00	0.00	13.00	228.00	0.00	0.08	0.05	0.00	0.13	59.38	40.63	0.00	1
Antioquia	Caucasia	214.10	1.00	10.00	0.00	85.00	1385.00	9.00	0.01	0.01	0.00	0.02	61.97	38.03	0.00	1
Antioquia	Dabeiba	77.39	1.00	29.00	0.00	36.00	1886.00	17.00	0.03	0.02	0.00	0.04	64.37	35.63	0.00	1
Antioquia	El Bagre	4049.51	126.00	20.00	0.00	915.00	637.00	10.00	0.14	0.03	0.00	0.17	81.43	18.57	0.00	1
Antioquia	Gomez Plata	23.17	2.00	16.00	1.00	9.00	324.00	7.00	0.22	0.05	0.14	0.41	53.62	11.91	34.47	1
Antioquia	Ituango	1013.45	31.00	26.00	2.00	329.00	1936.00	56.00	0.09	0.01	0.04	0.14	65.72	9.37	24.91	1
Antioquia	Maceo	7.95	1.00	26.00	1.00	3.00	344.00	28.00	0.33	0.08	0.04	0.44	74.97	17.00	8.03	1
Antioquia	Narino	144.43	4.00	4.00	0.00	71.00	256.00	0.00	0.06	0.02	0.00	0.07	78.29	21.71	0.00	1
Antioquia	Nechi	1577.59	23.00	45.00	0.00	267.00	768.00	0.00	0.09	0.06	0.00	0.14	59.52	40.48	0.00	1
Antioquia	Necocli	79.56	1.00	16.00	0.00	44.00	1253.00	0.00	0.02	0.01	0.00	0.04	64.03	35.97	0.00	1
Antioquia	Puerto Nare	112.80	6.00	22.00	0.00	48.00	545.00	0.00	0.13	0.04	0.00	0.17	75.59	24.41	0.00	1
Antioquia	Remedios	1719.81	111.00	112.00	13.00	597.00	1210.00	112.00	0.19	0.09	0.12	0.39	47.12	23.46	29.42	1
Antioquia	Rionegro	32.81	1.00	11.00	0.00	18.00	1556.00	11.00	0.06	0.01	0.00	0.06	88.71	11.29	0.00	1
Antioquia	San Carlos	153.01	5.00	19.00	0.00	67.00	1071.00	0.00	0.07	0.02	0.00	0.09	80.79	19.21	0.00	1
Antioquia	San Luis	558.13	55.00	16.00	0.00	239.00	275.00	0.00	0.23	0.06	0.00	0.29	79.82	20.18	0.00	1
Antioquia	San Rafael	16.25	1.00	8.00	0.00	14.00	338.00	1.00	0.07	0.02	0.00	0.10	75.11	24.89	0.00	1
Antioquia	San Roque	65.54	4.00	13.00	0.00	25.00	387.00	22.00	0.16	0.03	0.00	0.19	82.65	17.35	0.00	1
Antioquia	Segovia	1956.79	155.00	51.00	5.00	612.00	545.00	43.00	0.25	0.09	0.12	0.46	54.69	20.21	25.11	1
Antioquia	Sonson	238.65	11.00	27.00	0.00	95.00	1188.00	0.00	0.12	0.02	0.00	0.14	83.59	16.41	0.00	1
Antioquia	Taraza	5371.15	53.00	2.00	0.00	970.00	654.00	11.00	0.05	0.00	0.00	0.06	94.70	5.30	0.00	1
Antioquia	Turbo	196.56	2.00	35.00	0.00	153.00	2825.00	3.00	0.01	0.01	0.00	0.03	51.34	48.66	0.00	1
Antioquia	Valdivia	2323.27	28.00	0.00	0.00	327.00	254.00	88.00	0.09	0.00	0.00	0.09	100.00	0.00	0.00	1
Antioquia	Yolombo	119.19	1.00	21.00	1.00	28.00	954.00	46.00	0.04	0.02	0.02	0.08	44.94	27.70	27.36	1
Antioquia	Yondo	544.13	16.00	268.00	4.00	207.00	1714.00	66.00	0.08	0.16	0.06	0.29	26.27	53.14	20.60	2
Antioquia	Zaragoza	3477.46	222.00	25.00	0.00	615.00	376.00	13.00	0.36	0.07	0.00	0.43	84.45	15.55	0.00	1
Bolivar	Achi	92.69	7.00	45.00	0.00	56.00	906.00	7.00	0.13	0.05	0.00	0.17	63.23	28.44	0.00	1

Density of fires per municipality

Department	Municipio	Coca increment	Forest Fires Increment coca	Fires non coca	Fires rest coca	Area Coca Increment (km2)	Area non coca (km2)	Area Coca Rest (km2)	Fires increment/km2	Fires non coca/km2	Fires rest coca/km2	Sum Densities	Fires increment/km2 (%)	Fires non coca/km2 (%)	Fires rest coca/km2(%)	Classification
Bolivar	Arenal	807.84	14.00	20.00	1.00	210.00	246.00	5.00	0.07	0.08	0.20	0.35	19.16	23.36	57.48	3
Bolivar	Cantagallo	2676.00	56.00	79.00	10.00	409.00	371.00	59.00	0.14	0.21	0.17	0.52	26.36	41.00	32.64	2
Bolivar	Montecristo	2501.47	67.00	32.00	3.00	741.00	1323.00	19.00	0.09	0.02	0.16	0.27	33.18	8.88	57.94	3
Bolivar	Morales	1100.98	22.00	33.00	0.00	332.00	964.00	13.00	0.07	0.03	0.00	0.10	65.94	34.06	0.00	1
Bolivar	Rio Viejo	1666.19	16.00	46.00	2.00	500.00	815.00	16.00	0.03	0.06	0.13	0.21	14.99	26.44	58.56	3
Bolivar	San Jacinto del C	374.34	13.00	102.00	0.00	144.00	413.00	0.00	0.09	0.25	0.00	0.34	26.77	73.23	0.00	2
Bolivar	San Pablo	4070.94	105.00	82.00	1.00	667.00	1360.00	24.00	0.16	0.06	0.04	0.26	60.69	23.25	16.06	1
Bolivar	Santa Rosa del S	5973.54	98.00	14.00	2.00	1215.00	1014.00	41.00	0.08	0.01	0.05	0.14	56.31	9.64	34.05	1
Bolivar	Simiti	3193.53	21.00	130.00	1.00	459.00	898.00	100.00	0.05	0.14	0.01	0.20	22.82	72.20	4.99	2
Bolivar	Tiquisio	935.89	4.00	13.00	0.00	363.00	296.00	0.00	0.01	0.04	0.00	0.05	20.06	79.94	0.00	2
Boyaca	Cubara	59.43	1.00	32.00	0.00	27.00	1061.00	48.00	0.04	0.03	0.00	0.07	55.12	44.88	0.00	1
Boyaca	Muzo	42.11	1.00	2.00	0.00	27.00	100.00	0.00	0.04	0.02	0.00	0.06	64.94	35.06	0.00	1
Boyaca	Otanche	603.72	20.00	3.00	0.00	233.00	268.00	16.00	0.09	0.01	0.00	0.10	88.46	11.54	0.00	1
Boyaca	Pauna	108.85	2.00	2.00	0.00	76.00	203.00	2.00	0.03	0.01	0.00	0.04	72.76	27.24	0.00	1
Boyaca	Puerto Boyaca	645.77	25.00	11.00	0.00	135.00	1375.00	0.00	0.19	0.01	0.00	0.19	95.86	4.14	0.00	1
Boyaca	San Pablo Borbu	49.35	2.00	4.00	0.00	24.00	108.00	12.00	0.08	0.04	0.00	0.12	69.23	30.77	0.00	1
Caqueta	Belen de los And	548.10	5.00	0.00	0.00	315.00	839.00	44.00	0.02	0.00	0.00	0.02	100.00	0.00	0.00	1
Caqueta	Cartagena del Ch	9509.87	555.00	310.00	108.00	2425.00	9974.00	494.00	0.23	0.03	0.22	0.48	47.82	6.49	45.68	4
Caqueta	Curillo	1430.24	11.00	2.00	0.00	371.00	120.00	12.00	0.03	0.02	0.00	0.05	64.02	35.98	0.00	1
Caqueta	El Doncello	359.76	2.00	33.00	0.00	173.00	855.00	14.00	0.01	0.04	0.00	0.05	23.05	76.95	0.00	2
Caqueta	Florencia	150.80	2.00	7.00	0.00	132.00	2217.00	9.00	0.02	0.00	0.00	0.02	82.75	17.25	0.00	1
Caqueta	Milan	1854.91	10.00	12.00	1.00	564.00	617.00	74.00	0.02	0.02	0.01	0.05	34.98	38.37	26.66	7
Caqueta	Solano	5165.81	358.00	212.00	77.00	1555.00	39096.00	238.00	0.23	0.01	0.32	0.56	41.17	0.97	57.86	4
Caqueta	Valparaiso	2166.34	12.00	8.00	0.00	714.00	530.00	6.00	0.02	0.02	0.00	0.03	52.68	47.32	0.00	1
Cordoba	Tierralta	3803.34	30.00	18.00	0.00	1218.00	3806.00	1.00	0.02	0.00	0.00	0.03	83.89	16.11	0.00	1
Cundinamarca	Yacopi	282.95	2.00	8.00	0.00	133.00	859.00	19.00	0.02	0.01	0.00	0.02	61.75	38.25	0.00	1
Putumayo	Puerto Caicedo	2839.24	33.00	1.00	0.00	692.00	62.00	26.00	0.05	0.02	0.00	0.06	74.73	25.27	0.00	1
Putumayo	Puerto Guzman	8790.63	476.00	104.00	27.00	2285.00	1984.00	129.00	0.21	0.05	0.21	0.47	44.32	11.15	44.53	4
Putumayo	Puerto Leguizam	8495.70	390.00	367.00	45.00	1728.00	9068.00	242.00	0.23	0.04	0.19	0.45	49.92	8.95	41.13	4
Putumayo	San Francisco	427.32	14.00	2.00	0.00	177.00	871.00	0.00	0.08	0.00	0.00	0.08	97.18	2.82	0.00	1
Santander	Bolivar	2385.21	64.00	0.00	0.00	538.00	892.00	16.00	0.12	0.00	0.00	0.12	100.00	0.00	0.00	1
Santander	Puerto Parra	142.02	5.00	6.00	0.00	59.00	640.00	49.00	0.08	0.01	0.00	0.09	90.04	9.96	0.00	1
Santander	Cimitarra	883.24	14.00	80.00	2.00	302.00	2494.00	63.00	0.05	0.03	0.03	0.11	42.07	29.11	28.81	1
Santander	La Belleza	328.46	8.00	2.00	1.00	106.00	188.00	14.00	0.08	0.01	0.07	0.16	47.91	6.75	45.34	1
Santander	Santa Helena de	153.54	2.00	2.00	0.00	66.00	313.00	1.00	0.03	0.01	0.00	0.04	82.59	17.41	0.00	1
Santander	Sucre	950.95	11.00	3.00	0.00	291.00	564.00	3.00	0.04	0.01	0.00	0.04	87.66	12.34	0.00	1

Coca Increment - Fires – Deforestation

Municipality - department	Total deforestation area 2001- 2010 (Ha)	Fires 2001-2010	Municipality - department	Total deforestation area 2001-	Fires 2001-2010	Municipality - department	Total deforestation area 2001- 2010 (Ha)	Fires 2001-2010	Municipality - department	Total deforestation area 2001- 2010 (Ha)	Fires 2001-2010
Abriaqui Antioquia	118	6	Arroyohondo Bolivar	108	0	Buritica Antioquia	544	1	Cerete Cordoba	0	0
Achi Bolivar	3156	0	Ayapel Cordoba	4208	0	Busbanza Boyaca	0	0	Cerinza Boyaca	27	0
Agua de Dios Cundinamarca	2	0	Barbosa Antioquia	381	0	Cabrera Cundinamarca	701	0	Cerrito Santander	229	0
Aguada Santander	73	0	Barbosa Santander	35	0	Cabrera Santander	361	0	Cerro San Antonio	0	0
Alban Cundinamarca	150	0	Barichara Santander	205	0	Caceres Antioquia	4090	54	Chaguani Cundinamarca	28	0
Albania Caqueta	386	0	Barrancabermeja Santar	9472	4	Cachipay Cundinamarca	12	0	Charala Santander	842	0
Albania Santander	216	0	Barranco de Loba Bolivar	141	0	Caicedo Antioquia	815	0	Charta Santander	1528	0
Alejandria Antioquia	472	0	Belen Boyaca	67	0	Cajica Cundinamarca	5	0	Chia Cundinamarca	98	0
Almeida Boyaca	699	0	Belen de los Andaqui Cac	4927	6	Caldas Antioquia	1036	2	Chigorodo Antioquia	395	0
Altos del Rosario Bolivar	277	0	Bello Antioquia	443	0	Caldas Boyaca	30	0	Chima Cordoba	184	0
Amaga Antioquia	328	0	Belmira Antioquia	60	1	California Santander	234	0	Chima Santander	373	0
Amalfi Antioquia	3881	31	Beltran Cundinamarca	21	0	Campamento Antioquia	243	0	Chinavita Boyaca	623	0
Anapoima Cundinamarca	18	0	Berbeo Boyaca	88	0	Campohermoso Boyaca	2750	0	Chinu Cordoba	45	0
Andes Antioquia	3213	0	Betania Antioquia	1212	0	Canalete Cordoba	20	0	Chipaque Cundinamarca	91	0
Angelopolis Antioquia	563	0	Beteitiva Boyaca	10	0	Canasgordas Antioquia	264	1	Chipata Santander	67	0
Angostura Antioquia	101	0	Betulia Antioquia	1433	1	Cantagallo Bolivar	5473	58	Chiquinquira Boyaca	70	0
Anolaima Cundinamarca	66	0	Betulia Santander	2043	6	Caparrapi Cundinamarca	2522	0	Chiquiza Boyaca	21	0
Anori Antioquia	5661	66	Bituima Cundinamarca	27	0	Capitanejo Santander	170	0	Chiscas Boyaca	1891	0
Anza Antioquia	505	0	Blank_	0	0	Caqueza Cundinamarca	18	0	Chita Boyaca	800	1
Apartado Antioquia	840	0	Boavita Boyaca	85	0	Caracoli Antioquia	843	0	Chitaraque Boyaca	879	0
Aquitania Boyaca	742	0	Bojaca Cundinamarca	27	0	Caramanta Antioquia	55	0	Chivata Boyaca	0	0
Aratoca Santander	2211	0	Bolivar Santander	7956	33	Carcasi Santander	1797	0	Chivor Boyaca	357	0
Arbelaez Cundinamarca	153	0	Boyaca Boyaca	3	0	Carepa Antioquia	1066	0	Choachi Cundinamarca	194	0
Arboletes Antioquia	327	0	Briceno Antioquia	896	0	Carmen de Carupa Cundinamarc	130	0	Choconta Cundinamarca	99	0
Arcabuco Boyaca	207	0	Briceno Boyaca	114	0	Carmen de Viboral Antioquia	816	2	Cicuco Bolivar	0	0
Arenal Bolivar	652	1	Bucaramanga Santander	562	0	Carolina Antioquia	27	0	Cienaga de Oro Cordoba	520	0
Argelia Antioquia	1143	0	Buenavista	15	0	Cartagena del Chaira Caqueta	85525	828	Cienega Boyaca	4	0
Arjona Bolivar	2440	0	Buenavista Boyaca	209	0	Caucasia Antioquia	1797	0	Cimitarra Santander	18672	15

Coca Increment - Fires – Deforestation

Municipality - department	Total deforestation area 2001- 2010 (Ha)	Fires 2001-2010	Municipality - department	Total deforestation area 2001- 2010 (Ha)	Fires 2001-2010	Municipality - department	Total deforestation area 2001- 2010 (Ha)	Fires 2001-2010	Municipality - department	Total deforestation area 2001- 2010 (Ha)	Fires 2001-2010
Cisneros Antioquia	68	0	El Bagre Antioquia	9353	143	Funza Cundinamarca	0	0	Guatape Antioquia	137	0
Ciudad Bolivar Antioquia	1251	0	El Carmen de Bolivar Boliva	8240	1	Fuquene Cundinamarca	7	0	Guataqui Cundinamarca	0	0
Cocorna Antioquia	1296	0	El Carmen de Chucuri Santa	5359	2	Fusagasuga Cundinamarc	180	0	Guatavita Cundinamarca	186	0
Cogua Cundinamarca	29	0	El Cocuy Boyaca	71	0	Gachala Cundinamarca	1358	1	Guateque Boyaca	312	0
Colon Putumayo	48	0	El Colegio Cundinamarca	74	0	Gachancipa Cundinamarc	4	0	Guavata Santander	121	0
Combita Boyaca	27	0	El Doncello Caqueta	6837	39	Gachantiva Boyaca	51	0	Guayabal de Siquima Cundinam	48	0
Concepcion Antioquia	282	0	El Espino Boyaca	755	0	Gacheta Cundinamarca	1372	0	Guayabetal Cundinamarca	179	1
Concepcion Santander	1062	0	El Florian Santander	318	0	Galan Santander	510	0	Guayata Boyaca	1248	1
Concordia Antioquia	719	0	El Guacamayo Santander	374	0	Gama Cundinamarca	983	0	Guepsa Santander	137	0
Confines Santander	585	0	El Guamo Bolivar	1923	0	Gambita Santander	2309	1	Guican Boyaca	1772	8
Contratacion Santander	243	0	El Paujil Caqueta	4688	15	Gameza Boyaca	17	0	Gutierrez Cundinamarca	450	10
Copacabana Antioquia	552	0	El Penon Bolivar	109	0	Garagoa Boyaca	1302	0	Hatillo de Loba Bolivar	86	0
Coper Boyaca	501	0	El Penon Cundinamarca	219	0	Giraldo Antioquia	29	0	Hato Santander	753	0
Cordoba Bolivar	1172	0	El Penon Santander	559	0	Girardot Cundinamarca	0	0	Heliconia Antioquia	705	0
Coromoro Santander	1231	0	El Playon Santander	1131	3	Girardota Antioquia	317	0	Hispania Antioquia	158	0
Corrales Boyaca	3	0	El Rosal Cundinamarca	31	0	Giron Santander	2093	1	Itagui Antioquia	26	0
Cota Cundinamarca	30	0	Encino Santander	1148	0	Gomez Plata Antioquia	723	0	Ituango Antioquia	3773	1
Cotorra Cordoba	0	0	Entrerrios Antioquia	80	0	Granada Antioquia	360	0	Iza Boyaca	3	0
Covarachia Boyaca	421	0	Envigado Antioquia	642	0	Granada Cundinamarca	47	0	Jardin Antioquia	1417	0
Cubara Boyaca	2226	19	Facatativa Cundinamarca	89	0	Guaca Santander	1555	4	Jenesano Boyaca	8	0
Cucaita Boyaca	10	0	Firavitoba Boyaca	1	0	Guacamayas Boyaca	249	0	Jerico Antioquia	688	0
Cucunuba Cundinamarca	12	0	Florencia Caqueta	9553	19	Guacheta Cundinamarca	25	0	Jerico Boyaca	7	0
Cuitiva Boyaca	11	0	Floresta Boyaca	14	0	Guadalupe Antioquia	102	0	Jerusalen Cundinamarca	18	0
Curillo Caqueta	2157	4	Floridablanca Santander	501	0	Guadalupe Santander	407	0	Jesus Maria Santander	85	0
Curiti Santander	2764	0	Fomeque Cundinamarca	673	0	Guaduas Cundinamarca	1435	0	Jordan Santander	211	0
Dabeiba Antioquia	3472	7	Fosca Cundinamarca	110	2	Guamal Bolivar	0	0	Junin Cundinamarca	722	0
Don Matias Antioquia	177	0	Fredonia Antioquia	807	0	Guapota Santander	217	0	La Apartada Cordoba	72	0
Duitama Boyaca	197	0	Frontino Antioquia	2740	0	Guarne Antioquia	497	0	La Belleza Santander	1167	8
Ebejico Antioquia	1039	0	Funes	3	0	Guasca Cundinamarca	420	0	La Calera Cundinamarca	338	0

Coca Increment - Fires – Deforestation

Municipality – department	Total deforestation area 2001- 2010 (Ha)	Fires 2001-2010
La Capilla Boyaca	122	0
La Ceja Antioquia	358	0
La Estrella Antioquia	208	2
La Mesa Cundinamarca	25	0
La Montanita Caqueta	10962	23
La Palma Cundinamarca	457	0
La Paz Santander	797	0
La Pena Cundinamarca	375	0
La Pintada Antioquia	86	0
La Union Antioquia	239	0
La Uvita Boyaca	96	0
La Vega Cundinamarca	1080	0
La Victoria Boyaca	33	0
Labranzagrande Boyaca	1357	2
Landazuri Santander	4019	4
Lebrija Santander	1124	0
Lenguazaque Cundinamar	9	0
Liborina Antioquia	198	0
Lorica Cordoba	175	0
Los Cordobas Cordoba	61	0
Los Santos Santander	934	0
Macanal Boyaca	1252	0
Macaravita Boyaca	469	0
Maceo Antioquia	1484	1
Macheta Cundinamarca	819	0
Madrid Cundinamarca	21	0
Magangue Bolivar	2811	1
Mahates Bolivar	1155	1
Malaga Santander	140	0

Municipality – department	Total deforestation area 2001- 2010 (Ha)	Fires 2001-2010
Manati	9	0
Manta Cundinamarca	1308	0
Margarita Bolivar	122	0
Maria La Baja Bolivar	1786	0
Marinilla Antioquia	217	0
Maripi Boyaca	861	0
Matanza Santander	1024	0
Medellin Antioquia	1457	0
Medina Cundinamarca	6106	2
Milan Caqueta	7598	5
Miraflores Boyaca	1488	0
Mocoa Putumayo	1992	3
Mogotes Santander	3206	0
Molagavita Santander	1397	0
Momil Cordoba	39	0
Mompos Bolivar	5	0
Mongua Boyaca	719	3
Mongui Boyaca	9	0
Moniquira Boyaca	319	0
Monitos Cordoba	15	0
Montebello Antioquia	237	0
Montecristo Bolivar	6281	73
Montelibano Cordoba	3680	11
Monteria Cordoba	267	0
Morales Bolivar	2252	10
Morelia Caqueta	435	0
Mosquera Cundinamarca	0	0
Motavita Boyaca	1	0
Mulata Antioquia	630	1

Municipality – department	Total deforestation area 2001- 2010 (Ha)	Fires 2001-2010
Murindo Antioquia	169	0
Muzo Boyaca	493	0
Narino Antioquia	804	0
Narino Cundinamarca	0	0
Nechi Antioquia	5120	17
Necocli Antioquia	3996	5
Nemocon Cundinamarca	22	1
Nilo Cundinamarca	198	0
Nimaima Cundinamarca	164	0
Nobsa Boyaca	4	0
Nocaima Cundinamarca	886	0
Nuevo Colon Boyaca	9	0
Ocamonte Santander	183	0
Oiba Santander	1172	0
Oicata Boyaca	4	0
Olaya Antioquia	66	0
Onzaga Santander	1004	1
Orito Putumayo	13085	3
Ospina Perez Cundinama	300	0
Otanche Boyaca	1898	9
Ovejas	5	0
Pachavita Boyaca	313	0
Pacho Cundinamarca	933	0
Pacoa Cundinamarca	93	2
Paez Boyaca	2873	1
Paime Cundinamarca	583	0
Paipa Boyaca	550	0
Pajarito Boyaca	410	3
Palmar Santander	32	0

Municipality – department	Total deforestation area 2001- 2010 (Ha)	Fires 2001-2010
Palmas del Socorro Santander	276	0
Pandi Cundinamarca	58	0
Panqueba Boyaca	83	0
Paramo Santander	123	0
Paratebueno Cundinamarca	5340	0
Pasca Cundinamarca	152	0
Pauna Boyaca	1088	0
Paya Boyaca	719	9
Paz De Rio Boyaca	137	0
Penol Antioquia	319	0
Peque Antioquia	999	1
Pesca Boyaca	132	0
Piedecuesta Santander	3542	0
Piedras	0	0
Pinchote Santander	341	0
Pinillos Bolivar	1141	0
Pisba Boyaca	763	2
Planeta Rica Cordoba	263	0
Pueblo Nuevo Cordoba	1737	2
Pueblorrico Antioquia	423	0
Puente Nacional Santander	266	0
Puerto Asis Putumayo	10457	45
Puerto Berrio Antioquia	7780	7
Puerto Boyaca Boyaca	2546	7
Puerto Caicedo Putumayo	4041	33
Puerto Escondido Cordoba	26	0
Puerto Guzman Putumayo	30134	429
Puerto Leguizamo Putumayo	27196	495
Puerto Libertador Cordoba	5060	4

Coca Increment - Fires – Deforestation

Municipality – department	Total deforestation area 2001- 2010	Fires 2001-2010	Municipality – department	Total deforestation area 2001- 2010	Fires 2001-2010	Municipality – department	Total deforestation area 2001- 2010	Fires 2001-2010	Municipality – department	Total deforestation area 2001- 2010	Fires 2001-2010
Puerto Nare Antioquia	2464	0	Salgar Antioquia	1511	0	San Jose de Miranda Santander	148	0	Santa Rosa Bolivar	361	0
Puerto Parra Santander	9331	17	Samaca Boyaca	80	0	San Jose De Pare Boyaca	394	0	Santa Rosa de Osos Antioquia	448	3
Puerto Rico Caqueta	15685	52	San Alberto	29	0	San Juan de Rioseco Cundinam	8	0	Santa Rosa del Sur Bolivar	5490	85
Puerto Salgar Cundinamarca	307	0	San Andres Antioquia	143	0	San Juan de Uraba Antioquia	102	0	Santa Sofia Boyaca	4	0
Puerto Triunfo Antioquia	853	0	San Andres de Sotave Cordoba	57	0	San Juan Nepomuceno Bolivar	5768	7	Santafe de Antioquia Antioquia	369	1
Puerto Wilches Santander	10303	6	San Andres Santander	2809	0	San Luis Antioquia	3666	5	Santafe de Bogota D. Cundinamarc	490	0
Puli Cundinamarca	10	0	San Antero Cordoba	89	0	San Luis de Gaceno Boyaca	3584	0	Santana Boyaca	905	0
Purisima Cordoba	3	0	San Antonio de Teque Cundinar	103	0	San Marcos Cordoba	100	0	Santiago Putumayo	408	0
Quebradanegra Cundinamarc	266	0	San Benito Abad	82	0	San Martin	21	0	Santo Domingo Antioquia	631	0
Quetame Cundinamarca	159	0	San Benito Santander	242	0	San Martin de Loba Bolivar	301	0	Santuario Antioquia	158	0
Quipama Boyaca	541	0	San Bernardo Cundinamarca	315	0	San Mateo Boyaca	241	0	Sasaima Cundinamarca	102	0
Quipile Cundinamarca	66	0	San Bernardo del Vie Cordoba	86	1	San Miguel de Sema Boyaca	14	0	Sativanorte Boyaca	106	0
Rafael Reyes Cundinamarca	53	0	San Carlos Antioquia	3174	8	San Miguel Putumayo	2615	1	Sativasur Boyaca	31	0
Ramiriqui Boyaca	110	0	San Carlos Cordoba	108	0	San Miguel Santander	1120	0	Segovia Antioquia	5421	183
Raquira Boyaca	122	0	San Cayetano Cundinamarca	1001	0	San Pablo Bolivar	8981	67	Sesquile Cundinamarca	39	0
Regidor Bolivar	39	0	San Cristobal	46	0	San Pablo Borbur Boyaca	488	0	Siachoque Boyaca	0	0
Remedios Antioquia	13621	131	San Eduardo Boyaca	135	0	San Pedro Antioquia	174	0	Sibate Cundinamarca	52	0
Retiro Antioquia	2686	3	San Estanislao Bolivar	226	0	San Pedro De Uraba Antioquia	164	0	Sibundoy Putumayo	75	0
Ricaurte Cundinamarca	1	0	San Fernando Bolivar	5	0	San Pelayo Cordoba	5	0	Silvania Cundinamarca	215	0
Rio Viejo Bolivar	1943	6	San Francisco Antioquia	3098	7	San Rafael Antioquia	1105	1	Simacota Santander	10348	13
Rionegro Antioquia	656	0	San Francisco Cundinamarca	420	0	San Roque Antioquia	942	0	Simijaca Cundinamarca	24	0
Rionegro Santander	3682	1	San Francisco Putumayo	781	0	San Rosa Viterbo Boyaca	31	0	Simiti Bolivar	10020	7
Rondon Boyaca	244	0	San Gil Santander	713	0	San Vicente Antioquia	463	0	Soacha Cundinamarca	43	0
Sabana de Torres Santander	6051	21	San Jacinto Bolivar	3779	4	San Vicente de Chucu Santand	9828	11	Soata Boyaca	85	0
Sabanalarga Antioquia	413	0	San Jacinto del Cauc Bolivar	3876	5	San Vicente del Cagu Caqueta	136811	2604	Socha Boyaca	99	0
Sabaneta Antioquia	29	0	San Jeronimo Antioquia	550	0	Santa Barbara Antioquia	402	1	Socorro Santander	1013	0
Saboya Boyaca	62	0	San Joaquin Santander	451	0	Santa Barbara Santander	1071	2	Socota Boyaca	866	3
Sachica Boyaca	0	0	San Jose de la Fragu Caqueta	2961	9	Santa Helena del Opo Santande	1984	1	Sogamoso Boyaca	20	0
Sahagun Cordoba	55	0	San Jose De La Monta Antioquia	29	0	Santa Maria Boyaca	2492	0	Solano Caqueta	47710	483

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Solita Caqueta	2502	8	Tenjo Cundinamarca	48	0	Ubaque Cundinamarca	90	0	Viracacha Boyaca	13	0
Somondoco Boyaca	1350	0	Tenza Boyaca	297	0	Ubate Cundinamarca	7	0	Yacopi Cundinamarca	3966	1
Sonson Antioquia	4130	7	Tibacuy Cundinamarca	50	0	Umbita Boyaca	828	0	Yali Antioquia	1526	0
Sopetran Antioquia	236	0	Tibana Boyaca	34	0	Une Cundinamarca	91	0	Yarumal Antioquia	582	0
Soplaviento Bolivar	32	0	Tibasosa Boyaca	12	0	Uramita Antioquia	127	0	Yolombo Antioquia	3261	5
Sopo Cundinamarca	41	0	Tibirita Boyaca	411	0	Urrao Antioquia	4632	6	Yondo Antioquia	17046	20
Sora Boyaca	0	0	Tierralta Cordoba	9036	50	Utica Cundinamarca	67	0	Zambrano Bolivar	2541	0
Soraca Boyaca	2	0	Tinjaca Boyaca	13	0	Valdivia Antioquia	2171	0	Zapatoca Santander	1034	0
Sotaquira Boyaca	367	0	Tipacoque Boyaca	32	0	Valencia Cordoba	830	0	Zaragoza Antioquia	4840	126
Suaita Santander	2069	0	Tiquisio Bolivar	995	1	Valle del Guamuez Putumayo	5572	8	Zetaquira Boyaca	273	0
Suaza	0	0	Titiribi Antioquia	581	0	Valle San Jose Santander	115	0	Zipacon Cundinamarca	85	0
Subachoque Cundinamarca	34	0	Toca Boyaca	4	0	Valparaiso Antioquia	100	0	Zipaquira Cundinamarca	38	0
Sucre Santander	2554	3	Tocaima Cundinamarca	12	0	Valparaiso Caqueta	6217	3			
Suesca Cundinamarca	38	0	Tocancipa Cundinamarca	12	0	Vegachi Antioquia	2774	3			
Supata Cundinamarca	1071	0	Togui Boyaca	257	0	Velez Santander	2379	2			
Surata Santander	1981	0	Toledo Antioquia	210	0	Venecia Antioquia	303	0			
Susa Cundinamarca	15	0	Tona Santander	1128	0	Ventaquemada Boyaca	25	0			
Susacon Boyaca	103	0	Topaga Boyaca	17	0	Vergara Cundinamarca	1035	0			
Sutamarchan Boyaca	2	0	Topaipi Cundinamarca	529	0	Vetas Santander	162	0			
Sutatausa Cundinamarca	21	0	Tota Boyaca	11	0	Viani Cundinamarca	66	0			
Sutatenza Boyaca	34	0	Tunja Boyaca	28	0	Vigia Del Fuerte Antioquia	1736	0			
Tabio Cundinamarca	13	0	Tununga Boyaca	196	0	Villa de Leyva Boyaca	50	0			
Talaigua Nuevo Bolivar	8	0	Turbaco Bolivar	1267	0	Villagarzon Putumayo	2312	3			
Tamesis Antioquia	362	0	Turbana Bolivar	406	0	Villagomez Cundinamarca	252	0			
Taraza Antioquia	9247	19	Turbo Antioquia	9627	7	Villanueva Bolivar	477	0			
Tarso Antioquia	914	0	Turmeque Boyaca	34	0	Villanueva Santander	477	0			
Tasco Boyaca	52	0	Tuta Boyaca	5	0	Villapinzon Cundinamarca	534	0			
Tausa Cundinamarca	15	0	Tutaza Boyaca	74	0	Villeta Cundinamarca	358	0			
Tena Cundinamarca	6	0	Ubala Cundinamarca	2723	3	Viota Cundinamarca	188	0			