Deforestation in the Colombian Amazon Biome: Socioeconomic and Socio-Environmental Conflict Drivers

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Abstract

Colombia, a megadiverse country, harbors over 10% of global biodiversity, much of it within the Amazon biome, which covers 43% of its land. Despite its ecological importance, the region faces deforestation driven by land conversion, coca cultivation, illegal mining, and armed conflict, exacerbating biodiversity loss and ecosystem degradation. Socioeconomic conditions in the biome both influence and are affected by these threats, yet data remains scarce. This study estimates indicators across four dimensions—socioeconomic, forest cover, water ecosystems, and socio-ecological conflicts—revealing precarious living conditions, especially for indigenous communities. Notably, areas with higher indigenous populations show greater forest conservation. The northwestern zone remains the most threatened.

Key words: Biodiversity, Indicators, Socioeconomic conditions, Deforestation, Socio-environmental conflicts, Poverty, Colombian Amazon Biome.
JEL Classification: C31, C36, D62, O13, O44, Q01, Q15, Q23, Q24, Q56.

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1 Introduction

The Amazon region spans eight South American countries—Bolivia, Brazil, Colombia, Ecuador, Guyana, Peru, Suriname, and Venezuela—as well as one territory (French Guiana), covering a total area of 8,470,209 km² (RAISG, 2022). This region contains the largest expanse of tropical rainforest in the world, with a high level of endemism: 22% of the world's species are found exclusively here (Miloslavich et al., 2010). Its diverse landscapes host nearly 10% of the world's fauna, 18% of vascular plant species, 14% of bird species, 9% of mammals, 8% of amphibians, and 18% of tropical fish. Its extensive hydrological network supplies fresh water and nutrients to the oceans, accounting for between 15% and 20% of the world's river discharge. Additionally, its vegetation and soils enable the sequestration of between 150 and 200 billion tons of carbon annually. The preservation of this ecosystem is crucial for approximately 33.5 million inhabitants, 63% of whom live in urban areas. Furthermore, conserving the Amazon is fundamental to safeguarding over 410 Indigenous groups, who collectively occupy 27.5% of its territory (RAISG, 2020).

In particular, the Colombian Amazon Biome (CAB) covers 483,164 km², representing 42.3% of the national territory, 5.71% of the total regional Amazon, and 6.4% of the territory of the countries belonging to the Amazon Cooperation Treaty Organization[1] (Guio Rodríguez and Rojas Suárez, 2019).

The immense biological diversity of the Colombian Amazon is represented by at least 170 types of ecosystems. The combination of soil types, proximity to the Andean mountains, the influence of Orinoquian flora, and the rocky outcrops of the Guiana Shield make the Colombian Amazon an exceptionally diverse region in terms of both flora and fauna. For instance, it hosts 8,200 recorded plant species (Guio Rodríguez and Rojas Suárez, 2019). According to Romero et al. (2009), out of the 4,932 vertebrate species (fish, birds, amphibians, reptiles, and mammals) recorded in Colombia at that time, 39.8% inhabit the Amazon. Additionally, the Colombian Amazon region is home to between 1,300 and 1,500 bird species, accounting for 75% of all bird species found in the country (Cárdenas López et al., 2019).

The Colombian Amazon Biome provides a wide range of ecosystem services at local, regional, and global scales, including food and fiber production, cultural and intangible services, carbon sequestration, water and climate regulation, recreation and ecotourism, habitat for numerous species, and more.

The region is also characterized by its rich hydrographic network. The major river basins in the Amazon Biome include the Putumayo, Caquetá, Apaporis, Vaupés, Guainía, Inírida, Guaviare, and Vichada rivers. This hydrological system is critical for fresh water supply, transportation, and climate regulation, benefiting both local populations and communities beyond national borders.

Despite its importance in biodiversity conservation, ecosystem services, and Indigenous community protection—including some groups in voluntary isolation—the Colombian Amazon faces increasing pressures that threaten the preservation of its forests. These forests are a central component of the complex web of ecological relationships that sustain the biome's extraordinary biodiversity.

Understanding the Amazon Biome requires not only identifying the dynamics and inten-

[1]The Amazon Cooperation Treaty (ACT), signed on July 3, 1978, and ratified by the eight countries that share the Amazon—Bolivia, Brazil, Colombia, Ecuador, Guyana, Peru, Suriname, and Venezuela—is the legal instrument that recognizes the transboundary nature of the Amazon region. It was approved by Colombia through Law 74 of 1979 and ratified on August 2, 1980.

sity of its degradation, along with its direct and underlying drivers, but also gaining insights into the characteristics of the diverse populations inhabiting the region. Meisel Roca et al. (2013) analyzed the economic geography of the Colombian Amazon, describing its main physical, demographic, social, and economic characteristics. Their study focused on what they termed the "Legal Amazon," which includes the departments of Amazonas, Caquetá, Guainía, Guaviare, Putumayo, and Vaupés. Based on the 2005 census, they found that the Colombian Amazon was one of the least prosperous regions, with living conditions significantly lower than those in the rest of the country. This was attributed to geographical isolation, a lack of legal economic opportunities, and other factors.

The population of the Amazon both influences and is directly affected by the conservation and maintenance of the biome, creating ongoing interactions and feedback loops. Thus, understanding the characteristics of households in the Amazon Biome is essential for designing policies that support both forest protection and human well-being. However, to the best of our knowledge, although some reports and studies analyze specific indicators such as population density and poverty, there has been no recent and comprehensive demographic and socioeconomic analysis of the region using data from Colombia's latest national census (2018).

Meanwhile, numerous studies have investigated the drivers of deforestation in the Amazon, employing a range of methodologies and yielding diverse findings. These methods include statistical quantitative models, spatial-temporal models, qualitative analyses, and hybrid approaches combining the above. Some studies examine changes over time using time-series data, while others explore municipal-level differences using cross-sectional data. Panel data analyses have also been used to integrate both approaches.

Against this backdrop, this study pursues two key objectives. First, it seeks to estimate indicators for the Colombian Amazon Biome across four dimensions: (1) socioeconomic and demographic factors, (2) socio-environmental conflicts, (3) freshwater-associated ecosystems, and (4) terrestrial ecosystems (forests). Within each dimension, indicators are further categorized. Second, this study aims to analyze interactions between these indicators—both within and across categories—to provide insights into their relevance for explaining deforestation patterns in the Colombian Amazon Biome. Because the complexity of the interactions in explaining deforestation, we propose different approaches to better understand how the set of calculated variables contribute to explaining deforestation.

This document is structured as follows: In addition to this introduction, Section 2 presents a literature review on deforestation drivers in the Amazon. Section 3 describes the data and methodological approaches used in this study. We present the estimated indicators for the four proposed dimensions. In addition, we analyze significant interactions between indicators and categories, using traditional and machine learning (ML) approach. Section 4 presents results of traditional and ML approach. Finally, we offer a discussion on the relevance of this research for global conservation dialogues in Section 5.

2 Literature Review

Deforestation in the Amazon is the result of the combination of multiple factors involving biophysical, economic, demographic, and institutional variables. Regarding the key determinants of deforestation in the region, most commonly identified in the literature, are: illegal land grabbing and agricultural expansion (Busch and Ferretti-Gallon, 2023; Armenteras et al., 2013a, 2017; González-González et al., 2021a; Lim et al., 2017; Hänggli et al., 2023; Tebbutt et al., 2021), the planting of illicit crops (Dávalos et al., 2021, 2016), armed conflict (Cantillo and Garza, 2022; Bautista-Cespedes et al., 2021; Liévano-Latorre et al., 2021; Armenteras et al., 2019; Clerici et al., 2020; Murillo-Sandoval et al., 2020; Prem et al., 2020; Fergusson Talero et al., 2014) and mining (Hänggli et al., 2023; González-González et al., 2021b).

Studies analyze these factors individually or in various combinations. Models are even found that identify interrelationships between these determinants, particularly between armed conflict and illicit crops (Armenteras et al., 2013b; Quiroga-Angel et al., 2022; Hoffmann et al., 2018; Rincón-Ruiz et al., 2013; Berenguer et al., 2021) and between coca crops and poverty (Hoffmann et al., 2018; Dávalos et al., 2016; Dávalos and Dávalos, 2020) - the latter in the Colombian Amazon - as key associations in the dynamics of deforestation.

Not all investigations include socio-economic or demographic factors, although there are studies that incorporate variables such as education (Mena et al., 2006), poverty (Mena et al., 2006), population density (Mena et al., 2006; Quiroga-Angel et al., 2022; Hänggli et al., 2023), migration (Dávalos et al., 2016), urbanization and road infrastructure (Hänggli et al., 2023; Dávalos et al., 2016; Mena et al., 2006; Merry et al., 2009; Asner et al., 2006). Additionally, several of these studies incorporate biophysical variables.

Some of these studies could be classified into two types of models that have been proposed to analyze the loss of forest cover (Rudel and Roper, 1997): impoverishment models and frontier models. Dávalos et al. (2021) explain that the former are based on the role of poverty in deforestation to expand subsistence agriculture (including the planting of illicit crops), while the latter are based on the presence of powerful actors seeking economic development in forest covers.

On the other hand, following the literature, Bautista-Cespedes et al. (2021) classify the determinants of deforestation in the Colombian Amazon as direct: illicit crops, agricultural expansion, extensive livestock farming, infrastructure development and wood extraction; and underlying: Poverty, armed conflict, forced displacement and land grabbing (Armenteras et al., 2006, 2013a, 2019; Etter et al., 2006; Sánchez-Cuervo and Aide, 2013; Castro-Nunez et al., 2017a; Murad and Pearse, 2018; Hoffmann et al., 2018; Landholm et al., 2019; Negret et al., 2019; Furumo and Lambin, 2020).

Land grabbing, agricultural expansion for agribusiness and livestock (pastures) are presented as some of the most relevant factors in the expansion of the agricultural frontier of the Amazon, above subsistence or small-scale crops and even illicit crops (Murillo-Sandoval et al., 2018; Tebbutt et al., 2021). In the Colombian Amazon, illegal land grabbing is generated by expectations of future titling, by the opportunity to acquire land at low prices and accumulate large extensions, and by the possibility of speculation (Sánchez García and Wong, 2024). Land grabbing is associated with the presence of illegal groups, the construction of roads, the presence of weak institutions, and the absence and lack of governance (Tebbutt et al., 2021). According to Sánchez García and Wong (2024), the conversion of forests to pastures is reinforced by the power of large landowners (latifundistas), who increase their social power, as well as by the presence of drug traffickers and other illegal actors who use this mechanism to legitimize their economic activities through money laundering. The planting of pastures and livestock have been the mechanisms generally used to legalize informal or illegal properties. On the contrary, the same authors show that coca crops do not precede livestock activities.

A significant portion of the literature has focused on the role of illicit crops and deforestation in the Amazon, particularly the Colombian Amazon, due to the complexities and dynamics associated with those two factors in the country.

Although several studies find a significant and direct relationship between the presence of illicit crops and deforestation, some authors claim that this association is mediated by armed conflict (through, for example, forced displacement), the presence of other land uses such as pastures, and eradication programs (Dávalos et al., 2021; Hoffmann et al., 2018; Díaz and Sánchez, 2004; Negret et al., 2019; Dávalos et al., 2009; Rincón-Ruiz and Kallis, 2013). For other authors, the role of illicit crops, particularly coca, is negligible or becomes blurred when demographic or other variables such as road infrastructure, armed conflict or illicit crop eradication programs are included (Hänggli et al., 2023; Negret et al., 2019; Dávalos et al., 2016, 2011).

Based on the positive relationship between illicit crops and deforestation found by Quiroga-Angel et al. (2022), these authors suggest the development of studies that explain the determinants of illicit crop planting. In particular, they recommend identifying the relationship with variables such as poverty. In this sense, Dávalos et al. (2021) examine the presence of illicit crops and population growth as determinants of deforestation under the impoverishment model, and infrastructure as a determinant in a frontier model.

Regarding armed conflict, there is no consensus in the literature. While some authors find that greater conflict intensity leads to greater deforestation (Liévano-Latorre et al., 2021; Negret et al., 2019; Bautista-Cespedes et al., 2021) - through, for example, migration due to forced displacement (Dávalos et al., 2016), land grabbing (Cantillo and Garza, 2022; Negret et al., 2019), or illicit crops (González-González et al., 2021b), others claim that the presence of armed groups has had positive effects on forest conservation by prohibiting the development of infrastructure or productive investments (Murillo-Sandoval et al., 2020) and the forced and mass displacement, which implies the recovery of the forest in abandoned lands (Hoffmann et al., 2018; Castro-Nunez et al., 2017b; Murillo-Sandoval et al., 2020; Clerici et al., 2020).

In particular, Bautista-Cespedes et al. (2021) show that armed conflict has caused population displacement; also, that the installation of anti-personnel mines has allowed forest regeneration, while the establishment of illicit crops, promoted by illegal armed groups, causes deforestation (Sánchez-Cuervo et al., 2012; Castro-Nunez et al., 2017a; Ibáñez and Vélez, 2008; Fergusson Talero et al., 2014; Baumann and Kuemmerle, 2016; Morales, 2017; Bautista-Cespedes et al., 2021).

When analyzed solely in terms of armed conflict, Cantillo and Garza (2022) confirm that the strategy and ideology of armed actors determine the spatiotemporal patterns of deforestation or conservation. Specifically, the authors emphasize that, in municipalities with a greater presence of guerrillas, the tendency towards deforestation is lower, while a greater presence of paramilitary groups is related to a greater tendency towards deforestation. The motivation of the guerrillas is due, among other things, to strategic reasons (Álvarez, 2003). In the case of the paramilitaries, their far-right ideology is in line with the expansion of large estates for livestock and agribusiness.

On the other hand, González-González et al. (2021a) find that the effect of armed conflict on deforestation depends on geographic proximity. Specifically, these authors show that in the Colombian Amazon the presence of conflict exhibits a positive association with deforestation, although this relationship is reduced with the distance to the conflict zones and its relationship with deforestation becomes negative and significant. These results would indicate that, in the Colombian Amazon, the presence of armed groups promotes deforestation on the local scale while reducing it on the regional scale, perhaps due to land abandonment.

Bautista-Cespedes et al. (2021) highlight that the distance to areas with events related to the conflict and to mined areas serve as determinants of deforestation: (i) greater proximity to conflict events, greater deforestation, and (ii) greater proximity to mined areas, less deforestation.

Regarding variables not related to the conflict, the study by Bautista-Cespedes et al. (2021) shows that deforestation is greater in (i) lowlands than in highlands and (ii) in proximity to populated centers. When the authors perform stepwise regressions in frontier zone models, elevation, distance to agricultural frontier boundaries, and distance to roads were significant variables. On the other hand, the authors highlight that, of the conflict-related variables included in the model, the distance to mined areas was positive and significant in all periods, while armed conflict events were only so in two of the three periods analyzed.

According to several studies, the peace agreement signed in 2016 by the government of Colombia and the FARC-EP has generated an increase in deforestation, mainly in the Colombian Amazon. In particular, the demobilization of that guerrilla group opened a door for land grabbers, drug traffickers, other illegal armed groups, ranchers, chieftains and other actors to illegally access the forest reserve of the Amazon, even affecting protected areas and indigenous reservations (Sánchez García and Wong, 2024). In this regard, Murillo-Sandoval et al. (2018) assert that, since the peace process initiated in 2012 and the signing of the agreement between the government and the FARC-EP in 2016, there is evidence of the explosive conversion of forests to livestock farming outside the agricultural frontier, even in protected areas, as demonstrated by Clerici et al. (2020), who found a "dramatic and highly significant increase" in the deforestation of protected areas.

On the other hand, according to the literature, road infrastructure has contributed significantly to deforestation due, among other things, to the flow of migrants, including displaced populations (Hänggli et al., 2023; Hoffmann et al., 2018; Berenguer et al., 2021; Dávalos et al., 2016). In particular, Hoffmann et al. (2018) confirm that road construction is indirectly associated with deforestation through migration and the provision of services, as roads provide access to previously conserved sites. Similarly, road construction facilitates access to markets, in addition to promoting colonization and expansion of the agricultural frontier (Mena et al., 2006), which is reflected by the distinctive fishbone pattern (Hänggli et al., 2023). The increase in road infrastructure also generates speculation, facilitates connection with urban centers for the sale of products and supply of food, inputs and services, favors the extraction of natural resources, including wood, and generates expectations about land appreciation.

Related to road infrastructure, González-González et al. (2021b) show that the distance to mining concessions in the Colombian Amazon is a cause of deforestation, along with distance to populated centers, distance to roads, and distance to previously deforested areas, with the last variable being the most relevant.

Regarding demographic variables, the role of population (density, size, and growth) has been evaluated and demonstrated as a determinant of deforestation (Dávalos et al., 2021; Hänggli et al., 2023). In this sense, Mena et al. (2006) argue that most models that evaluate the determinants of deforestation incorporate demographic factors but do not include socioeconomic factors. These authors, using census data, analyze the determinants of deforestation at the parish level in the Ecuadorian Amazon in two periods: 1986-1996 and 1996-2002. The study finds results that differ between the two periods. In the decade from 1986 to 1996, deforestation is negatively related to poverty, the percentage of households with aqueducts, and the percentage of households with electricity. On the other hand, road density and population density are significant and positive determinants of deforestation. For the period 1996-2002, deforestation in the Ecuadorian Amazon is explained by population and road density, primary education and the percentage of households with electricity. Hänggli et al. (2023) also find that higher education is associated with higher deforestation in the

Ecuadorian and Brazilian Amazon. The study by Mena et al. (2006) is one of the few that involve various socioeconomic factors as underlying causes in the explanation of deforestation in the Amazon. However, some authors have shown that deforestation in the Ecuadorian and Brazilian Amazon has few determinants in common with deforestation in the Colombian Amazon (Armenteras et al., 2006; Viña and Estévez, 2013).

Limited socioeconomic and demographic information at the municipal and recent scale about the population that inhabits the Colombian Amazon limits the comprehensive understanding of the biome and is one of the obstacles to the design of sustainable development strategies in the region. On the other hand, the multiplicity of studies that analyze the determinants of deforestation has allowed us to approach the understanding of forest loss in the Colombian Amazon; however, a comprehensive model that allows us to understand the relationship between direct and underlying causes of deforestation in the CAB and the associations between each type of determinant has not been evaluated.

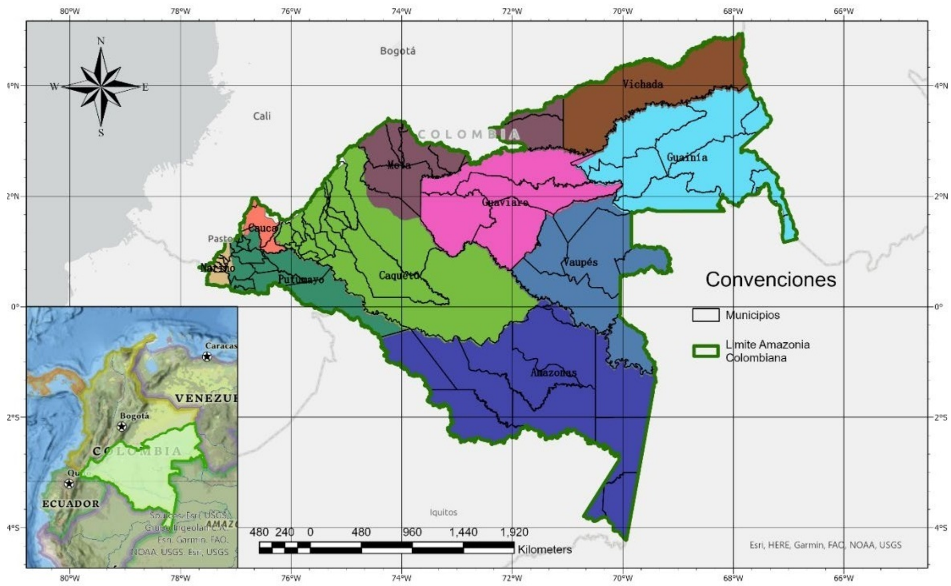
In this sense, this study seeks to carry out the socioeconomic and demographic characterization of the population of the Colombian Amazon, based on municipal census information, and to identify the interactions between the socioeconomic and demographic variables, and the variables of socio-environmental conflict, deforestation, and freshwater.

3 Data and Methods

3.1 Study zone

The Colombian Amazon biome is located in the southern part of the country and comprises six entire departments (Caquetá - CQ, Guaviare - GV, Guainía - GN, Vaupés - VP, Amazonas - AM, and Putumayo - PT) and four partially included departments (Vichada - VC, Meta - MT, Nariño - NR, and Cauca - CC). In the latter case, some municipalities from these departments also partially form part of the Colombian Amazon Biome (CAB). The Colombian Amazon biome (CAB) borders Brazil and Peru to the southeast and Ecuador to the south (Figure 1).

Figure 1: *The Colombian Amazon biome and its departments and municipalities*



Specifically, the region includes 43 fully incorporated municipalities and 16 partially included ones (Table 1). Additionally, it contains 18 non-municipalized areas, which correspond to "entities that do not fall within the territorial framework established by the Constitution, as they do not meet the legal requirements for their creation as municipalities, particularly in terms of population and resources" (Ruling 054 of 2023 of the Constitutional Court of Colombia).

The Colombian Amazon biome borders Brazil and Peru to the southeast and Ecuador to the south. Within this biome, there are two subregions distinguished by their territorial, ecological, demographic, and social characteristics and dynamics (Guio Rodríguez and Rojas Suárez, 2019): i) The Northwestern Amazon or Andean foothills, and ii) The Southeastern Amazon or lowlands.

The first subregion is located in the Andean-Amazonian transition zone, encompassing the departments of Putumayo, Caquetá, and Guaviare, as well as the Amazonian territories of Meta, Nariño, and Cauca. It covers 37% of the Colombian Amazon and is home to 86% of its population.

The Southeastern Amazon or lowlands subregion includes the departments of Amazonas, Guainía, and Vaupés, as well as part of Vichada. This area comprises the remaining 63% of the Colombian Amazon biome and houses 14% of its population, primarily indigenous communities (Guio Rodríguez and Rojas Suárez, 2019).

Additionally, out of the total municipalities that are part of the Colombian Amazon, 36 are classified as beneficiaries of the Development Programs with a Territorial Approach (PDET)[2], as defined in point one of the Comprehensive Rural Reform of the Peace Agreement signed between the Government of Colombia and the FARC-EP in 2016. These municipalities are characterized by a high presence of illicit crops, armed conflict, high levels of poverty, and

[2]A planning and management instrument of the National Government designed to prioritize and accelerate the implementation of sectoral plans and programs within the framework of the Comprehensive Rural Reform (RRI) and the relevant measures established in the Final Peace Agreement.

Table 1: *Political-administrative distribution in the Amazon biome*

Departments	Municipalities		Non-municipalized districts
	Complete	Partial	
Caquetá, CQ	16: Florencia, Albania, Belén de los Andaquíes, El Doncello, El Paujil, La Montañita, Milán, Morelia, San José Del Fragua, Valparaíso, Cartagena Del Chairá, San Vicente Del Caguán, Solano, Solita, Curillo, Puerto Rico	0	0
Guaviare, GV	4: San José Del Guaviare, Calamar, El Retorno, Miraflores	0	0
Guainía, GN	2: Inírida, Barrancominas	0	6: San Felipe, Puerto Colombia, La Guadalupe, Cacahual, Pana Pana, Morichal
Vaupés, VP	3: Mitú, Carurú, Taraira	0	3: Pacoa, Papunahua, Yavaraté
Amazonas, AM	2: Leticia, Puerto Nariño	0	9: El Encanto, La Chorrera, La Pedrera, La Victoria, Mirití – Paraná, Puerto Alegría, Puerto Arica, Puerto Santander, Tarapacá
Putumayo, PT	13: Mocoa, Colón, Orito, Sibundoy, San Francisco, San Miguel, Santiago, Valle Del Guamuez, Villagarzón, Puerto Caicedo, Puerto Asís, Puerto Guzmán, Puerto Leguízamo	0	0
Vichada, VC	0	1: Cumaribo	0
Meta, MT	1: La Macarena	8: Mapiripán, Mesetas, Uribe, Puerto Concordia, Puerto Gaitán, Puerto Rico, San Juan de Arama, Vistahermosa.	0
Nariño, NR	0	6: Córdoba, Funes, Ipiales, Pasto, Potosí, Puerres.	0
Cauca, CC	2: Piamonte, Santa Rosa	1: San Sebastián.	0
6 completos 4 parciales	**43**	**16**	**18**

state neglect.

The Colombian Amazon region is home to a vast indigenous cultural heritage. According to Fundación Alisos (2011), 64 different ethnic groups reside in the area, most of whom are organized within Indigenous Reserves. Some of these groups are currently considered to be in isolation (Guio Rodríguez and Rojas Suárez, 2019; Fundación Alisos, 2011). According to the DANE Geovisor, as of 2024, there are 235 registered Indigenous Reserves.

In addition to the conservation role played by Indigenous Reserves, another conservation measure is the system of National Natural Parks. Approximately 24% of the Amazon biome is designated as National Natural Parks (PNN) (Guio Rodríguez and Rojas Suárez, 2019). The region contains 16 nationally protected areas: Tinigua, Amacayacu, Serranía del Chiribiquete, Cahuinarí, Sierra de la Macarena, Yaigojé-Apaporis, Serranía de los Churumbelos, Cueva de los Guácharos, Río Puré, Puinawai, Nukak, La Paya, Alto Fragua Indi Wasi, the Orito Ingi Ande Sanctuary of Flora and Medicinal Plants, and Cordillera de los Picachos. According to figures from the GAIA Amazonas Foundation, National Natural Parks cover 10.7 million hectares of the Colombian Amazon[3]. Among these, the Serranía de Chiribiquete National Park stands out for its vast extension, covering 4,268,095 hectares.

Another conservation tool implemented in the region is the system of areas established under Law 2 of 1959, which designates forest reserves for the conservation and preservation of forests, water sources, and wildlife. Initially, the entire Amazon region was included under this designation; however, certain areas have since been removed to allow for other activities. The Law 2 forest reserve areas originally covered 34,579,127 hectares, but 6,009,552 hectares have been withdrawn to date.

Additionally, as of December 2023, there were five Peasant Reserve Zones (ZRC) in the region, with two more in the process of being established. These zones were created under Law 160 of 1994. Peasant Reserve Zones are areas of colonization where rural land ownership is regulated, limited, and organized to prevent land concentration and land grabbing, promote smallholder farming, and facilitate the transition from subsistence farming to medium-scale rural entrepreneurship (Law 160, 1994, Article 79). As of early 2024, the established ZRCs covered an area of 947,751 hectares.

3.2 Dimensions, categories, and analysis indicators

This study proposes a characterization of the Colombian Amazon biome based on four dimensions of analysis:

1. Social Aspects: Provides a diagnosis of the human population conditions in the biome, using demographic, social, economic, and institutional indicators.

2. Terrestrial Ecosystems: Describes the condition and degree of degradation of terrestrial ecosystems, mainly the forest cover in the biome.

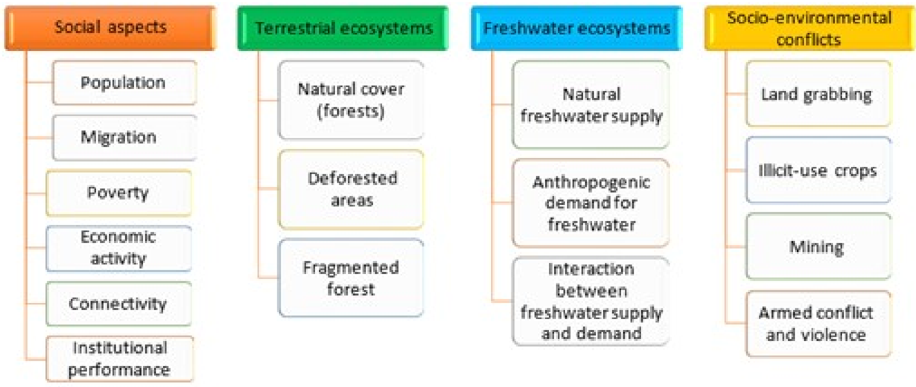
3. Freshwater Ecosystems: Includes a set of indicators that approximate the conditions of natural supply and human demand for water provided by freshwater-associated ecosystems.

4. Socio-environmental Conflicts: Reflects the conflicts generated by human activities on the terrestrial and freshwater ecosystems in the Amazon biome.

[3]See "https://www.gaiaamazonas.org/noticias/2020-07-10$_t$erritorios − indigenas − y − areas − protegidas − de − la − amazoniaperdieron − menos − del − 1 − de − sus − areas − de − bosque − en − treinta − anos/"

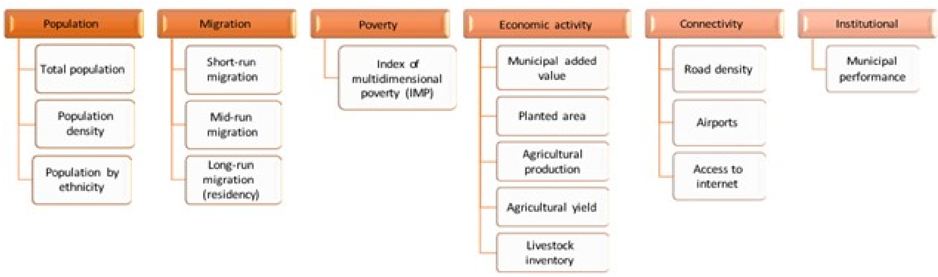
Categories of analysis are proposed for each of these dimensions, each grouping several indicators. These categories are presented in Figure 2.

Figure 2: *Dimensions and categories for analyzing the status of the Amazon biome*



The social-aspects dimension includes demographic, socioeconomic, and institutional indicators, presented and analyzed at the municipal and departmental levels for the years 2018 or 2019, depending on the available information. These are grouped into six categories, as shown in Figure 3.

Figure 3: *Categories and indicators of social aspects*

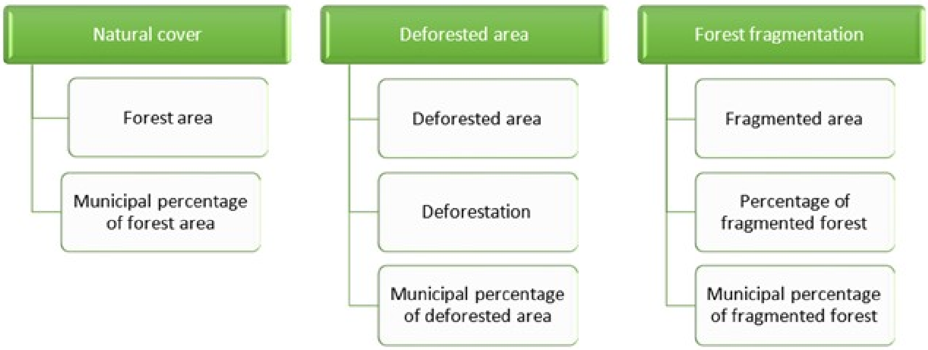


The information for the social aspects dimension was taken from: (i) the 2018 National Census (population, migration, and poverty indicators), (ii) the National Department of Statistics – DANE (economic activity indicators), (iii) the Gran Encuesta Integrada de Hogares (GIEH) (unemployment), (iv) UPRA- Ministry of Agriculture (agricultural information), (v) Ministry of Transport (roads and airports), (vi) Min-TIC (internet access), and (vii) DNP (institutional performance).

As some municipalities are only partially included in the CAB and there is no detailed information available at a smaller scale, it was necessary to use weighting to calculate some values. Indicators in the Population and Agricultural Activity categories were weighted based on the municipal area. The indicators for Migration, Municipal Value Added, and Digital Connectivity were weighted by population. The indicators for poverty and institutional performance take the value for the entire municipality. Other indicators with spatial information, such as road density and airports, were estimated directly from maps prepared by IDEAM-SINCHI.

The terrestrial ecosystems dimension includes three categories: natural cover, deforested area, and forest fragmentation (Figure 4). The indicators in these categories are constructed using maps provided by IDEAM-SINCHI. Data is available for the years 2002, 2007, 2012, 2014, 2016, 2018, and 2020. To ensure compatibility with census information, data from 2018 were used.

Figure 4: *Categories and indicators of terrestrial ecosystems*



In this case, the municipal estimates are constructed by aggregating the pixels reported on the maps for each indicator and municipality that is wholly or partially included in the CAB.

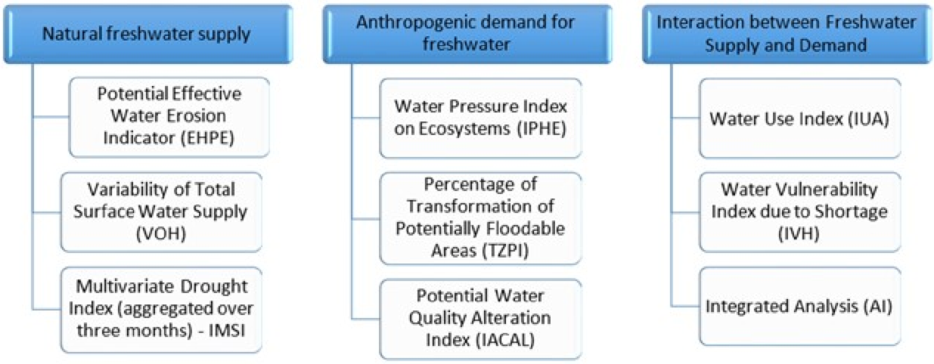
Forest cover is measured in two ways: the absolute value in hectares (forest area) and the proportion of the departmental or municipal territory covered by forests (percentage of municipal area in forest). Deforestation and fragmentation are measured in three ways: the first is the absolute value in hectares (deforested or fragmented areas). The second is the percentage of these areas relative to the forest area within the municipality or department (deforestation or percentage of fragmented forest). The third is the percentage of these areas relative to the total surface area of the municipality or department (percentage of municipal area deforested or fragmented).

Since the forest area is smaller than the total surface of the municipality, the indicators associated with the second measure will yield higher values than those of the third. However, as forest cover in the biome tends to occupy a large proportion of the territory, these two measures are often similar in aggregate values, although at the municipal level, more significant differences may emerge.

Regarding freshwater ecosystems, the National Water Status Report (ENA) provides a variety of data on the country's water conditions (Instituto de Hidrología, Meteorología y Estudios Ambientales (IDEAM), 2023). For this study, some of the indicators estimated in the ENA are extracted and grouped into the categories mentioned in Figure 5. For the Amazon biome, IDEAM defines 11 hydrological zones and 57 subzones. In the Amazon Basin, these subzones can span more than one municipality, and a single municipality may cover one or more subzones.

To present the municipal-level data, this study weights the indicator values reported by Instituto de Hidrología, Meteorología y Estudios Ambientales (IDEAM) (2023) for each subzone proportionally to the area of each municipality within them. Some of the indicators proposed by IDEAM were adjusted to allow all of them to be expressed on a categorical scale of 0 to 4, where the indicator status can be very low, low, medium, high, or very high, respectively. In all cases, the very low and low values correspond to desirable indicator conditions.

Figure 5: Categories and indicators of the status of freshwater ecosystems



The indicators are calculated and analyzed at the municipal and departmental levels for 2022, which is the most recent report from IDEAM. While these indicators do not directly assess the status of aquatic ecosystems, they do provide an approximation of the freshwater provision services.

While these indicators do not directly analyze the state of aquatic ecosystems, they do provide an approximation of the condition of freshwater provision services. The first category, *natural freshwater supply*, examines the behavior of subzones in terms of their ability to produce freshwater over time and the potential threats to that capacity. The second category, *anthropogenic demand for freshwater*, looks at how human activities impact freshwater provision in the subzones, including the needs of people, habitat transformations, and water quality changes. Finally, the third category —the *interaction between demand and supply*— analyzes what happens to freshwater systems when supply and demand variables are combined, using three indicators developed by IDEAM: The Water Use Index, the Water Vulnerability Index, and the Integrated Analysis Indicator.

The socio-environmental conflicts dimension includes four categories which, in the literature, are frequently linked with the loss of coverage in the Colombian Amazon biome: land grabbing, illicit-use crop cultivation, mining, and armed conflict and violence (Figure 6).

Figure 6: Categories and indicators of socio-environmental conflicts

The information for this dimension comes from various sources: (i) SINCHI-IDEAM (deforestation and fires), (ii) the UNODC Illicit-use Monitoring System (illicit-use crop cultivation), (iii) the National Mining Agency and RAISG (legal and illegal mining), (iv) INDEPAZ (presence of armed groups), (v) the Victims Unit (expulsion and reception of displaced populations), and (vi) the Ministry of Defense (acts of war, homicides, and homicide rates).

For municipalities that are only partially included, the indicators for land grabbing, illicit-use crop cultivation, and mining are built using spatial data corresponding to the municipality's area within the CAB. Meanwhile, for the presence of armed groups, acts of war, and homicide rates, the indicator value for the entire municipality is used. For the expulsion and reception of displaced populations, the indicators are weighted by population. As with the other indicators, the most recent data available, closest to 2018, is used.

3.3 Interactions

As an input for building a model to identify the determinants of deforestation, interactions between and within dimensions, categories, and indicators are calculated using Pearson correlations. This step provides an initial insight into direct and underlying relationships.

As shown in Figure 2, each dimension consists of several categories, and within each category, there are multiple indicators. Given their nature, it is likely that the indicators within each category are related to each other. In some cases, it is more effective to analyze correlations at the category level rather than at the indicator level. Therefore, we need to construct an index to aggregate the indicators within each category. To achieve this, we propose standardizing the indicators using Equation 1.

$$X_i est = \frac{X_i - X_{min}}{(X_{max} - X_{min})} \tag{1}$$

To calculate the index value for each category j, we average the values of all the indicators within that category (Equation 2).

$$Y_{i,j} = \frac{\sum_1^n X_{i,j}}{n} \tag{2}$$

In other words, the index value for category j ($Y_{i,j}$) will be the average of the n indicators in that category ($X_{i,j}$) for each municipality i. The same method is used to calculate the index for each dimension: a simple average of the indices of each category in that dimension.

This procedure yields:

- The list of individual indicators for each municipality i, standardized to values between 0 and 1,
- The list of indices for each category for each municipality i, standardized to values between 0 and 1,

We apply Pearson correlation analysis for all pairs of included variables (indicators, and categories). For this study, we selected interactions that are significant with a p-value < 0.01 and show (i) a correlation with deforestation and (ii) correlations between variables that showed significant correlations with deforestation.

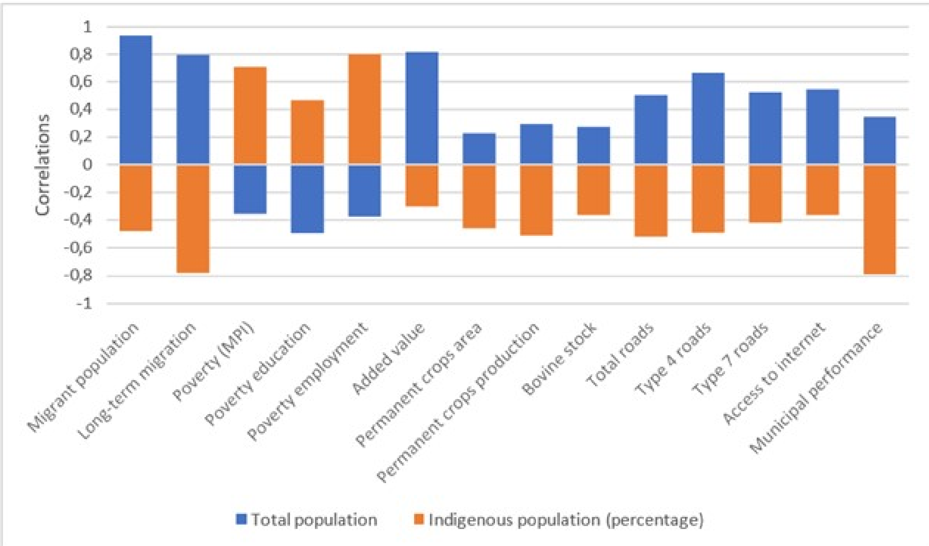
Some of the selected relationships provide preliminary signs of causality, based on which we build an econometric model to identify the drivers of deforestation in the Colombian Amazon.

3.4 Interaction between indicators

Based on the collected indicator data, relationships between them and their categories were analyzed. This correlation analysis helps understand how socio-economic performance indicators and socio-environmental conflicts can be linked to terrestrial and aquatic ecosystem conservation indicators, forming the basis for developing models to establish causal relationships or determinants of deforestation.

First, it is observed that municipalities with larger total populations and those with a higher proportion of Indigenous populations exhibit opposing trends in socio-economic indicators. More populous municipalities tend to have higher migrant populations, lower poverty levels, greater economic activity, larger areas and production of permanent crops, larger cattle inventories, more road infrastructure, better internet access, and stronger institutional performance. In contrast, municipalities with higher Indigenous populations show the inverse trends across all these indicators: fewer migrants, higher poverty, reduced economic activity, smaller permanent crop areas and production, smaller cattle inventories, fewer roads, poorer internet access, and weaker institutional performance (Figure 7).

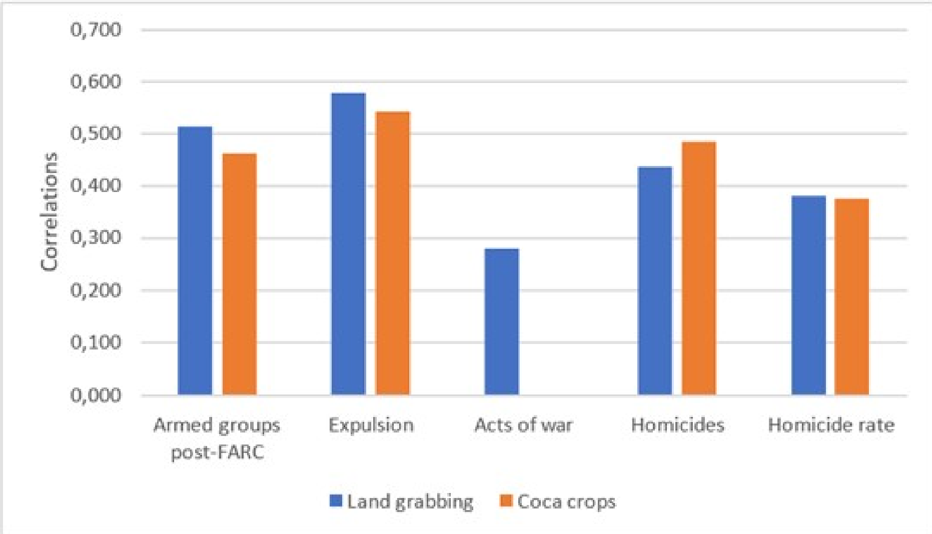
Figure 7: *Main correlations of total population indicators and percentage of indigenous population with other social indicators*



Municipalities with a greater presence of post-FARC armed groups are characterized by higher expulsion of displaced populations, greater presence of military actions, and higher levels and rates of homicides. These municipalities tend to be associated with areas where there is more land grabbing (pasture expansion and burning) and where there is a greater presence of illicit crops (coca) (Figure 8)[4].

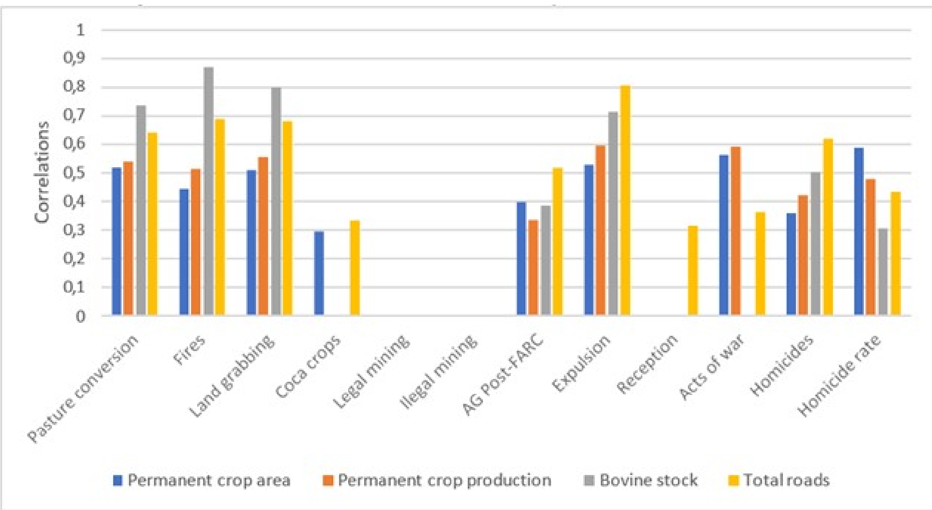
[4]The detailed correlations between indicators and categories are available upon request.

Figure 8: *Main correlations between land grabbing and the presence of illicit-use crops indicators and conflict indicators associated with violence*



On the other hand, the presence of permanent crops, livestock inventory, and road infrastructure are positively associated with land grabbing, the presence of armed groups and military actions, the expulsion of displaced populations, and homicides. While livestock activity is more strongly related to land grabbing, the existence of roads is more closely linked to the presence of armed groups, population displacement, and homicides. Specifically, roads of types V, VI, and VII play a more significant role in these relationships. Similarly, municipalities with higher migration rates and better economic performance are associated with socio-environmental conflicts such as land grabbing, armed conflict, and homicides. On the other hand, a higher proportion of Indigenous population is associated with lower levels of all these socio-environmental conflicts, while both legal and illegal mining activities are related to municipalities with a higher proportion of Indigenous population (Figure 9) and greater poverty.

Figure 9: *Correlations between socio-environmental conflicts and socioeconomic variables*



The various measures of deforestation in municipalities of the Amazon biome are positively associated with different socio-environmental conflicts, except for mining. Thus, municipalities with higher deforestation are those with a greater presence of armed groups, military actions, population displacement, and homicides. Additionally, the existence of more deforestation in municipalities is related to greater land grabbing and the presence of coca crops. Forest fragmentation also corresponds positively with pasture expansion processes, the presence of coca crops, and violence problems due to armed groups and homicides, although not with the presence of mining activities. In contrast, the presence of natural forest is associated with municipalities having fewer coca crops and fewer homicides, but more mining activity (Table 2).

Instituto Igarapé and InSight Crime (2021), citing IDEAM (2018), identify seven drivers of deforestation in Colombia: 1) pasture expansion, 2) infrastructure development, 3) expansion of agricultural activities in restricted areas, 4) extensive livestock farming, 5) illicit crops, 6) illegal logging, and 7) illegal mining. Our results confirm this assertion for the first five; we do not have information on illegal logging and did not find a strong relationship with mining activity.

In terms of socio-economic indicators and categories, municipalities with more forest cover are related to those with smaller total populations, less migration, more poverty, and less connectivity, both in terms of roads and internet access. On the other hand, municipalities with a higher proportion of Indigenous population are those where greater natural forest cover is observed (Table 2).

In the case of deforestation and forest fragmentation, the relationship with socio-economic indicators is inverted. In municipalities with more deforestation and forest fragmentation, there is a greater likelihood of migrant populations, presence of permanent crops, and more roads. As expected, municipalities with a higher proportion of Indigenous population are those where deforestation and fragmentation phenomena are less frequent (Table 2).

Municipalities with a greater demand for water services are positively related to those with larger populations, more migration, more permanent crops, more roads, and better institutional performance, as well as less poverty. Municipalities with a higher proportion of Indigenous population and the presence of mining exhibit less pressure on water resources.

Table 2: *Correlations between categories of terrestrial ecosystems and socio-environmental conflicts and social categories*

	Forest	**Deforestation**	**Fragmentation**
Dimension:			
Socio-environmental conflicts		**0.789**	**0.463**
Land grabbing		0.8	
Pasture conversion		0.815	0.312
Fires		0.664	
Coca crops	-0.303	0.399	0.534
Mining	0.41		-0.293
Violence		0.734	0.503
Conflict		0.656	0.443
Homicides	-0.367	0.737	0.524
Dimension: Social		**0.574**	**0.334**
Total population	-0.31		
Indigenous population	0.606	-0.531	-0.578
Migration	-0.451	0.683	0.689
Poverty	0.619		-0.478
Economic activity		0,550	0.322
GDP			
Temporary			
Permanent		0.625	0.392
Livestock		0.65	
Connectivity	-0.409	0.51	0.509
Roads	-0.478	0.552	0.547
Airports	0.396		
Internet	-0.344		
Institutional performance			

Municipalities with greater pressure on water supply are related to those with more permanent crops, larger livestock inventories, and greater connectivity, especially in terms of roads. This translates to municipalities where indicators of interaction between supply and demand reflect greater pressure on water being related to those with more permanent crops, more economic activity, more roads, and better institutional performance (Table 3).

Table 3: *Correlations between categories of freshwater ecosystems and categories of socio-environmental conflicts and social performance*

	Freshwater dimension	**Demand**	**Supply**	**Interaction**
Socio-environmental conflicts				
Land grabbing				
Pasture conversion				
Fires				
Coca crops				
Mining		-0.399		
Violence	0.365	0.312		0.292
Conflict	0.316			
Homicides	0.395	0.433		
Social	0.36		0.357	0.331
Total population		0.428		
Indigenous population	-0.466	-0.605		
Migration	0.42	0.497		
Poverty	-0.49	-0.741		
Economic	0.457	0.392	0.402	0.345
GDP				
Temporary				
Permanent	0.39	0.292	0.343	0.337
Livestock			0.307	
Connectivity	0.519	0.57	0.373	0.3
Roads	0.56	0.631	0.369	0.323
Airports		-0.335		
Internet		0.419		
Institutional performance	0.389	0.348		0.351

3.5 Methods

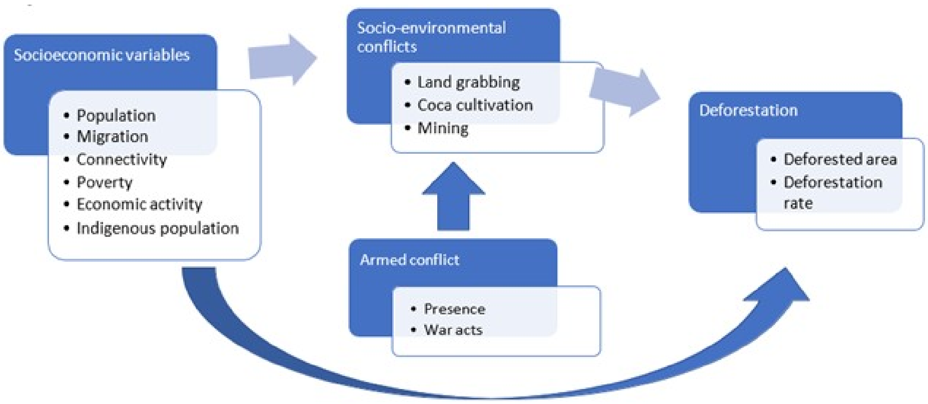
3.5.1 Two-stage OLS: Traditional Approach

The literature analyzed reveals a strong association between deforestation and different socio-environmental conflicts (armed conflict, land grabbing, coca cultivation, and mining). In turn, these different conflicts are strongly associated with socioeconomic variables and they are also related to deforestation decisions. There is also clearly an endogenous relationship between several of these socioeconomic and conflict variables with deforestation, so causality is not evident. Hence, a model that identifies the drivers of deforestation in the CAB must consider the endogenous nature of these variables that determine land use behaviors and their relationship with socioeconomic variables.

A two-stage model is proposed to meet this identification challenge and consider endogeneity. While the first stage models the categories of environmental conflicts as a function of socioeconomic variables, in the second stage, estimators of these conflicts are used to explain deforestation, together with a set of other variables.

One variable that plays a key role in both deforestation decisions and the existence of socio- environmental conflicts is armed conflict. However, the channel through which the effects on deforestation are produced is not clear. We suggest that the variables associated with armed conflict are used to explain other socio-environmental conflicts, but not to directly explain deforestation. A graphical representation of the model is presented in Figure 10.

Figure 10: *Graphical model of the relationships between deforestation, socioeconomic variables, and socio-environmental conflict variables*



Econometrically, this model implies a two-stage system. In the first stage, each of the socio- environmental conflicts is regressed on the armed conflict and socioeconomic variables. Following the main results of the literature and the data available for the proposed variables, this stage would be represented by the following equations:

$$land\_gabbing = f_1\,(armed\_conflict, migration, roads, fragmented\_forest)$$

$$coca\_cultivation = f_2\,(armed\_conflict, roads, indigenous\_population)$$

$$mining = f_3\,(armed\_conflict, natural\_cover, indigenous\_population, region)$$

In the second stage, the estimators from the first stage are used to explain deforestation. Given that the drivers behind each socio-environmental conflict might be different, the second stage also needs to be differentiated. Therefore, we have three second-stage equations:

$$Deforestation = f(land\_gr\hat{a}bbing, roads, indigenous\_population, poverty)$$

$$Deforestation = f(coca\_cul\hat{t}ivation, roads, indigenous\_population, poverty)$$

$$Deforestation = f(mi\hat{n}ing, roads, indigenous\_population, poverty)$$

3.5.2 Two-stage OLS: ML approach

Due to the large number of variables composed of indicators for each category and dimension, analyzing the relationship between these variables and deforestation becomes a challenge. For this reason, we propose using regularization methods to improve the selection of variables that best explain deforestation, land grabbing, coca cultivation, and/or mining. The technique used is known as LASSO (Least Absolute Shrinkage and Selection Operator), which improves predictive accuracy and interpretability by selecting a subset of relevant explanatory variables. This method, introduced by Tibshirani (1996), is particularly useful in our case, where we have a large number of variables with high potential correlations among them.

The method works by estimating a linear regression with the proposed relationship for y_i, whether related to land grabbing, coca cultivation, mining, or deforestation, penalizing the coefficients of variables with lower predictive power. This penalty forces some coefficients to zero, effectively selecting the most relevant variables and reducing the model's complexity.

LASSO is an extension of standard Ordinary Least Squares (OLS) regression that imposes a penalty:

$$\min_{\beta} \sum_{i=1}^{n} \left(y_i - \beta_0 - \sum_{j=1}^{p} x_{ij}\beta_j \right)^2 + \lambda \sum_{j=2}^{p} |\beta_j| \gamma_j \tag{3}$$

Where $\lambda > 0$ is the level of penalty chosen using Belloni et al. (2012). γ_j are penalty loadings, which are chosen to ensure equivariance of coefficient estimates to rescaling of x_{ij} and can also be chosen to address heteroskedasticity, clustering, and non-Gaussian errors.

The result of this technique will be the selection of the set of variables with the greatest explanatory power. Thinking in terms of two-stage least squares models, it represents the set of variables with the greatest relevance in the first stage. After selecting the set of variables, we will proceed to perform two exercises: i) estimate a two-stage linear regression model as is done in the traditional approach, and ii) estimate an XGBoost model to capture non-linearities and find out which factors contribute to explaining deforestation in the CAB.

3.5.3 Extreme Gradient Boosting (XGBoost) Model

XGBoost is a machine learning (ML) algorithm based on decision trees. This technique enhances the predictive power of models in the presence of nonlinear relationships, complex interactions, and large sets of covariates (Chen and Guestrin, 2016). XGBoost optimizes an objective function composed of a loss function and a complexity penalty to prevent model overfitting.

$$\xi = \sum_{i=1}^{N} L(y_i, \hat{y}_i) + \sum_{k=1}^{m} \Omega(f_k) \tag{4}$$

Where $L(.)$ is a differentiable convex loss function that measures the difference between the prediction $\hat{y}_i$ and the target y_i. The algorithm, through an iterative process of order m, aims to predict each value for every row i.

$$\xi^m = \sum_{i=1}^{N} (y_i - \hat{y}_i{}^{m-1} + f_m(x_i))^2 + \Omega(f_t) \tag{5}$$

$\Omega(f)$ is the complexity penalty, where T is the number of tree leaves and w_j are leaf weights. Which is expressed in the following function:

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{6}$$

We implemented the XGBoost model in R, as designed by Chen and Guestrin (2016). To identify the best model based on the squared error, we performed a cross-validation technique for the learning rate (η), loss reduction regularization (γ), maximum tree depth (T), L2 regularization (λ), proportion of data used in each iteration (Sub Sample), and proportion of columns used in each iteration (Col Sample). Table 4 presents the parameters used according to the notation of the XGBoost package. The result is an estimation of the predictive power of each variable on deforestation.

Table 4: *Main hyper-parameters space*

Hyper-Parameter	Optimal Value	Other Values
T	12	(3,6,9,12)
η	0.3	(0.01,0.05,0.1,0.3)
γ	1	(0,0.1,1,5)
λ	1	(0,0.1,1,10)
Sub Sample	0.5	(0.5.0.7,1)
Col Sample	0.7	(0.5,0.7,1)

4 Results

4.1 Two-stage OLS: Traditional Approach

In the first step, a regression for each socio-environmental conflict is set up, after recognizing the variables reported in the literature as well as the results from the correlation analysis. We include a variable called "region", to capture the effect of being in the northwestern (region = 1) or in the eastern (region = 0) part of the CAB. Results from this first stage are presented in Table 5.

In all the equations of the first stage is observed that armed conflict, proxied by the presence of post-FARC armed groups, is only significant in determining coca crops. Furthermore, while land grabbing and coca cultivation are associated positively with armed conflict, illegal mining is associated negatively. One explanation is that illegal mining in CAB occurs more frequently in scattered and isolated places at the east region, still without the effective control of armed groups.

Roads play a significant role in defining land grabbing and coca crops. However, different types of roads relate in different ways to these activities. Coca cultivation does not occur in proximities to primary roads, but instead close to type-3 roads. Land grabbing occurs in places even more isolated, so type-5 to type-7 roads are more closely related to it.

It is also relevant to highlight that municipalities where the share of the indigenous population is larger are those where coca cultivation and mining are less frequent.

Table 5: *First-stage results for socio-environmental conflicts*

Covariates	Land grabbing Pasture conversion	Coca crops	Illegal Mining
Presence of post-FARC AG	1,273	374.4*	-1.24
	(1,251)	(207)	(1.01)
Type 5-7 roads	15.65***		
	(4.37)		
Type 1 roads		-9.93**	
		(4.19)	
Type 3 roads		161.1***	
		(57.6)	
Long-term migration (percentage)	10,618**		
	(4,874)		
Fragmented forest (percentage)	-34,630***		
	(9,437)		
Natural cover			0.35*
			(0.16)
Indigenous population (percentage)		-820.2*	-5.51**
		(427.4)	(2.73)
Region	1,673	362.8	-13.27*
	(3,914)	(351)	(6.69)
Constant	-7,671	-36.02	20.33*
	(6,499)	(752)	(10.88)
Observations	77	77	77
R-squared	0,561	0,296	0,254

Source: Authors' calculations based on data from SINCHI, and IDEAM. Note: Asterisks denote the p-value: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$. Robust standard errors in parentheses.

The results of the second stage are presented in Table 6. The most relevant result from the analysis is that, according to our data and the model specification, the main drivers of deforestation is land grabbing. On the contrary, coca cropas and illegal mining does not seem to explain deforestation.

Table 6: *Results for the second stage, explaining deforestation*

Covariates	Land grabbing	Coca crops	Illegal Mining
Pasture conversion	0.98***		
	(0.06)		
Coca crops		4.33	
		(2.95)	
Illegal mining			72.89
			(241.9)
Poverty	-2.03	259.6***	166.4***
	(13.19)	(96.5)	(56.07)
Indigenous population (percentage)	-260.2	-9,084*	-13,478***
	(1,355)	(5,366)	(4,263)
Type 7 roads			26.71*
			(15.00)
Region		6,581	
		(4,654)	
Constant	-415.5	-13,722	-1,961
	(620.9)	(7,009)	(2,751)
Observations	77	77	77
R-squared	0,939	0,02	0,310

Source: Authors' calculations based on data from SINCHI, and IDEAM. Note: Asterisks denote the p-value: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$. Robust standard errors in parentheses.

Poverty plays an important role in deforestation processes, as municipalities with higher levels of poverty tend to be more prone to deforestation, no matter the conflict that is mediated. On the other hand, we reinforce the idea that the presence of larger shares of the indigenous population plays an important role in controlling deforestation and governing its territories.

4.2 Two-stage OLS: ML approach

When we use a variable selection technique based on their relevance in explaining deforestation in CAB, we find some differences compared to the traditional approach. Table 7 presents the results for the first stage.

We find that degradation, fragmented forests, and fires are significant factors explaining land grabbing. For coca crops, acts of violence, such as the presence of post-FARC armed groups and homicides, are positively correlated, while fires, primary roads, the number of received populations (mainly in cities), and water erosion are negatively correlated.

Finally, for illegal mining, only the region contributes to explaining its presence, showing a negative correlation—that is, there is less illegal mining in the northwestern part of CAB compared to its presence in the eastern part.

Table 7: *First-stage results for socio-environmental conflicts using LASSO*

Covariates	**Land grabbing Pasture conversion**	**Coca crops**	**Illegal Mining**
Population Expulsed	7.58		
	(7.72)		
Degradation	2.25*		
	(1.13)		
Fragmented forest	0.51***	0.05	
	(0.16)	(0.04)	
Fires	0.06***	-0.03***	
	(0.02)	(0.007)	
Fragmented forest (percentage)		30,485*	
		(15,298)	
Fragmented forest (municipal percentage)		5,086*	
		(2,619)	
Presence of post-FARC AG		991.9***	
		(358.9)	
Homicides		260.9***	
		(40.1)	
Type 7 roads		4.94**	
		(2.10)	
Type 5 roads		-5.01	
		(5.25)	
Type 1 roads		-42.63**	
		(17.16)	
Pop. Urban		0.11	
		(0.18)	
Population recived		-4.35***	
		(1.13)	
EHPE		-1,117**	
		(431.4)	
Indigenous population (percentage)			0.0002
			(0.0003)
Municipal Importance			0.11
			(0.09)
Region	695.4	350	-5.79***
	(1,221)	(720)	(1.93)
Constant	-0.001**	502.3	4.91**
	(0.06)	(616.7)	(1.97)
Observations	77	77	77
R-squared	0,845	0,829	0,249

Source: Authors' calculations based on data from SINCHI, and IDEAM. Note: Asterisks denote the p-value: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$. Robust standard errors in parentheses.

Table 8 presents the results of the second stage. We do not find statistical significance for any of the analyzed socio-environmental conflict variables. However, we find that expelled population, as a measure of conflict associated with the activity of armed groups, contributes to explaining deforestation. Similarly, fires, pasture conversion, and the expansion of permanent crops drive deforestation, while acts of violence and a higher integrated analysis index reduce deforestation. Regarding acts of violence, these tend to deter economic activities that increase deforestation, while the integrated analysis index reflects better conditions of water sources, which are characteristic of areas with lower anthropogenic pressure.

Table 8: *Results for the second stage, explaining deforestation using LASSO*

Covariates	**Land grabbing**	**Coca crops**	**Illegal Mining**
Land grabbing	0.70		
	(0.55)		
Coca crops		-0.13	
		(0.11)	
Illegal Mining			18.14
			(51.03)
Degradation	0.03		
	(1.23)		
Fragmented forest	0.09		
	(0.36)		
Fires	0.03	0.0002	0.013*
	(0.04)	(0.01)	(0.007)
Population Expulsed		8.91**	5.91**
		(3.63)	(2.26)
Pasture Conversion		0.8**	0.74***
		(0.07)	(0.03)
Degradation		0.4	0.85***
		(0.4)	(0.29)
Permanent crops		0.54***	
		(0.19)	
Cattle		0.004	0.002
		(0.006)	(0.005)
Natural cover		0.0001	
		(0.003)	
Acts of war		-448**	
		(192.1)	
AI		-872.2***	
		(293.6)	
Constant	-353.3	1,076**	-321.5
	(551)	(532.1)	(290.4)
Observations	77	77	77
R-squared	0,869	0,984	0,976

Source: Authors' calculations based on data from SINCHI, and IDEAM. Note: Asterisks denote the p-value: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$. Robust standard errors in parentheses.

4.3 Extreme Gradient Boosting (XGBoost) Model

The results presented so far are diverse and reveal the complex relationship between deforestation and socioeconomic, environmental, and conflict-related variables. The XGBoost model allows us to capture these complexities, identifying the variables that best explain deforestation while considering potential non-linear relationships.

Table 9 presents the results of the XGBoost model. The *gain* column indicates the average contribution of each variable to deforestation prediction, *cover* shows the proportion of iterations in which the variable was used, and *frequency* represents how often the variable was selected in the decision trees. From the results, we observe that Pasture Conversion contributes to 68% of deforestation predictions, while expelled population and fires contribute 14% and 13%, respectively. Cattle account for 2%, permanent crops for 2%, and forest degradation explains 1%.

Table 9: *Results for XGBoost Model: Deforestation*

Variable	Gain	Cover	Frequency	OLS
Pasture Conversion (ha)	0.68	0.25	0.25	0.72***
				(0.03)
Population Expulsed (# Pob)	0.14	0.23	0.29	4.20*
				(2.33)
Fires (ha)	0.13	0.11	0.1	0.01**
				(0.006)
Cattle (# cows)	0.02	0.1	0.08	0.0007
				(0.005)
Permanent Crops (ha)	0.02	0.14	0.12	0.27**
				(0.13)
Degradation (ha)	0.01	0.16	0.16	0.99***
				(0.29)

Source: Authors' calculations based on data from SINCHI, and IDEAM. Note: Asterisks denote the p-value: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.10$. The last column presents the results of a linear regression model. Standard errors are shown in parentheses.

The last column of Table 9 presents an Ordinary Least Squares estimation to express the direction of the relationship between the explanatory variables and deforestation. As observed, the analyzed variables contribute to explaining the increase in deforestation. For example, an increase in pastureland hectares, expelled population, burned hectares, number of cattle, hectares of permanent crops, and degraded hectares all contribute to a higher deforestation rate.

5 Discussion

This study focused on achieving two main objectives. First, to characterize the Amazon biome through social and environmental indicators. Second, to estimate and analyze interactions between indicators, both within and across categories, to understand the significance of these relationships in designing explanatory models of deforestation in the Colombian Amazon biome. The characterization of the Colombian Amazon biome was based on four analytical dimensions: Social (socioeconomic and demographic information), Terrestrial Ecosystems (forests), Freshwater Ecosystems, and Socio-environmental Conflicts. Each dimension was organized into categories, which were then represented by a set of indicators. To achieve the second objective, Pearson correlations were estimated between indicators and categories across different dimensions, and significant associations were analyzed.

Among the key findings, we highlight the high levels of poverty in the biome's population compared to the national average, particularly pronounced in non-municipalized areas and, in general, in municipalities with a higher percentage of Indigenous populations. Additionally, significant differences were observed in forest cover, deforestation, illicit crop cultivation, armed conflict, pasture expansion, fires, and illegal mining. More importantly for this study, there were marked socio-economic differences between the departments in the foothill zone (Northwestern Amazon) and those in the plains region (Eastern Amazon). The economy is stronger in the northwestern region, and poverty levels are lower. However, this is also where socio-environmental conflicts (except for illegal mining) occur with greater intensity or frequency. In this same region, forest loss is much more accelerated and is associated with a higher presence of roads, greater connectivity, higher added value, and increased agricultural and livestock production. Our analysis confirms a positive and significant relationship between forest conservation and the presence of Indigenous communities, aligning with previous studies.

The analysis of socio-economic factors in the CAB is significantly constrained by a lack of information compared to other regions of the country. Just as accessing many territories in the Amazon is difficult, so is finding and gathering data to understand the social and economic dynamics of its inhabitants. This limitation hinders the monitoring of economic, demographic, and productive activities, as well as various socio-environmental conflicts.

The last national census, conducted in 2018, despite significant efforts, did not fully cover the CAB population. Census data collection in areas with dispersed populations across vast territories is limited, as a proper census cannot be conducted in such regions. In these cases, data is collected from a sample and later adjusted to estimate census indicators. Furthermore, among the 77 territorial entities within the CAB, 18 are non-municipalized areas (CNM), where information production is even scarcer. For instance, agricultural or livestock activity and digital connectivity indicators are not reported for these areas. Additionally, institutional performance is not measured in CNMs since there is no centralized governing body (such as a mayor's office) to generate or manage the data.

When the analysis is conducted at the level of Indigenous reserves, the limitations become even more pronounced. For these crucial administrative entities within the CAB, disaggregated information is virtually non-existent for most indicators. The most reliable socio-economic data is available only at the municipal level.

Furthermore, considering the vastness of the CAB—covering 483,164 km^2, equivalent to 42.3% of Colombia's national territory—there are only 77 territorial entities, meaning each one covers a large area. On average, each municipality or CNM spans 627,000 hectares, compared to the national average of 102,000 hectares. Excluding the CAB, the national average drops further to 63,000 hectares. This means that the average area of a municipality or CNM in the CAB is 10 times larger than that of one outside the CAB, leading to a dilution of statistical figures across the vast region.

In terms of population distribution, significant disparities also emerge. While the national average population per municipality or CNM is 39,000 people, in the CAB, this average drops to 13,000. In other words, the population density in CAB municipalities and CNMs is three times lower than the national average.

This disparity weakens the statistical power of the data, as there are very few observations for such large territories, making it difficult to estimate correlations or develop meaningful statistical models. Under these conditions, data collection in the CAB is complex, costly, and uncertain.

This contrasts with spatialized information, such as satellite imagery, which is increasingly available in greater quantity and quality, often in near real-time, even for remote regions. Such data allows for detailed identification of land cover changes, including pasture expansion and deforestation. Additionally, proxies such as nighttime lights can help infer economic activity levels in certain areas. However, despite these technological advances, knowledge of the populations inhabiting the CAB remains limited.

Harmonizing socio-economic and satellite data poses a significant methodological challenge, as vast areas only have a single data point associated with the municipality or CNM. More granular analyses are not possible due to the difficulty of obtaining information at the village or district level in this region.

Another challenge is the internal validity of some indicators. For example, some researchers question the applicability of the Multidimensional Poverty Index (IPM) in Indigenous territories. Concerns include the suitability of three IPM dimensions for Indigenous populations. First, the housing dimension: while traditional dwellings align with Indigenous customs and are adapted to the natural environment and climate, they may pose health risks by hosting disease vectors. Consequently, the index may either penalize or overlook these structures. Second, the measure of formal employment inherently disadvantages rural and Indigenous communities, where subsistence economies focused on household and community well-being prevail. Lastly, the health component tends to undervalue traditional medicinal practices, which are widely used in the region, especially where access to Western healthcare is limited. However, this study does not aim to validate or challenge the effectiveness of these traditional practices.

Similarly, Acosta et al. (2020) argue that Indigenous well-being cannot be assessed solely through objective measures like wealth or access to health and education but must also incorporate subjective well-being indicators. These authors propose 15 Indigenous Human Well-Being Indicators, which, to our knowledge, have only been applied in the Amazon department.

Ruiz-Santacruz (2022) also discusses the difficulty of characterizing Indigenous populations in terms of poverty and housing quality. He notes that these concepts differ between rural and urban settings and that what is defined as "monetary poverty" in Western frameworks does not necessarily apply to some Indigenous communities. However, he acknowledges that both Indigenous and Western perspectives agree that poverty correlates with reduced well-being. In this regard, he argues that the IPM remains an appropriate indicator because it provides a standardized national measure applicable to all citizens.

The debate over the most suitable methodologies and indicators for measuring well-being from an Indigenous perspective remains ongoing.

Despite these challenges, the available data is a key resource for beginning to understand the socio-economic conditions of the Colombian Amazon population. The findings from this study also provide valuable lessons.

In this study, we estimated statistics for various indicators at municipal, departmental, and regional levels for the entire CAB. The municipal-level analysis further highlights the high heterogeneity among CAB municipalities, reflecting geographic, biophysical, and historical differences across all dimensions. This information not only provides a regional (CAB) context but also helps understand the specific conditions of smaller administrative units, enabling the design of policies, plans, and strategies that align national objectives with local needs. Additionally, given the large number of variables considered and the various interactions between them, Machine Learning (ML) techniques are employed to account for this complexity.

A novel aspect of this study is the inclusion of freshwater-related variables, particularly those linked to water supply and demand. The IDEAM has been making significant efforts to design and refine methodologies for estimating such indicators, which are published biennially in the National Water Report (ENA). To our knowledge, these data have not previously been integrated with socio-economic and socio-environmental conflict indicators. Given the Amazon region's critical role in hydrological regulation at local, national, and global scales, understanding hydrological dynamics and water supply-demand relationships is essential.

This study found concerning water-related trends in some CAB areas, particularly in the Northwestern foothill zone. Again, the municipal-level detail of these indicators provides crucial information for local management.

Using the available spatial and socio-economic data, numerous studies have analyzed deforestation in Colombia to identify its drivers. However, most studies fail to reach a consensus or provide definitive conclusions. As shown in the literature review, research varies in several aspects, including the definition of tested determinants, assessments of underlying and direct deforestation causes, and the relationships between them.

The next step of this study is to develop causality models based on these interactions. However, we emphasize the value of descriptive statistics, both for characterizing this population and as a foundation for policy design in environmental and well-being sectors. Given the complexity, variability, simultaneity, dynamism, and interrelation of deforestation drivers, we also stress the importance of correlation-based mental models before attempting causal inference through econometric models.

Colombia is globally recognized as a megadiverse country, with the Colombian Amazon Biome (CAB) being one of the most significant repositories of biodiversity in both the country and Latin America. At the same time, understanding the relationship between society and this vast biodiversity, as well as the role of local and Indigenous communities in its sustainable management, is crucial to ensuring that the flow of nature's contributions to people is maintained and enhanced.

As mentioned above, much of the conservation in the CAB takes place in areas where the well-being of the local population is precarious—communities facing extreme poverty and limited access to effective social welfare systems to meet their needs for health, education, and housing, among others. The inequitable distribution of biodiversity benefits remains a pressing issue in the Colombian Amazon Biome.

Therefore, understanding and monitoring the socio-economic conditions of the CAB's inhabitants—residing in a globally strategic area for conservation—not only enables tracking compliance with the Convention on Biological Diversity (CBD) mandate but also facilitates the identification and implementation of nature- and community-based mechanisms that promote long-overdue well-being for these populations. Furthermore, we hope this essential characterization and interaction analysis between indicators and categories will contribute to elucidating the deforestation problem in the Amazon biome.

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