Comparing deforestation rates and patterns along the Colombian-Ecuadorian border

Bachelorarbeit

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Abstract

Tropical deforestation and the continuing destruction of wildlife habitat are currently one of the major ecological challenges. Precise analyses and understanding of causes and drivers of deforestation are often limited as they can be highly complex. Border areas allow direct comparison of different deforestation dynamics and processes which can then be linked to underlying drivers and causes.

This study analyzes deforestation rates, spatial patterns of deforestation and landscape fragmentation along the Colombian-Ecuadorian border in the tropical Amazon using Landsat satellite data from 1986, 1999 and 2013. Cloud free data for each year was obtained by image compositing. Change detection classification was carried out with the aim to map stable forest and non-forest as well as deforested areas between 1986-1999 and 1999-2013. Apart from visual interpretation of deforestation patterns in both countries, classification maps were used to calculate landscape metrics for analyzing forest fragmentation.

Classification results yielded high accuracy with an overall accuracy of 93.48% for Colombia and 93.97% for Ecuador. Although deforestation rates in Colombia were higher during the first time period, second time period showed higher rates for Ecuador. Armed conflict and coca cultivation have an impact on deforestation rates in Colombia, while deforestation in Ecuador can be traced back to state-led migration process in the study area. Besides, forest in Colombia appears more fragmented than in Ecuador. In both countries, forest fragmentation increased over the time. Deforestation patterns were defined as *diffuse* for Colombia and *fishbone* for Ecuador.

The analysis of dense time series can be used to enhance understanding of relationship between deforestation rates and socioeconomic processes between countries.

Resumen

La deforestación tropical y la destrucción progresiva del habitat de la fauna silvestre es actualmente uno de los mayores desafíos ecológicos. El análisis detallado y el entendimento de las causas y los orígenes de deforestación suele está limitado por la alta complejidad de los mismos. Las regiones entre fronteras ofrecen una comparación directa de diferentes dinámicas y procesos de deforestación que pueden ser asociados después a sus causas y orígenes fundamentales.

Este estudio analiza las tasas de deforestación, los patrones espaciales de deforestación y la fragmentación del paisaje en la frontera de Colombia con Ecuador en la Amazonia tropical, utilizando datos de imágenes satelitales Landsat de los años 1986, 1999 y 2013. Los datos libres de nubes son conseguidos a través de composiciones de imágenes. Se realizó una clasificación de detección de cambios con el fin de mapear el bosque primario permanente y el no bosque, como también áreas deforestadas entre 1986-1999 y 1999-2013. Además de lainterpretación visual de patrones de deforestación en ambos países, los mapas clasificados se utilizaron para calcular métricas del paisaje para analizar la fragmentación del bosque.

La clasificación presenta alta precisión con una exactitud general de 93.48% para Colombia y 93.97% para Ecuador. Las tasas de deforestación fueron mas altas en Colombia durante el primer periodo de estudio, mientras que las tasas en el segundo periodo fueron más altas en Ecuador. Las tasas de deforestación en Colombia se pueden atribuir al conflicto armado y a los cultivos de coca y en Ecuador a un proceso de migración en el área del estudio motivado por el gobierno. Según los resultados de las métricas de pasiaje, el bosque en Colombia aparece más fragmentado que en Ecuador. La fragmentación del bosque se aumenta durante el tiempo en ambos países. Los patrones de deforestación son descritos como *difusos* para Colombia y *fishbone* para Ecuador.

El análisis de series cronológicas más densas pueden servir para aumentar el entendimiento sobre las relaciones entre la intensidad de deforestación y los procesos socioeconómicos entre ambos países.

Table of content

List of Figures

List of Tables

1. Introduction

Deforestation and thus the change in terrestrial ecosystems is one of the many aspects that Steffen et al. (2011) point out as outcomes of the *anthropocene*. It is a topic of high relevance, since it directly affects two of the three most emerging planetary boundaries: biodiversity loss and climate change (Rockstrom 2009).

On a global scale, deforestation takes place in every biome and ecosystem. Regarding absolute numbers, the tropical forests are most affected by deforestation from 2000 onwards (Hansen et al. 2013). A third of all deforestation worldwide occurs in the tropics and half of this amount precisely to South American tropical forest (Hansen et al. 2013).

South America represents the largest tropical forest worldwide together also with the highest biodiversity rates and important aboveground carbon stocks (Aide et al. 2013, Lapola et al. 2014). The moist and tropical Amazon rainforest still shows the highest amounts of forest loss during the last years (Aide et al. 2013)

Most of the deforestation in South America occurred in Brazil, Paraguay and Argentina (Aide et al. 2013; Hansen et al. 2013). Nevertheless, loss of native forests also occurs in other countries sharing the Amazon basin, like Colombia and Ecuador (Perz et al. 2005). Together with Peru, these countries share most of the Napo rainforest in the Western Amazon. As a former *biogeographical refugium*, the Napo rainforest is among the Amazonian areas with highest biodiversity (Haffer 1969, Myers et al. 2000, Sierra 2000) and is also listed as one of the deforestation hotspots in the tropics (Achard 2002). Therefore, the Napo rainforest is an important subject to further analysis of deforestation.

Geist & Lambin (2001) study drivers of tropical deforestation. They claim that dividing drivers into social and natural spheres is often difficult. As natural factors tend to be similar in borderlands and can therefore be excluded from the analysis, the geographical focus of this study will be on the Colombian-Ecuadorian borderlands, especially the western parts of the department Putumayo in Colombia and the province Sucumbíos in Ecuador. Differences in deforestation rates and patterns can thus be attributed to underlying socioeconomic factors (e.g. policy decisions or migration). Examining the last decades, socioeconomic processes in Putumayo and Sucumbíos have been very different, with Putumayo being the epicenter of coca cultivation in Colombia and thus highly involved in the Colombian civil war, which proved to be have triggering effect on deforestation (Etter et al. 2006). On the other side, Sucumbíos represents one of the most popular destinations for inner rural migration in Ecuador with a colonization process guided by the government.

Remote sensing has been a useful instrument to study and quantify deforestation in the Amazon rain forest (Myers 1988, Skole & Tucker 1993). The Landsat mission provides multispectral data with a spatial resolution of 30m from 1982 onwards (USGS 2013). It is therefore an attractive data source for analyzing deforestation processes in spatial detail (Griffiths et al. 2014, Hansen et al. 2013). The Colombian-Ecuadorian border has already been studied on basis of Landsat data by Sierra (2000) and Viña et al. (2004). Yet, both studies analyze deforestation processes only until 1996, leaving a gap for studies analyzing deforestation trends until the present. Furthermore, mentioned studies have not made use of the opening of the Landsat archive in 2008. Open data access allows to encounter the challenge of cloud covered images using pixel compositing. This method dynamically replaces cloudy pixels of a scene using temporally adjacent scenes in order to produce a composed cloud free image (Griffiths et al. 2013). Since cloud cover is one of the major challenges for remote sensing studies in general and specifically in the Amazon (Asner 2001), compositing offers the opportunity to enhance data quality for this study.

Based on the composites, a change detection classification will be performed to identify deforested areas over time and analyze deforestation rates in Colombia and Ecuador. It was decided to analyze three different target years, stretching from first available Landsat 5 TM data to the present, representing two equivalent time periods to be studied. In comparison to their adjacent years, the years 1986, 1999 and 2013 show best availability of Landsat data for image compositing.

Apart from quantifying the temporal dynamics of deforestation over time, the spatial pattern of deforestation and forest fragmentation is also related to socioeconomic drivers (Geist & Lambin 2001). A variety of landscape metrics have been developed in the last decades to study and quantify landscape fragmentation. Most of the metrics have their origin in conservation science or landscape ecology (Uumeaa et al. 2009). The software FRAGSTATS (McGarigal 2015) contains a multitude of different landscape metrics. It already has been applied successfully to study and compare deforestation patterns in the Amazon (Batistella et al. 2000, Viña & Estevez 2013).

Therefore, the research questions of this study are:

- How do deforestation rates differ from another from 1986-1999 and 1999-2013 in Colombia and Ecuador?
- How do deforestation patterns and forest fragmentation in Colombia and Ecuador evolve over time?

2. Study area

2.1. Size and range

The study area is located between 0°35'57" degrees north (73 km north of the equator) and 0°03'27" degrees south (7 km south of the equator). It stretches from 77°17'28" to 76°12'57" west. The spatial dimensions are 80 km in direction north south and 120 km in direction east west. Colombian territory covers 49.4% (4762 km²) of the study area, whereas Ecuador covers 50.6% (4877 km²). This way, both countries are almost equally represented in spatial terms in this study.

The Colombian study site is mostly covered by the department Putumayo and its *municipios* San Miguel, Valle de Guamuez, Puerto Asís and Orito. Small parts in the west of the study area belong to the neighboring department Nariño. On the Ecuadorian side, the study area is entirely covered by the province of Sucumbíos and its *cantones* Lago Agrio and Cascales. The most important urban environments within the study area are Lago Agrio in Ecuador (55,000 inhabitants) and Puerto Asís in Colombia (30,000 inhabitants). Another larger settlement is La Hormiga in Colombia with 15,000 inhabitants (DANE 2010, INEC 2010).

Figure 1: Overview map with study area

2.2. Geomorphological and hydrological aspects

The study area is located in a landscape called *piedemonte*. It is characterized by its position between the Andes in the west and the vast flatlands of the tropical Amazon rainforest in the east. Most rivers flow down the Andes eastwards, carrying large quantities of sediment which accumulates in the *piedemonte*, where slope gradually declines. The landscape is coined by hilly structures and underlies strong fluvial influences, leaving terraces behind (Brücher 1970). The soils in the study area are barely suitable for farming. Fertile land can be found close to rivers, which are periodically flooded and so supplied with necessary nutrients for farming (Robertson & Castiblanco 2012). Riverbeds are inconsistent, as streams can easily change their direction of flow, depending on precipitation intensity (Brücher 1970). Elevation in the study area ranges from 2350 meters in the northwest (foothills of the Andes) to 250 meters in the eastern parts towards the Amazonian flatlands. Interviews have revealed that elevations higher than 800 meters are not considered as *piedemonte* by the local population (Hoffmann 2016). Most of the study area shows elevations between 250 and 350 meters. Areas with steep slope are located towards the west of the study area.

2.3. Climate

The climate in the study area is characteristic for tropical rainforest climate, with minor oscillation of monthly mean temperatures (around 1 – 3°C). The mean annual temperature of Puerto Asís, located on the Colombian side of the study area, is 24.8°C. Precipitation in this area varies between 2500 and 4000 mm annual rainfall, with increasing amount towards the *cordilleras* in the west, where topographic rain due to the westerlies occur. In the flatlands, convectional precipitation prevails (Brücher 1970).

The Colombian meteorological institute (IDEAM) provides detailed data for Mocoa, capital of the department Putumayo and located north of the study area. Here, rainfall occurs over 20 days per each month, indicating that explicit discrimination between dry and wet seasons cannot be made as, for instance, in the eastern Brazilian Amazon. Nevertheless, heaviest rainfalls occur from April to June. Average sunshine hours per day range between 2 hours in June to 4 hours in October, reflecting the high average cloud cover at the Andean foothills (IDEAM 2016).

2.4. Colonization processes and governance

2.4.1. Ecuador

The province of Sucumbíos was almost untouched by colonization before the late 1960's. In 1967, oil was discovered in the region by the US Company Texaco Chevron (Kimmerling 2006). The Ecuadorian government gave permission for oil extraction to these foreign companies, but they were responsible for the infrastructure development (Viña et al. 2004). On top of that, the government obliged Texaco also to build additional infrastructure of civil use, such as paved roads and bridges (Wasserstrom 2013). In this way, a basis was given for the colonization process. Sucumbíos offered vast land for landless farmers from the highlands as well as employment around the oil extraction sector (Wasserstrom 2013). The province became the hotspot destination for inner Ecuadorian migration, with peaks around 1980 (Pichón 1997). Nevertheless, census data reveals, that Sucumbíos still remained the province with the fastest growing population between 1990 and 2001 (INEC 2016). The colonization process was officially declared as finished by the government in 1994 (Wasserstrom2013). As a consequence of a severe economic crisis in 2000, inner migration declined and people sought better economic conditions in foreign countries, which led to declining population growth rates (INEC 2016, Jokisch & Pribilsky 2002).

Colonized land is coined by smallholding farms. Most of the parcels are low-cleared areas with forest covering over 50% of the parcel. Common crops are coffee and cocoa, while cattle ranching is only playing a minor role. Commercial logging, cattle ranching and large scale commercial plantations are barely existent in the study area (Pichón et al. 2001). All in all, colonization in Sucumbíos was intended by the Ecuadorian government and land allocation mostly happened legally.

2.4.2. Colombia

The colonization of Putumayo started earlier than in Sucumbíos with the extraction of quina (*cinchona officinalis*) and rubber trees (*hevea brasiliensis*) at the beginning of the 20th century (Brücher 1970, Ramírez 2006). Settling in the study area was also facilitated by the construction of a road to Puerto Asís in 1912 (CNMH 2015). Consequently, migration to

Putumayo continued, as population from the highlands fled from political violence or was displaced from its former lands (Ramírez 2006), which led to agricultural expansion and commercial logging (CNMH 2015).

Similar to Ecuador, oil extraction influenced economic progress in Putumayo. First perforations were made in 1963 (CNMH 2015). Equally, operating oil company Texaco was obliged to build the necessary infrastructure for oil extraction, but no additional infrastructure for civil use like in Sucumbíos (Viña et al. 2004).

In the end of the 1970's, the big operating drug cartels from Cali and Medellín introduced the cultivation of coca in Putumayo. A report of the Centro Nacional de Memoria Histórica (CNMH) states that:

> *With its vast forests, with an open agrarian frontier and recent unstable human settlements, Putumayo was practically terrain with inexistent presence of police and justice, which in combination with its geographic location and proximity to Peru made it favorable for the deceptive business practice of the cartels.*
>
> (CNMH 2015, p. 181, translated by author)

During the Colombian civil war in 1984, the guerilla movement *Fuerzas Armadas Revolucionarias de Colombia* (FARC) expanded their territory to Putumayo and obliged cartels to submit to them. Coca cultivation still remained a very important aspect, as the FARC and also paramilitary forces depended highly economical on it (Trujillo & Badel 1998). This led to a remarkable increase in coca cultivation in 1990's which finally peaked in 2000, while coca production in Peru and Bolivia decreased (Díaz & Sánchez 2004). Farmers mostly had a positive attitude towards the cultivation of coca as it was economically more attractive than other crops and had direct benefits for them (Ramírez 2001). The Colombian Government tried to combat extensive coca crops by aerial fumigations in southern Putumayo, leading to severe defoliation of the local vegetation in 2001 (Messina & Delameter 2006). In the following years, coca cultivation diminished in Putumayo and remained low from thereon. However, in the recent years cultivation has increased slightly again, although the civil war is about to come to an end. Still, the safety situation in Putumayo remains tense (FIP 2014).

Summarizing, the colonization process in Putumayo took place over a broader period and is marked by different historical and socioeconomic aspects. Nevertheless, one can conclude that migration, colonization and thus agricultural expansion occurred without governmental intention. Especially before 2000, the influence of Colombian governance and policies in southern Putumayo has been practically inexistent as a result of the armed conflict. Consequently, land allocation took place often illegally (CNMH 2015), making agricultural expansion and deforestation uncontrollable for the authorities.

3. Data and Methods

3.1. Data

The selected study area along the Colombian Ecuadorian border is covered by the WRS-2 (Landsat Worldwide Reference System) footprint path 010/ row 63 (see **figure 1**). For image compositing, several images around a target date or year are necessary in order to obtain cloud free composites (Griffiths et al.2013). The selection of the target years 1986, 1999 and 2013 is based on covering a broad temporal range, being almost equally temporarily distributed, coinciding with relevant historical aspects and data availability.

The amount of acquired images per target year varies depending on data availability and quality of available data. Imagery with low quality due to haze for example is avoided since it may influence compositing negatively. The manually selected scenes used in this study are listed in **table 1**, resulting in five images for target year 1986, thirteen for 1999 and eight for 2013. Images are downloaded as *Level 1T* products and *Surface reflectance* products.

Apart from satellite images, an elevation model from the Shuttle Radar Topography Mission (SRTM) is also acquired for masking of mountains.

Table 1: Acquired Landsat data for the study listed by target years

Target Year 1986				**Target Year 1999**				**Target Year 2013**			
Landsat generation and sensor	**Year**	**DOY**	**Cloud cover (%)**	**Landsat generation and sensor**	**Year**	**DOY**	**Cloud cover (%)**	**Landsat generation and sensor**	**Year**	**DOY**	**Cloud cover (%)**
5 TM	1985	24	40.95	5 TM	1998	268	59.71	7 ETM +	2013	157	59.05
5 TM	1986	91	12.24	5 TM	1998	364	32.74	8 OLI	2013	245	80.01
5 TM	1986	235	74.98	5 TM	1999	175	60.71	7 ETM +	2013	301	50.13
5 TM	1986	283	38.3	5 TM	1999	191	75.9	8 OLI	2013	309	33.53
5 TM	1987	286	70.79	7 ETM +	1999	231	27.6	8 OLI	2013	357	62.9
				5 TM	1999	239	19.76	8 OLI	2014	24	42.75
				5 TM	1999	255	12.96	7 ETM +	2014	48	28.79
				5 TM	1999	319	75.65	8 OLI	2014	104	24.08
				7 ETM +	2000	26	22.34				
				7 ETM +	2000	74	29.52				
				5 TM	2000	226	35.86				
				7 ETM +	2000	298	51.18				
				7 ETM +	2000	314	72.66				

3.2. Preprocessing and compositing

The United States Geological Survey (USGS) provides differently preprocessed Landsat products. *Level 1T* and *Surface reflectance* products are delivered already with a radiometric and geometric correction (USGS 2016). For *Surface reflectance* products, atmospheric correction is also provided in the product. Atmospheric correction is carried out for Landsat 5 TM and Landsat 7 ETM+ images with the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS) (Masek et al. 2006). Landsat 8 OLI imagery is corrected by Landsat Surface Reflectance Code (LaSRC) (Vermote et al. 2016). All acquired Landsat Surface reflectance scenes are stacked and reduced to the relevant six bands of surface reflectance including three visible bands (blue, green and red), one near infrared band and two short waved infrared (SWIR) bands.

The removal of non-terrestrial features like clouds and their shadows is often preferable, as they are not relevant to the research subject and falsify image statistics and classification by extreme high or low reflectance values. The *Fmask* algorithm by Zhu & Woodcock (2011) is able to detect cloud, cloud shadow, ice/snow and water in an image. The algorithm requires top of atmosphere data, therefore the *Level 1T* product scenes are used as input. It is then applied to all acquired images, using a ten percent threshold for cloud probability. That means that all pixels which have a greater than ten percent probability to represent clouds, cloud shadows, ice/snow or water are assigned to the corresponding Fmask class. Pixels which are not labeled as clear are masked out from each stacked *Surface reflectance* image. Apart from cloud masking, Fmask is used to derive a water mask that includes all pixels that at least once are labeled as water by the algorithm. By applying the water mask, riverbed changing streams can be excluded from the classification process as they are not relevant for the research question. Additionally, the SRTM elevation model is applied for masking out elevations higher than 800 meter, which do not account for the relevant *piedemonte* study area.

Afterwards, masked images undergo a Tasseled Cap transformation (TC), introduced by Crist & Kauth (1986). TC is a linear band transformation which helps to emphasize relevant physical characteristics of the images. It is based on principal components analysis (PCA), which is known for the reduction of noise caused by statistical artifacts or haze (Albertz 2009, Campbell & Wynne 2011). Although applying cloud masking, haze is often not recognized and can therefore lead to confusion in image processing. TC has been successfully used for mapping deforestation in the Amazon (Müller et al. 2016). Therefore, TC is chosen to be the basis for the following classification.

The transformation requires input vectors that are applied to multispectral datasets. Those are defined for Landsat 5 TM data by Crist & Kauth (1986). For Landsat 7 ETM + 8 OLI sensors, the modified vector is provided by Huang et al. (2002). Output of the TC transformation are three orthogonal indices; TC Brightness (relates to soil), TC Greenness (relates to photosynthetic vegetation) and TC Wetness (relates to canopy and moisture) (Lillesand et al. 2015).

To obtain cloud free imagery in regions with high cloud cover, image compositing has proven to be a suitable solution to that problem (Griffiths et al. 2013). Cloud free pixels from several images of a target year are merged together to a single image. The pixel value in this composite image depends on the function implemented by the user. To avoid influence of outliers (e.g. undetected clouds or cloud shadows), the median is chosen as an adequate function for the compositing process (Flood 2013). As the input data are TC indices, median composites are created for each index and then stacked together, resulting in the TC median composite for a target year. A graphical example for the compositing process is given in **figure 2**.

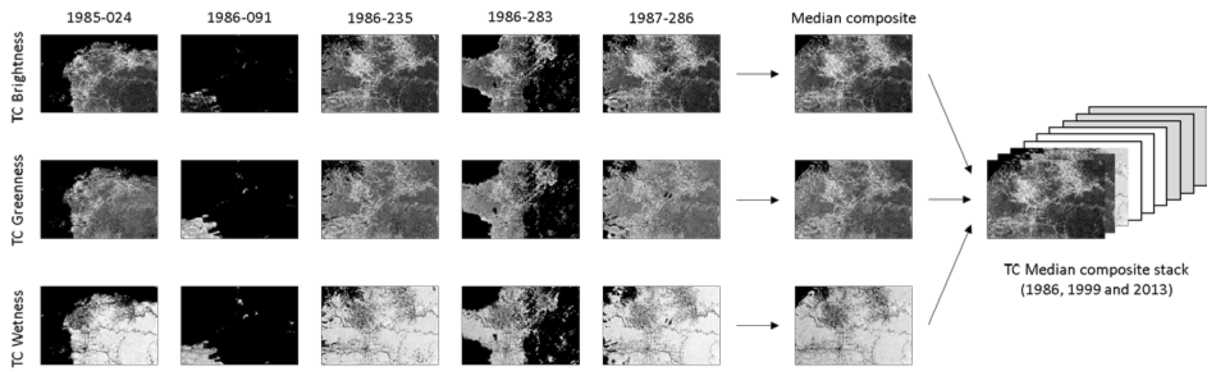

Figure 2: Compositing example for target year 1986

Repeating the compositing process for each target year, the final image stack contains nine layers (three TC indices from three target years). A post classification change detection with several classification images provokes error propagation (Burnicki et al. 2007, Coppin et al. 2004). An integrated change detection based on a single multi-temporal image stack is more appealing as error propagation can be avoided and therefore chosen for this study.

3.3. Classification

The supervised classification is carried out using the machine learning algorithm *random forest* by Breiman (1999). The classifier draws several random samples from input data. Based on those, a classification tree is created for each sample, generating a random decision tree forest. Pixels are classified then by all decision trees and assigned to the class with the major vote of all trees. Random forest has been widely used in remote sensing and change detection and proves to yield robust results (Pal 2005). The classifier is embedded in the Image RF tool of the EnMap-Box software (van der Linden et al. 2015), which is used in this study.

For the integrated change detection, four classes are defined to be classified.

PF	Stable primary forest
DF 1999	Primary forest deforested by 1999
DF 2013	Primary forest deforested by 2013
NF	Non primary forest

A preliminary classification of the image stack with the four classes is done by the author's visual interpretation, sampling training data manually for each class. Labeling of pixels is based mainly on visual interpretation of Landsat imagery as well as high resolution imagery from Google Earth™ in some cases. In order to support a non-biased selection of training pixels for the random forest classification, a random equalized stratified sample is drawn from the preliminary classification map with 100 pixels per class. This way, training pixels are randomly distributed in space. The drawn pixels are verified and in case of mislabeling by the preliminary classification relabeled to the correct class. If then a class has less than 100 pixels, additional pixels are added manually to ensure that each class is trained with at least 100 pixels. For the NF class, further pixels are added for surfaces with low probability of random occurrence (e.g. concrete in cities, roads or sandbanks). **Table 2** shows the total amount of training pixels per class.

Subsequently, the randomly sampled training pixels for the four classes are used as input for model training. The TC median composite stack is used as image input to create the random forest model on. Parametrizations of random forest are left on default settings with 100 trees. The model is then applied again to the image stack to obtain the classification.

3.3.1. Postprocessing

To avoid misclassified isolated pixels in the final classification, it is common to smoothen the resulting raster after the classification (Caras & Karnieli 2015). In this case, a moving window with a majority filter is applied. The moving window has a size of 3 by 3 pixels. The center pixel is assigned to the class with the majority pixel count in the moving window (Lillesand et al. 2015).

3.4. Validation

The resulting classification map is validated making use of a stratified random sampling design. Cochran (1977) developed an equation for calculating the minimum necessary total amount of validation pixels in order to achieve sound accuracy values. One possibility is to apportion the total amount among the classes by their mapped area proportion. However, this can lead to extreme low values in spatially underrepresented classes (e.g. change classes). Moreover, Olofsson et al. (2014) recommend that pixel allocation should be at least 50 pixels per class. On the other hand, a disproportional allocation of validation pixels leads to a bias, which can be leveled out by an area adjustment calculation, resulting in a single area estimation for the entire study area (Olofsson et al. 2013). For comparison purposes, validation and accuracy assessment is carried out for each country independently.

Table 2: Allocation of training and validation pixels per class

Class	Training pixels	Validation (Colombia)	Validation (Ecuador)
PF	106	114	194
DF 1999	100	64	60
DF 2013	100	60	60
NF	150	127	60
Total	456	365	375

For both countries, the adequate total number of validation pixels is calculated with the equation of Cochran (1977). The standard error is specified as 0.015. The desired user's accuracies are specified as 0.95 for the stable forest class (PF), 0.90 for the stable non forest class (NF) and 0.85 for the change classes (DF 1999 and DF 2013). Olofsson et al. (2014) suggest a minimum of 50 validation pixels per class. For this study, a minimum of 60 pixels per class was determined. Therefore, some change classes are oversampled while other classes contain an area proportioned number of pixels. The exact allocation of validation pixels for both countries is shown in **table 2**. Pixels are validated by visual interpretation of Landsat imagery and high resolution data from Google Earth^{TM}, dating back until 2002.

3.5. Pattern and fragmentation analysis

FRAGSTATS software by McGarigal (2015) is incorporated in the software *CRAN R* (R development core team 2011) with the package *SDMTools* (van der Waal et al. 2015). Using this package, 38 different metrics are offered to the user. Most of them are highly auto-correlated and therefore redundant. It is up to the user to choose the appropriate landscape metrics for his research (Uumeaa 2012).

For this study, all indices that are not comparable are excluded as well as indices based on minimum or maximum values, since the aim is to make a comparison of two areas (Colombia and Ecuador) that are not of the same size. Standardized metrics and metrics based on the mean are more appealing since they can be compared to each other independently. The indices shown in **table 3** are chosen for the analysis of fragmentation due to deforestation:

Table 3: List of landscape metrics used in the study

Metric	Description	Unit
Number of patches	Absolute number of patches of certain class.	Absolute numbers
Landscape shape index (LSI)	A standardized index adjusted for square shapes (suitable for raster datasets) and is representative for edge density (Patton 1975).	No specified unit, but as LSI rises, landscape becomes more irregular.
Mean patch area	Average size of a patch of certain class.	Square meters
Mean fractal dimension index	Reflects average of the complexity of a patch.	No specified unit, but approaches 1 for simple shapes and 2 for highly complex shapes.
Mean core area	Average area of a patch located in the center of a patch, leaving a certain distance to the patch perimeter	Square meters
Core area / total patch area ratio:	The ratio of mean core area and mean patch area. In this way, the effect of size changes in mean patch area on the core area can be expressed. As core area is also related to shape complexity, this metric also allows further insight on this.	Percentage
Landscape division index	Reflects the probability that two randomly placed pixel are NOT in the same patch (Jaeger 2000). Representative for fragmentation and connectivity.	Percentage

As input data for calculating landscape metrics with *SDMTools*, binary forest/ non-forest maps are computed for each target year (1986, 1999 and 2013) from the classification map, for each country respectively. This way, it is possible to compare fragmentation of forest and non-forest over time in Colombia and Ecuador.

4. Results

4.1. Compositing

Although derived from several images, compositing results do not provide entirely cloud free data. **Figure 3** depicts the count of clear observation pixels in the composites of the target years. Especially in the northwest of the study area, no clear observations are taken from any acquired Landsat image. Nevertheless, compositing makes clear observation possible for 95.6% of the pixels in 1986, 99.5% in 1999 and 98.9% in 2013.

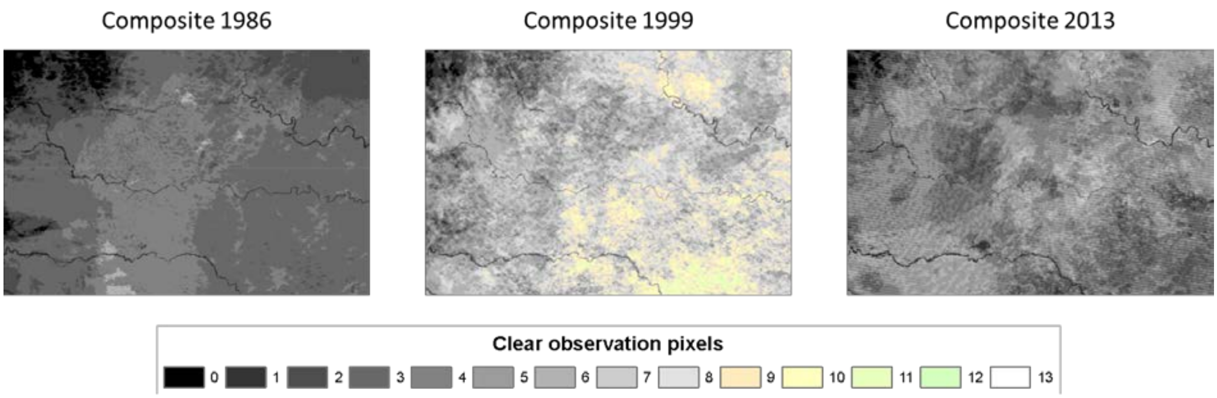

Figure 3: Clear pixel count for each target year composite

4.2. Classification

The change detection classification yields good overall accuracies on both sides of the border. For Colombia, the overall accuracy is 93.48% (with a standard error of 1.28%) while Ecuador's overall accuracy is 93.97% (with a standard error of 1.22%). Both confusion matrices are shown below in **table 4** and **5**. User’s accuracy reflects the possibility that a pixel truly belongs to the class that it is classified as. Producer’s accuracy reflects the possibility that a reference pixel is correctly classified (Lillesand et al. 2015). Error of commission is complementary to user’s accuracy while error of omission is complementary to producer’s accuracy. Sample counts are not adjusted to sampling bias, but accuracy and error values have undergone area adjustment, meaning that they are calculated with sample count values adjusted to the area proportion of the class they represent (Olofsson et al. 2013).

Table 4: Confusion matrix and accuracy values for Colombia

Map class	Reference class PF	DF 1999	DF 2013	NF	Sum	User's accuracy (%)	Error of commission (%)
PF	108	1	1	4	114	94.74	5.26
DF 1999	2	58	0	4	64	90.63	9.37
DF 2013	7	1	51	1	60	85	15
NF	1	5	0	121	127	95.28	4.72
Sum	118	65	52	130	365		
Producer's accuracy (%)	95.06	90.04	95	93.57			
Error of omission(%)	4.94	9.96	5	6.43	**Overall accuracy (%) 93.48**		

Classification results for Colombia show best user's accuracy for the stable non-forest class and best producer's accuracy for stable forest. Accuracies are mostly over 90%. Only change class DF 2013 shows lower values when looking at its user's accuracy (85%), but at the same time high values for producer's accuracy. There is no class specific confusion among the classes. Change classes DF 1999 and DF 2013 show almost no confusion among themselves. Confusion of validation pixels labeled as stable classes PF and NF does not affect producer's accuracy strongly because of area adjustment.

Table 5: Confusion matrix and accuracy values for Ecuador

Map class	Reference class PF	DF 1999	DF 2013	NF	Sum	User's accuracy (%)	Error of commission (%)
PF	187	2	4	1	194	96.39	3.61
DF 1999	3	55	0	2	60	91.67	8.33
DF 2013	1	4	52	3	60	86.67	13.33
NF	3	2	1	54	60	90	10
Sum	194	63	57	60	374		
Producer's accuracy (%)	97.62	84.05	82.72	93.1			
Error of omission(%)	2.38	15.95	17.28	6.9	**Overall accuracy (%) 93.97**		

Classification results for Ecuador show best user's accuracy values for stable forest class and best producer's accuracy as well, both attributed by values over 95%. Stable non-forest class NF shows also good accuracies with values of 90% for user's accuracy and 93.1 for producer's accuracy. Change classes DF 1999 and DF 2013 show more confusion among themselves than in Columbia and yield lower producer's accuracies, resulting in errors of omission of more than 15%. User's accuracy yield better values for the change classes, especially for DF 1999 with 91.67%.

4.3. Area distribution

Figure 4 shows the result map with the spatial distribution of classes in Colombia and Ecuador. Due to cloud cover and masking of water and elevations higher than 800 meters, 9.96% of the Colombian share of the study area and 1.3% of the Ecuadorian remain unclassified.

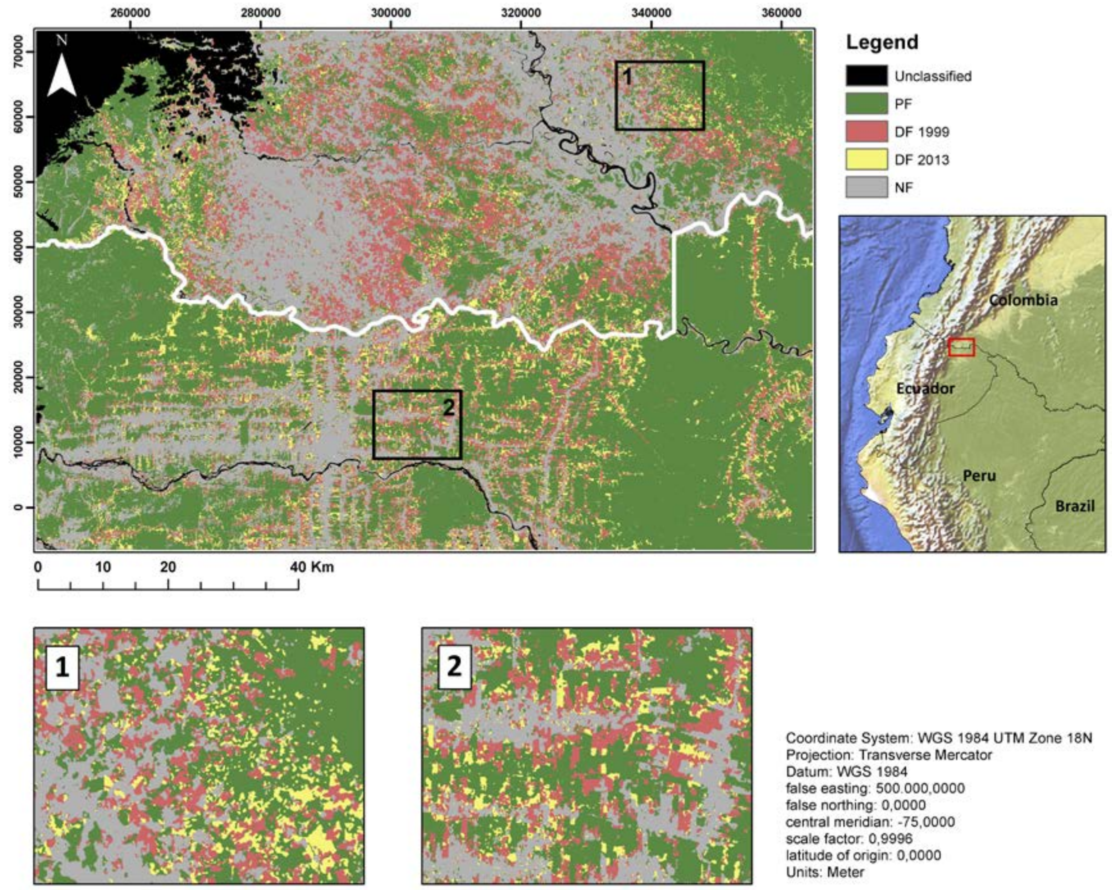

Figure 4: Classification map with two subsets for spatial detail; Subset one shows an example for Colombia, subset two for Ecuador

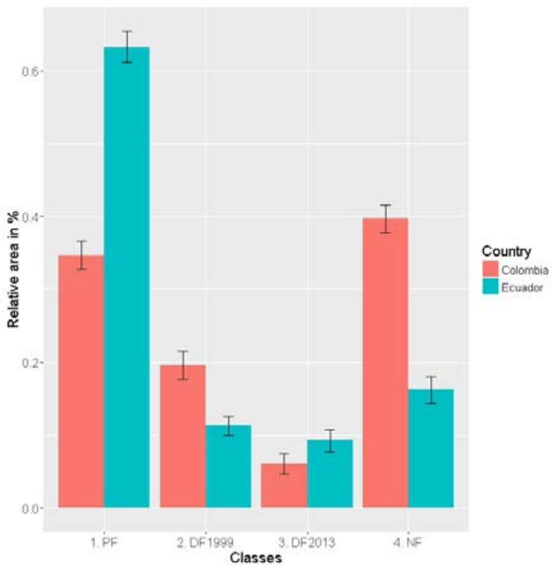

Figure 5: Relative share of classes with error bars

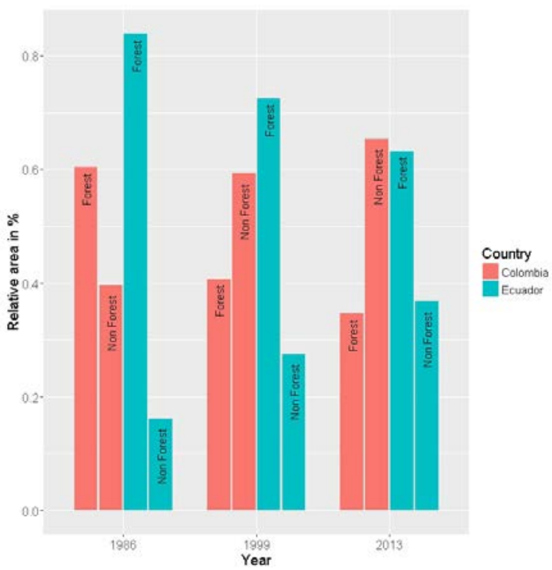

Figure 6: Dynamic change of forest and non-forest

Figure 5 depicts the relative shares of the different classes in Colombia and Ecuador with error bars indicating the 95% confidence intervals for the class estimations. The largest class in Colombia is the stable non-forest class (NF), occupying 39.6% of its share. Around 34.6% of the Colombian share is classified as stable primary forest (PF). The larger change class is DF 1999 with 19.6% of Colombian territory being deforested between 1986 and 1999. Second change class DF 2013 only accounts for 6.1% of the total Colombian area.

Classification reveals that Ecuador's most prevailing class is stable primary forest (PF), holding 63.2% of the its share. The remaining classes show lower values with the stable non-forest class (NF) being the second largest class in Ecuador (16.2%). Both change classes show low shares. DF 1999 indicates that the deforested area between 1986 and 1999 was slightly larger (11.3%) than in the following period from 1999 to 2013 (9.3%).

Differences in temporal change of forest / non-forest land cover fractions between Colombia and Ecuador become clearer looking at **figure 6**. In 1986, forest in Colombia covers 60.4% of the study area, as forest in Ecuador 83.8% with only 16.2% being converted to non-forest at that time. From thereon, deforested area constantly rises in Ecuador until reaching a relative cover of 36.8% in 2013. On the Colombian side, deforestation increases remarkably until 1999 when occupying 59.3% of the area. Yet, between 1999 and 2013 strong increase diminishes (65.4% non-forest in 2013), while deforestation rates in Ecuador remain almost constant over time.

4.4. Pattern and fragmentation (landscape metrics)

Results of landscape metrics show that most metrics increase during study the whole study period. Metrics-wise results are plotted and shown in **figure 7-13**. Plots show landscape metrics in a temporal, countrywise and land cover dimension.

Number of patches:

Number of forest patches increases similarly in both countries. The increase is higher in the first time period and then becomes weaker. Yet, the total number of patches is constantly lower in Ecuador although sharing a larger area. Colombia's forest however can be described as patchier.

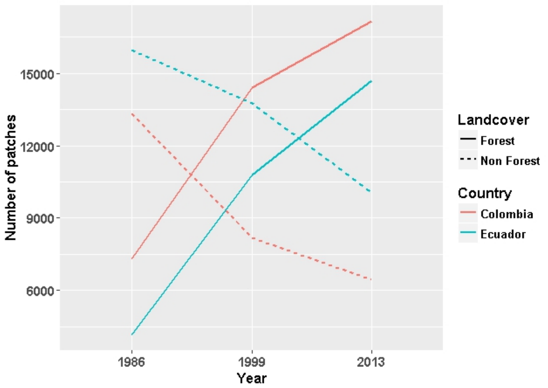

Figure 7: Number of patches

As number of forest patches increases, number of non-forest patches decreases in both countries. The decrease until 1999 is stronger in Colombia. In the second time period, decrease is stronger in Ecuador. Contrary to forest patches, Ecuador's number of non-forest patches is constantly higher than Colombia's, suggesting that Ecuador's non-forested landscape is patchier.

Mean patch area:

As the number of patches increases, the mean patch area of forest patches consequently decreases. The reverse effect occurs for the non-forest patches. The strength of the decline varies over the years. In the first time period, forest mean patch area diminishes 4.88 ha/year in Ecuador (1.8 ha/year in Colombia). Whereas in the second time period, this rate only accounts to a shrinkage of 0.82 ha/year (0.26 ha/year in Colombia). Colombian mean patch area of non-forest patches becomes larger than forest patches between 1986 and 1999. Ecuador's forest mean patch area declines but remains larger than non-forest mean patch area.

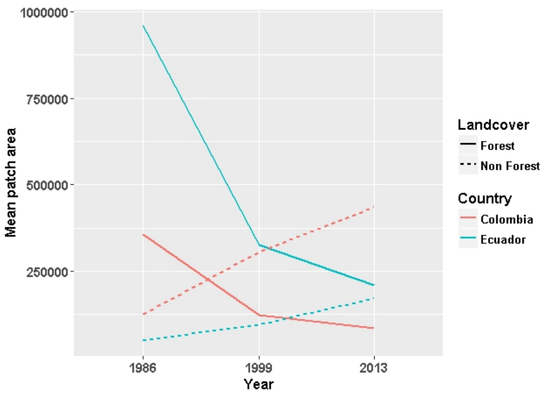

Figure 8: Mean patch area

Mean core area:

Figure 9 underlines the strong relationship between mean patch area and mean core area. Trends seem almost identical to the metrics shown in **figure 8.**

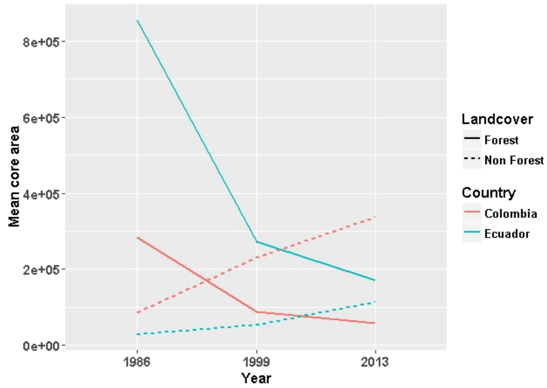

Figure 9: Mean core area

Core area / total patch area ratio:

Figure 10 quantifies the relationship between mean core area and mean patch area. Values for Ecuadorian forest patches are higher than Colombian, yet both declining over time. Non-forest patches values increase over the time with Colombian patches representing higher values.

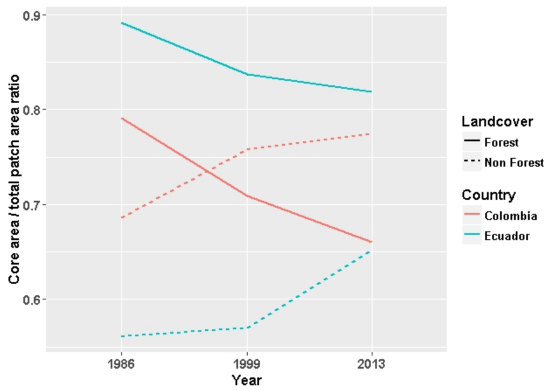

Figure 10: Core area / total patch area ratio

Mean fractal dimension index:

All index values are close to one, indicating that in general patches have a simple perimeter. Yet, Colombian forest patches show higher values than Ecuadorian and vice versa for non-forest patches. Forest patches index declines while non-forest patches perimeter complexity increases over the years.

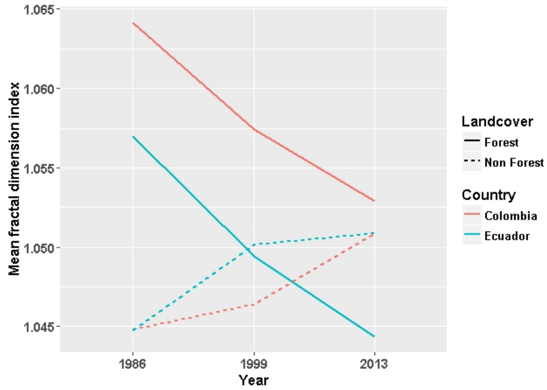

Figure 11: Mean fractal dimension index

Landscape shape index (LSI):

LSI indicates increasing values for forest patches over the years. Increase becomes lesser during the observed time periods. Colombian forest patches show higher values than Ecuadorian, indicating that forest landscape is more fragmented. Non-forest patches of Ecuador show an irregular trend, while Colombian patches decrease slightly over time.

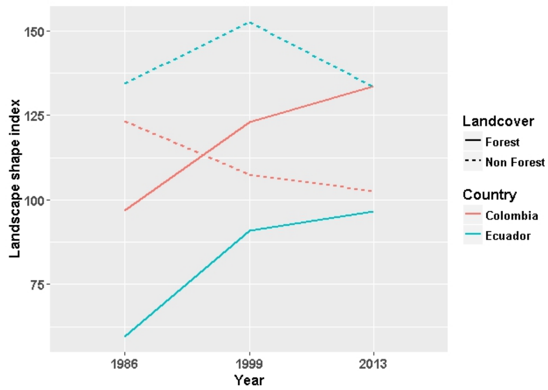

Figure 12: Landscape shape index

Landscape division index:

Index values show increase over time for forest patches and decrease for non-forest patches. While the probability that two randomly placed pixel are not in the same patch was still around 80% in Ecuador in 1986 (95% in Colombia) it rises up to 95% in 2013 (98% in Colombia).

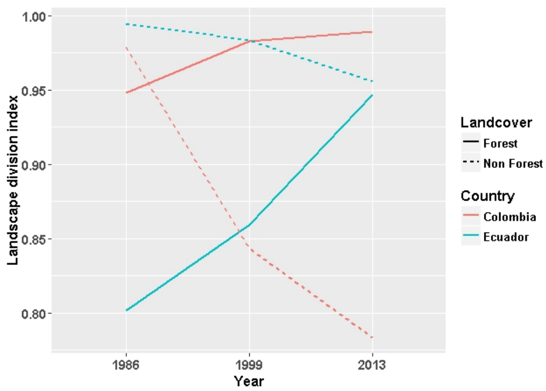

Figure 13: Landscape division index

Increase in Ecuador is therefore more drastic than in Colombia. On the other hand, one can observe a drastic decrease of probability for non-forest patches in Colombia, reaching till values lower than 80% in 2013.

5. Discussion

Various differences between deforestation rates and fragmentation patterns have been demonstrated above. The following chapter will focus on discussing and interpreting these differences and the methods that were applied during the classification process.

5.1. Methods

Median compositing provided a solid basis for the change detection analysis. Yet, some artefacts (e.g. haze or cloud shadows) still remain in the median composite. Including more imagery and broadening the window of potentially considered acquisition dates could help to build cleaner image composites. Furthermore, Griffiths et al. (2013) apply a more sophisticated compositing approach by including further parameters such as pixel-to-cloud distance. Griffiths et al. (2013) also derive metrics from the compositing process, which could be derived as well in for this case when including more images and later be helpful in the classification process.

Pixel labeling in training and validation process was based widely on visual Landsat image interpretation and, if available, high resolution data from Google Earth™. Yet, the high resolution data only offers area-wide detailed imagery from the year 2006 onwards, some areas from 2002. Thus, only land cover of 2013 and to a lesser extent of 1999 can be validated with Google Earth™. Landsat's spatial resolution of 30 meters does often not allow a totally reliable classification of a pixel. However, best efforts were made during the training and validation to assign pixels to their corresponding class.

The classification itself provided very good results. TC as input data for random forest classification proved to be solid, especially TC Brightness and TC Wetness proved to be valid indicators for discriminating forest and non-forest areas. There was no obvious categorical misclassification of pixels. However, some patches in the north west of the study area were misclassified as intentionally deforested when probably caused by natural disturbances. Forest disturbances caused by landslides are natural components of the local ecosystem and even important for it (Richter 2009). They occur mostly in the mountainous regions of the Andes, where high precipitation also prevails (Lozano et al. 2005).

A limitation concerning labeling and interpretation was time series density. Leaving gaps of thirteen and fourteen years in each time period, deforestation becomes more difficult to identify than in the case of denser time series. Vegetation succession on abandoned cleared plots occurs fast in the Amazon (Moran et al. 2000). Deforested plots therefore may appear as secondary forest after over ten years of vegetation succession. Applying dense time series with annual data would enhance the understanding of land cover and land use dynamics in the study area and thus lead to more accurate mapping. Yet, this present study already shows that data availability is scarce and that creation of annual imagery may lead to difficulties in data quality. A bi-annual compositing approach would be a promising and feasible approach.

Apart from improving map accuracies, dense time series and annual deforestation rates can give more insight about the linkages between land cover dynamics and socioeconomic processes in the past. In this study, it is obligatory to generalize results from classification and landscape metrics over thirteen and fourteen years respectively, which results limiting when making linkages to socioeconomic processes.

5.2. Deforestation rates

There are several connections between deforestation rates or landscape metrics on the one side and armed conflict, coca cultivation and migration on the other side, which will be discussed in this section.

Many studies have proven that the introduction of illicit crops (coca) is related to forest clearing in that area in Colombia (Álvarez 2007, Armenteras et al. 2006, Etter et al. 2006) and also especially in southern Putumayo (Viña et al. 2004). Deforestation rates calculated in this study for Colombia also coincide with changes in coca production in Putumayo. The United Nations Office on Drugs and Crime (UNODC) evaluates coca cultivation in Colombia annually. Data from these reports show, that coca cultivation intensified rapidly between 1995 and 2000 (**figure 14**). This trend does not apply to coca cultivation on a national level in the same way, as Putumayo's share of national production in 1995 was 12.4% and rose to 40.4% in 2000 (**figure 14**). The department became the hotspot for illicit crops in Colombia during this time and there was high demand for further land to cultivate on (Viña et al. 2004). Calculated deforestation rates of almost 20% between 1986 and 1999 can be related to this pressure. After 2000, the governmental program *Plan Colombia* became effective in

Putumayo with large aerial fumigations using glyphosate. Fumigation were especially severe in 2001 and 2002 (CNMH 2015) but aerial spraying prevails until 2014 as well (UNODC 2015). Rigorous governmental policy led to a significant decrease of coca cultivation in Putumayo (**figure 14**). Another reason for this shrinkage is that coca farmers received compensation paying if they would change to substitutional crops (Ramírez 2001). These policy changes and decreasing coca cultivation are also reflected in the decreasing deforestation rates between 1999 and 2013.

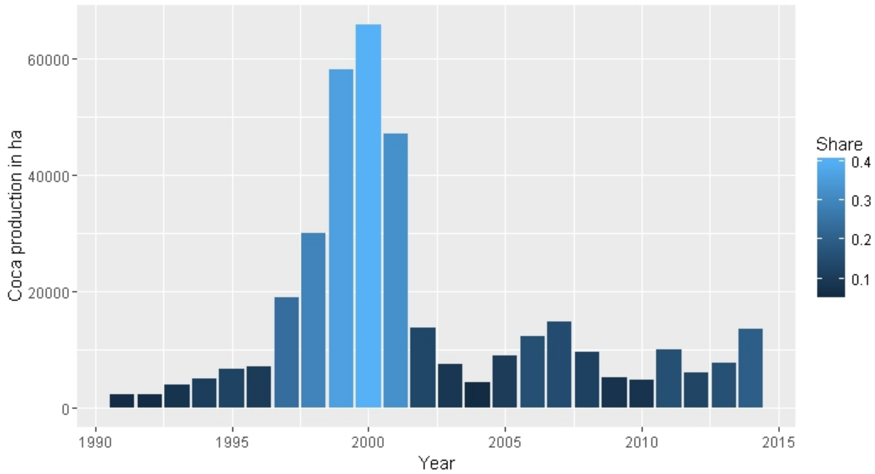

Figure 14: Coca production in Putumayo in hectare. Colors indicate the relative share of Putumayo's production on national scale. Data source: UNODC 2015

Deforestation rates in Ecuador appear more equilibrated over the two time periods than in Colombia. However, some drivers of deforestation have also changed here over time.

The economic crisis in Ecuador in 2000 and the change of the national currency to US-Dollar had significant effects on the external trade of the country. Not being able to devaluate its own currency anymore, Ecuador's exportation of primary goods declined after the economic crisis (Larrea 2004). Although mostly in minor scales, coffee production was an important economic component in Sucumbíos and in 1990 around 10% of the national coffee output was produced here (Marquette 1998). Coffee farmers also suffered from export decline after 2000 (Vega & Purdy 2013), which can imply mitigating effects on agricultural expansion.

Another effect of the economic crisis was a mass migration of Ecuadorians towards foreign countries (Jokisch & Pribilsky 2002). This led to a population growth decline from 2000 onwards in comparison to the decades before, when Sucumbíos was the Ecuadorian province with the highest population growth rates. From 1990 to 2001, annual population growth rate was 4.67%, turning into 3.48% from 2001 to 2010 (INEC 2010).

Still, population growth continued to a lesser extent, triggering further agricultural expansion. Pichón et al. (2001) describe that forest clearing intensity of a property depends on the length of settlement. Settlers expand their agricultural activity gradually on their lots with the duration of their, as they accumulate sufficient money over the time for new investments (Pichón et al. 2001).

Another possible triggering driver for deforestation in Sucumbíos is the improving infrastructure. The government of Rafael Correa has made large investments in public infrastructure from 2007 onwards (Becker 2013). Thus, remote areas of Sucumbíos became more accessible over time, facilitating agricultural expansion there.

Demographic changes, agricultural expansion, economic factors, market accessibility and infrastructure are all factors listed as potential drivers for tropical deforestation (Geist & Lambin 2001). Ecuador's slight decline of deforestation from 1999 to 2013 can therefore be attributed to a synergy of all changes within these drivers triggering or mitigating deforestation.

Viña et al. (2004) have studied deforestation rates for the study area from 1973-1985 and 1985-1996. Deforestation trends from this study show that deforestation rates from 1973 to 1985 were lower than the second period, suggesting that deforestation between 1985 and 1999 was more severe than the decades before and after. For Ecuador, Viña et al. (2004) detected decreasing deforestation rates from the first time period (1973-1985) to the second (1985-1996). Considering the results of this study, this declining trend can be extended for the time period 1999-2013 as well. Sierra (2013) describes a similar trend for Ecuador for the time periods 1990-2000 and 2000-2008.

At this point it is important to stress that this study only focuses on deforestation as a forest transition process and hence ignores natural succession or afforestation. Hansen et al. (2013) mapped deforestation and reforestation on a global level from 2000 onwards. Although being a global product and therefore not specifically adapted to the study area, their model shows widespread reforestation in southern Putumayo. Moreover, Colombia experienced reforestation and vegetation gain in different parts of the country, which can be linked to land abandonment as consequence of the armed conflict (Sánchez-Cuervo et al. 2012, Aguilar et al. 2015). However, there are no evidences for such linkages in Putumayo yet. Another important aspect is the definition of reforestation. Hansen et al. (2013) define forest as vegetation higher than 5 meters. As succession of vegetation is fast in the tropical Amazon (Moran et al. 2000), global deforestation mapping does not provide sufficient information to draw conclusions about long term forest gain trends. Still, recent developments in the Colombian armed conflict and its influence on forest loss and gain remains an important topic and deserves further investigation.

5.3. Deforestation pattern and fragmentation

Geist & Lambin (2001) distinguish between different types of deforestation patterns that are product of different underlying causes. From a visual interpretation of the classification map, the Colombian deforestation pattern can be classified as a *diffuse pattern*, while the Ecuadorian pattern is a so-called *fishbone pattern*. Diffuse patterns are typical for smallholders' agriculture and traditional farming and the deforestation is characterized by small cleared patches inside the forest. The fishbone pattern is characterized by deforested lots reaching often orthogonally into the forest from a road. Studying different examples of deforestation patterns, Geist & Lambin (2001) came to the conclusion that a fishbone pattern corresponds to pro-deforestation governance and strong policy making in the study area. In Ecuador, colonization of Sucumbíos and agricultural expansion in the northeast Amazon was an official governmental process until 1994 (Wasserstrom 2013). The relationship between governance and the deforestation pattern in Ecuador therefore matches with the findings of Geist & Lambin (2001). Results from their study also show that the diffuse deforestation pattern is linked to policy failures. This is also proven to be the case in Colombia, considering illegal land allocation, armed conflict and the cultivation of illicit crops.

Generally, most of the presented landscape metrics in this study emphasize the ongoing deforestation processes in both countries. Yet, selected metrics contain important data for comparing fragmentation processes on both sides on different levels.

The forest in Colombia is more fragmented, as the number of forest patches is constantly higher than in Ecuador and still growing, suggesting that fragmentation of forest will continue. Moreover, the mean size of Colombian non-forest patches is clearly larger than Ecuadorian. This indicates that either cultivation lots are larger or new generated lots are merged to already existing ones. Knowing that most of the farmers in Putumayo are smallholders, the latter is more probable.

However, the mean fractal dimension index reveals that non-forest patches in Ecuador have more complex shapes in average, as cleared parcels in a fishbone pattern tend to have oblong rectangular shapes while cleared patches in the diffuse pattern in Colombia result in less complex and rounder shapes.

From ecological aspects, Colombian forest fragmentation is more damaging to native fauna than Ecuadorian. The ratio between the mean core area and the mean total patch area implies that only 66% of an average Colombian forest patch accounts for core area in 2013, while in Ecuador this values accounts for 82%. The size of the core area is an important factor in habitat fragmentation as the occurrence of animal species is correlated to it (Smith et al. 2011).

Colombian habitat fragmentation is emphasized by the landscape division index, as the probability of two individuals not to be located randomly in the same forest patch is 98% in 2013, which indicates that connectivity among forest patches is extremely low. Yet, Ecuador has experienced a degrading forest connectivity over the last years, as values in 1986 still were around 80% and reached 95% in 2013 (**figure 13**).

The obtained landscape metrics in this study are supported by calculated metrics from Viña & Estévez (2013) who also analyzed forest fragmentation along the Colombian-Ecuadorian border. Although not explicitly the same metrics were used, results and trends agree with the findings of this study as in both forest becomes patchier and more fragmented with stronger fragmentation indicators for Colombia. Batistella et al. (2000) provide another example of landscape metrics application in the context of deforestation in the Amazon, also trying to quantify differences between a diffuse and a fishbone deforestation pattern. Results reveal that the latter one appears to be more fragmented, contrary to the case of Putumayo and Sucumbíos. Yet, in both cases the pattern with a higher share of deforested area shows more advanced fragmentation.

Therefore, it is questionable to what extent landscape metrics can be used to differentiate between certain deforestation patterns or if they rather only reflect the expansion of deforestation.

6. Conclusion

The results of this study allow drawing several linkages between dynamics and differences of deforestation rates and patterns and changing socioeconomic conditions and governance in Colombia and Ecuador.

Especially in Colombia, the direct influence of growing of illicit crops on the forest and environment is noticeable due to the decline of coca cultivation and deforestation rates in Putumayo (Colombia) in the second study period. Several factors with intensifying or mitigating properties are detected for explaining almost stable deforestation dynamics in Sucumbíos (Ecuador). Yet, data gaps of thirteen and fourteen years between the studied composites complicate more accurate determination of deforestation drivers.

Visual interpretation of deforestation patterns proves the influence of governmental absence in Putumayo and pro-deforestation policies in Sucumbíos on spatial patterns as described by Geist & Lambin (2001). The quantifying approach using landscape metrics reveals that forest is more fragmented in Colombia and that fragmentation increases over time in both countries. However, this approach also shows limitations when making direct links between forest fragmentation and governance without considering the deforestation rates and total amount of deforested area.

The results of this study support conservation planning on both sides of the border. With the Colombian peace treaty signed June 2016, the longest conflict in the western world comes to an end (Nussio 2016). Anyhow, the implications of peace in Colombia for the environment remain uncertain. The presence of guerilla troops inhibited the establishment of large extractive industry in many cases (Álvarez 2001). Therefore, forest area protection should be considered in southern Putumayo in order not to push further deforestation and forest fragmentation. A region severely marked by armed conflict and coca cultivation, southern Putumayo will be an interesting area for remote sensing monitoring in the following years in order to enhance understanding of the impact of socioeconomic transitional periods on land use change and forest dynamics.

Combining Landsat data with upcoming Sentinel-2 imagery will improve data availability for the study area (Masek 2015) and thus enable denser time series for better monitoring and more accurate mapping in the future.

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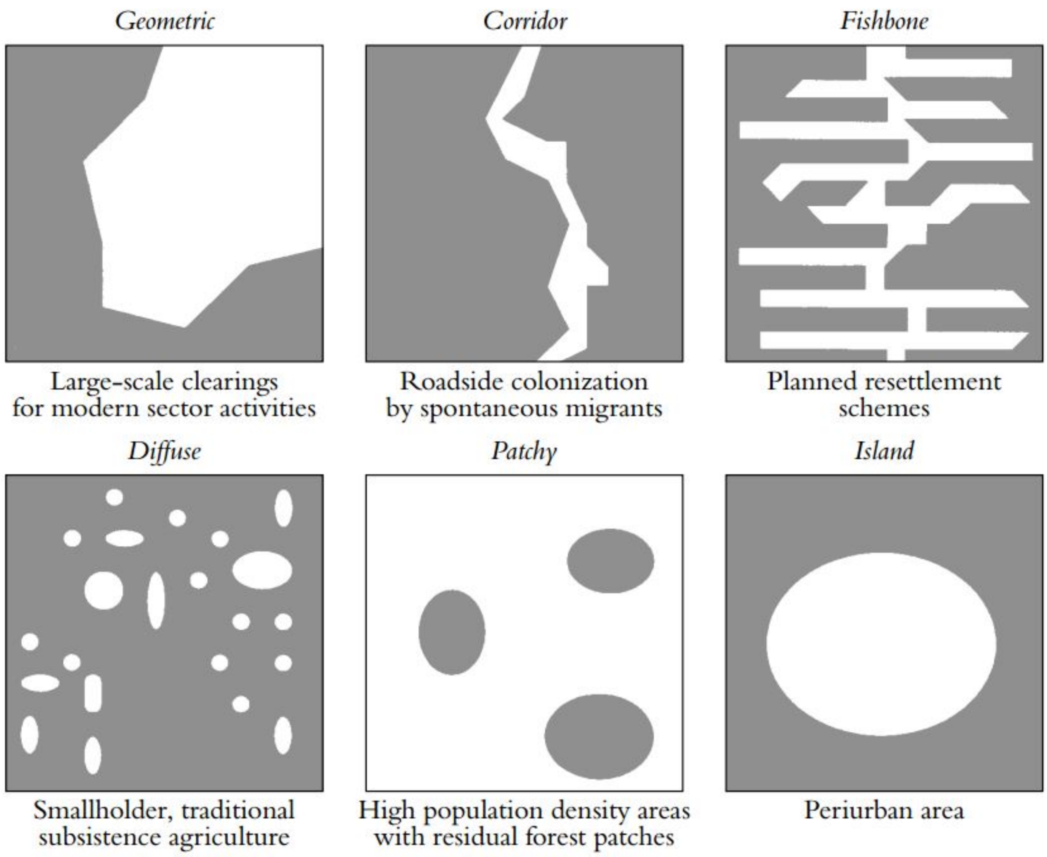
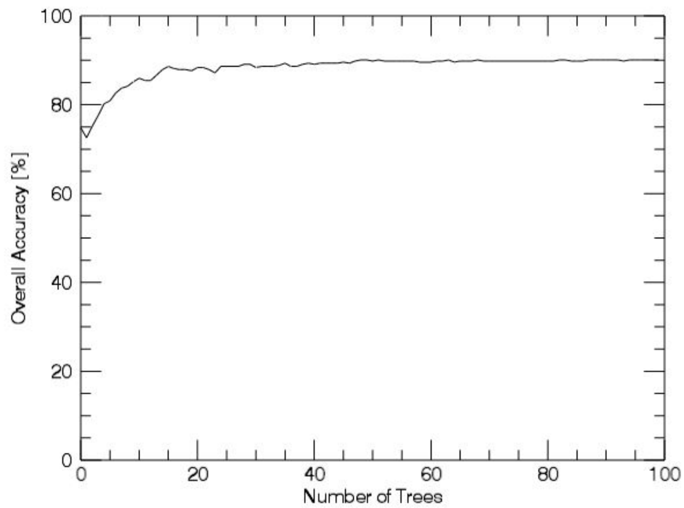
Appendix

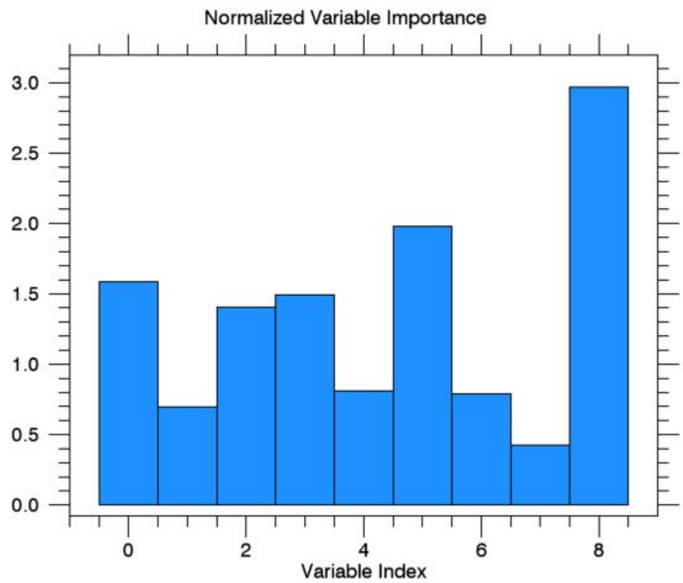
1. Appendix: Deforestation patterns described by Geist & Lambin (2001), p. 66.



2. Appendix: Learning curve (out-of-bag-accuracy) of the random forest model. Taken from the html report imploded in the Image RF application (Enmap Box, van der Linden et al. 2015).



3. Appendix: Normalized variable importance of random forest input variables (TC composite stack). Taken from the html report imploded in the Image RF application (Enmap Box, van der Linden et al. 2015). Variable index: 0=TC Brightness 1986, 1=TC Greenness 1986, 2=TC Wetness 1986, 3=TC Brightness 1999, 4=TC Greenness 1999, 5=TC Wetness 1999, 6=TC Brightness 2013, 7=TC Greenness 2013, 8=TC Wetness 2013.



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