Uncovering Sub-Regional Drivers of Deforestation in the Amazon: A Tool for Targeted Solutions

Key takeaways

1.

The expansion of agricultural land use—pastures and cropland—is the main driver of deforestation across the Amazon region[1]. However, the data presented here also show substantial areas of forest degradation throughout the Amazon; highlight the important role of mining in driving deforestation in the Guiana Shield; and indicate that land speculation and indirect land-use change are likely to be prominent drivers of deforestation.

2.

Agriculture-driven deforestation shows a declining trend in most Amazon countries in recent years (2017-2022), with the exception of Brazil—where it is relatively stable—and Ecuador—where it is much higher than historical levels. Despite cropland expansion accounting for only 22% of total deforestation between 2017-2022, compared to 78% from cattle ranching, trends indicate that it is becoming a more prevalent driver of deforestation across the Amazon region, particularly in Bolivia, Ecuador, Peru, and Venezuela. Sub-national deforestation patterns across the Amazon reveal distinct drivers (2017-2021), with pasture dominating in the eastern and central portions of the Amazon—but advancing into the interior of the region,and crop expansion—particularly soy in Bolivia and staples like maize, rice, and cassava in Peru and Venezuela—prevailing in the western, southern, and northwestern subregions. These results highlight the need for targeted strategies and interventions to address deforestation, tailored to specific sub-national contexts.

3.

A key limitation in uncovering explicit drivers of deforestation is the availability of high-quality land use data. Such data is crucial for understanding complex land-use change dynamics and for accurate attribution of deforestation to specific commodities. Additionally, this data is essential for gaining deeper insights into the impacts of socio-economic factors, such as market dynamics, trade, and finance, on deforestation at a more granular, sub-national scale. Closing this data gap requires active collaboration among state agencies, research institutions, NGOs, and the private sector, ensuring comprehensive data collection, knowledge sharing, and resource coordination to better inform policy actions towards effectively halting deforestation.

[1] We are referring here to the Amazon limits as defined by the Amazon Network of Georeferenced Socio-Environmental Information RAISG [1].

Summary

This technical brief provides the first region-wide analysis of the commodity-specific agricultural drivers of deforestation across the Amazon region at a sub-national level, offering insights to inform more effective and equitable conservation policy. We achieve this by integrating sub-national agricultural production statistics with satellite data on land use and commodity production for each country within the Amazon region. By enhancing the granularity of commodity-specific deforestation, this information can empower (sub-)regional and national actors, as well as policymakers, to develop targeted solutions that support sustainable land use planning and forest conservation policies tailored to each distinct country and sub-national realities.

Introduction

The Amazon rainforest, a cornerstone of global biodiversity and climate regulation, is approaching a critical tipping point [2]. Deforestation rates, despite showing historical signs of reduction, continue to persist, pushing these ecosystems toward a tipping point from which recovery may become increasingly difficult [3,4]. Historical successes, such as the significant reductions in deforestation achieved under Brazil's 'Action Plan for the Prevention and Control of Deforestation in the Legal Amazon (PPCDAM)' program phases 1 and 2 (2004-2011) [5], demonstrate that curbing deforestation is possible. However, these gains were not sustained, and despite the persistence of sectoral and voluntary commitments such as the soy moratorium [6], the absence of strictly enforced public policies meant deforestation rates in the Brazilian Amazon rose again in the period after 2010, and in particular, after 2019 [7]. Moreover, while the Brazilian Amazon has historically been a major contributor to overall deforestation in the region, recent trends indicate fast-growing deforestation in the western Amazon, particularly within the Andean-Amazon countries [8]. Achieving a more comprehensive understanding of diverse deforestation drivers and their associated trends across and within the Amazon countries at sub-national level is crucial for informing public and private policy strategies and actions, monitoring their implementation, and assessing their effectiveness in halting deforestation.

The upcoming convergence of the UN Convention on Biological Diversity COP16 and UN Climate Change Conference COP30, both of which are taking place in Amazonian countries, presents a unique opportunity to strengthen international collaboration among these countries, as well as with the global community. The recent Belem Declaration (Amazon Presidential Summit, 2023), signed by the members of the Amazon Cooperation Treaty Organization (ACTO), renewed their regional commitment to jointly mitigate climate change, sustain biodiversity, address illegal deforestation, and promote forest conservation, paving the way for more sustained and effective change [9].

However, ACTO must operate under circumstances that are significantly more challenging than previous private and public policy have had to deal with [10]. Despite attempts by some sub-national jurisdictions to curb rising deforestation rates, large areas of the Amazon basin are facing an unprecedented crisis in 2024: the most devastating fire season ever recorded [11]. These fires, often linked to deliberate forest-clearing practices and the obstruction of access for fire brigades and environmental agencies, amplify rainforest degradation by intensifying regional droughts and creating the dry conditions in which fires thrive, decimating biodiversity at an unprecedented scale [12]. These relentless assaults are driven by a complex interplay of factors, including agricultural expansion—particularly the push of low-productivity cattle ranching into the forested frontiers fuelled indirectly by the pressures of expanding soy production, such as in Brazil [13]. Addressing the damage to the Amazon rainforest caused by these complex socio-economic and environmental factors requires active monitoring to identify and mitigate these threats.

> Leveraging the best available spatial and statistical datasets, this technical brief identifies commodity-specific direct drivers of deforestation at the finest possible spatial scale.

Understanding these sub-regional deforestation patterns can enable decision-makers to tailor sustainable land use policies to each sub-national boundary without losing sight of the disparities across countries and different subregions of the Amazon. This approach allows the identification of key commodities and deforestation hotspots, enabling evaluation of the effectiveness of conservation policies. Such learning can help the adoption of successful strategies in other regions. Tracking and addressing the trade of deforestation-risk commodities at a sub-national scale can also inform actionable measures by the responsible stakeholders, thereby pinpointing areas where urgent action is needed to combat deforestation more effectively.

Deforestation assessments and opportunities for improvement

Accurately estimating deforestation and linking it to the production of commodities poses several methodological challenges. Current efforts are often limited to the national level, primarily relying on assessments that use nationally aggregated agricultural statistics (e.g., FAOSTAT), which can obscure land use dynamics at a more granular scale [14]. Moreover, the lack of widespread integration of spatially explicit data in these assessments—due to computational challenges in processing large datasets—reduces their accuracy in identifying the drivers of deforestation [15]. However, in rapidly evolving agricultural systems, correlating deforestation rates with production statistics without considering the actual spatial expansion of agriculture can lead to erroneous conclusions. For instance, crops expanding over non-forested lands (e.g., natural non-forest ecosystems or degraded pastures) are incorrectly associated with deforestation [16], resulting in misplaced accountability and ineffective policy responses. Addressing these challenges requires more refined spatial data to enhance the accuracy and relevance of deforestation analysis, allowing for better-informed conservation strategies.

Furthermore, when using satellite data, it is crucial to recognize that not all detected changes in tree cover represent deforestation (Figure 1); some may reflect forest degradation or losses due to other disturbances (e.g., forest fires). **Identifying deforestation—where natural forests are converted to other land uses—and linking it to commodity production requires the integration of high-quality spatial and statistical datasets that can help identify these finer land use and land-use change dynamics over time.**

Additionally, it is also important to acknowledge that while such data is readily available in Brazil [17,18], it has historically been lacking in most other Amazonian countries. Our deforestation attribution approach aims to address these challenges by integrating the best available spatial (e.g., MapBiomas [17]) and statistical datasets, enhancing deforestation attribution across the entire Amazon region. By leveraging high-quality, detailed data, we aim to enhance the accuracy and granularity of deforestation assessments, enabling more effective and targeted conservation efforts. Our analysis uses the boundaries for the Amazon region of RAISG [1], which are larger than the Amazon biome (see also Figure 1).

Box 1: Deforestation attribution model

The deforestation attribution in this technical brief is based on the Deforestation Driver and Carbon Emission (DeDuCE) model [19], which has emerged as a powerful tool for tracking global drivers of deforestation by integrating the best available spatial and statistical datasets for multiple countries and commodities (e.g., supporting Global Biodiversity Framework's Target 16 through 'The Global Environmental Impacts of Consumption (GEIC) Indicator' [20,21]). For this Technical Brief, we have incorporated new sub-national data on agricultural land use for the Amazon countries to be able to provide a more granular understanding of commodity-driven deforestation across the Amazon region.

The model achieves this by overlaying global spatio-temporal data on tree cover loss (from the Global Forest Change dataset (GFC) [22]; identifying complete removal of tree cover, i.e., vegetation greater than 5 metres in height, at a 30-m pixel scale) with datasets on crop commodities (e.g., soy [23]), land use (e.g., MapBiomas [17]), dominant drivers of forest loss [24], among other forest management and disturbances datasets (e.g., fire-induced tree cover loss [25]), to identify deforestation and its drivers using the best available data per pixel. Distinguishing between deforestation and forest degradation is enabled by the spatio-temporal coverage of the MapBiomas dataset (see Box 2 for more information).

In instances where deforestation cannot be directly associated with a specific commodity, the model utilised agricultural statistics—at the national and sub-national level—to infer the most likely or potential drivers of forest loss. For deforestation attribution for Amazonian countries, the Global Subnational Agricultural Production (GSAP) dataset [26] is used, wherever available. The GSAP dataset is a collection of official sub-national data from sources like national statistical offices, agricultural ministries, censuses, and surveys. This data has been scraped from source materials, processed, and then cleaned using AI-based optical character recognition and pattern matching to extract information on agricultural statistics. To ensure consistency, geographical units, crops, and measurements were standardised with GADM [27] and FAO crop codes [28].

Details of the modelling framework, along with the spatial and statistical datasets used as inputs, are available in Singh and Persson [19]. Commodity-level deforestation estimates for each country and region are available at https://www.deforestationfootprint.earth/Amazon.

Amazon deforestation (2001-2022)

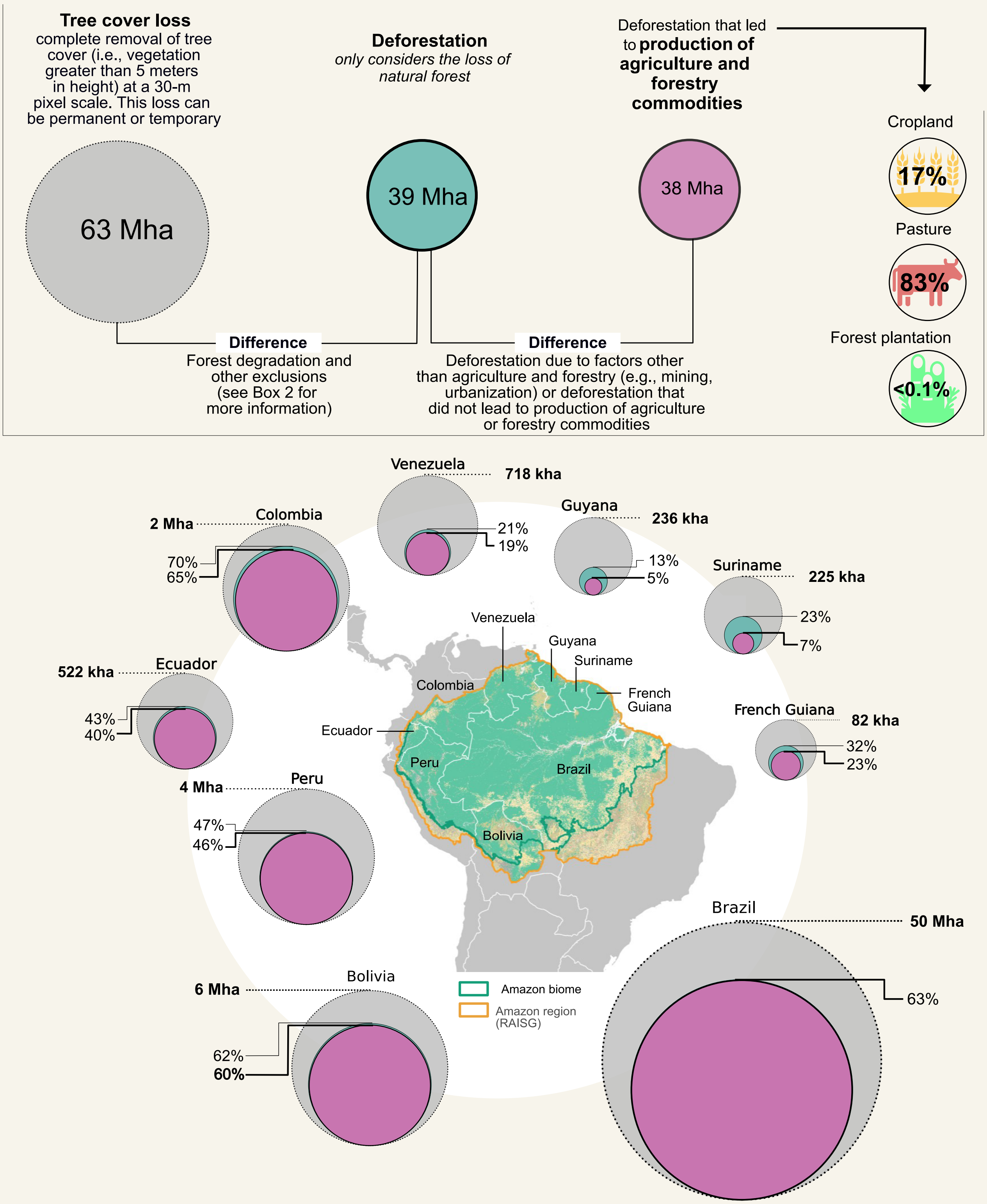

Figure 1. Assessing deforestation linked to agriculture and forestry activities from global tree cover loss estimates (2001-2022). The deforestation assessment undertaken here corresponds to the maximum combined extent of both the Amazon biome and the Amazon delineation as defined by RAISG [1].

Insights from national and sub-national deforestation assessment

Not all tree cover loss is deforestation, but the majority of deforestation is driven by cattle ranching and crop cultivation. The results from the DeDuCE model identify agriculture (i.e., due to pastures and crop commodities) and forestry as the major drivers of deforestation in the Amazon, accounting for 38 million hectares (Mha) of the total 39 Mha deforested between 2001 and 2022 (Figure 1). Of this deforestation, pasture expansion is responsible for nearly 83%, with crop commodities contributing 17%, and forest plantations (primarily for timber) representing a minor share. Deforestation driven by agriculture is particularly significant in Bolivia, Brazil, Colombia, Ecuador, French Guiana, Peru, and Venezuela. Only a small portion of deforestation is attributed to agriculture in Guyana and Suriname, since mining activities are a major driver of deforestation in these countries [29]. Mining operations in other Amazonian countries also contribute to deforestation [30,31]. Although the direct land-use change from mining operations is relatively limited, their indirect impacts—such as farming around mines and forest-clearing for settlements, and further incursion of miners into forestlands—are often several times greater than the deforestation directly linked to mining activities [32,33]. Additionally, mining leads to significant environmental impacts such as river sedimentation and water contamination. In the case of illegal gold mining, the use of toxic mercury results in grave repercussions for the health of local and indigenous communities, and affects the wildlife in the region [34].

An analysis of the temporal trends in agriculture-driven deforestation (Figure 2) reveals widely heterogeneous patterns across the Amazon. In recent years (2017-2022), most countries, particularly Bolivia, Guyana, Peru, and Venezuela, have shown a slowdown in agricultural deforestation. Despite a decreasing trend in agricultural-driven deforestation (Figure 2), the Bolivian Amazon also shows an increasing tree cover loss (see link in Box 2). This discrepancy may be attributed to a rise in forest degradation caused by forest fires in recent years (2019–2023). While many of these fires are deliberately set to clear land for agriculture [35,36], Bolivia has also experienced increasingly hot and dry conditions in recent years due to the combination of climate change and the El Niño phenomenon [37]. Under these conditions, fires can sometimes spread uncontrollably into forested areas, disrupting local communities. In contrast, Brazil's deforestation rates have remained relatively stable, while Ecuador has shown a noticeable increase. Interestingly, while pasture expansion remains the primary driver of deforestation across Brazil, Colombia and Guianas (Figure 1), certain countries, such as Bolivia, Ecuador, Peru, and Venezuela, have witnessed more deforestation driven by crop commodities in recent years (Figure 2).

Land speculation impacts are not apparent but significant. For Amazonian countries, not all deforestation due to agriculture and forestry activities is directly tied to commodity production. Our results suggest that between 2-16% of the deforested area in the Amazon remains unproductive or associated with commodities other than agriculture (Figure 1). In many cases, immediate drivers of deforestation (i.e., the establishment of agricultural land after deforestation) often mask a deeper, more insidious force: land speculation driven by anticipated future profits from commodity production [38]. Financial drivers, particularly those related to the land market and not directly linked to the production of specific commodities, pose a significant challenge for conventional attribution methodologies. These drivers typically involve purchasing forested land with the intent to clear it for future agricultural expansion, engage in illegal activities, or simply hold it as a speculative investment.

Often during the waiting period, selective logging or small-scale clearing may take place, leading to temporary forest degradation without immediate conversion [39]. This speculative process operates on a temporal scale different from that of direct drivers of deforestation, and often does not show a clear or immediate conversion from forest to agricultural land. These regions may fall under the category of tree cover loss not directly associated with deforestation, including 14 Mha of loss over forest formations and 1 Mha of fire-induced forest degradation (Box 2). **These values suggest a potential risk to the Amazon that is comparable to the deforestation driven directly by the expansion of productive agricultural land (Figure 1).**

Additionally, the detection of scarce vegetation, often classified as pasture by satellite data, may result in deforestation being attributed to cattle ranching (Figure 1), even though the land remains at a low level of productivity while awaiting appreciation or a future sale for the production of another commodity [40], while some can stay over time as pasture for beef production. Consequently, the impact of certain commodities, such as soy, may often be underestimated, while the impact of others, like cattle pasture, might be overstated.

Box 2: Degradation — Tree cover loss not associated with deforestation

The debate surrounding whether the tree cover loss detected by satellite data constitutes deforestation has been ongoing for some time [41]. Tree cover loss data captures the annual loss of all trees taller than five metres within a 30-metre pixel between 2001 and 2022. This includes the loss of trees in both natural forests and plantations or tree crops, and it can result from human activities or natural disturbances. Moreover, the loss can be permanent or temporary.

To distinguish between deforestation (where natural forests are permanently converted to other land uses) and forest degradation (where forest structure deteriorates without full tree cover removal due to natural or human disturbances), we use the spatio-temporal coverage of the MapBiomas dataset. When associating drivers of loss with specific tree cover loss pixels in a given year, we also check the land use of that pixel in the year 2000 to assess the initial state of the ecosystem. For example, if we detect tree cover loss (from the GFC dataset) linked to agriculture (from the MapBiomas dataset) in 2010, but the pixel was already classified as agricultural land in 2000, we consider this as loss over managed land systems and not as a loss of natural forest.

This gives us several combinations which we classify as forest degradation and other exclusions (24 Mha), the majority of which are due to:

1.
Tree cover loss detected over forest formations (14 Mha): In cases where tree cover loss is identified by the Global Forest Change (GFC) dataset, but MapBiomas classifies the pixel as forest formations in both 2000 and the year of loss, we classify it as degradation. Such losses can be expected in some forest areas as they experience natural cycles of tree loss and regrowth, e.g., from droughts, windthrows, pests, diseases, or natural die-offs. These events can be detected as "tree cover loss" but don't represent permanent deforestation. Additionally, selective logging, where specific trees are removed while others are left intact, creates temporary canopy gaps which may regenerate over time, restoring the tree cover to its original state. We also find that some such patterns along forest edges (e.g., small-scale clearing and minor construction activities) may cause temporary canopy loss that is detected by satellite data. While these are often small-scale and reversible, these could happen both because of model uncertainties in GFC (suggesting tree cover loss over the edges of forest formations) and MapBiomas (classifying the edges of deforested land use as forest formation).

2.
Tree cover loss in non-forest natural formations (4 Mha): When GFC detects tree cover loss but MapBiomas classifies the pixel as non-forest natural formations in both 2000 and the year of loss. This includes natural ecosystems like savannas and flooded forests, which are prone to disturbances such as fires or (flash) floods—part of their natural cycles—that result in apparent tree cover loss. While part of these ecosystems might experience permanent loss of tree cover, they are not considered natural forests in our analysis, and are thus not included in deforestation estimates.

3.
Tree cover loss on pre-existing agricultural and plantation land (5 Mha): Tree cover loss detected on land classified as agricultural in 2000 suggests these areas were deforested before 2000, experienced some regrowth, and were later cleared again, often due to rotational clearing on established plantations or shifting agricultural practices.

4.
Fire-induced forest degradation (<1 Mha): Our deforestation attribution framework assumes a lag of up to three years from the year of tree cover loss to allow for the establishment of agricultural land. This helps distinguish between deliberate clearing of forest by fire and losses due to natural fires. Tree cover loss not followed by commodity-driven land use change within this timeframe is categorised as fire-induced forest degradation.

While we suggest such dynamics based on spatial patterns of tree cover loss and MapBiomas land use, it is important to acknowledge that both datasets rely on algorithms to classify land cover and land cover dynamics. Errors or biases in these algorithms (e.g., due to cloud cover, sensor errors, or misinterpretation of spectral signals) could lead to discrepancies between detected tree cover loss and the Mapbiomas land cover classification.

It's also important to note that while some of this degradation may result in the permanent loss of natural forest ecosystems, which has serious impacts on climate and biodiversity [42], linking them to commodity production and assessing their potential impacts is challenging, and is not the primary focus of this technical brief.

Tree cover loss statistics for each country and region are available at https://www.deforestationfootprint.earth/Amazon.

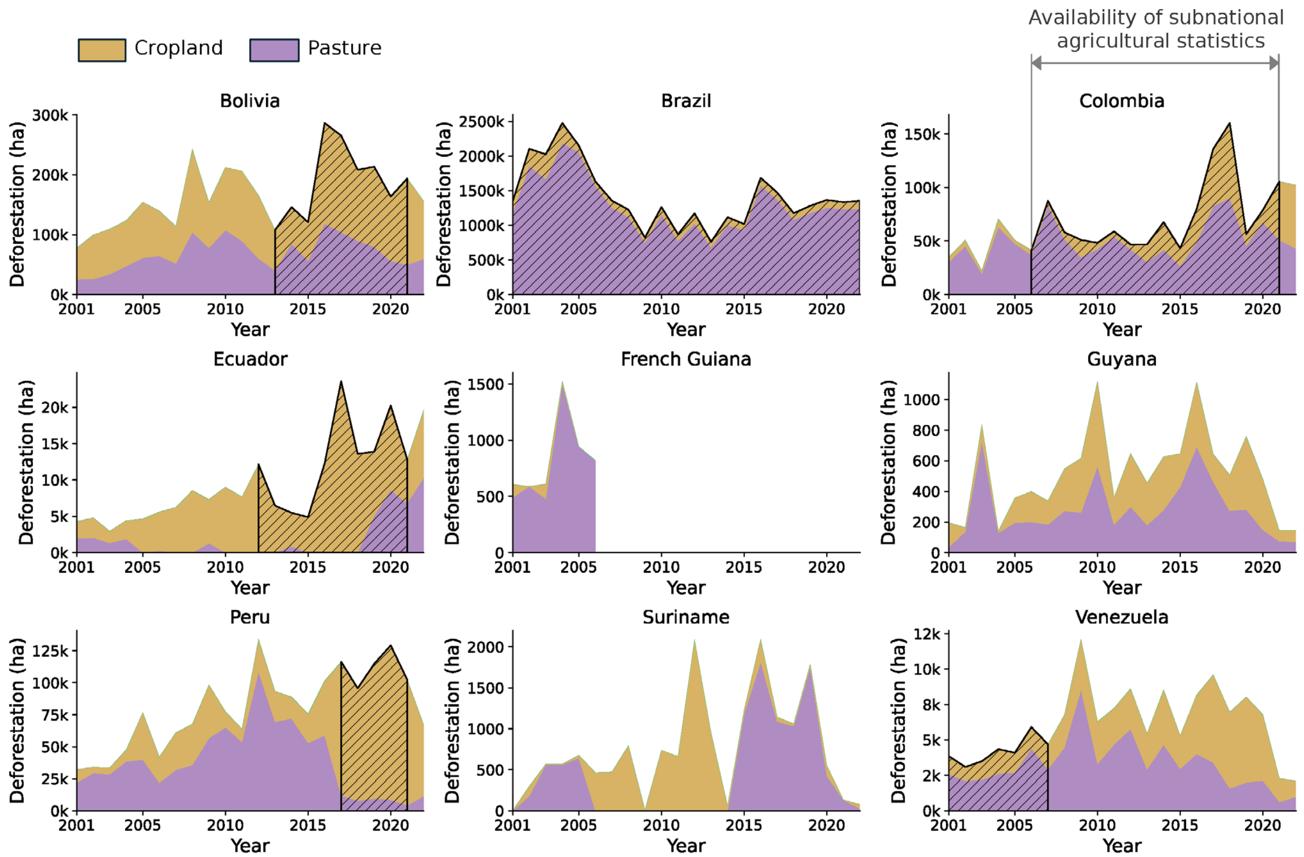

Figure 2. Deforestation trends in the Amazon driven by the production of commodities associated with cropland, pasture and forest plantation expansion (2001-2022). While deforestation from forest plantation expansion is included in this plot, its impact is less prominent due to the comparatively smaller area affected when contrasted with cropland and pasture-driven deforestation. The hatched area represents the time frame during which sub-national agricultural statistics were available and utilised for sub-national deforestation attribution in the DeDuCE model.

Sub-national deforestation estimates reveal contrasting patterns:

While national-level deforestation estimates are crucial for understanding the role of agriculture and forestry in forest loss across the Amazon region (Figures 1 and 2), they may not be sufficient for developing targeted strategies to address deforestation within specific subregions. The deforestation estimates derived from this sub-national DeDuCE model reveal contrasting patterns across the Amazon basin (Figure 3).

In the eastern and central Amazon, pasture (primarily for cattle meat production) plays a dominant role in driving deforestation (mostly observed in the Brazilian Amazon). Meanwhile, in the western Amazon (parts of Bolivia, Ecuador, and Venezuela), deforestation is largely driven by crop expansion, with both crops and pasture being significant drivers in the southern and northwestern subregions (Figure 3). Furthermore, in areas of the eastern Brazilian Amazon, southern Bolivian Amazon, and Colombian Amazon, deforestation is being driven by both pasture expansion and crop commodities, particularly due to the cultivation of soy, cocoa, maize and rice (Figures 3 and 4).

We find that soy-related deforestation is particularly prominent in the Bolivian Amazon, cocoa and oil palm plantations drive deforestation in Colombia, Ecuador and Peru. Furthermore, staple crops like maize, rice, and cassava contribute significantly to deforestation in the Peruvian and Venezuelan Amazon (Figure 4).

These staple crops are vital for future food security, as they make up half of the average human diet [43], yet they often receive less attention compared to cash crops when estimating their role in deforestation. Illicit production (e.g., coca crops), can also contribute to the discrepancy between deforestation rates and reported agricultural production—such as in the case of Colombia, Bolivia and Peru—as they are not reported in official statistics [44].

The availability of sub-national deforestation estimates also highlights spatial heterogeneity in trends across different national and sub-national jurisdictions (Figures 2 and 5). While deforestation for cattle production is slowing in both the eastern and western Amazon, the central Brazilian Amazon has experienced a significant increase in recent years (Figure 5). The most plausible explanation for this pattern is the indirect effects of soy expansion, which has displaced pastures deforested before 2008, subsequently driving cattle ranchers to open new natural areas in the central Amazon. These trends are not apparent at the national level, where pasture-induced deforestation in Brazil has remained stable in recent years, but highlight the continuous advancement of the deforestation frontier into the interior of the Amazon region (Figures 3 and 4). Moreover, while soy-related deforestation is decreasing in Bolivia, a moderate increase is observed in the eastern Brazilian Amazon. Similar spatially varied patterns are also evident for maize and rice across different sub-national jurisdictions (Figure 5).

Total Deforestation (2017-2021): 8.9 Mha Subnational estimates for: Bolivia, Brazil, Colombia, Ecuador and Peru
National estimates for Guyana, Suriname and Venezuela

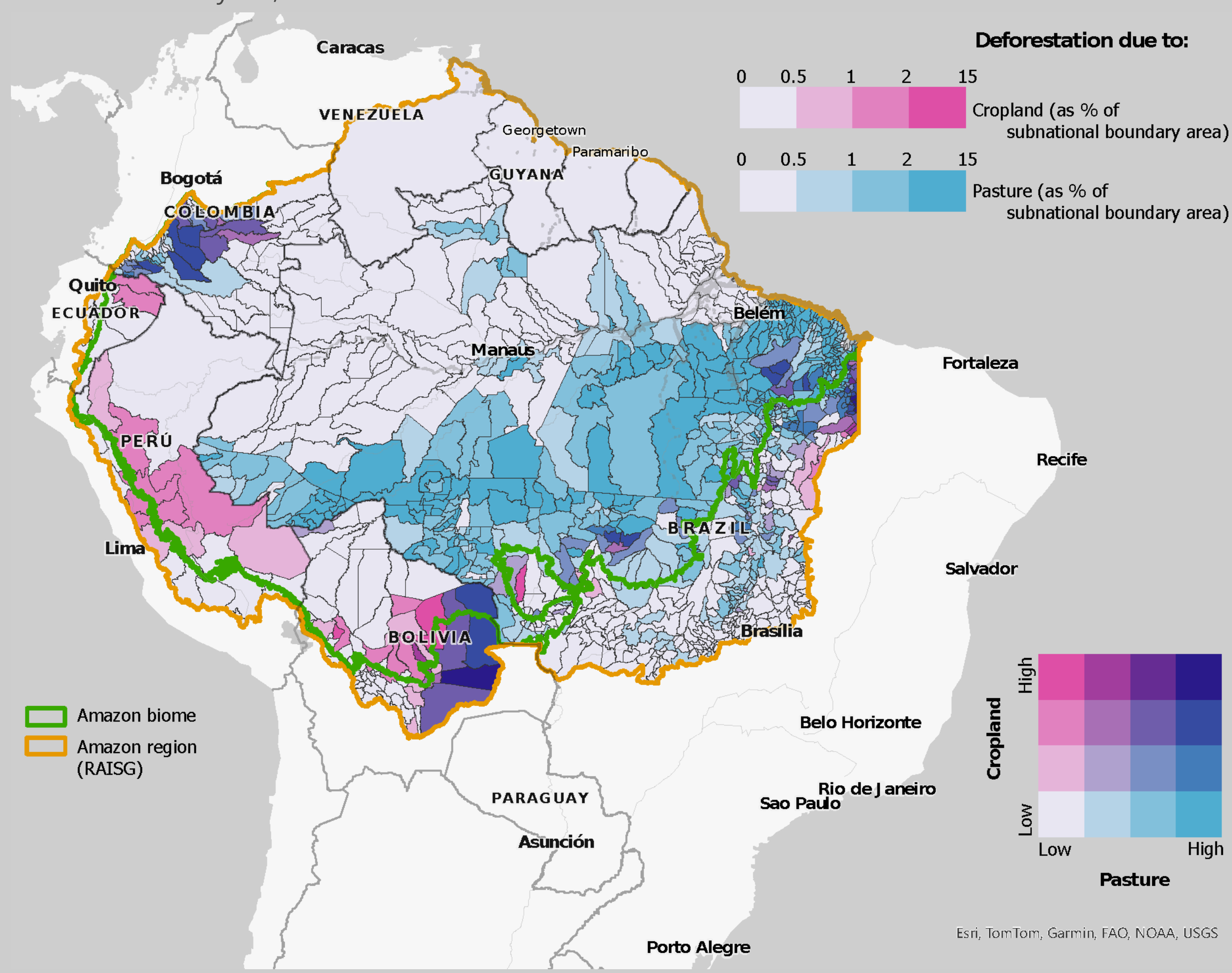

Figure 3. Croplands and pastures as the dominant drivers of deforestation within the Amazon, represented as a percentage of the sub-national boundary area. Here, total deforestation values refer to deforestation associated with the production of agriculture and forestry commodities.

Total Deforestation (2017-2021): 8.9 Mha
Subnational estimates for: Bolivia, Brazil, Colombia, Ecuador and Peru
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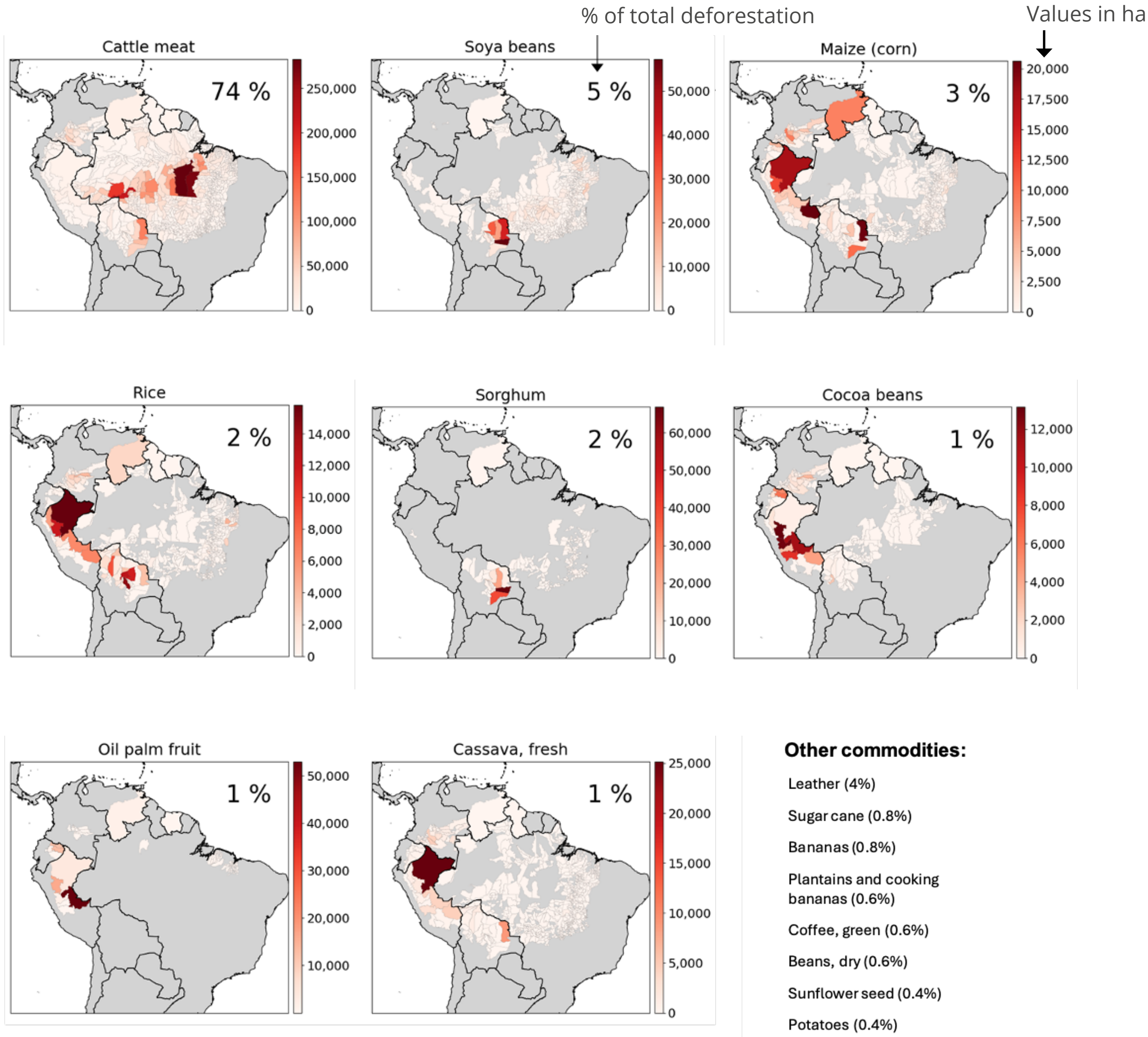

Figure 4. The subplots also highlight major deforestation-risk commodities (values in ha) within the Amazon. Deforestation estimates from 2017 to 2021 are used for this analysis, as this period aligns with the availability of sub-national agricultural statistics for most Amazonian countries. Moreover, the total area of pasture-induced deforestation is primarily attributed to cattle meat production (95%), with leather contributing the remaining 5%. However, we do not display leather in the figures above, as it shares the same spatial extent as cattle meat. Here, total deforestation values refer to deforestation associated with the production of agriculture and forestry commodities. Detailed estimates of deforestation for each national and sub-national boundary are available at https://www.deforestationfootprint.earth/Amazon.

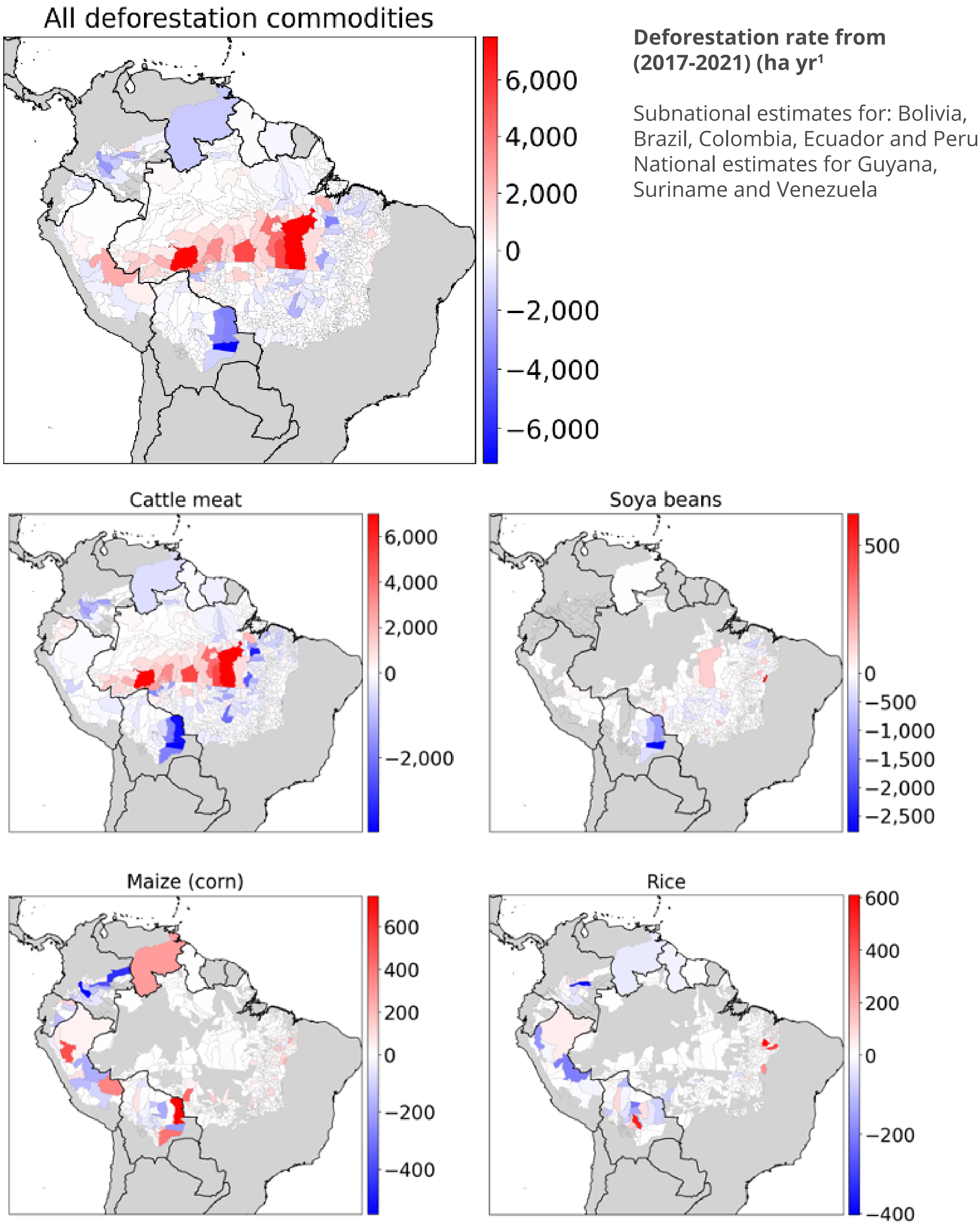

Figure 5. Deforestation rates of all (agriculture and forestry commodities) and some major risk commodities in the Amazon. Positive values (in red) indicate increasing deforestation rates, while negative values (in blue) reflect a decrease in deforestation. We applied a linear regression model to estimate the rate of deforestation for different commodities within each sub-national boundary between 2017-2021.

Data-Driven Pathways to Reduce Deforestation

Halting deforestation requires an accurate and up-to-date understanding of its drivers and dynamics, to inform effective public and private policies and mechanisms. This technical brief aims to provide such actionable, spatially explicit data using the DeDuCE model, offering a pathway to more effective interventions for both public and private sectors. The detailed mapping of deforestation drivers, linking forest loss to specific commodities and land uses at a sub-national level, provides crucial insights for action by policymakers, businesses, and other stakeholders across national and international levels.

Private sector commitments should address cross-commodity and sub-national dynamics to effectively tackle deforestation.

To address deforestation leakage, **companies need to move beyond monitoring single commodities and adopt a more complete assessment of their activities and impacts.** The granularity of the data presented here addresses a long-standing excuse for inaction by the private sector: the lack of multi-commodity, sub-national deforestation data. As an example of this dynamic, while deforestation directly linked to the expansion of soy crops dramatically decreased in the Amazon as a consequence of the Soy Moratorium in Brazil, deforestation continues to rise, now linked to the direct expansion of pasturelands for cattle ranching (Figure 3), potentially as an indirect effect of the expansion of soy over previously established pastures. Strengthening and promoting multi-sectoral and cross-commodity partnerships or working groups can help prevent, detect and mitigate those effects. Multi-sectoral groups such as the Brazilian Coalition on Climate, Forests and Agriculture, which convenes members from various sectors to address shared challenges in controlling deforestation, are crucial for tackling these complex interconnected issues.

Companies operating in the Amazon should expand their commitments to the entire Amazon instead of addressing single countries.

While companies have committed to controlling direct deforestation on commodity supply chains in a single country, globally relevant drivers linked to the same commodities continue to cause significant deforestation in other countries in the Amazon, often associated with the presence of the same actors. **Companies operating across the Amazon basin should adopt region-wide zero deforestation and conversion commitments,** recognizing that deforestation transcends national borders and biomes as demonstrated by the results presented here (Figure 3). Industry leaders should spearhead this effort by establishing best practices and encouraging competitors to adopt an agreed-upon set of minimum standards that address both the environmental and social components of sustainable production in the Amazon.

Consumer markets should recognize the uneven distribution of commodity deforestation and varying levels of preparedness for environmental compliance within the Amazon.

The fact that commodity deforestation is distributed unevenly across the Amazon region means that targeted support from consumer countries, including investments in land use mapping and traceability systems for environmental compliance, and programs to support the smallholder producers should be targeted accordingly.

Governments should use sub-national deforestation estimates to prioritise the implementation of critical measures to eliminate deforestation.

Governments can take into consideration sub-national deforestation estimates, such as those provided by DeDuCE, as a tool to support the implementation of public traceability systems and MRV, or other measures to achieve deforestation and conversion-free supply chains at national scale. By prioritising their implementation in the most threatened regions identified by the model, the impact on deforestation would be increased in the short-term.

Governments should strengthen regulations for commodities targeting the domestic market

While international regulations on commodity imports are crucial for reducing deforestation, their effectiveness is limited to commodities traded internationally, and can be further undermined by the potential leakage of impacts to the domestic market. To mitigate this risk and ensure the sustainability of both internal and external markets, Amazonian governments must significantly strengthen their monitoring of domestic supply chains for key forest risk commodities as they prepare to comply with standards for internationally traded commodities. Initiatives like the Brazilian government's Agro+ Sustentabilidade platform [45], designed to support producers and companies within the country to increase transparency and manage impacts on agricultural commodity supply chains, can effectively pinpoint where interventions are needed to prevent the spread of deforestation across the value chain.

Need for better data and data development for understanding complex land-use change dynamics

Remote sensing datasets on land use and commodities:

Advancements in remote sensing technologies are crucial for improving the monitoring of land-use changes and commodity-driven deforestation in the Amazon. Investments in high-resolution satellite imagery—such as Sentinel-2, Landsat 8, Amazonia-1, and commercial satellites like Planet—enhance the ability to capture detailed, frequent observations of dynamic land use patterns. However, creating detailed maps of land use and commodities from satellite data requires extensive field samples for training spatial models. This can be achieved through collaboration among governments, research institutions, NGOs, and the private sector, ensuring comprehensive data collection and resource sharing.

Such cooperation also makes remote sensing data processing for land use mapping more accessible. A recent exemplary initiative in this area is MapBiomas, which leverages multi-sectoral partnerships to facilitate the development of land cover and land use products from 1985 until the present. Simultaneously, it prioritises empowering local organisations to produce their own maps, combining local knowledge and reference datasets. It has developed as a regional initiative in South America and is building its presence in Southeast Asia, with the already well-developed MapBiomas Indonesia, and more recently expanding into Africa [46].

Agricultural statistics at the sub-national level:

Pixel-level datasets, while offering comprehensive assessments of deforestation drivers, often focus on specific commodities or regions, limiting their effectiveness in guiding localised conservation efforts. Sub-national agricultural statistics help address these gaps left by selective mapping by offering a more detailed perspective, enabling the mapping of deforestation drivers linked to specific commodities (e.g., soy, cattle, maize, rice) at a sub-regional scale, particularly where spatial data is limited or unavailable. Standardising data collection methods across regions is key to improving the consistency and reliability of sub-national agricultural statistics. This could involve leveraging digital tools and mobile applications for data collection, and engaging local communities and authorities to ensure that the data reflects on-the-ground realities. Integrating this statistical data with geographic information systems (e.g., Brazil's Rural Environmental Registry) can also allow for spatial analysis of agricultural expansion at a more granular level. Promoting transparency and data sharing among governmental agencies, NGOs, and academic institutions can further enhance the quality of agricultural statistics, providing a robust foundation for targeted policies and interventions aimed at halting deforestation.

Development of sub-national data is especially advantageous, as these sub-national boundaries or jurisdictions are often the focus of regional land use policies and practices. Furthermore, since biomes rarely align with national borders, this level of granularity is essential for accurate biome-level assessments. It allows for distinguishing deforestation dynamics and drivers within the Amazon biome compared to adjacent biomes like the Caatinga and Cerrado.

Towards UNFCCC COP30

The UN Conferences on Biodiversity (COP 16) in Colombia (2024) and the Climate Change Conference (COP 30) in Brazil (2025) present a pivotal opportunity to take bold action to curb deforestation in the Amazon. These events set the stage for developing, debating, and adapting comprehensive strategies for forest conservation and climate change mitigation.

Targets 1 and 2 of the Global Biodiversity Framework introduce specific measures to plan and manage all areas, aiming not only to reduce biodiversity loss, but also to restore 30% of degraded ecosystems, respectively. Target 3 focuses on conserving 30% of land, waters, and seas, however, due to the risk of reaching an ecological tipping point at 20 to 25% forest loss [47], to effectively protect the Amazon, neighbouring countries must adopt more ambitious goals for this region, similar to Brazil's Forest Code that states for most of the biome 80% protection inside private land, with 30% conservation as a minimum requirement, not a target.

Delivering on these international commitments will require leveraging data-driven insights on Amazon-wide deforestation that can enable targeted interventions, enhance supply chain transparency, and drive scalable, cross-sectoral solutions for reducing and mitigating deforestation. A crucial element in these efforts is the availability of robust datasets that go beyond solely identifying deforestation in the Amazon and disentangle the domestic, regional, and international supply chains driving it, as well as the financial actors and sectors involved, in order to promote greater accountability among all stakeholders.

As such, the next phase of this study aims to produce insights by COP30 on the trade and finance aspects related to the commodity-driven deforestation assessment presented in this technical brief.


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