

Assessing CO₂ Emissions from Deforestation and Fires in Bolivia during 2010-2023

Estimación de las emisiones de CO₂ por deforestación e incendios en Bolivia entre 2010 y 2023

*Lykke E. Andersen **
*Fabiana Argandoña ***
*Carla Olmos ****
*Diego Calderón *****

*Sebastián Miranda ******
*Álvaro Muñoz ******
*Sergio Choque ******

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- * Ph.D. in Economics. Aarhus University, Denmark. Executive Director of the Sustainable Development Solutions Network (SDSN) in Bolivia.
Contacto: lykkeandersen@upb.edu
ORCID: <https://orcid.org/0000-0003-0219-0090>
 - ** Environmental Engineer. Universidad Católica Boliviana "San Pablo". Bachelor's Degree in Economics. Universidad Mayor de San Andrés. Researcher and coordinator of the technical team at the Sustainable Development Solutions Network (SDSN) Bolivia.
Contacto: fabiana.argandoña@sdsnbolivia.org
ORCID: <https://orcid.org/0009-0002-1173-6593>
 - *** Environmental Engineer. Universidad Mayor de San Andrés. Researcher in climate change and sustainable development studies at the Sustainable Development Solutions Network (SDSN) Bolivia.
Contacto: carla.olmos@sdsnbolivia.org
ORCID: <https://orcid.org/0009-0006-2219-9067>
 - **** Geographical Engineer. Universidad Mayor de San Andrés. Researcher at the Sustainable Development Solutions Network (SDSN) Bolivia.
Contacto: diego.calderon@sdsnbolivia.org
ORCID: <https://orcid.org/0009-0007-2236-0049>
 - ***** Graduate in Geographic Engineering and Cadastre and Land Management. Universidad Mayor de San Andrés. Researcher in the area of geographic information analysis and processing at the Sustainable Development Solutions Network (SDSN) Bolivia.
Contacto: sebastian.miranda@sdsnbolivia.org
ORCID: <https://orcid.org/0009-0009-7772-4668>
 - ***** Graduate in Geographic Engineering. Universidad Mayor de San Andrés. Researcher in the field of geography at the Sustainable Development Solutions Network (SDSN) Bolivia.
Contacto: alvaro.munoz@sdsnbolivia.org
ORCID: <https://orcid.org/0009-0004-5766-0939>
 - ***** Geographical Engineer. Universidad Mayor de San Andrés. Expert in geographical and quantitative information analysis, as well as database management and generation. Conservation Strategy Fund (CSF).
Contacto: sergio.choque@sdsnbolivia.org
ORCID: <https://orcid.org/0009-0002-3648-2526>

Abstract*****

This report estimates annual CO₂ emissions from deforestation and fires in Bolivia from 2010 to 2023, considering both emissions and absorptions resulting from land clearing, land use change, fires, and forest regeneration.

Using high-resolution annual land cover maps from MapBiomass Bolivia (1985-2023), and a global biomass density map, we track carbon pool changes at a 30x30m resolution. We developed a bookkeeping model to monitor carbon storage across 1.2 billion land cover pixels nationwide. Fortunately, 93% of these pixels showed no significant forest change, allowing us to focus on the 80 million pixels that experienced changes during the period of analysis. These pixels were categorized into 1,278 classes of change based on the year, original land cover, resulting land cover and forest type.

To estimate emissions from forest degradation due to fires, we used the Global Fires Emissions Database and subtracted emissions from deforestation within burned areas to prevent double counting. Our results indicate that CO₂ emissions from deforestation and forest degradation due to fires in Bolivia frequently exceed 200 million tCO₂ per year –70 million tCO₂ from deforestation and 126 million tCO₂ from degradation on average—making Bolivia a significant contributor to global warming, with per capita emissions among the highest in the world. Alarming, an increasing share of these emissions results from forest burning with no apparent productive purpose.

Keywords: Deforestation; fires; carbon emissions; Bolivia.

Resumen

Este informe estima las emisiones anuales de CO₂ derivadas de la deforestación y los incendios en Bolivia entre 2010 y 2023, considerando tanto las emisiones como las absorciones derivadas del desmonte, el cambio de uso del suelo, los incendios y la regeneración forestal. Utilizando mapas anuales de cobertura terrestre de alta resolución de MapBiomass Bolivia

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(1985-2023) y un mapa global de densidad de biomasa, monitoreamos los cambios en los depósitos de carbono con una resolución de 30x30 m. Desarrollamos un modelo contable para monitorear el almacenamiento de carbono en 1200 millones de píxeles de cobertura terrestre a nivel nacional. Afortunadamente, el 93% de estos píxeles no mostró cambios significativos en el bosque, lo que nos permitió centrarnos en los 80 millones de píxeles que experimentaron cambios durante el período de análisis. Estos píxeles se categorizaron en 1.278 clases de cambio según el año, la cobertura terrestre original, la cobertura terrestre resultante y el tipo de bosque.

Para estimar las emisiones derivadas de la degradación forestal causada por incendios, utilizamos la Base de Datos Global de Emisiones de Incendios y restamos las emisiones derivadas de la deforestación en las áreas quemadas, para evitar la doble contabilización. Nuestros resultados indican que las emisiones de CO₂ derivadas de la deforestación y la degradación forestal causadas por incendios en Bolivia superan con frecuencia los 200 millones de toneladas de CO₂ anuales (70 millones de toneladas de CO₂ por deforestación y 126 millones de toneladas de CO₂ por degradación, en promedio). Esto convierte a Bolivia en un contribuyente significativo al calentamiento global, con emisiones per cápita entre las más altas del mundo. Resulta alarmante que una proporción cada vez mayor de estas emisiones se deba a la quema de bosques sin un propósito productivo aparente.

Palabras clave: Deforestación; incendios; emisiones de carbono; Bolivia.

Classification/ Clasificación JEL: Q50, Q54.

1. Introduction

Bolivia has approximately 55 million hectares of forests, covering nearly half of its national territory. These ecosystems represent not only a strategic reserve of environmental services (Andersen *et al.*, 2025) but also a critical global carbon sink. However, in recent years, the country has experienced rising deforestation and wildfires, leading to significant carbon emissions. According to official reports land-use change, is the country's largest source of CO₂ emissions, accounting for over 50% of total emissions (APMT, 2020). Consequently, Bolivia ranks among the top 20 countries for land-use change emissions from 2010-2022 (Friedlingstein *et al.*, 2023). Further, the Global Carbon Atlas in 2023 placed Bolivia as the

10th highest emitter from land-use change, 3rd in *per capita* emissions for this sector, and 81st in CO₂ emissions from fossil fuels (Global Carbon Atlas, 2023).

The Agriculture, Forestry, and Other Land Use (AFOLU) sector remains one of the few that includes greenhouse gas (GHG) absorption processes. However, some national inventories—particularly in data-limited countries—simplify these dynamics by assuming static scenarios or ignoring ecosystem recovery post-deforestation. The present study employs a dynamic modeling approach based on a pixel-level carbon bookkeeping model. This method tracks carbon flows by forest type, land-use change category, year accounting deforestation and forest regrowth, while incorporating changes in carbon pools (aboveground biomass, belowground biomass, and soil organic carbon).

These recovering areas not only recapture part of previously released carbon but also highlight the dynamism of Bolivia's forest landscapes. On the other hand, estimating fire emissions remains fraught with technical and methodological challenges (Viglione, 2023). Based on the available data, this study includes some insights and a preliminary gross estimation of fire emissions resulting from vegetation degradation.

Our study builds upon the foundational work of Andersen *et al.* (2016), who developed a carbon bookkeeping model to estimate net CO₂ emissions from deforestation in Bolivia during 1990-2000 and 2000-2010. Their methodology, which accounted for deforestation at a 10×10 km resolution, provided critical insights into spatial and temporal variations in emissions across Bolivia's diverse forest types. Their pioneering work revealed rising emissions and consistently high *per capita* CO₂ outputs but faced limitations in the spatial and temporal granularity of the data and excluded fire-induced degradation. Our research advances this framework by incorporating high-resolution land-cover transitions from MapBiomass with 30×30 m resolution from 2010 to 2023 and integrating fire emission data from GFED, enabling pixel-level tracking and explicit quantification of degradation.

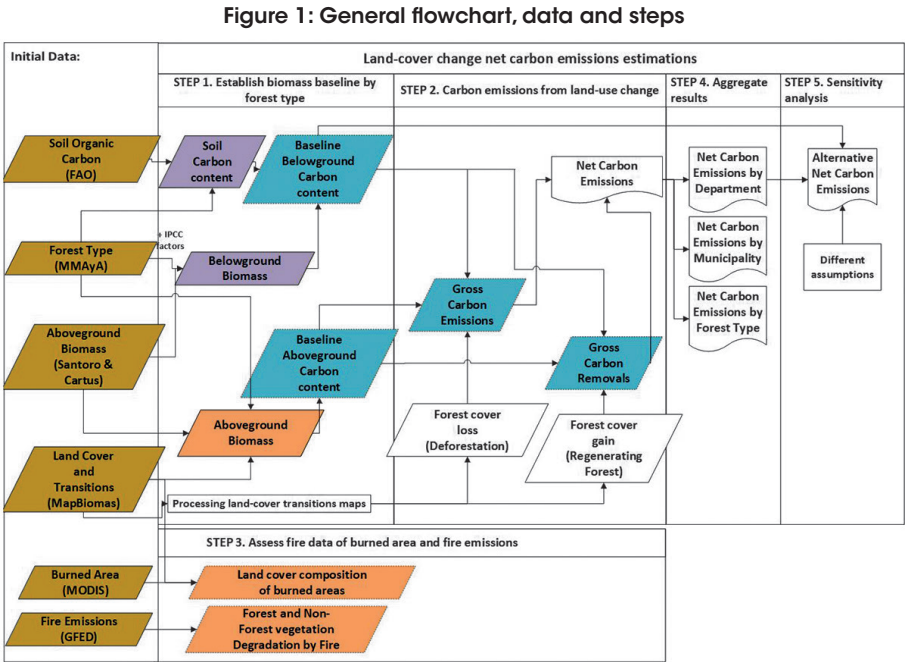
2. Data and methods

2.1. General workflow

This study primarily focuses on estimating deforestation emissions based on the principles of bookkeeping models. In addition, we conduct an exploratory analysis of fire-related emissions, offering insights that contribute to the broader discussion on this topic. The following steps outline the general workflow.

- **Step 1.** Establish biomass baseline by forest type. The first step is to establish a baseline for forest biomass by forest type to estimate emissions and removals within these diverse ecosystems.
- **Step 2.** Estimate carbon emissions from land-use change and forest loss. Subsequently, an assessment of land cover and land cover transition data will be conducted to establish a timeline for annual emission estimations, primarily focusing on deforestation and conversion to other land uses. Following the principles of bookkeeping models, land use and land-use change will be central to the emissions analysis. This approach will provide an overview of forest loss, gain, and dynamics.
- **Step 3.** Assess fire data of burned area and fire emissions. The next step in analysing and understanding land-use dynamics will be the assessment of fire data and fire emissions data.
- **Step 4.** Aggregate results. Finally, aggregated results will be estimated for the country. Given that data treatment, analysis, and research decisions made in the preceding steps, gross emissions are estimated using the principles of bookkeeping models. This involves implementing response curves for different carbon pools to estimate gross and net emissions and removals. Deforestation analysis is performed at a 100-meter grid scale, while fire analysis uses a 500-meter grid scale. For reporting purposes, aggregated data for Bolivia, as well as aggregated results by department and municipality, are calculated.
- **Step 5.** Sensitivity analysis. By varying certain assumptions, we explore alternative outcomes.

Figure 1 presents the relation between data sources and processes:



Source: Authors' elaboration.

2.2. Deforestation emissions accounting method

2.2.1. Bookkeeping models

After revising different methodological approaches to calculate land-use and land-use change emissions, a bookkeeping model approach was chosen, as one of the main advantages are their high traceability, which allows attributing fluxes to specific places, causes, and thus to specific stakeholders. These models make it possible to track carbon stored in vegetation and soils before and after a land-use change event, while excluding the additional ecosystems response to environmental changes (IPCC, 2024).

Therefore, as the present study focuses on land use and land-use change, bookkeeping models are an appropriate choice due to their advantages in Land-use, Land-Use Change, and

Forestry (LULUCF) emissions analysis. Additionally, this aligns with the approach taken by the Global Carbon Budget (GCB), which also relies on bookkeeping models for this specific sector.

Bookkeeping (BK) models estimate emissions from individual land use activities, with a primary focus on agricultural land use changes and the regrowth of secondary forests from abandonment of agriculture. BK models track each land-use and land-cover change (LULCC), allowing fluxes to be presented as either gross emissions and removals or as a net flux. BK approaches combine land cover data with carbon density data for biomass and soil for different ecosystem types. These models track how carbon decays to the atmosphere, or how carbon is removed from the atmosphere following land cover changes (Poulter *et al.*, 2022).

However, it is important to acknowledge the limitations of bookkeeping models. These models depend on predefined parameters and assumptions about carbon density dynamics, typically using exponential, logistic, and linear functions to represent carbon changes. While these functions are based on theoretical frameworks and experimental data, their applicability may vary depending on specific conditions. For the present study, previously established functions will be adopted to ensure consistency and comparability with existing research.

Many studies worldwide have utilized the bookkeeping model approach. Our methodological approach is based on the insights of the following bookkeeping models reviewed for this study: Houghton (Houghton & Castanho, 2023), BLUE (Hansis *et al.*, 2015), LUCE (Qin *et al.*, 2024), and Andersen *et al.* (2016). All of these models are based on principles established by Houghton *et al.* (1983), utilize IPCC parameters, and focus on key land-use changes derived from land cover and land cover transition maps. BLUE, LUCE, and Andersen include an assessment at a grid level, which is also a purpose of the present study. In the following section, the equations, assumptions, and adaptations –based on the reference models–will be established to ensure methodological consistency and applicability to the study area.

2.2.2. Carbon Pools

Models typically define the carbon pools considered in the accounting process. In this study, the following carbon pools will be taken into account:

Vegetation: Forest vegetation acts as an emission source when deforested and as a carbon sink when it regrows. Forest vegetation is a key dataset in this study. Both above-ground and

below-ground biomass are taken into account. The data sources and dynamics considered are described in the following sections.

Soil: Soil carbon changes following land cover transitions are considered, with emissions occurring when deforestation takes place and carbon sequestration happening during regrowth. Despite uncertainties regarding the soil carbon pool, bookkeeping models usually include soil carbon changes due to land use change as part of the estimations. The estimations are based on soil carbon density data and incorporate temporal response curves to account for changes in soil carbon following land-use transitions. Soil carbon data usually have greater uncertainties than above ground data.

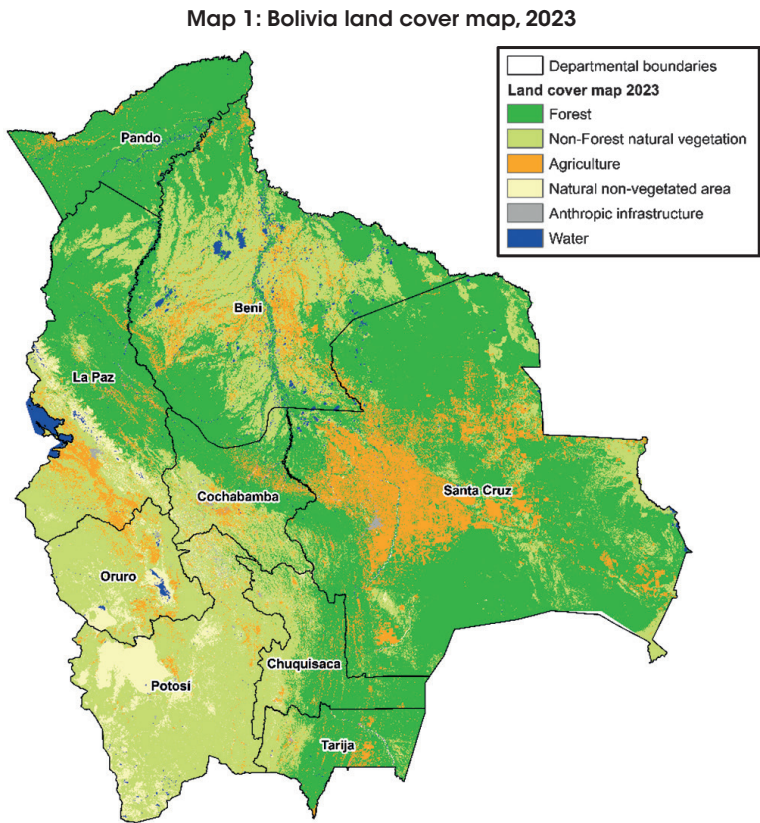
The source for soil properties is provided by FAO's Global Soil Organic Carbon Map (GSOCmap v.1.5), the first global map developed through a consultative and participatory process with member countries, coordinated by the Global Soil Partnership. This map can be considered a baseline, as it represents the best available national-level estimate of SOC (FAO & ITPS, 2020). An average value by forest type is calculated from this map and combined with belowground biomass estimates.

Atmosphere: This is the receiving pool of gross emissions, while gross removals extract carbon from the atmosphere, balancing the fluxes of the land-use change process. The atmosphere is assumed to be the final recipient of net emissions resulting from land cover change. Therefore, it is not explicitly discussed in the following sections, as we assume that any net emissions or removals from land cover changes result in an equivalent gain or loss of carbon in the atmosphere.

2.2.3. Land Use and Transitions to be accounted for

The classification of land-use transitions in this study follows approaches from Andersen *et al.* (2016) and LUCE, considering both anthropogenic and non-anthropogenic changes. Revising data sources, MapBiomas Bolivia (MapBiomas Bolivia, 2024) arises as the most appropriate source for land cover and land cover transitions maps for Bolivia. This independent source reports the longest available annual data for Bolivia from 1985 to 2023. This source offers an accurate approximation to direct measurements for a vast country like Bolivia, which covers approximately 109.8 million hectares and includes over 50 million hectares of forest.

MapBiomass Bolivia has recently released its Collection 2 of maps, which includes two sets: one for land cover maps and another for land cover transition maps elaborated based on Landsat satellite images with a spatial resolution of 30 meters. The transition maps undergo an additional filtering process to eliminate isolated or edge pixels. Therefore, there may be minor differences between using land cover and land cover transitions maps (MapBiomass, 2024). The resulting land cover maps classify the data into six main categories and 19 subcategories. The six primary categories are: Forest, Non-Forest natural formation, Farming, Non-vegetated area, Water body, and Not observed (RAISG, 2024). We adapted this classification following the correspondence table provided in Table 1. An example of the resulting land cover map (for year 2023) is shown on Map 1.



Source: Authors' elaboration based on MapBiomass Bolivia (2024). Original land use categories were adapted for this study.

Table 1
Adaptation of the land use types, based on the original MapBiomass classification

Adapted classification	Original MapBiomass Classification	MapBiomass class codes
Forest	Forest; Open Forest; Flooded Forest	3;4;6
Non-Forest Natural Vegetation	Wetland; Grassland/Herbaceous; Other non-forest natural formation; Shrubland	11;12;13;66
Agriculture	Pasture; Agriculture; Mosaic of uses	15;18;21
Natural non-vegetated area	Beach, dune and sand spot; Rocky outcrop; Salt flat; Other non-vegetated natural area	23;29;61;68
Anthropic infrastructure	Urban infrastructure; Other non-vegetated anthropic area; Mining	24;25;30
Water	River, lake; glacier	33;34

Source: Authors' elaboration based on MapBiomass Bolivia (2024).

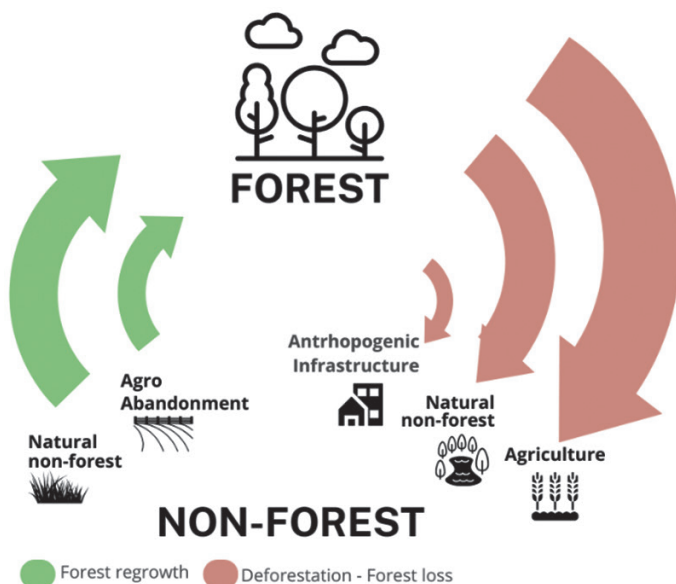
Deforestation: Deforestation is taken into account from the pixels changing from forest land cover to other non-forest land cover, annually from 2010 to 2023. The term deforestation typically implies human intervention. According to the Cambridge Dictionary, it is defined as “the cutting down of trees in a large area, or the destruction of forests by people” (Cambridge University Press). In contrast, the FAO (2023) defines deforestation as “the conversion of forest to other land use, regardless of whether it is human-induced or not” emphasizing a change in land use.

Deforestation can be categorized based on its apparent cause and subsequent land use:

- Clearly Anthropogenic Deforestation:
 - ♦ Conversion of forest to agricultural use, including crops, pasture, and mosaics of uses (as classified by MapBiomass).
 - ♦ Conversion of forest to urban areas, mining, or other anthropogenic infrastructure (as classified by MapBiomass).
- Not Clearly Anthropogenic Deforestation:
 - ♦ Non-agricultural deforestation, where forest loss occurs but there is no visible land use afterward. Although the cause may still be anthropogenic, it is not immediately linked to a subsequent human activity.

To avoid confusion, and given that our data primarily reflect land cover and land cover changes –without reliably distinguishing human causes or capturing actual land use changes not yet reflected in land cover– we use the terms ‘deforestation’ and ‘forest cover loss’ interchangeably throughout this study. Both terms encompass explicitly anthropogenic and not clearly anthropogenic deforestation.

Figure 2: Land use and transitions considered in this study



Source: Authors' elaboration

Regenerating Forest (Forest Age Classification): Regenerating Forest is taken into account from pixels changing from any non-forest land cover to forest land cover, annually from 1986 to 2023. Forest age is considered to estimate its carbon absorption. Only the most recent regrowth event for each pixel is taken into account, if the pixel remained classified as forest at least until the beginning of the study period in 2010. Regeneration is categorized based on whether the regrowth occurs after human activities:

- Anthropogenic Regrowth:
 - ♦ Forest regrowth following agricultural abandonment.

- Non-Anthropogenic Regrowth:
 - ♦ Forest regrowth from other land uses not directly related to human abandonment.

Throughout this document, ‘regrowth’ encompasses both explicitly anthropogenic and non-anthropogenic regrowth.

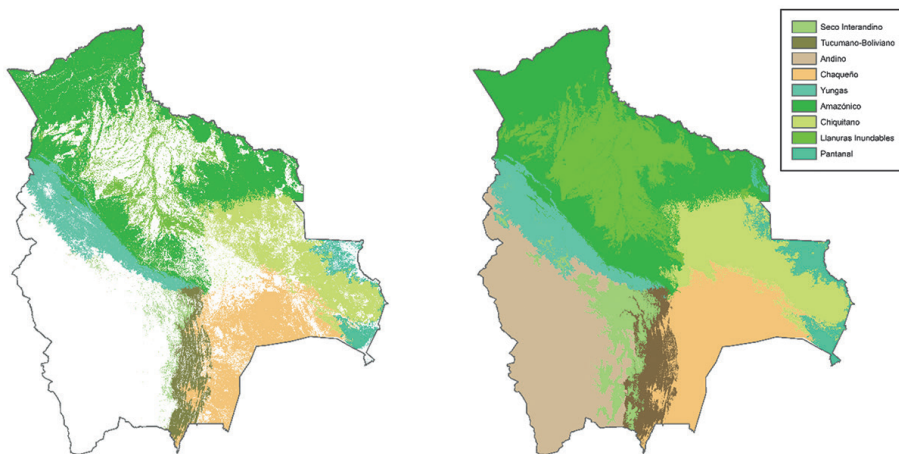
A forest type map is used to complement forest information, as MapBiomass Bolivia provides data on land use and transitions but does not include details on forest types. The most recent forest type map was published in 2022 by the Ministry of Environment and Water (MMAyA, 2022). By forest extension the main type in Bolivia is the Amazon forest followed by Chaqueño and Chiquitano forest. The nine major forest types identified in the data source are used for the present analysis.

Since the available map identifies forest areas only for the year 2022, we created a “forest type zone” map by combining the 2022 forest type data with an ecoregion map (Ibisch & Merida, 2003). By integrating the Forest Type dataset (MMAyA, 2022) with the Ecoregion dataset (Ibisch & Mérida, 2003), we produced a new dataset comprising the nine forest categories defined by MMAyA, applied across the entire country. This represents a potential forest type map for Bolivia, assuming full forest cover.

This adjustment is essential because our land use and transition analysis covers both current forest areas and historical forest changes, while the 2022 forest type map only reflects areas that remained forested as of that year, excluding areas deforested earlier. In the deforestation analysis, it allows us to identify the original forest type associated with each land cover change. In the fire emissions analysis, the forest type map is used as a reference to determine the ecozone, even in areas that are currently non-forest or have never been forested, helping to contextualize fire dynamics across different ecological regions.

While deforestation emissions are calculated at a 30x30 meter resolution, results of CO₂ emissions from deforestation are presented at a 100x100 meter resolution. The rescaling method used for the MapBiomass and forest type data is based on the ‘nearest neighbor’ approach, which is the recommended method for rescaling categorical (class) data.

Map 2: Current and potential forest type in Bolivia



Left: Original forest type map of 2022 (MMAyA, 2022). Right: Potential forest type zone.
Source: Authors' elaboration.

2.2.4. Principal Assumptions

Deforestation estimations. To estimate CO₂ emissions from deforestation with models, it is necessary to make some assumptions. The most important ones are presented below:

- Aboveground biomass is almost completely removed. The assumption that aboveground biomass is almost completely removed after deforestation to agricultural use is widely applied in bookkeeping models. As Hansis *et al.* (2015) states: “For clearing, it is assumed that the respective biomass of the source type is completely removed, with none leftover in the target cover type”. Similarly, Andersen *et al.* (2016) assumes that after a land-use change to agriculture, aboveground biomass is reduced to the level of crops or pastures biomass. This assumption is kept for the present study. The year of a deforestation event, the baseline biomass changes to the destination land cover, which are explained below.
- ♦ Deforestation to agriculture or pasture: the biomass content is adjusted to the default values for these land uses, following IPCC (2006) guidelines.
- ♦ Deforestation to urban areas: aboveground biomass is assumed to be completely removed (zero biomass).

- ♦ Deforestation with no apparent land use (non-use deforestation): the remaining biomass is assumed to correspond to the average natural non-forest vegetation biomass, estimated using Santoro & Cartus biomass maps overlaid with natural non-forest vegetation cover from MapBiomass, by forest type zones.
- Belowground carbon is assumed to decompose gradually. Belowground carbon, which includes soil carbon and belowground biomass, is assumed to decompose gradually after deforestation following a linear function over 20 years, ultimately resulting in a 25% loss of its initial carbon content.
- ♦ Soil carbon averages are obtained from soil maps. Values are estimated as an average by forest type to account for spatial variability.
- ♦ Belowground biomass is estimated using average carbon content in intact forests, stratified by forest type. The IPCC (2006) root-to-shoot ratios are applied to estimate belowground biomass.
- ♦ As assumed in Andersen *et al.* (2016) based on literature, we assume no carbon emissions from soils if there is no apparent agricultural use after deforestation, when forests turn to natural non-forest cover.

2.2.5. Equations and Parameters

- Establish biomass baseline by forest type

Intact forest since 1985 was identified using land cover and transition data from MapBiomass Bolivia (2024). After extracting this area (in pixels), this undisturbed forest is utilized to extract the aboveground biomass from the biomass map provided by Santoro & Cartus (2024) available at ESA Biomass Climate Change Initiative (CCI Biomass). This source makes available global aboveground biomass maps for the year 2010 and from 2015 annually till 2021 with a 100 meters pixel resolution. Biomass estimates are important for assessing the carbon removal (or emission) capacity of different types of ecosystems, as it directly correlates to an ecosystem's ability to sequester or release carbon. As with other bookkeeping models, this study uses a single baseline biomass dataset from the year 2010 to estimate potential carbon emissions or absorptions based on the average biomass of each forest type. Average biomass in intact forests was also calculated for the years 2015 to 2021, yielding similar results and thereby ensuring consistency in biomass estimates for intact forest areas. While we use average estimates of biomass for each type of

forest for our central emissions estimates, it is important to keep in mind that deforestation and forest fires may not target average forest, but rather less dense forest. This possibility will be explored in the sensitivity analysis.

Belowground biomass is estimated by applying the R factor (Ratio of Belowground Biomass to Aboveground Biomass) (from table 4.4 in Volume IV, Section 4, (IPCC, 2019, p. 4.18)), which represents the relationship between below-ground and above-ground biomass, as direct measurements or estimations are not available.

Table 2
Aboveground and belowground biomass data by forest types (tons of biomass/ha)

Forest type	Aboveground Biomass				Belowground Biomass	
	Average biomass (t/ha)	Percentile 75th (t/ha)	Percentile 50th (t/ha)	Percentile 25th (t/ha)	Ratio of belowground to aboveground biomass	Average belowground biomass (t/ha)
Amazónico	224	263	221	184	0.221	49
Yungas	189	229	186	145	0.283	54
Chiquitano	152	181	157	127	0.284	43
Tucumano – Boliviano	144	201	152	101	0.283	41
Llanuras Inundables	143	172	129	77	0.221	32
Pantanal	107	132	115	76	0.285	31
Seco Interandino	65	102	57	22	0.348	23
Chaqueño	54	69	43	27	0.334	18
Andino	50	82	35	7	0.348	17

Source: Authors' elaboration based on Forest map 2022 (MMAyA, 2022), Land cover and transitions maps (MapBiomass Bolivia, 2024), Biomass map (Santoro & Cartus, 2024) and IPCC default values for ratios of belowground biomass. The table presents values in tons of biomass; carbon content is assumed to be half of the biomass, as is commonly established.

- Forest Regrowth curves

The underlying principle of the following equation, as seen in the bookkeeping models BLUE and LUCE, is that carbon reservoirs do not remain disturbed indefinitely. Instead, they follow a predictable trajectory toward a new stable state determined by post-disturbance land use.

- Aboveground biomass

In the case of regenerating forests, carbon content increases rapidly in the early years, then slows as the forest matures, eventually reaching a stable carbon level typical of mature forests. This predictable pattern allows for simplified modelling without significant loss

of accuracy. Since various models adopt similar functional approaches, we apply the function proposed by Andersen et al. (2016), as shown below:

$$CAR_{v,a} = \frac{CAP_v}{1 + e^{\alpha_v - \beta_v a}}$$

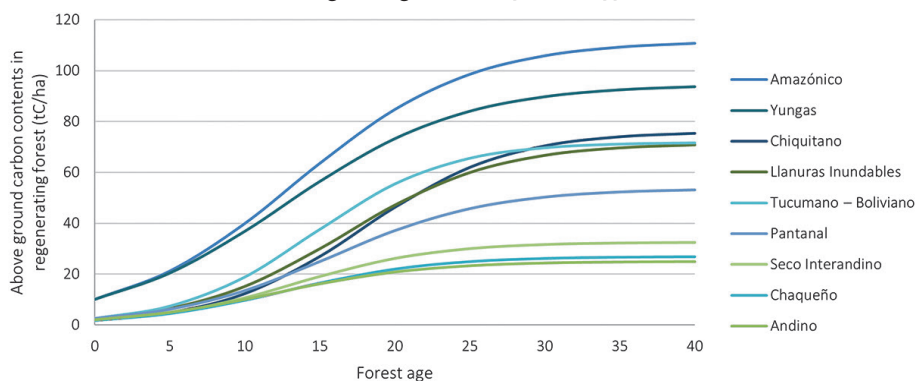
Where CAR_{va} represents the amount of carbon during regeneration at age a for a forest type v and CAP_v is the amount of carbon of a mature forest of the same type v . The parameters α_v and β_v determine the exact shape of the logistic function which vary across the nine forest types as shown in Figure 3.

Based on the parameters established by Houghton and Hackler (2001), it is estimated that tropical rainforests in Bolivia take 40 years to regenerate and reach the carbon content of intact forests, while dry or seasonal forests require 35 years to recover their original carbon content. Based on the Bolivian forest types, four of the nine forest types can be considered dry forest (*Andino*, *Chaqueño*, *Seco Interandino* and *Tucumano Boliviano*) while the other five are most likely tropical rainforest (*Amazónico*, *Chiquitano*, *Llanuras Inundables*, *Pantanal* and *Yungas*).

To calculate the parameters α_v and β_v , two assumptions are made: First, different initial carbon content values are assumed at the beginning of regeneration. Based on the fact that most deforestation occurs to make way for agricultural uses, the regeneration curves assume carbon recovery begins from the minimum aboveground carbon content typical of agricultural uses, specific to each forest type. These values range from 2 tC/ha for most forest type zones to 10 tC/ha in the Amazonian and Yungas forest type zones, according to IPCC (2019).

Second, forest regeneration is assumed to take between 35 and 40 years to reach 99% of its maximum carbon content. The average maximum carbon content by forest type is the one estimated as the baseline biomass since it represents average biomass content in old forest and is the value assumed for variable CAP_v , which varies across the nine forest types, ranging from 25 tC/ha in the Andean forest type to 112 tC/ha in the Amazonian forest type. Taking into account the time to recover and the maximum reached carbon content, nine separate logistic functions were estimated, resulting in a unique regrowth curve for each forest type.

Figure 3: Evolution of aboveground carbon content in regrowing forests, by forest type.



Source: Authors' elaboration

■ Belowground biomass

As noted by Andersen *et al.* (2016), various literature reviews indicate that soil carbon is resilient to aboveground disturbances, remaining relatively stable even in degraded forests or areas converted to pasture. Based on the assumptions of Houghton and Hackler (2001), the model assumes that belowground carbon regenerates linearly, following a curve with half the slope of the belowground carbon decomposition curve.

2.3. Assessment of burned area and fire emissions data

Fire emissions are not always included in AFOLU emissions estimations. While some estimations include emissions from burned peatlands, fire emissions have often been calculated separately from LULUCF emissions. Studies like the Global Carbon Budget have only recently begun, incorporating fires into their estimations and separated from LULUCF estimations.

Some burned forest may be completely lost and thus accounted for as deforestation by transition maps. However, other burned forest may remain as forest, but degraded. In these cases, transitions maps will not identify them as forest loss. Fires and fire emissions require separate analysis to understand their impact on forest loss, as well as their dynamics with land cover transitions, forest degradation, and regeneration.

Besides the difficulties in distinguishing human-caused fires from natural ones (GCB, 2025), other difficulties to estimate fire emissions are the variations in fire intensity, and the complexity of post-fire ecosystem recovery. On-the-ground observations are often impractical, making satellites the primary tool for monitoring. However, remote sensing has limitations, such as misidentifying fire signals and struggling to detect small fires. Ground-based data is often inconsistent and difficult to access, complicating emissions model validation. Estimating emissions remains complex, as it depends on factors such as vegetation type and fuel composition of vegetation, fire intensity, and landscape features.

These challenges make it difficult to perform primary estimations of fire emissions. Therefore, to incorporate fire emissions into the analysis, existing fire emission datasets will be used to assess their impact and relevance in Bolivia. This analysis requires two key data sources and their analysis:

- **Burned Area** which will enable the assessment of land cover affected by fires and other spatial analyses.
- **Fire emissions** to analyse and utilize global fire emission estimation data to assess the impact, magnitude, and other relevant characteristics of fires in Bolivia. Integrating these estimates with deforestation-related emissions will help ensure the avoidance of double counting.

Concerning burned area, given the available data and the need to analyse the period from 2010 to 2023, it seems reasonable to use MODIS data on burned areas, specifically the MCD64A1 Version 6.1 product. This product is derived from MODIS satellite images and provides burned area maps based on calculations from its sensors (Giglio *et al.*, 2019).

For fire emissions, the Global Fires Emissions Database (GFED) (Van Wees *et al.*, 2022) is used. The GFED is based on a global fire emissions model at a 500 m spatial resolution, integrating multiple remote sensing datasets to estimate biomass burning fuel consumption and emissions. The GFED framework estimates emissions from satellite-based data on vegetation cover, productivity, and burned areas. From the information available, the national territory of Bolivia is extracted for the period 2010-2022, since there's no data available for 2023. The main concern regarding this segment of the analysis is the potential for double counting emissions in areas where both fire and deforestation have occurred, as deforestation

emissions are already included in the bookkeeping calculations. To avoid this overlap and obtain an approximation of degradation emissions we can use the following assumption:

Degradation emissions = Total fire emissions – deforestation emissions within burned areas

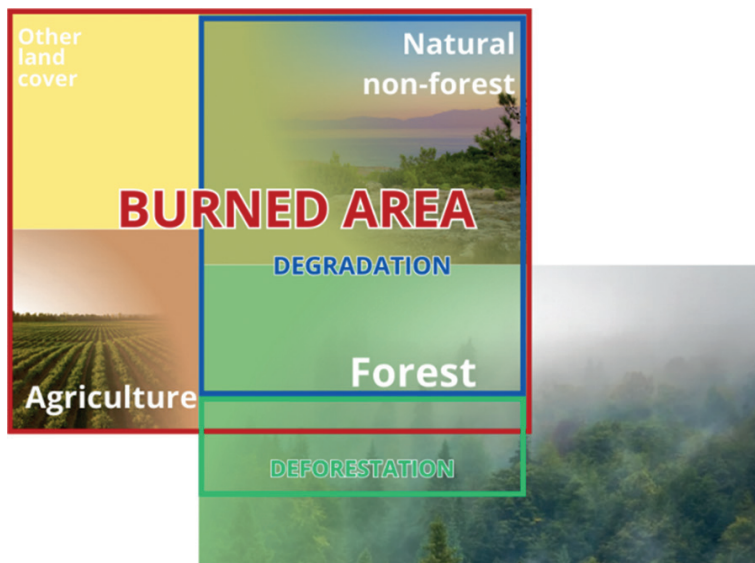
Where:

- **Total fire emissions** include emissions from deforestation (meaning total forest cover loss), forest degradation, and non-forest vegetation degradation. These estimates are based on data from the GFED.
- **Deforestation emissions** refer to emissions resulting from the complete conversion of forest cover to other land cover types. These are primarily estimated using the bookkeeping model, incorporating spatial and temporal overlap with burned areas. Deforestation emissions occur both within and outside burned areas. Only deforestation emissions inside burned areas should be considered to avoid double-counting.
- **Degradation emissions** represent estimated emissions from fires affecting both forest and non-forest vegetation. The resulting degradation emissions include both forest and non-forest vegetation degradation. In the case of forests, this includes areas that remain classified as forest in land cover maps despite being affected by fire.

Both deforestation and forest degradation contribute to greenhouse gas emissions. Fires may destroy the forest entirely (causing deforestation) in some cases, while in other cases, they may leave a degraded forest with lower quality and productivity (Lanly, 2003). The overlaps between forest, burned areas, degradation and deforestation is presented on Figure 4.

Although many gases are emitted from fires, numerous sources agree that the primary greenhouse gas (GHG) released is carbon dioxide (CO₂), with methane (CH₄), nitrous oxide (N₂O) and others being minor components (Sims *et al.*, 2024). These emissions are generally estimated based on the amount of biomass burned. For the present analysis, all biomass burned will be considered as CO₂ emissions, since CO₂ accounts for more than 90% of fire-related emissions. This approach also facilitates comparison with deforestation emissions.

Figure 4: Forest, burned area, degradation and deforestation overlaps



Source: Authors' elaboration.

It is important to take into account that fire CO₂ emissions from the Global Fires Emissions Database represent gross carbon fluxes, while carbon recovery post-fire is not fully accounted for (Friedlingstein *et al.*, 2023). Note that the biomass data used in GFED differs from the dataset employed in this study, introducing an additional source of uncertainty in this specific calculation. Therefore, these results are included in the discussion section rather than in the main results section, as they represent preliminary estimates that require further analysis to reduce uncertainty.

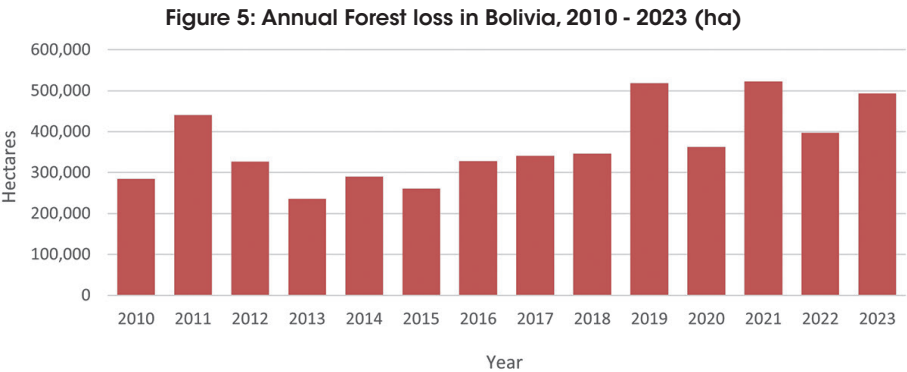
All fire-related data is available at a pixel resolution of 500 meters. Since the fire analysis was conducted separately, its results are also at a 500-meter resolution. When this data is compared with deforestation data –which is mostly analyzed at aggregated scales such as national, municipal or forest type zones– the aggregation ensures that the results remain comparable.

3. Results

3.1. Carbon emissions from land-use change – Deforestation

3.1.1. Gross emissions

To estimate gross emissions, from both aboveground and belowground carbon content (including belowground biomass and soil carbon), forest loss since 2010 was taken into account. The deforested surface tends to increase over time, and it is mostly located in the department of Santa Cruz. Figure 5 shows the annual forest loss over 2010-2023.

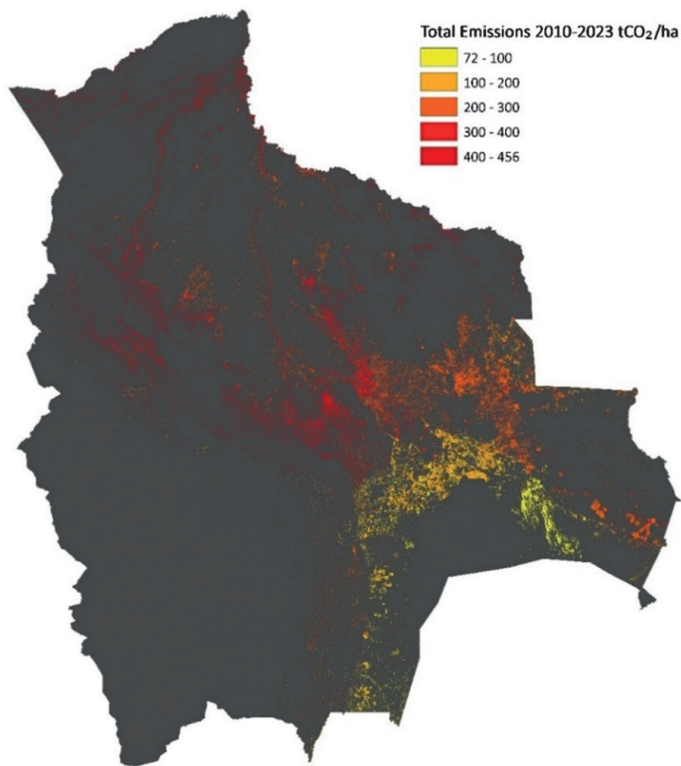


Source: Authors' elaboration based on MapBiomass Bolivia (2024).

Emissions occur where deforestation takes place; however, the amount of emissions per hectare varies depending on the forest type. Over the entire analysis period, the highest emissions per hectare are found in the northern regions of Bolivia, even though the total amount of deforestation is greater in the eastern part of the country. Similarly, within the department of Santa Cruz –which has the highest total deforestation– emissions per hectare are greater in the north, where forest types are predominantly Amazónico and Chiquitano. In contrast, the southern part of the department, dominated by Chaco and Pantanal forests, shows lower emissions per hectare.

For reporting and comparability purposes, the assumption is that all carbon emissions are released as CO₂. Carbon (C) emissions are converted to carbon dioxide (CO₂) using a conversion factor of 3,664. Map 3 shows spatial distribution of gross emissions whiles Table 3 presents results of cumulative gross emissions and deforested area during the study period by forest type.

Map 3: Gross emissions from forest loss in Bolivia 2010-2023



Source: Authors' elaboration.

Table 3
Total deforestation and gross emissions by forest type

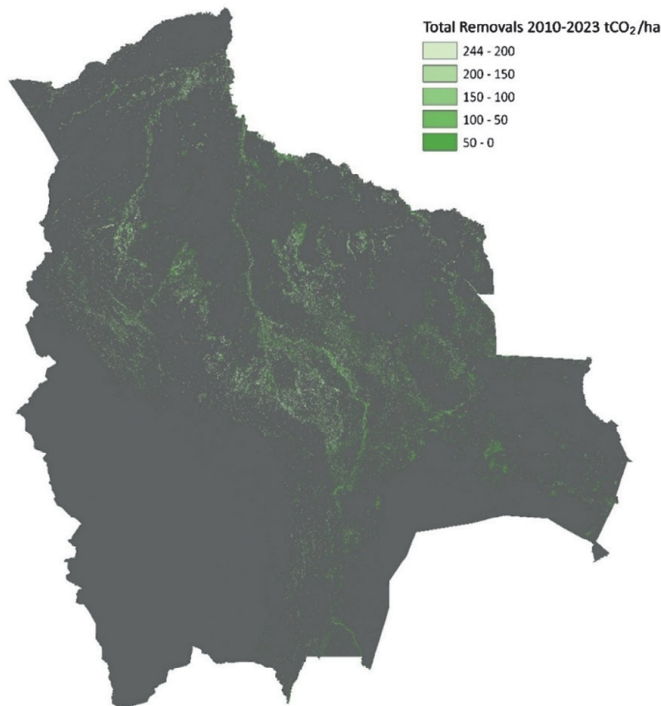
Forest type	Deforestation, 2010-2023 (ha)	Total Gross emissions, 2010-2023 (tCO ₂)
Amazónico	1,390,986	515,836,471
Chiquitano	1,407,882	389,084,009
Chaqueño	1,370,162	139,716,441
Llanuras Inundables	451,175	112,531,968
Yungas	214,549	70,962,057
Tucumano – Boliviano	126,311	34,225,703
Pantanal	151,439	29,497,381
Seco Interandino	32,216	3,873,437
Andino	3,750	342,157
Bolivia	5,148,469	1,296,069,625

Source: Authors' elaboration. Deforestation includes the total area that has lost forest between 2010 and 2023.

3.1.2. Gross removals

To estimate gross removals, regrowing forests established since 1985 and still standing at the beginning of our analysis period were considered, accounting for their carbon removals starting from 2010. Based on forest regrowth curves, younger forest removes higher carbon quantities than older forest. The capacity to remove carbon also depends on the forest type.

Map 4: Gross removals from forest regrowth in Bolivia 2010-2023



Source: Authors' elaboration.

Table 4
Total forest regrowth and gross removals by forest type

Forest type	Regrowing forest by 2023 (ha)	Total Gross removals, 2010-2023 (tCO ₂)
Amazónico	1,467,242	185,808,365
Chiquitano	587,997	38,694,366
Llanuras Inundables	608,884	33,262,695
Yungas	279,453	30,215,575
Chaqueño	469,506	16,844,942
Tucumano – Boliviano	122,778	10,901,629
Pantanal	95,455	4,259,554
Seco Interandino	38,866	1,441,251
Andino	5,017	158,205
Bolivia	3,675,199	321,586,581

Source: Authors' elaboration. The regrowing forest by 2023 includes forest that have been regenerating since the first transition map, representing forest aged between 1 and 37 years.

3.1.3. Net fluxes

The difference between gross emissions from deforestation and gross removals from forest regrowth are the net emissions. Both gross and net emissions reveal an increasing trend.

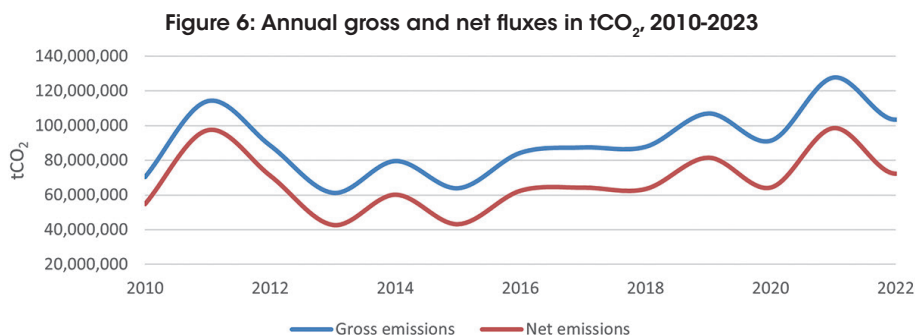


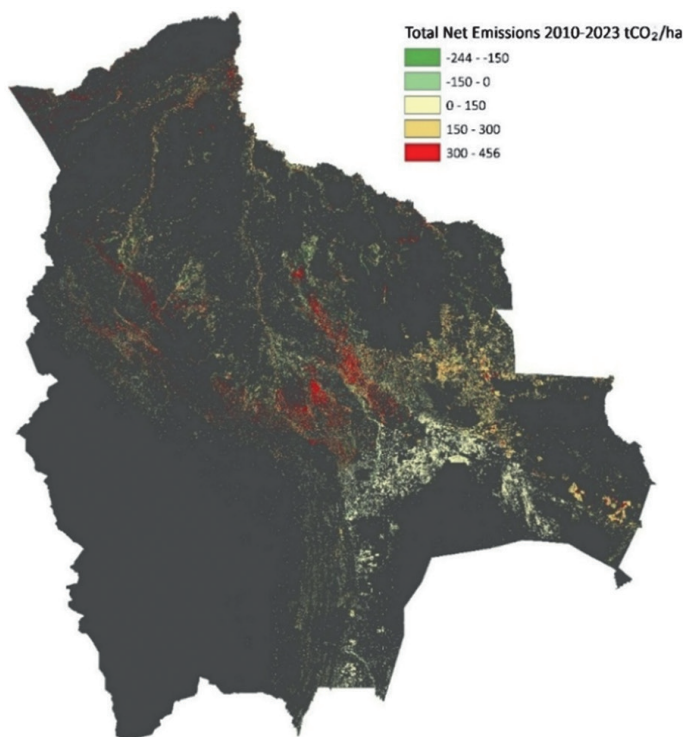
Table 5
Annual gross and net fluxes in tCO₂, 2010-2023

Year	Gross emissions	Gross removals	Net emissions
2010	70,298,334	15,596,420	54,701,914
2011	114,008,338	16,598,778	97,409,559
2012	88,444,942	17,325,381	71,119,561
2013	61,195,298	18,592,989	42,602,309
2014	79,514,407	19,401,399	60,113,008
2015	63,837,235	20,807,307	43,029,928
2016	84,264,743	21,862,016	62,402,727
2017	87,342,563	23,124,118	64,218,445
2018	87,690,467	24,298,907	63,391,560
2019	106,894,064	25,357,840	81,536,224
2020	91,211,892	26,950,907	64,260,985
2021	127,589,997	28,961,165	98,628,832
2022	103,342,167	31,076,186	72,265,981
2023	130,435,179	31,633,169	98,802,010
Total 2010-2023	1,296,069,625	321,586,581	974,483,044

Source: Authors' elaboration.

The net emissions map can be obtained spatially by overlapping maps of gross emissions and gross removals. The next map shows the distribution of net emissions.

Map 5: Net emissions in Bolivia 2010-2023



Source: Authors' elaboration.

All forest type zones produce net carbon emissions, but it is interesting to analyse cases separately. For example, Amazon forest has the highest gross emissions and highest gross removals ranking second in the net emissions, while Chiquitano forest has lower removals reaching the first place in net emissions.

Table 6
Cumulative gross and net fluxes by forest type in tCO₂, total of the period 2010-2023

Forest type	Gross emissions	Gross removals	Net emissions	% of total net emissions
Chiquitano	389,084,009	38,694,366	350,389,643	36%
Amazónico	515,836,471	185,808,365	330,028,107	34%
Chaqueño	139,716,441	16,844,942	122,871,499	13%
Llanuras Inundables	112,531,968	33,262,695	79,269,273	8%
Yungas	70,962,057	30,215,575	40,746,482	4%
Pantanal	29,497,381	4,259,554	25,237,827	3%
Tucumano – Boliviano	34,225,703	10,901,629	23,324,074	2%
Seco Interandino	3,873,437	1,441,251	2,432,186	0%
Andino	342,157	158,205	183,952	0%
Bolivia	1,296,069,625	321,586,581	974,483,044	100%

Source: Authors' elaboration.

Table 7 shows results relative to population and GDP, revealing an average annual emission of 6,6 tCO₂ *per capita*, much higher than the global average of emissions from land-use change of about 1.4 tCO₂ *per capita* (Global Carbon Atlas, 2023).

Table 7
Annual net fluxes per capita and per GDP unit, 2010-2023

Year	Net emissions (tCO ₂)	Net emissions per capita (tCO ₂ /person)	Net emissions per GDP unit (kgCO ₂ /Bs)
2010	54,701,914	5.6	1.7
2011	97,409,559	9.8	2.8
2012	71,119,561	7.1	2.0
2013	42,602,309	4.2	1.1
2014	60,113,008	5.9	1.5
2015	43,029,928	4.1	1.0
2016	62,402,727	6.0	1.4
2017	64,218,445	6.1	1.4
2018	63,391,560	5.9	1.3
2019	81,536,224	7.6	1.7
2020	64,260,985	5.9	1.4
2021	98,628,832	9.0	2.1
2022	72,265,981	6.5	1.5
2023	98,802,010	8.8	1.9
Average		6.6	1.6

Source: Authors' elaboration.

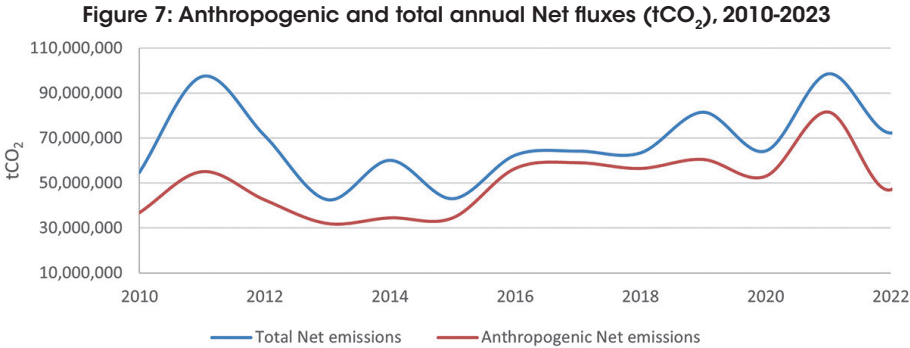
Note: Bs. is the abbreviation for the local currency, Bolivianos. At the official exchange rate, 1 Bs. ≈ US\$ 0.14, while in the informal market, 1 Bs. ≈ US\$ 0.07.

Forest cover loss can result from both human activities and natural factors. However, even when deforestation does not lead to an immediately clear human land use, it cannot be definitively ruled out as anthropogenic. In contrast, deforested areas where agriculture or infrastructure development is observed can be more confidently attributed to human-driven deforestation, and thus anthropogenic emissions. To ensure a comprehensive analysis, forest cover gains from agricultural abandonment were also considered as part of human-induced land-use changes. The results of this disaggregation are presented in Table 8 and Figure 7.

Table 8
Annual gross and net anthropogenic fluxes (tCO₂), 2010-2023

Year	Gross emissions	Gross removals	Net emissions	Total net emissions from clearly anthropogenic emissions (%)
2010	41,925,118	5,127,005	36,798,112	67%
2011	60,611,036	5,512,947	55,098,090	57%
2012	48,425,671	5,902,678	42,522,993	60%
2013	38,533,133	6,509,418	32,023,715	75%
2014	41,385,545	6,843,278	34,542,267	57%
2015	41,789,444	7,342,381	34,447,062	80%
2016	64,236,451	7,735,225	56,501,227	91%
2017	67,530,568	8,453,428	59,077,140	92%
2018	65,522,805	9,017,396	56,505,409	89%
2019	70,073,983	9,530,493	60,543,490	74%
2020	63,176,549	10,142,618	53,033,931	83%
2021	92,281,776	10,632,623	81,649,153	83%
2022	58,011,169	10,968,795	47,042,374	65%
2023	109,928,948	12,333,818	97,595,131	99%
Total 2010 - 2023	863,432,196	116,052,103	747,380,094	77%

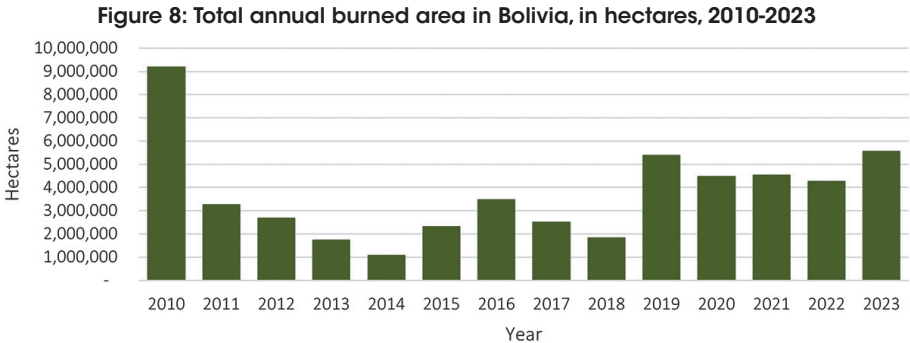
Source: Authors' elaboration.



3.2. Burned area and fire emissions

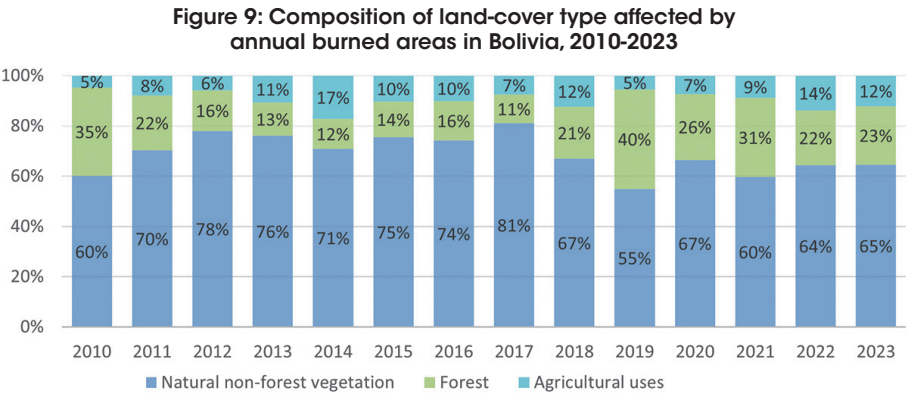
3.2.1. Burned area

As previously mentioned, the primary source for burned area data in this study is the MODIS burned area product. According to this dataset, burned area trends do not exhibit a stable pattern. However, in recent years, there has been an overall increase in burned surface area compared to the period before 2018, with the exception of 2010, which recorded an unusually high value. Figure 8 illustrates the total burned area in Bolivia from 2010 to 2023 according to MODIS data.



Source: Authors' elaboration based on MODIS (Giglio *et al.*, 2019).

Significant differences emerge when the data is disaggregated by land cover type. Figure 9 depicts this variation across different land cover categories. Natural non-forest vegetation is the main land cover within burned areas, followed by forest with a worrying 40% of the land cover affected by fire in 2019 and it exceeds 20% since then.

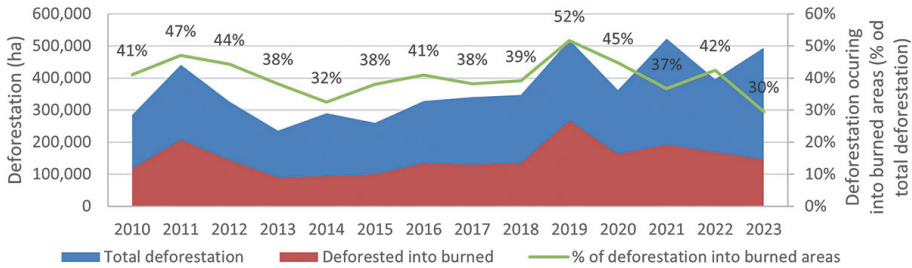


Source: Authors' elaboration based on MapBiomass Bolivia (2024) and MODIS (Giglio *et al.*, 2019).

Deforestation areas reach a maximum of about 500 thousand hectares annually and the average is about 360 thousand hectares per year. On the other hand, burned areas reached a total of more than 9 million hectares in 2010 and the minimum per year is over 1 million hectares. Forest within burned areas reached 3 million hectares in 2010 and 2 million hectares in 2019. Given that data we can conclude that forests are importantly affected by fires but only a small proportion of fires result in complete forest cover loss (deforestation).

Another important question is: how much of total deforestation occurs within burned areas? It is evident that deforestation is not a high proportion of burned areas, but burned areas represent a quite high proportion of the total deforested areas. On average, 40% of deforestation occurs within burned areas during the period of analysis (Figure 10).

Figure 10: Forest loss in burned areas in Bolivia in hectares, 2010-2023



Source: Authors' elaboration based on MapBiomass Bolivia (2024) and MODIS (Giglio *et al.*, 2019)

The analysis of burned areas suggests that fire emissions are primarily associated with the degradation of forest and non-forest vegetation, as the extent of deforestation within burned areas is smaller than that of burned forest and total burned areas.

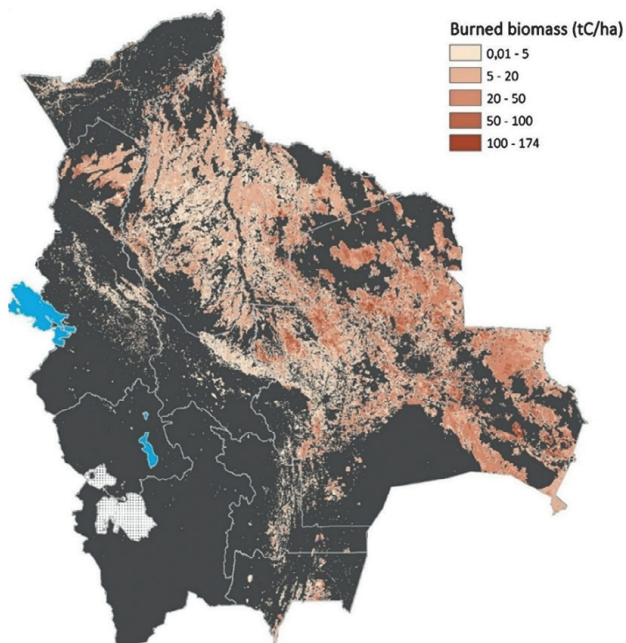
3.2.2. Fire emissions estimates 2010-2022

As previously mentioned, the data on fire emissions –expressed in terms of biomass burned and converted to carbon emissions– used in this analysis is sourced from the Global Fire Emissions Database (GFED). For consistency and ease of comparison with CO₂ emissions from deforestation, we focus on CO₂ emissions (Van Wees *et al.*, 2022). Spatial distribution of biomass burned offered by GFED is presented on map 6.

To identify the ecosystems most affected by fires, the “forest type zone” map is used as a reference to determine ecozones. This approach helps contextualize fire dynamics across broader ecological regions, recognizing that these zones include a variety of land cover types –not just forests. Based on this classification, and considering all areas affected by fire at least once between 2010 and 2022, the *Llanura Inundable* (flooded savanna) in the department of Beni stands out as the most impacted region. These savannas are predominantly wet for most of the year, but during the dry season (approximately June to October), they dry out considerably –coinciding with the peak fire season, often driven by agricultural practices.

However, because this area is primarily covered by non-forest vegetation, its fire-related emissions are relatively low. In contrast, the Chiquitano and Amazonian forest zones, where forests are the dominant land cover type, experience significantly higher fire emissions. This difference is reflected in Table 9.

Map 6: Total burned biomass in Bolivia 2010-2022



Source: Authors' elaboration based on GFED.

Table 9
Total burned area and total fire emissions by forest type zones, 2010-2022

Forest type zone	Total burned area 2010-2022 (ha)	Total fire emissions 2010-2022 (tCO ₂)
Chiquitano	3,615,175	528,611,000
Amazónico	3,234,275	386,069,985
Llanuras Inundables	8,682,750	333,915,528
Chaqueño	1,936,375	236,894,687
Pantanal	2,058,250	185,871,735
Tucumano – Boliviano	205,700	14,506,536
Yungas	112,875	8,338,657
Seco Interandino	35,650	856,809
Andino	95,800	796,610

Source: Authors' elaboration.

Note: "Total burned area" refers to the cumulative extent of land affected by fire during the study period, regardless of the number of times it burned. For example, if a surface burned multiple times, it is counted only once in this table. This differs from fire emission estimates, where emissions are accounted for each year a fire is recorded.

3.2.3. Fire emissions from forest degradation

Fire emissions estimates account for all burned vegetation emissions, including both forest and non-forest biomass. Also, these estimates encompass forest loss emissions as well as emissions from burned forests that remain as forest. To estimate the vegetation (forest and non-forest) degradation component, the approach used is to subtract deforestation-related emissions within burned areas from the total fire emissions estimates. Since previous results indicate that burned areas are significantly larger than deforested areas, and that less than half of the deforested areas are burned, the contribution of forest loss emissions within total fire emissions is expected to be relatively low. The results in Table 10 are consistent with the expected results.

Table 10
Fire emissions from degradation (tCO₂), 2010-2022

Year	Total fire emissions	Deforestation emissions within fire emissions area	Estimated emissions by vegetation degradation (forest and non-forest)
2010	327,003,752	6,321,279	320,682,473
2011	95,939,847	10,206,842	85,733,005
2012	63,349,127	7,841,899	55,507,228
2013	37,932,645	5,323,794	32,608,851
2014	32,535,906	6,901,800	25,634,106
2015	63,333,713	5,476,081	57,857,632
2016	123,506,171	7,258,626	116,247,545
2017	83,220,377	7,466,187	75,754,190
2018	74,671,144	7,417,110	67,254,034
2019	254,211,134	9,046,468	245,164,666
2020	173,223,478	7,544,756	165,678,722
2021	188,544,798	10,770,227	177,774,571
2022	182,655,519	8,494,051	174,161,468

Source: Authors' elaboration.

Table 11 shows that most of the areas impacted by fires correspond to natural non-forest vegetation. However, we cannot attribute the majority of emissions to this type of vegetation degradation, since forests store significantly larger quantities of biomass. This is also evident in Map 6, where the department of Beni –with a large extent of natural non-forest vegetation– shows a wide area affected by fire emissions. In contrast, the department of Santa Cruz –where

a greater extent of burned forest is found— exhibits higher fire emissions in terms of tons of carbon per hectare.

Table 11
Land cover composition in burned area in 2023 by forest type zone

Forest type zone	Natural non-forest vegetation	Forest	Pasture	Agriculture	Mosaic of uses	Non-vegetated area	Total
Llanuras Inundables	52.46%	5.42%	6.54%	0.17%	0.06%	0.43%	65.08%
Amazónico	6.56%	14.24%	0.95%	1.47%	0.29%	0.21%	23.72%
Pantanal	3.77%	0.27%	0.09%	0.00%	0.02%	0.00%	4.16%
Chiquitano	0.32%	1.39%	0.50%	0.62%	0.43%	0.01%	3.28%
Chaqueño	0.66%	1.25%	0.21%	0.59%	0.06%	0.01%	2.79%
Yungas	0.19%	0.48%	0.00%	0.02%	0.01%	0.01%	0.71%
Andino	0.13%	0.01%	0.00%	0.00%	0.00%	0.03%	0.17%
Seco Interandino	0.04%	0.01%	0.00%	0.00%	0.00%	0.00%	0.05%
Tucumano – Boliviano	0.02%	0.01%	0.00%	0.00%	0.01%	0.00%	0.04%
Total	64.15%	23.08%	8.29%	2.88%	0.89%	0.71%	100.00%

Source: Authors' elaboration.

Note: This table does not reflect forest cover loss; it only shows land cover types as classified in the year 2023 within burned areas.

To separate forest degradation from non-forest vegetation degradation is not an easy task. For example, if a fire emission pixel shows a total of 100 tons of carbon (in a 500m pixel), the pixel could be composed half of non-forest and half of forest. However, those 100 tons of carbon emissions will not be evenly split between the two. The majority of emissions are likely to come from the forest portion due to its higher biomass. Depending on the forest type zone, the median carbon content in natural non-forest vegetation ranges from nearly 0 tC/ha in the *Andino* forest type zone to 20 tC/ha in the *Amazónico* forest type zone. Moreover, the differences between the average and median values are much greater in natural non-forest vegetation than in forests. Therefore, this separation needs further analysis.

Another important consideration is that the estimated degradation emissions represent gross emissions. While fire-induced carbon losses may be partially offset by post-fire vegetation regeneration, this process is neither consistent nor easily predictable. As discussed below, evidence shows that regeneration does not always occur following fire events.

For example, a study conducted by Maillard (2023) aimed to estimate post-fire regeneration trends in Bolivian ecosystems using the Normalized Difference Vegetation Index (NDVI), a widely used indicator for assessing vegetation dynamics derived from satellite imagery.

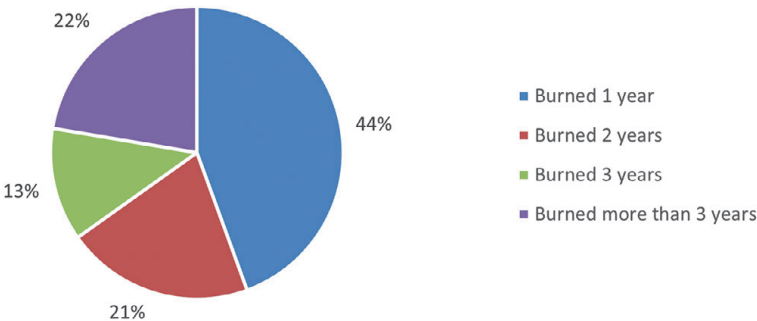
One key finding of the study was the recurrence of fires, meaning that some areas burn repeatedly over different years. The research also highlighted that different ecosystems respond differently to fire. For instance, the Chiquitano and Chaco ecoregions are better adapted to recover from fires, as many of their plant species are resilient to dry conditions and occasional natural fires. However, even in these fire-adapted regions, post-fire regeneration does not always occur.

Maillard (2023) found that 54% of the burned areas in Bolivia showed a significant increase in NDVI, indicating vegetation regeneration. Meanwhile, 30% of the areas exhibited mixed trends –both increasing and decreasing NDVI values– but these trends were not statistically significant. In contrast, 16% of the burned areas displayed a significant decreasing NDVI trend, suggesting ongoing degradation. Nearly half of the areas showing signs of regeneration were located in savannas, particularly in the department of Beni, where forest cover is minimal and the landscape is predominantly composed of natural non-forest vegetation.

Based on MODIS data from 2010 to 2023, we estimated the recurrence of fires across the same areas. The analysis shows that most burned areas were affected by fire in more than one year, either in consecutive or non-consecutive years. As shown in the following graph, 44% of the total burned area burned only once during the 2010-2023 period, while the remaining 56% burned in two or more years.

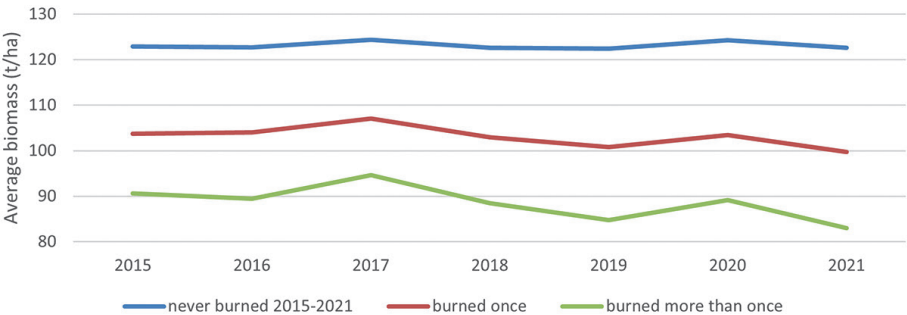
In addition, we estimated biomass changes looking forward to assess emissions from forest degradation caused by fire. The results show that biomass in unburned areas remained generally stable. In contrast, biomass in burned areas exhibited fluctuations with a slight decreasing trend, while areas that burned more than once showed more pronounced fluctuations and a clearer downward trend. Figure 12 shows the general trends.

Figure 11: Recurrency of burned areas, 2010-2023



Source: Authors' elaboration.

Figure 12: Average Forest biomass within burned areas, 2015-2021



Source: Authors' elaboration based on GFED.

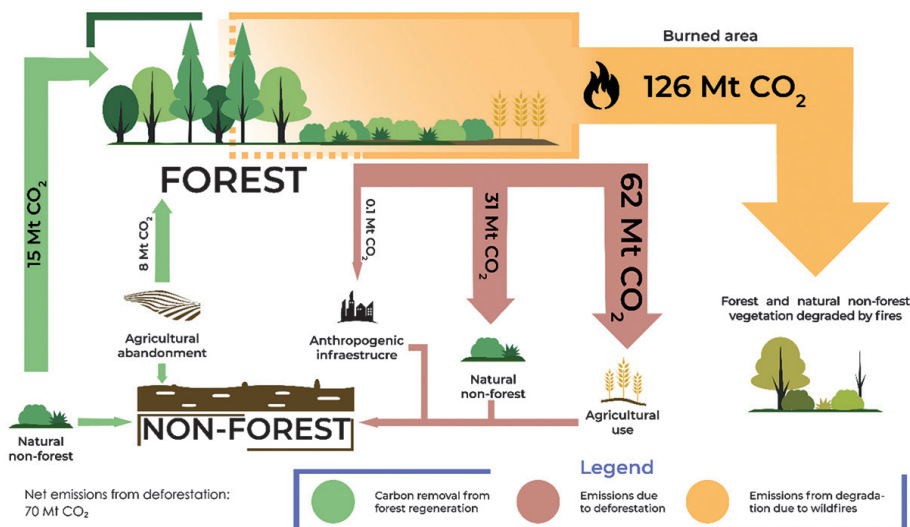
3.3. National results

Figure 13 summarizes the average annual carbon flows between different pools for the period 2010-2023. The largest flow –126 million tons of CO₂ per year– comes from fires that degrade forests without completely removing forest cover and to a lesser extent, from the degradation of natural non-forest vegetation. This is particularly concerning, as these emissions occur without any associated land-use change or productive land use that could offset the environmental cost.

The second largest flow –62 Mt CO₂ per year– is from deforestation driven by conversion of forest to agricultural land, while the third most important flow is from forest to natural

non-forest (31 Mt CO₂ per year). The latter changes are also problematic, as they appear to generate no clear economic benefit while contributing to forest loss. However, there are also significant changes from natural non-forest to forest, highlighting the dynamic and reversible nature of some land cover changes. This environmental fluidity adds complexity to estimating carbon emissions and removals.

Figure 13: Average annual carbon flows from land use change and fires, 2010-2023



Source: Authors' elaboration.

3.4. Subnational level results

3.4.1. Departmental level

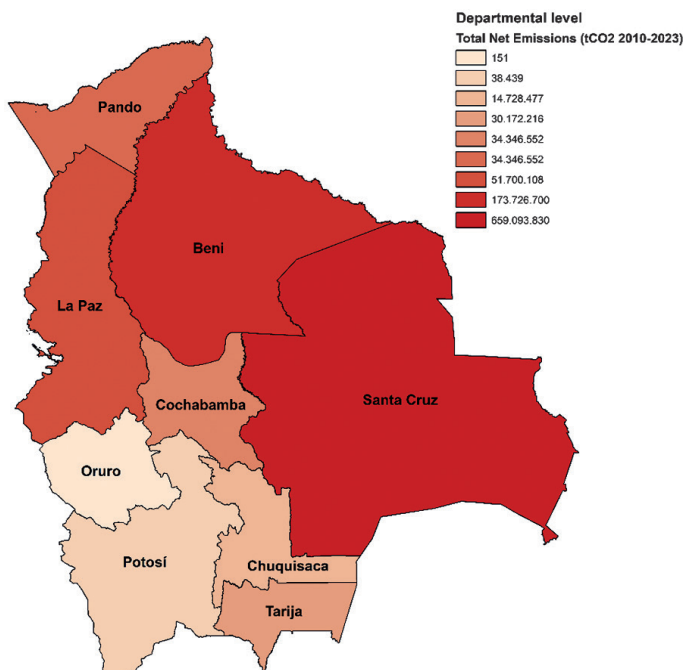
While total emissions from deforestation are highest in Santa Cruz, emissions *per capita* and *per GDP unit* are higher in Beni and Pando (see Table 12).

Table 12
Net emissions by deforestation by department, 2010-2023

Department	Total Net Emissions (tCO ₂ 2010-2023)	Average tCO ₂ /year	Average tCO ₂ /year/person	Average kgCO ₂ /year/Bs.
Santa Cruz	659,093,830	47,078,131	16.6	3.4
Beni	173,726,700	12,409,050	27.9	8.6
La Paz	51,700,108	3,692,865	1.3	0.3
Pando	34,346,552	2,453,325	20.8	6.6
Cochabamba	30,172,216	2,155,158	1.2	0.3
Tarija	14,728,477	1,052,034	2.1	0.3
Chuquisaca	10,676,571	762,612	1.3	0.4
Potosí	38,439	2,746	0.0	0.0
Oruro	151	11	0.0	0.0
Bolivia	974,483,044	69,605,932	6.6	1.6

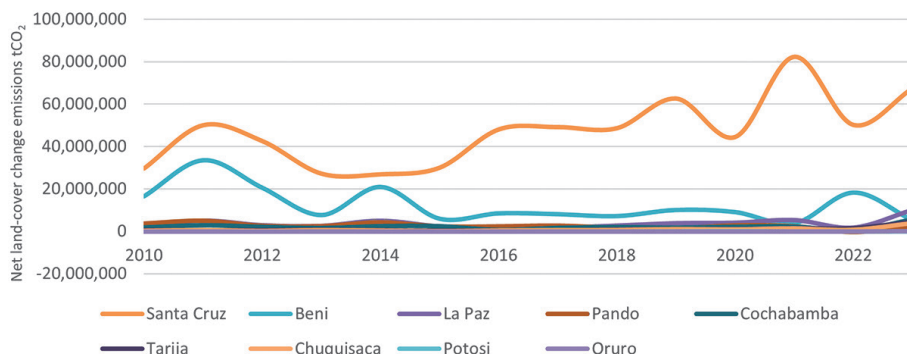
Source: Authors' elaboration.

Map 7: Total burned biomass in Bolivia 2010-2022



Source: Authors' elaboration.

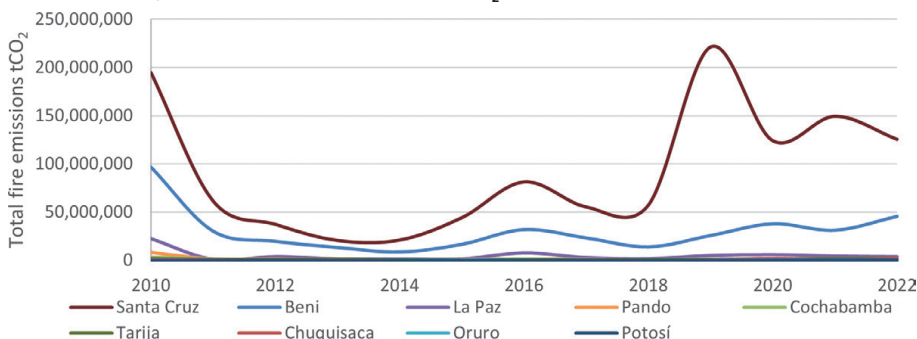
Figure 14: Net land-cover change emissions, by department, 2010-2022 (tCO₂)



Source: Authors' elaboration.

Fire emissions follow a similar pattern, as Santa Cruz is the department with highest emissions followed by Beni, while the remaining departments have experienced very low fire emissions most years.

Figure 15: Total fire emissions tCO₂, by department, 2010-2022

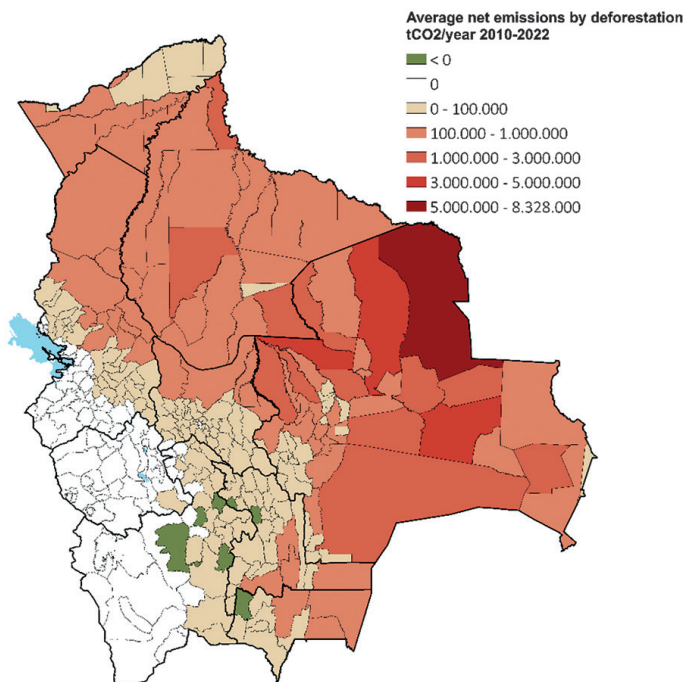


Source: Authors' elaboration.

3.4.2. Municipal level

In Bolivia there are 343 municipalities. Only 7 of them are net carbon sinks during the period of analysis with a maximum annual average of 65 tCO₂ net emissions in the municipality of Icla, department of Chuquisaca. Most municipalities especially in the southwest has almost zero emissions since there is almost no forest cover, while the east concentrates the municipalities with higher emissions.

Map 8: Average Net emissions from deforestation, 2010-2023



Source: Authors' elaboration.

To identify the municipalities with the highest net emissions from land-cover change, we used a combination of three key criteria: 1) Highest absolute emissions; 2) Highest emissions *per capita*; and 3) Highest emissions as a percentage of municipal biomass stock. The top 25 municipalities identified by each criteria are presented in Table 12 below.

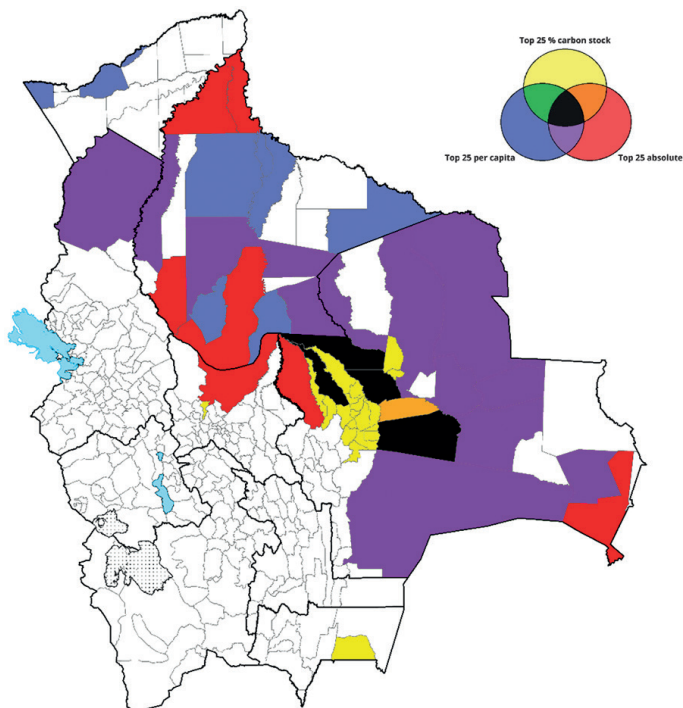
Table 13
Top 25 municipalities – by different measures of net
emissions from deforestation, 2010-2023

Absolute net emissions			Percentage of municipality's carbon stock		Emissions per capita	
Municipality	Average tCO ₂ /year	% of country emissions	Municipality	% emissions/ carbon stock	Municipality	Average tCO ₂ / person/year
San Ignacio de Velasco	8,327,712	12%	Colcapirhua	4.18%	El Carmen Rivero Tórrez	317
El Puente	3,657,417	5%	San Julián	4.09%	Puerto Siles	243
San José de Chiquitos	3,381,242	5%	Okinawa Uno	3.00%	El Puente	223
Concepción	3,347,241	5%	Cuatro Cañadas	2.23%	San Rafael	222
Ascención de Guarayos	2,747,962	4%	Santa Rosa del Sara	2.16%	San Miguel de Velasco	175
Pailón	2,712,631	4%	Fernández Alonso	1.79%	San Javier	150
Charagua	2,522,711	4%	Santa Cruz de la Sierra	1.76%	San Ignacio de Velasco	145
Santa Rosa del Sara	2,415,050	3%	Cotoca	1.74%	Concepción	142
Yapacaní	2,408,021	3%	Pailón	1.71%	Territorio Indígena Multietnico	129
San Miguel de Velasco	2,248,361	3%	Portachuelo	1.66%	Bella Flor	125
El Carmen Rivero Tórrez	2,238,589	3%	Colpa Bélgica	1.51%	Santa Rosa del Sara	119
San Julián	1,750,913	3%	Mineros	1.45%	San Andrés	107
San Rafael	1,604,501	2%	Tiquipaya	1.27%	Bolpebra	106
San Andrés	1,477,371	2%	Warnes	1.24%	Loreto	103
Santa Ana de Yacuma	1,391,468	2%	El Puente	1.20%	San José de Chiquitos	103
Guayaramerín	1,020,706	1%	San Pedro	1.10%	Ascención de Guarayos	94
San Borja	985,062	1%	San Ramón	0.93%	Baures	93
San Javier	902,678	1%	San Juan	0.91%	Santa Ana de Yacuma	80
Villa Tunari	896,614	1%	San Carlos	0.86%	Ixiamas	75
Puerto Suarez	845,820	1%	Montero	0.85%	Charagua	72
Ixiamas	810,880	1%	Porongo	0.75%	Exaltación	67
Riberalta	807,209	1%	Yacuibá	0.64%	San Joaquín	65
Cuatro Cañadas	803,958	1%	San Javier	0.59%	Reyes	63
Reyes	740,348	1%	La Guardia	0.59%	Pailón	60
San Ignacio	724,790	1%	General Saavedra	0.58%	San Julián	56

Source: Authors' elaboration.

The map below shows the top 25 municipalities by each criterion, and the intersection between criteria. In black, we see seven municipalities that rank within the top 25 according to all three emissions criteria. All are located in the department of Santa Cruz. Almost all of the municipalities losing a high percentage of their carbon stock are also located in this department, whereas municipalities with high *per capita* emissions, are found mainly in Pando and Beni. The black municipalities are clearly the most concerning

Map 9: Municipalities with higher emissions from deforestation in Bolivia



Source: Authors' elaboration.

3.5. Sensitivity analysis

The use of average biomass as the basis for biomass loss by forest type represents a key difference from other studies. Default IPCC biomass values for forest types are closer to the 75th percentile of biomass estimates derived from the biomass map used in this study

(Santoro & Cartus, 2024). To calculate average biomass, we combined data from intact forests up to 2010, using MapBiomass data to track intact forests from 1985 to 2010. Forests classified as intact until 2010 could be assumed to be at least 25 years old but mature forest could be older but not identifiable from the available data. Given that older forests likely fall within the 75th percentile of biomass content, we conducted an alternative bookkeeping model simulation using this higher biomass estimate.

Using the 75th percentile biomass as the default assumption led to a 23% increase in net emissions from land-cover changes, while the overall composition of net emissions across forest types remained similar. However, it is also possible that deforestation and fires would favour pixels with relatively open forest, which are cheaper to clear and which burn more easily. Thus, we redo the calculations using the 25th percentile biomass value for each forest type. This assumption implies that less dense forests are deforested first and that newly regrown forests contain lower biomass density than the average. Applying this lower biomass assumption results in a 27% reduction in net emissions.

Other modifications were applied to test the sensitivity of the results. Increasing soil carbon loss to 35% over 20 years –assuming more intensive agricultural use– led to a marginal increase of just 2% in net emissions.

3.6. Results in the Context of Other Studies

3.6.1. Comparison of results with previous studies

A previous study developed by Andersen *et al.* (2016) found an estimated average annual net emission of 65 Mt CO₂ for 1990-2000 and 93 Mt CO₂ for 2000-2010. Our results for the period 2010-2023 show an annual average of 70 Mt CO₂, with peaks exceeding 98 Mt CO₂ in recent years (2021 and 2023). This indicates that pressure on forests and their respective emissions have remained at high levels over the past three decades. *Per capita* emissions were reported at 9.4 and 10.4 tCO₂/person/year for the 1990s and 2000s, respectively. Our study finds an average of 6.6 tCO₂/person/year for 2010-2023 from deforestation only, while it is about 18.9 tCO₂/person/year taking both deforestation and fires into account.

3.6.2. Comparison of anthropogenic emission results with national and international sources

The first Biennial Transparency Report (1 BTR) (APMT, 2024) presents the results of the National Greenhouse Gas Inventory for the year 2022, which accounts for anthropogenic emissions and removals generated within the Bolivian territory. The 1 BTR, report total net emissions of 46.4 MtCO₂ for the LULUCF sector, while our study identifies 47.0 MtCO₂ of anthropogenic origin estimated emissions for the same year. These are the comparable results given that the official national reports are required to report only anthropogenic emissions.

The results of this study were also compared with the estimates of the Global Carbon Atlas for the period 2010-2023, a coincidence in the order of magnitude of net CO₂ emissions associated with land use change is observed. The differences can be explained by the resolution of the data and methodological assumptions, but together both results show a general consistency in the magnitude and trend of emissions from the forest sector.

Table 14
Comparable results of tCO2 emissions with Global Carbon Budget, 2010-2023

	Net emissions - Global Carbon Atlas	Net emissions results - present study
Cumulative emissions 2010-2023	852,246,400	974,483,044
Average annual emissions 2010-2023	60,874,743	70,752,394

Source: Authors' elaboration based on Global Carbon Atlas (2023).

4. Discussion

This study aimed to quantify and present CO₂ emissions from deforestation and degradation by forest fires in Bolivia. Separate analyses were conducted, and results are presented independently. To estimate degradation emissions, we subtracted deforestation-related emissions from fire-affected areas. However, integrating both into a single final estimate presents challenges that require careful consideration.

Table 14 shows net emissions from deforestation alongside fire-related emissions, where emissions from deforested areas have been excluded from total fire emissions. Additionally, a “total emissions” category has been included by summing both components. However,

these results should be interpreted with caution, particularly regarding fire emissions. This complexity may explain why the Global Carbon Budget (GCB) reports land-use change emissions and fire emissions separately, as they are not directly comparable.

It is important to consider that:

- Degradation emissions account for biomass loss across all vegetation types, not just forests. Most burned areas consist of non-forest vegetation with very low carbon content, except in the Amazónico, Chiquitano, and Chaco Forest zones, where biomass averages ~20 tC/ha.
- Due to explanations exposed in the fire emissions from degradation results, it is very difficult to try to make an assumption of the biomass relationship between forest and non-forest vegetation to disaggregate fire emissions from forest degradation and non-forest vegetation degradation. It would require a more in-depth analysis focused specifically on that topic which goes beyond the scope and duration of the present study.
- Fire emissions reflect gross annual emissions from burning but do not account for subsequent regeneration. Unlike regrowth after deforestation –which can be tracked using land-use change and transition maps– post-fire regeneration is harder to quantify. Estimating net emissions from fires would require annual biomass maps and potentially additional data, such as fire intensity, fire duration, and other variables relevant to both the extent of degradation and post-fire regrowth rates. As shown by exploratory results presented in the fire analysis section, the annual biomass data we have, is not enough to support definitive conclusions.

With these considerations in mind, the following table provides an approximate estimate of total annual emissions from both fires and deforestation.

Table 15
Annual fluxes (tCO₂) from deforestation and degradation by fire, 2010-2022

Year	Deforestation Net emissions	Estimated emissions by degradation	Total emissions
2010	54,701,914	321,194,068	375,895,982
2011	97,409,559	90,947,327	188,356,887
2012	71,119,561	60,287,903	131,407,463
2013	42,602,309	36,514,693	79,117,002
2014	60,113,008	30,208,427	90,321,435
2015	43,029,928	61,160,012	104,189,940
2016	62,402,727	119,454,330	181,857,057
2017	64,218,445	79,566,359	143,784,803
2018	63,391,560	71,405,972	134,797,532
2019	81,536,224	245,912,314	327,448,539
2020	64,260,985	168,619,422	232,880,408
2021	98,628,832	181,667,620	280,296,452
2022	72,265,981	172,404,627	244,670,609

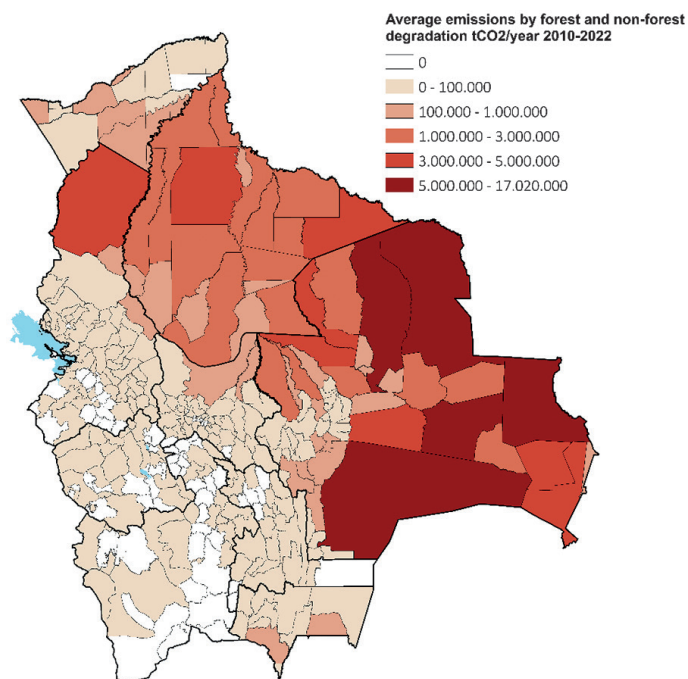
Source: Authors' elaboration.

Map 10 shows the distribution of the estimated emissions by degradation.

Although there is significant year-to-year variation, with 2010 standing out as an extreme year for forest fires, the past four years (2019-2022) have consistently recorded exceptionally high emissions from both deforestation and fire-induced forest degradation, as forest constitute a higher proportion of land cover within burned areas compared to the previous years.

While natural climate variability, including shifts in rainfall patterns and wind dynamics, will continue to drive fluctuations in deforestation and fire activity, Bolivia's forests are now more fragmented and frequently burned than ever before. As a result, they have become increasingly vulnerable to external threats, making them more susceptible to future degradation and carbon losses than in the past.

Map 10: Average emissions from degradation by fire, 2010-2022



Source: Authors' elaboration.

5. Conclusions

Deforestation rates in Bolivia remain high and continue to rise, leading to a corresponding increase in carbon emissions. The majority of emissions due to forest loss are directly attributable to anthropogenic activities, and even the smaller remaining portion cannot be discarded as influenced by human-driven factors.

The highest emissions are concentrated in the department of Santa Cruz, though recent trends show a slight geographical expansion compared to previous decades. Among the top 25 municipalities contributing the most to national emissions, most are located in Santa Cruz and Beni, with one in La Paz and another in Cochabamba.

While deforestation emissions are highly attributable to land-use change, fires affect much larger areas, and in most cases, no clear land-use change is observed following the fires.

Between 2010 and 2023, Bolivia lost over 5 million hectares of forest, leading to average annual emissions of around 70 million tons of CO₂ from deforestation. In addition, fire-related emissions from forest and non-forest vegetation degradation averaged 126 million tons of CO₂ per year. On a *per capita* basis, this translates to an annual average of approximately 6.6 tCO₂ from deforestation and 12.3 tCO₂ from fire-related degradation –emission levels that are high compared to those of other sectors and countries.

The different forest types present in Bolivia lead to variations in carbon emissions and removals. Forests such as the Amazonian, Yungas, and Chiquitano show high potential for both carbon absorption and emissions, while the Chaco forest currently stands out as a major emitter due to its large spatial extent of affected forest. This study provides guidance for prioritizing areas of focus; however, for smaller areas of interest, more detailed studies are recommended –particularly those incorporating field-based biomass measurements– for forest types with highly variable biomass content.

The estimates presented in this research represent one of the first efforts to disaggregate emissions from deforestation and forest degradation in Bolivia. However, a degree of uncertainty remains. Fire-related data, in particular, offers significant opportunities for further exploration and could be examined in greater depth in future analyses. For instance, further analysis of fire-related data –considering forest types, land cover categories, fire recurrence, and more detailed breakdowns– could enhance our understanding of fire emission dynamics. This includes explaining patterns such as the relatively low emissions from fire-related deforestation –partly due to the fact that about one-third of this deforestation occurs in the Chaco region, which has lower biomass density’.

6. Resources

An Excel workbook with all the calculations and results at the municipal level accompanies this article, as do raster maps of net carbon emissions from deforestation at the 100x100m resolution and total fire emissions at the 500x500m resolution. All files can be freely downloaded from the following folder:

<https://drive.google.com/drive/u/0/folders/1BoXRaWo55GiDYfh8HUhlWp9F1KfHh-x->

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