Geospatial Data Analytics for Policy Impact Assessment: Amazon Deforestation in Colombia

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Abstract – This project aims to assess the effectiveness of legal and social mechanisms implemented to reduce the rates of deforestation in the Colombian Amazonia by analyzing satellite imagery. This project combines remote sensing with policy analysis to provide a data-driven assessment of how well current conservation and post-conflict measures are protecting Colombia's Amazon rainforest.

1 Introduction

The Amazon Jungle, also known as Amazonia, is a tropical rainforest located in the Amazon River basin. The Amazon rainforest covers 6.7 million square kilometers, spanning Brazil, Bolivia, Peru, Ecuador, Colombia, Venezuela, Guyana, Suriname, and French Guiana. It is the largest area covered in trees in the world and home to 10% of the known species on Earth, making it one of the most important places for wildlife. Despite covering only around 1% of the planet's surface, the Amazon rain forest is home to 10% of all the wildlife species we know [1]. The Amazon Basin contains 40% of the world's remaining tropical forest, much of it still botanically intact. However, the clearing of forests for ranching, increasing agricultural crop production, and tree plantations of commercially important species —mostly exotics — have exacerbated the rates of deforestation, raising concerns about the possibility of large-scale extinctions of tree species.

This project uses satellite imagery to monitor and analyze deforestation in the Amazon rainforest. By leveraging high-resolution data from platforms such as PlanetScope and EarthData (NASA), I will study the vegetation loss through spectral indices like NDVI and NBR, combined with change detection techniques. The project focuses on identifying patterns and rates of deforestation over time in a defined area of interest within the Colombian Amazon Basin. Special attention is given to overcoming challenges such as cloud cover and data validation. Ultimately, the goal is to support conservation efforts by providing accurate, timely insights into forest degradation and land-use change.

2 Background

2.1 Historical and Socio-Environmental Context

In Colombia, the Armed Conflict has exacerbated the illegal logging of millions of hectares. Beginning in the 1980s, booming U.S. demand sparked successive "cocaine bonanzas," as remote-area farmers cleared hundreds of hectares of native forest to grow coca and reap unprecedented profits. The resulting deforestation has created vast, fragmented patches of degraded jungle throughout the Amazon basin. Coca (*Erythroxylum coca*) is a shrub native to South America. In its natural form, coca leaves contain mild alkaloids that provide gentle stimulation, aid digestion, and alleviate altitude sickness without producing any psychoactive effect. However, organized crime groups process these same leaves into cocaine, a potent and addictive stimulant. Because coca plants thrive in warm, humid environments, illicit plantations have proliferated across Colombia, Bolivia, and Peru. In response, a wide range of government agencies and NGOs have launched alternative livelihood programs—promoting sustainable agriculture, agroforestry, and ecotourism — to redirect local incomes away from illegal crops and toward environmentally sound practices that benefit both families and forests.

The first coca crops dedicated to the production of cocaine in Colombia were detected in 1986 [2]. Over the ensuing decades, competition among guerrilla factions (notably FARC), paramilitary groups, and government forces to control coca cultivation zones drove cultivation ever deeper into remote Amazonian forests, where illicit clearings and informal roads accelerated deforestation. With the 2016 Peace Agreement came the promise of dismantling these networks and reclaiming land for sustainable uses, but questions remain about how effectively the agreement has curtailed drug-related forest loss. By comparing satellite-derived deforestation rates before and after 2016, this project will assess whether reductions in coca-driven violence align with measurable improvements in forest conservation. The environmental degradation caused by the armed conflict in Colombia has been a tragic and often forgotten consequence of this protracted confrontation [3]. The presence of illegal armed groups in the lush jungles, fragile coastal areas, and high mountain paramos has affected Colombia's diverse ecosystems and natural resources due to the expansion of illicit crops, illegal mining, and deforestation that have left deep scars on the Colombian landscape [4].

2.2 Remote Sensing for Deforestation Monitoring

Traditional on-the-ground forestry surveys, which involve measuring and collecting data, are effective in accurately determining horizontal distances and establishing boundaries. However, these can be limiting due to accessibility and cost, which makes satellite-based monitoring the most reliable and cost-effective approach. Remote sensing provides detailed maps and data that can help track forest loss, identify areas of agriculture and mining, and quantify the impact of deforestation. Satellite imagery sources vary in spatial resolution, temporal frequency, and sensor type.

2.2.1 Landsat Satellite

Landsat provides moderate spatial resolution (30-meter) imagery, covering large areas with repeated data, enabling users to observe detailed human-scale processes, such as urbanization, but not individual houses. The Landsat system has contributed significantly to the understanding of the Earth's environment, spawned revolutionary uses of space-based data by the commercial value-added industry, and encouraged a new generation of commercial satellites that provide regional, high-resolution spatial images [5]. Since 1972, NASA has launched nine Landsat satellites with different spectral range bands.

Landsat 1–3 were equipped with a Multispectral Scanner (MSS), which recorded data in four spectral bands: two visible and two near-infrared. The next group, Landsat 4–7, carried either the Thematic Mapper (TM) or Enhanced Thematic Mapper (ETM+) sensors, which featured finer spatial resolution (i.e., pixel size) and increased radiometric resolution (i.e., bit depth) compared to the MSS. This group also had expanded spectral coverage, adding bands in the mid-infrared and thermal-infrared wavelengths. It is worth noting that the middle-infrared is often referred to as the shortwave infrared (SWIR) [6]. Landsat 8 and 9 introduced advanced sensors and spectral capabilities compared to earlier satellites. Landsat 8 has the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS) [7]. Landsat 9's OLI-2 sensor captures 14-bit data (vs. Landsat 8's 12-bit), allowing finer detection of subtle variations in brightness, particularly in dark (e.g., dense forests) and bright (e.g., snow) surfaces. Both satellites share identical 11 spectral bands, spatial resolutions (15–100 m), and swath width (185 km), ensuring seamless integration of data for long-term environmental monitoring[8].

2.2.2 Sentinel Satellite

Optical satellites (like Sentinel-2) capture images using sunlight reflected from Earth. They provide detailed color imagery, but struggle in conditions with cloudy weather or darkness. Radar satellites (like Sentinel-1) use microwaves to collect data through clouds, smoke, and even at night. However, their images look less intuitive to the human eye.

A 2020 study fused Sentinel-1 and Sentinel-2 data to map land cover in Italy. Radar provided cloud-free structural data, while optical data added spectral details, improving the accuracy in identifying crops, forests, and urban areas [9].

In Para, Brazil, PRODES and DETER data sets have been used to monitor the Amazon. They used Sentinel-1 and Sentinel-2 to obtain valuable data despite cloudy conditions, and Landsat-8 for historical comparisons. They trained a CNN on labeled PRODES data, where green, dense textures represent forests, while brown, fragmented patches indicate deforestation. This allowed the model to learn to recognize deforestation patterns, achieving more than 90% precision in segmenting deforestation areas and detecting small-scale illegal logging that manual methods often miss. [10]

By combining these two data types, we can obtain rich spectral details from optical satellites, as well as all-weather visibility and structural information from radar satellites.

2.2.3 Planet Scope

Planet Scope is a satellite imaging system that provides high-resolution continuous views of the Earth using hundreds of Dove satellites in orbit. Planet Scope provides daily, global imagery of the Earth using multi-spectral imagery (Blue, Green, Red, and Near-Infrared), and 3-5 meters resolution, which allows the user to see trees, roads, and fields cite planetmonitoring. Due to the vast number of satellites in orbit, Planet Scope can image the entire Earth's surface once per day [11]. One of the benefits of using this data is that PlanetScope can detect small-scale changes within days, such as forest clearing, new burn areas, changes in water levels, and changes in vegetation in fragile ecosystems like wetlands. Its cloud-based access allows easy integration with machine learning, GIS software, or APIs.

2.2.4 Forest Global Watch

Global Forest Watch (GFW) is a data-driven monitoring platform that leverages advances in computer science and data science to track forest change at a global scale. It integrates large volumes of satellite imagery with geospatial datasets using automated processing pipelines, cloud computing, and algorithmic change-detection methods to identify forest loss and gain over time. Machine learning and statistical models are used to classify land cover, reduce noise from atmospheric interference, and standardize measurements across regions and years. By transforming raw remote-sensing data into accessible visualizations and downloadable datasets, GFW enables reproducible analysis, supporting evidence-based research and policy evaluation in forest conservation.[12]

2.3 Change-Detection Methods

Several methods exist for identifying changes in deforestation, such as time-series analysis, deep learning, and image segmentation. Change detection involves analyzing temporal images to categorize and quantify forest disturbances across different time periods. In this research, spectral indices serve as a method for detecting changes. Spectral indices are formulations of wavelength bands extracted from multispectral or hyperspectral data that highlight particular surface features, including vegetation health, soil moisture, and water content. By exploiting differences in reflectance across the electromagnetic spectrum, these indices enable the detection of changes in vegetation health and forest structure that may not be apparent in individual spectral bands. Spectral indices have been successfully applied in prior remote-sensing studies, providing a quantitative and interpretable method for monitoring deforestation and recovery dynamics. [13]

2.3.1 Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) is a valuable tool for forest estimation because it provides a quantitative measure of vegetation productivity and biomass distribution derived from satellite imagery. NDVI is calculated from the ratio of near-infrared and red light reflectance, exploiting the principle that chlorophyll absorbs red wavelengths while leaf mesophyll structure scatters near-infrared radiation.[14]

$$NDVI = \frac{(NIR - Red)}{(NIR + Red)} \tag{1}$$

Because healthy, dense vegetation reflects more near-infrared light and absorbs more red light, higher NDVI values (closer to 1) indicate lush, healthy vegetation, while lower values (closer to 0 or negative) indicate bare ground, water, or stressed vegetation.

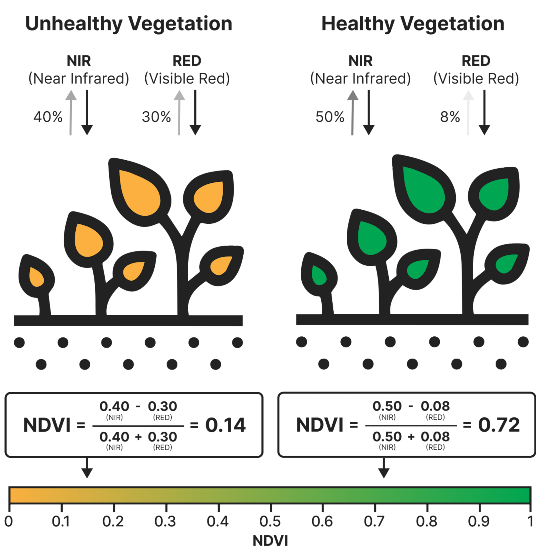

Figure 1: NDVI Values

2.3.2 Normalized Burned Ratio (NBR)

Normalized Burn Ratio (NBR) is a spectral index derived from satellite imagery that quantifies the severity and extent of forest disturbance, particularly in response to wildfires and deforestation events. NBR utilizes the near-infrared and shortwave-infrared bands of multispectral sensors to detect changes in vegetation moisture content and structural integrity, producing normalized values that facilitate temporal comparison of forest conditions. NBR is used to identify burned areas and measure burn severity by comparing NIR and shortwave-infrared (SWIR) bands of satellite imagery:

$$NBR = \frac{NIR - SWIR}{NIR + SWIR} \tag{2}$$

Because healthy vegetation reflects strongly in the NIR band, higher NBR values typically indicate healthy vegetation, while low values signal bare ground or recently burned areas. However, to measure *burn severity*, **difference normalized burn ratio** (dNBR) is used:

$$dNBR = NBR_{pre-fire} - NBR_{post-fire} \tag{3}$$

This index is particularly used because it will quantify how fire intensity has affected the land and to plan for recovery efforts.

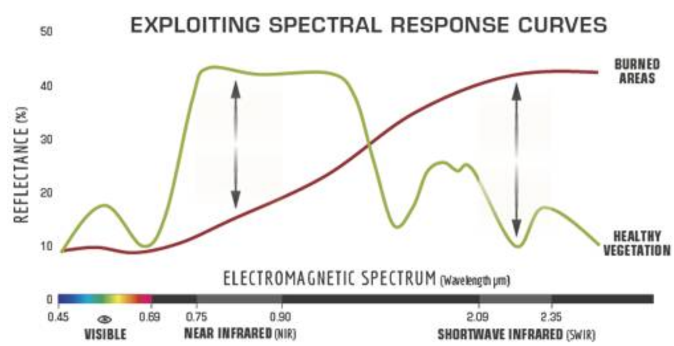

Figure 2: NBR Values

3 Methodology

The data architecture for this study follows a structured geospatial analysis pipeline that integrates satellite imagery, automated processing, and policy evaluation. Multitemporal satellite imagery of the Colombian Amazon serves as the primary data source and is first processed through geospatial mapping workflows to classify land cover and identify areas of forest, deforestation, and water across time. These processed outputs are then used in quantitative analyses to measure spatial and temporal patterns of forest change. The resulting metrics are subsequently combined with qualitative policy analysis to evaluate how observed deforestation trends align with major regulatory and institutional interventions. This architecture enables a clear separation between data ingestion, computational analysis, and interpretive assessment, supporting reproducibility and transparency in the methodology.

3.1 Data Collection

3.1.1 Landsat-Derived Land Cover Maps

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The primary dataset utilized in this study consists of annual land cover classification maps for the Colombian Amazon spanning 2001 through 2016, obtained from NASA EarthData. These maps were generated using the Continuous Change Detection and Classification (CCDC) algorithm. The CCDC algorithm operates by analyzing Landsat pixel surface reflectance values across the entire time series, identifying significant changes in spectral signatures that indicate land cover transitions. [15]

The classification process employed a Random Forest machine learning classifier trained on manually collected reference data. This supervised classification approach enabled the identification of eight distinct land cover categories:

- Forest.
- Natural grasslands.
- Urban development.
- Pastures.
- Secondary forest.
- Water bodies.
- Highly reflective surfaces.
- Unclassified areas.

The Random Forest classifier was selected for its ability to handle high-dimensional data and its robustness against overfitting, making it particularly suitable for complex tropical landscapes. The original training data used for classifier development were not included in the publicly available dataset whatsoever.

3.1.2 Modeled Deforestation Scenarios

: To complement the historical land cover data and facilitate analysis of potential future deforestation trajectories, I also incorporated modeled deforestation scenarios from NASA's EarthData, covering the period from 2002 to 2050. These projections encompass the broader PanAmazon area, which includes the Amazon River watershed, Brazil's Legal Amazon, and the Guiana region, providing regional context for deforestation patterns in the Colombian Amazon. [16]

The projections were generated using SimAmazonia, a spatially explicit simulation model that estimates monthly deforestation patterns across the Amazon Basin. The model generates two distinct scenarios representing divergent policy and development pathways:

1. **Business-as-Usual Scenario**: This scenario extrapolates historical deforestation trends observed between 1997 and 2002 into the future, incorporating both the baseline deforestation rates and their temporal variations. Additionally, this scenario accounts for the accelerating effect of paving major roadways, which historically has been a primary driver of increased forest clearing by improving access to previously remote areas.

2. **Governance Scenario**: This alternative scenario assumes the implementation of conservation-oriented policies, including a 50% cap on deforestation within each basin subregion. Furthermore, this scenario incorporates the protective effect of both existing and proposed Protected Areas (PAs), which are assumed to play a decisive role in limiting deforestation through enforcement and land-use restrictions.

The dataset is distributed as 94 GeoTIFF (.tif) files, with one file representing each year from 2003 to 2050 for both scenarios. These files are organized into two compressed archives (.zip), one per scenario, facilitating efficient data storage and transfer. Additionally, the dataset includes a comma-delimited file containing the input parameters derived from satellite-based deforestation maps that were used to calibrate and drive the SimAmazonia model.

3.1.3 Tree Cover Loss in Colombia - Global Forest Watch

For the data collection component of this study, deforestation metrics were obtained from Global Forest Watch, specifically the datasets on primary forest loss in Colombia (2001–2024) and overall tree cover loss in Colombia. Although these datasets are not exclusively restricted to the Amazon region, they provide a consistent and methodologically standardized basis for estimating national trends in deforestation. By using these data as a proxy, the analysis derives an approximate measure of deforestation rates relevant to the Colombian Amazon, while acknowledging the spatial aggregation as a limitation. This approach allows for longitudinal comparison across years and supports broader trend analysis in the absence of fully Amazon-specific historical datasets.

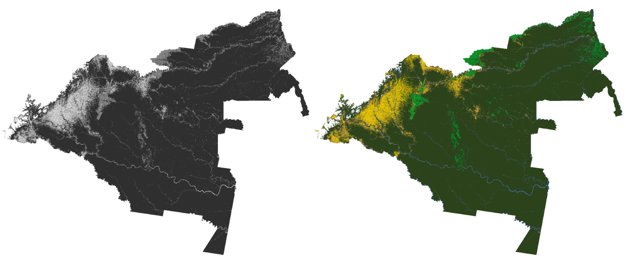
3.2 Preprocessing

3.2.1 Dataset 1

The two datasets were processed separately. First, the 16 annual Landsat-derived GeoTIFF files from the land cover dataset were imported into QGIS. To facilitate visual interpretation and temporal comparison of land cover changes, a color scheme was applied to each raster layer based on the land cover classification names. This color-coding process involved assigning distinct colors to each of the eight land cover classes. This standardized visualization approach enabled more intuitive identification of spatial patterns and temporal trends in land cover change throughout the Colombian Amazon region during the study period.

Value	Class Name	Color
0	Unclassified	Grey
1	Forest	Dark Green
2	Natural grasslands	Light Green
3	Urban	Red
4	Pastures	Yellow
5	Secondary forest	Pink
6	Water	Blue
7	Highly reflective surfaces	Purple

Table 1: Land Cover Classification Values



Before After

Figure 3: Before and After Coloring

3.2.2 Pixel Counting

A Python script (pixelcount.py) performs pixel-level analysis on the satellite imagery to quantify land cover classes across the datasets. The workflow begins by loading the TIFF files and then reading the raster data using the GDAL library. For each image, the script iterates through every pixel, classifying predefined land cover classes (Unclassified, Forest, Natural Grasslands, Urban, Pastures, Secondary Forest, Water, and Highly Reflective Surfaces) and counts the number of pixels belonging to each class within the image.

For each class, the script then calculates three metrics: pixel count, percentage relative to valid pixels, and area extent in hectares. Results are then written to a CSV file containing:

- Layer (file) name
- Class value and name
- Pixel count
- Percentage coverage
- Area in hectares

This output enables efficient temporal and spatial analysis of land cover composition across the entire dataset. Note that for this table, I excluded non-classified pixels and high-reflective areas and only kept the land cover areas of interest to optimize the table.

Year	Forest %	Grassland %	Pastures %	Secondary forest %	Urban %	Water %	Total
2001	88.83	3.08	5.32	1.29	0.06	1.35	99.93
2002	88.76	3.08	5.35	1.32	0.06	1.35	99.92
2003	88.67	3.08	5.41	1.34	0.06	1.35	99.91
2004	88.61	3.08	5.45	1.36	0.06	1.35	99.91
2005	88.48	3.09	5.55	1.39	0.06	1.35	99.92
2006	88.4	3.09	5.61	1.41	0.06	1.35	99.92
2007	88.33	3.09	5.66	1.43	0.06	1.35	99.92
2008	88.19	3.1	5.77	1.44	0.06	1.35	99.91
2009	88.06	3.1	5.88	1.45	0.06	1.35	99.9
2010	87.91	3.1	6.03	1.45	0.06	1.34	99.89
2011	87.8	3.1	6.11	1.46	0.06	1.34	99.87
2012	87.68	3.09	6.2	1.47	0.06	1.34	99.84
2013	87.56	3.08	6.26	1.47	0.06	1.34	99.77
2014	87.39	3.06	6.27	1.46	0.06	1.34	99.58
2015	87.22	3.01	6.15	1.43	0.06	1.33	99.2
2016	87.15	2.99	6.06	1.41	0.05	1.32	98.98
Total	**1409.04**	**49.22**	**93.08**	**22.58**	**0.95**	**21.5**	**1596.37**

Figure 4: Land Cover Change Table

3.2.3 Dataset #2

The second dataset contains 98 GEOTIFF files of satellite imagery across two possible scenarios: Business-as-usual, where there is no governmental or institutional intervention in deforestation, or ”Government”. TIFF files are raster images made of a grid of pixels, where each pixel stores a numeric value that represents a land-cover class corresponding to specific categories:

Value	Description
0	No data
1	Deforested
2	Forest
3	Non-Forest

Table 2: Land-cover class values used in the images.

When the TIFF is loaded, these values form a matrix, and counting how many pixels contain each number indicates the proportion of the area that belongs to each class. Because the TIFF also embeds spatial information such as pixel size and geographic location, these pixel counts can be directly converted into real-world area (in km^2). This structure allows the script to calculate the total number of pixels per class, their percentage of the image, and their corresponding area.

To facilitate computing efficiency and align with project-specific geographic interests, the dataset was spatially cropped to match the boundaries of the Colombian Amazon and the geographic extent of the first dataset using a vector-based clipping in QGIS. The cropping process was performed in three steps, as illustrated in Figure 7. Stage A represents the original imagery obtained from NASA Earth, which includes the full extent of the Amazon Region. Stage B represents the overlapping of a vector boundary to delineate the area of interest. Stage C shows the final cropped result. To ensure consistency, the same operation was applied across all 100 images using a batch processing workflow in QGIS, and then exported to Python to perform pixel counting and classification.

The pixelcounting.py code traverses a folder of TIFF files,

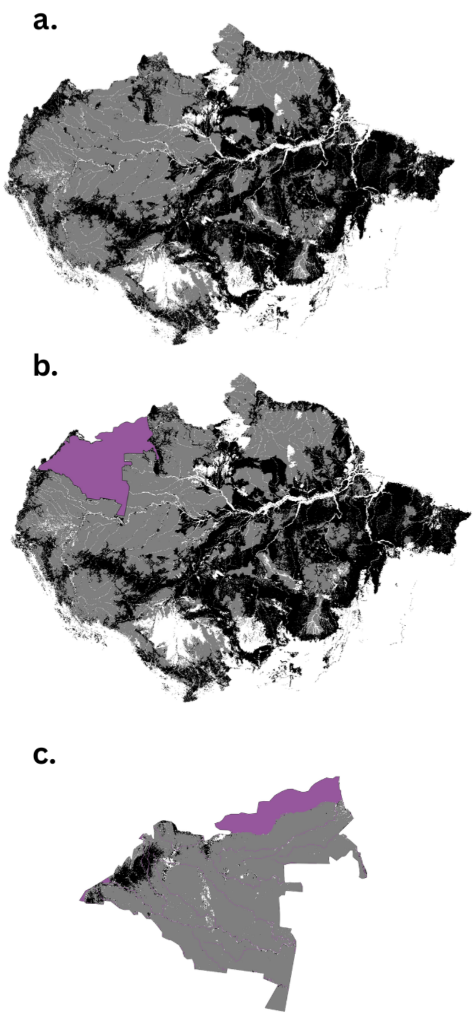


Figure 5: Dataset #2 Processing

reads each image, counts the number of pixels belonging to each land-cover class, calculates percentages and area, and saves all the results, with the year extracted from each filename, into a single CSV file. In this case, pixelcounting.py was run over the two datasets separately, resulting in two CSV files *(businessstats.csv and govstart.csv)*.

For illustration purposes, the bands were rendered in QGIS to change the colors and differentiate between the land covers as seen in Figures 5 and 6. Using these images, two visualizations were created to observe the visual change resulting from the loss of forest, and two files (business.mp4 and government.mp4) were generated.

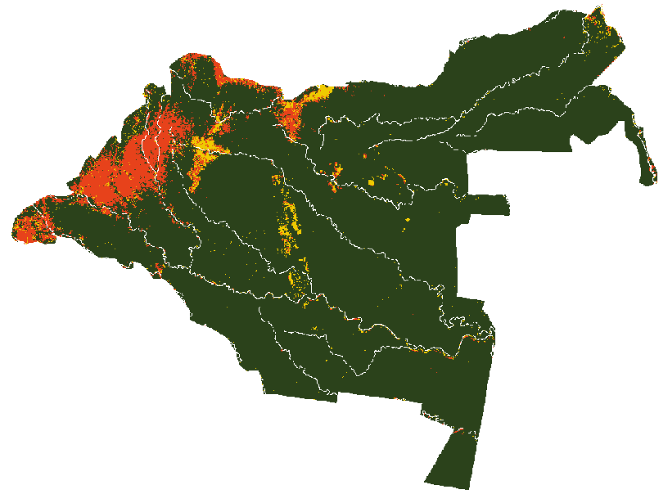


Figure 6: Raster with adjusted colors based on classification

Value	Color	Label
0		Not classified
1		Deforested
2		Forest
3		Non-forest

Figure 7: Class Values

3.3 Historical Data

To contextualize the quantitative findings on deforestation within the broader socio-political landscape of Colombia, a comprehensive timeline analysis was conducted. This approach involved systematically plotting the calculated deforestation rates and land cover change statistics along a temporal axis spanning the entire study period (2001-2016). This chronological framework enabled the identification of potential correlations between deforestation patterns and significant political, social, and policy events that occurred during this time frame.

A temporal analysis was developed that integrated major political milestones and policy implementations to assess their potential influence on deforestation dynamics, particularly in relation to the Colombian peace process in 2016. Additional events incorporated into the timeline included, but were not limited to: changes in environmental legislation, establishment of protected areas, shifts in agricultural policy, infrastructure development projects, and international agreements related to climate change and forest conservation. By overlaying these events onto the deforestation data timeline, it became possible to examine whether specific political or policy interventions corresponded with observable changes in deforestation rates.

The timeline analysis facilitated the identification of temporal inflection points where deforestation rates exhibited acceleration, deceleration, or stabilization. For each identified trend shift, the corresponding political and policy context was examined to determine whether major events may have influenced land use decisions in specific regions of the Colombian Amazon. This comparative approach allowed for the assessment of whether particular policy interventions appeared to have protective effects on forest cover, or conversely, whether certain developments may have inadvertently accelerated forest clearing activities.

Regional variations in the relationship between political events and deforestation patterns were also considered, recognizing that the impact of national-level policies may manifest differently across distinct geographical areas within the Colombian Amazon, particularly in regions with varying levels of state presence, infrastructure development, and historical conflict dynamics.

4 Results

4.1 2000-2016

Using the output from the pixel classification, a temporal analysis of land cover was conducted. The CSV results were imported into Microsoft Excel to generate scatter plots, which visualized the trends of the land cover categories. Figure 6 represents these land cover dynamics across the 2000-2016 study period.

This analysis reveals distinct patterns of land cover transformation across the Colombian Amazon.

- Forest cover exhibited the most substantial decline, decreasing by 1.68% over the 16-year period, representing a loss of 784,267 hectares.

- Natural grassland declined modestly by 0.09% (40,953 hectares), suggesting relatively stable grassland extent throughout the study period.

- Urban areas remained largely stable, with a minimal decrease of 0.01% (4,162 hectares) by 2016, indicating limited urban expansion within the study region during this timeframe.

- Crops and pastures increased substantially by 0.95% between 2000 and 2014, reflecting agricultural expansion during this period. However, this trend reversed between 2014 and 2016, with a subsequent decrease of 0.21%, suggesting a shift in land-use practices or agricultural intensity in the latter study years.

- Water bodies showed minimal change, declining by only 0.03%.

- Secondary forest increased by 0.12% (56,555 hectares), indicating forest regeneration and recovery of reforested areas, which partially offset primary forest losses and suggest the influence of reforestation initiatives or natural forest succession within the study region.

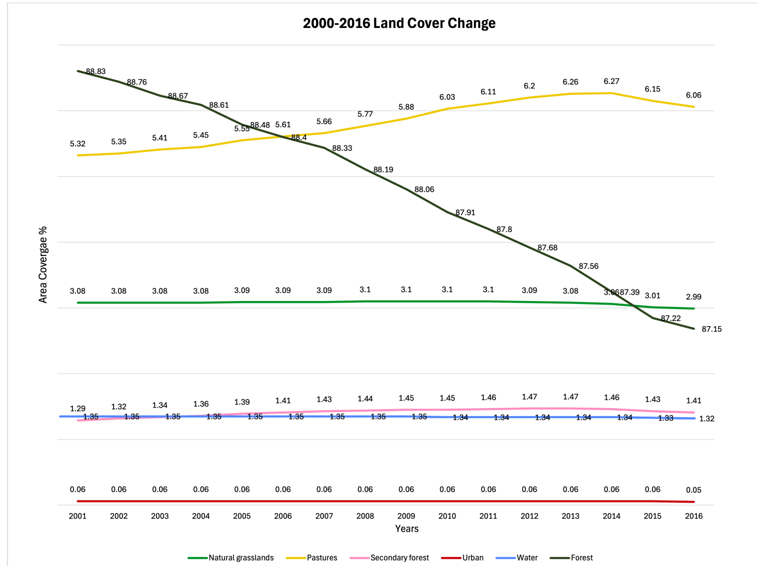


Figure 8: Land Cover Change Graph

4.2 2017-2050

For the second study time period, I used part of the second data set to calculate forest and deforestation rates. After applying the color bands and creating the two videos, I plotted the Area Coverage in km² and the coverage percentage.

4.2.1 Business-as-Usual:

The Business-as-Usual scenario assumes that deforestation in the Amazon will continue in the future at a similar rate to that of the past. Historical deforestation patterns observed between 1997 and 2002 are used as a baseline to project future forest loss. In addition to these existing trends, the scenario also accounts for further deforestation resulting from the paving of major roads, as improved access typically accelerates land clearing. The timing and location of road paving are predetermined, and their impact is estimated using observed deforestation data from the PRODES monitoring program. A simulation model is then used to estimate how deforestation unfolds month by month from 2003 to 2050.

Following the pixel counting and classification script, a dataset (businessnew.csv) was generated, containing the number of pixels, percentage, and area (km²) of forest, deforestation, non-forest, and unclassified land cover from 2002 to 2050. Subsequently, the two most significant variables were selected for visualization: the rate of change in forest coverage and the rate of change in deforestation.

This graph tells us two things: one, that Forest cover steadily declines from 2003 to 2050, and two, that the deforestation percentage steadily increases over the same period.

This indicates that, regardless of policy context, the model projects continued forest loss over time, rather than stabilization or recovery. However, in this scenario, we observe:

- Forest percentage declines more sharply, dropping from

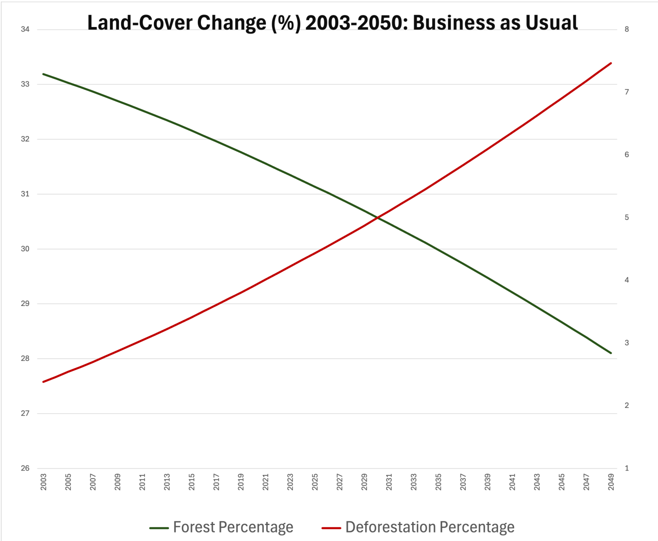


Figure 9: Land-Cover Change - BAU Scenario

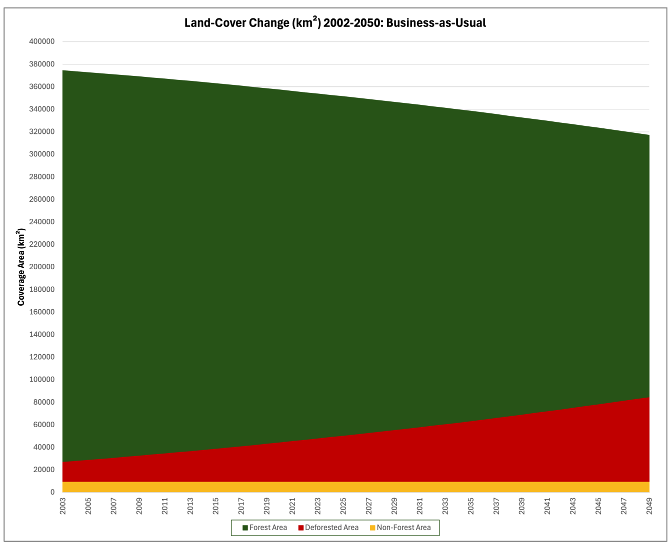


Figure 10: Land-Cover Area Change (km^2) - BAU Scenario

a little over 33% to around 28% by 2050.

- Deforestation percentage rises more rapidly, reaching over 7% by the end of the period.
- There is a loss of 69.000km2 over the span of 50 years.An area of a similar size to West Virginia..
- The gap between forest loss and deforestation gain widens over time, indicating accelerating pressure on forested land.

This stacked area shows the significant and continuous decrease in Forest Area under a BAU scenario. Starting in 2003, the total forest coverage is 374,500 km^2, and by the end of the prediction it is 315,00km^2. This persistent downward trend represents a major depletion of the region's natural resources. Simultaneously, the primary force behind this reduction is the rapid expansion of deforested areas. Starting at a comparatively low level, this deforested land category grows dramatically, accelerating over the period to reach approximately 85,000 square kilometers by 2050. The visual stacking of the areas confirms a clear land-use dynamic: as forest area shrinks, the deforested area expands to fill the space, indicating a direct conversion process.

This scenario reflects the absence of effective intervention, where historical trends of deforestation and infrastructure expansion continue to drive sustained forest conversion.

4.2.2 Governance:

The Governance scenario also considers current and past deforestation rates, but assumes a 50% limit imposed for deforested land within each subregion, and considers that existing and Protected Areas (PAs) play a decision role in limiting deforestation. The Colombian ecoregions proposed as PAs are the Apure/Villavicencio dry forest, Caqueta moist forests, Cordillera Oriental montane forests, and Magdalena Valley montane forests. Under this scenario:

- Forest cover still declines, but at a slower rate than in Business-as-Usual.
- There is a forest loss of 41,200km2 of forest.
- By 2050, forest percentage remains around 29–30%, noticeably higher than in the BAU case.
- Deforestation increases more gradually and appears to level off slightly in the final years, remaining closer to 6%.

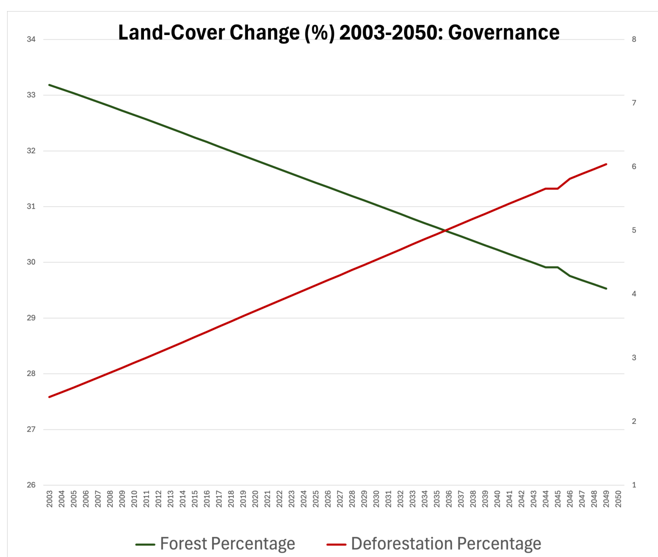


Figure 11: Land-Cover Change - Governance Scenario

In this scenario, the influence of governmental and environmental policies on deforestation is evident. While the decline in forest area is initially gradual, the policy scenario shows a clear reduction compared to the no-intervention scenario. A stacked graph was created to represent the area of each category, similar to the Business-as-Usual scenario. Although the initial forest area appears comparable, the most noticeable difference is the reduction in deforested areas under the policy scenario.

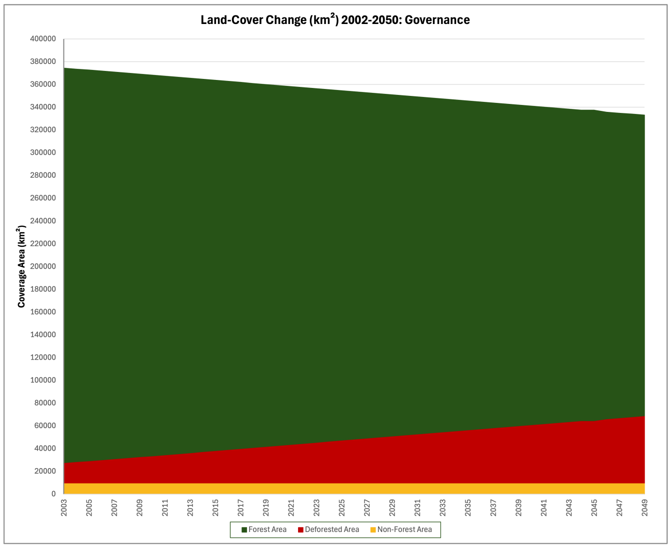


Figure 12: Land-Cover Area Change (km^2) - Government

4.3 Discussion

The Governance scenario demonstrates superior environmental outcomes compared to the Business as Usual scenario, as it projects substantially lower deforestation rates in the absence of policy intervention. The model predicts that proactive policy intervention can successfully mitigate the acceleration of forest loss and deforestation during the later years of the projection period. This conclusion is supported by the comparative analysis presented in the data (2044-2050).

Specifically, the forest cover projections reveal that the Governance scenario results in a net loss of 41,231 km² between the initial and final periods, compared to a loss of 58,981 km² under the Business as Usual scenario. This represents a difference of 17,750 km², or approximately 30% greater forest retention under the Governance scenario. Conversely, the deforestation extent projections indicate that under the Governance scenario, deforestation increases by 41,231 km², whereas the Business as Usual scenario projects an increase of 57,374 km² —a difference of 16,143 km². These findings suggest that policy-driven governance mechanisms can effectively constrain deforestation rates and preserve forest ecosystems over the projection period.

Models of this type face inherent limitations, as policy shifts and enforcement changes are difficult to quantify and incorporate into numerical projections. However, observed data provide a clear visual framework for assessing which periods and interventions coincide with changes in deforestation outcomes.

Scenario	Initial Area (km^2)	Final Area (km^2)	Change (km^2)
Business as Usual	374504	315523	-58981
Governance	374443	333212	-41231

Scenario	Initial Area (km^2)	Final Area (km^2)	Change (km^2)
Business as Usual	26866	84240	+57374
Governance	26927	68158	+41231

Table 3: Deforestation Area Changes Between Scenarios (2003-2050)

This study does not seek to validate the effectiveness of specific policies in preventing deforestation; rather, it demonstrates that policy can function as an incentive structure, while satellite imagery serves as a critical tool for assessing and monitoring its observable impacts over time.

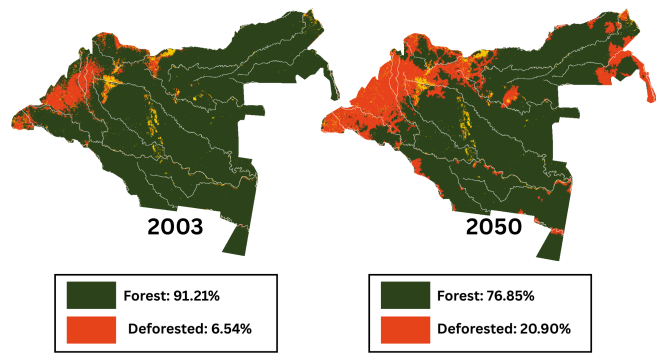


Figure 13: BUA Mapping

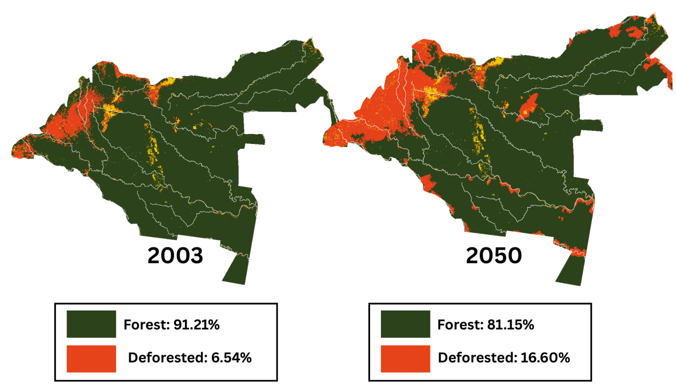


Figure 14: Governance Mapping

[Unverified]

What is clear from the comparison of these two datasets, under both modeled and observed conditions, is that forest area consistently declines while deforestation increases over time. This persistent trend highlights the importance of implementing effective mechanisms to monitor not only forest loss but also tree recovery and overall forest health, in order to sustain a functional and resilient environment. While the extraction of natural resources remains economically important—particularly for developing countries—systematic modeling and long-term study of logging dynamics, regeneration, and recovery cycles are essential for informed planning and sustainable management. Effective monitoring at the necessary spatial and temporal scales requires automation, where computer science plays a critical role through the development of satellite-based analysis pipelines, machine learning models for change detection, and scalable data-processing systems. Such approaches enable continuous and objective assessment of forest dynamics, supporting evidence-based decision-making for future conservation and development strategies.

4.4 Actual Figures

The first dataset encompassed data gathered from 2001 to 2016, while the second dataset spanned from 2003 to 2050 and was published in 2013, with data recorded from 2003 to 2012, and subsequent years modeled using predictive algorithms. The integration of these two distinct datasets enables a comparative analysis between projected and observed deforestation rates. This approach facilitates an assessment of the predictive accuracy and efficacy of the modeled dataset in forecasting trends of deforestation.

Figure 15 compares historical model projections of forest loss with observed present-day values from Global Forest Watch between 2003 and 2023. While the NASA model correctly captures the overall upward trend in forest loss, it underestimates the magnitude of observed deforestation across all years. Observed values exhibit substantial interannual variability and pronounced peaks, particularly after the mid-2010s, whereas the model follows a smooth, near-linear trajectory. This persistent gap indicates limited model sensitivity to episodic and non-linear drivers of deforestation, such as policy shifts, market pressures, or extreme environmental events. From a model-validation perspective, the agreement in trend direction suggests partial validity, but the systematic bias and growing divergence over time highlight weaknesses in scale accuracy and temporal responsiveness. Consequently, relying solely on the model would likely lead to conservative estimates of forest loss, underscoring the need for recalibration using recent observations or the incorporation of additional explanatory variables.

4.5 Policy Analysis

Colombia has relatively advanced and strong environmental laws and climate commitments. However, Amazon deforestation has surged mostly in post-conflict regions, revealing a deep connection between peacebuilding, land-use policy, and forest protection. The 2006 peace accord opened political space to link ”territorial peace” with conservation, but the lack of strong implementation and enforcement has allowed cattle ranching and illicit crop expansion to drive deforestation in former FARC territories.

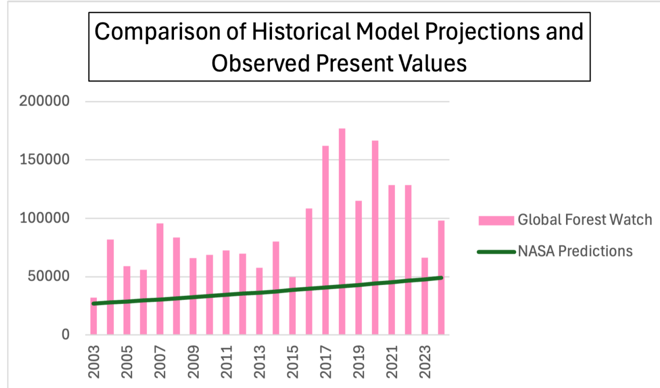


Figure 15: Comparison of Predicted and Observed Deforestation Rates (2003-2016)

Deforestation has increased sharply since the 2016 peace accord, particularly in the departments of Caquetá, Meta, and Guaviare. Studies show that many areas where FARC previously had a presence were prevented from land clearing. However, once the group demobilized, the conversion of forest to pasture and crops accelerated. [17] The peace process rural reform agenda, crop substitution programs, and ”territorial peace” language created an opening to connect peacebuilding with sustainable land use and forest governance. These provisions aim to support community-based conservation, clarify land rights, and strengthen environmental institutions in Colombia's former conflict zones, which are also its most biodiverse areas.

The 2016 Peace Accord with FARC included crop substitution programs (PNIS) that aimed to replace illicit coca with legal crops in Amazonian hostspots, reducing pressure on the forest previously protected by guerrilla control. The goal was to reduce illicit crop expansion into the forest by foresting rural development and territorial peace, but implementation has stalled due to delayed payments, lack of market access, and security threats from dissident groups.[18]

Efforts to integrate peace and environmental policy focus on three ideas: territorial planning, community rights, and climate/forest finance. In 2018, in Future Generations vs. Ministry of Environment (STC 4360 - 2018), the Supreme Court recognized the Colombian Amazon as an ”entity subject of rights”, entitled to protection, conservation, maintenance, and restoration. However, Colombia's recognition of the Amazon as a subject of rights has mainly produced orders and structural mandates against state authorities, not individual criminal trials “against” the Amazon's violators as such.

In 2016, Colombia introduced a carbon tax and forest credits. The forest credits are basically a way to turn ”not cutting the forest,” designed to both raise revenue and send a price signal against emissions and illegal logging. To avoid deforestation (measured in tons of CO_2 certified and then sold as credits to governments or companies that want to offset their emissions or comply with carbon tax rules. However, some question the efficiency of this method, because some Amazon projects used baselines well above official deforestation trends, allowing them to sell more credits than the real avoided deforestation, while companies used those credits to avoid paying the carbon tax.

Law 2111 of 2021 criminalized deforestation for the first time in Colombia, punishing the logging, burning, or destruction of forests without authorization with sentences of 8 to 15 years in prison and fines ranging from 300 to 50,000 times the monthly minimum wage. It also sanctions those who promote or finance deforestation and the invasion of areas of special ecological importance, aiming to target both the direct perpetrators and the economic and organized actors behind the expansion of the agricultural frontier and illegal activities. However, despite the severity of these penalties and the broadened scope of the law, it has failed to reverse the trend of forest loss, as deforestation rates increased in the year following its enactment. This highlights serious problems with implementation, state capacity, and territorial control in critical areas of the Amazon.

4.6 Challenges and Limitations

Satellite remote sensing has allowed scientists to support natural resource management like never before. However, a significant portion of data is not freely available. This limits access to information and slows the advancement of monitoring and analysis efforts. Additionally, SRS-based data analysis is expensive due to the costs of hardware, software, and qualified and trained staff. Another challenge is the complexity of integrating SRS-based data to *in situ* data. There is a lack of cooperation between local ecologists and satellite experts, which leads to SRS often being underused or undervalued [19].

1. **Data Acquisition** Different satellite or data sources offer varying trade-offs, including spatial resolution, revisit time, cost, and accessibility.

2. **Cloud Coverage:** This is one of the biggest challenges in tropical regions. Clouds often affect the clarity of the images, especially during the winter (rainy season in South America). For this, I could try using cloud masking algorithms, dry season data (which could limit the extent to which I can analyze deforestation rates), or use SAR images (e.g., Sentinel-1) that can penetrate clouds.

In-person field surveys play a crucial role in quantifying tree coverage by providing high-resolution, ground-truth data that satellite-based methods cannot fully capture, including species composition, tree health, understory density, and early-stage regeneration. In-person surveys are particularly valuable for validating remote-sensing models and correcting classification errors caused by cloud cover, sensor limitations, or spectral confusion. However, field surveys are labor-intensive, costly, and spatially limited, making them impractical for continuous monitoring across large or remote forested regions. As a result, they cannot scale at the temporal and geographic resolution required for long-term deforestation assessment. For this study, in-person surveys are best viewed as a complementary validation tool rather than a primary measurement method. Their limited coverage introduces uncertainty when extrapolating findings to regional or national scales, reinforcing the need for automated, satellite-based approaches that can provide consistent, repeatable, and large-scale forest monitoring while selectively incorporating field data for calibration and accuracy assessment.

4.7 Gaps in Existing Research

While several studies have analyzed the deforestation patterns of the Amazon, there are critical gaps in the literature, as very few examine the impact of the Peace Process (2016) in the Colombian Amazon and its effect on deforestation dynamics, leaving its measurable environmental effects largely undocumented. Additionally, most research has been conducted in the Brazilian Amazon, which has tended to exclude other countries, revealing a geographical bias. The active exclusion of Andean-Amazonian territory has prevented a comprehensive understanding of the problem as a whole, overlooking important transboundary dynamics and country-specific socio-political factors.

Excluding socio-political events from the analysis and development of monitoring projects is problematic because it fails to account for how armed conflicts, post-conflict transitions, and varying governance structures shape reforestation efforts across the Amazon basin. In Colombia's case, the demobilization of FARC, territorial control vacuums, and subsequent land-use changes represent a unique socio-political context that cannot be extrapolated from Brazilian case studies.

Existing deforestation monitoring frameworks often treat the issue as solely technical or ecological, inadequately excluding socio-political variables from their analytical models. This technical-only approach limits both the explanatory power of research and the effectiveness of intervention strategies. Without integrating variables such as territorial governance, armed group presence, coca cultivation dynamics, and land tenure insecurity, monitoring tools cannot fully capture the drivers of deforestation or predict future trends. The integration of socio-political context into technical analysis is essential for developing a holistic understanding and effective policy responses. Deforestation monitoring must evolve beyond satellite imagery analysis to incorporate conflict dynamics, institutional capacity, and local community perspectives. Only through this interdisciplinary approach can research produce tools capable of both quantifying deforestation rates and qualifying the complex causal mechanisms underlying forest loss, thereby informing evidence-based policy interventions.

5 Conclusion

In conclusion, geospatial analytics reveal that deforestation in Colombia's Amazon persists despite policy frameworks such as Ley 2111 de 2021, the 2016 Peace Accord's PNIS crop substitution program, and judicial innovations recognizing the Amazon as a rights-bearing entity. While mechanisms such as carbon credits and REDD+ aim to mobilize financial resources for sustainable development, their effectiveness is often constrained by uneven implementation and benefit distribution, reinforcing the need for continuous, transparent geospatial monitoring. This analysis demonstrates how data-driven policy assessment can support more adaptive and responsive environmental strategies. Computer science plays a central role in this process, enabling the automation of satellite-image processing, large-scale data integration, and change-detection modeling necessary to monitor deforestation and recovery over time. By leveraging computational methods, policymakers and researchers can move beyond static evaluations toward dynamic, evidence-based decision-making that aligns environmental protection with technological advancement.

6 Future Work

The future development of this project can focus on scaling, integration, and user accessibility to maximize its impact as an open-source conservation tool. The most critical step is to scale the analysis beyond the current defined area of interest to cover the entire Colombian Amazonia, and potentially even conduct cross-border monitoring in adjacent Amazonian regions. To enhance accuracy and real-world applicability, the tool will be improved by integrating additional causal factors, such as analyzing proximity to informal road networks, to better attribute deforestation to specific illicit activities like coca cultivation or illegal logging. The change detection capability will be transitioned into a near real-time monitoring system that automatically generates and flags small-scale deforestation hotspots for prompt local intervention. Finally, to fulfill the goal of empowering local communities, it would be ideal for the project to culminate in the development of a user-friendly web dashboard to visualize results and the creation of an educational module explaining the science behind remote sensing.

7 Acknowledgments

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