Archetypes of tropical moist forest change

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Contents

List of figures and tables

Figures

Tables

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1 Introduction

Forest conservation – including strategic reforestation and natural regeneration – is recognized not only for its climate and biodiversity benefits but also as one of the most cost-effective mitigation strategies, with evidence showing up to tenfold greater abatement potential below USD 20 per ton of CO_2 compared to IPCC projections (Busch et al. 2024; Griscom et al. 2017; Lewis et al. 2019). It is also essential for safeguarding livelihoods through the provisioning of food, materials and water (Hong and Saizen 2019; Sheil and Wunder 2002), and serving as cultural and economic foundations managed by Indigenous Peoples and local communities (Bray et al. 2003; Dawson et al. 2021).

There is growing interest from governments and companies to curb deforestation and forest degradation, for example through the Paris Agreement, supply chain commitments and the development of forest carbon markets (den Elzen et al. 2022; Lambin et al. 2018; UK COP26 2021; Cárdenas and Ayala 2023). However, forest loss and degradation continue at alarming rates in many tropical regions (FAO 2020; Hansen et al. 2013; Pacheco et al. 2021; Potapov et al. 2022; Vancutsem et al. 2021). Both outright deforestation and pervasive degradation extend deep into undisturbed forests (Bourgoin et al. 2024; JRC 2024), and diminish ecosystem resilience across the Amazon Basin (Blaschke et al. 2023).

Achieving national and international goals in forest conservation and restoration – such as those articulated in countries' NDCs, the Global Biodiversity Framework, the Bonn Challenge or the Glasgow Framework – depends on the ability to design and implement context-specific policies that effectively address the diverse and dynamic drivers of forest loss. However, policymakers and researchers face persistent challenges in understanding where and why deforestation occurs, how it evolves over time, and which interventions are likely to work under different conditions. Addressing these challenges requires: (i) access to accurate and spatially explicit data for monitoring forest cover and degradation; (ii) the capacity to detect and interpret spatio-temporal patterns of forest loss; (iii) analytical frameworks that relate these patterns to the complex interplay of direct and underlying drivers; and (iv) systems to assess the impacts of policies and interventions across diverse forest landscapes.

Advances in forest monitoring technologies, specifically in satellite-based remote sensing, now provide low-cost, high-resolution, frequently updated and consistent data on the extent, characteristics and changes in forest cover (Hansen et al. 2013; Potapov et al. 2022; Reiche et al. 2021; Vancutsem et al. 2021). National forest monitoring capacities in the tropics also continue to improve (Nesha et al. 2021). Despite the increasing availability of accurate and reliable data, our understanding of complex spatio-temporal deforestation patterns and the underlying interplay of drivers remains poor (Baumann et al. 2022; Pendrill et al. 2022). Effective policies and interventions also require sensitivity to local and national contexts to avoid inefficient one-size-fits-all solutions (Meyfroidt et al. 2022). On the other hand, identifying commonalities across contexts can support case-overlapping policy impact learning.

To address these challenges, we chose archetype analysis to provide an analytical framework to support both research and practice (Oberlack et al. 2019). Archetype analysis is an empirical, data-driven approach increasingly used in sustainability sciences (Eisenack et al. 2021; Oberlack et al. 2019; Seitz et al. 2019). It can help describing commonalities in deforestation processes and consider local circumstances (Meyfroidt et al. 2018). While global meta-analyses, such as those by Busch and Ferretti-Gallon (2023) and Börner et al. (2020), synthesise evidence on causal drivers and the effectiveness of policy interventions across multiple contexts, archetype analysis does not infer causality. By identifying recurring patterns while accounting for contextual differences, archetype analysis helps bridging the gap between highly localised insights and overly generalized, context-free recommendations, yet providing sufficient differentation to inform adaptive policy formulation. For example, Buchadas et al. (2022) applied archetype analysis to differentiate forest loss dynamics in tropical dry forest frontiers, demonstrating how to map spatio-temporal patterns with both thematic detail and generality. Similarly, Baumann et al. (2022) examined archetypical processes of agricultural area expansion in dry forests of the South American Chaco.

The study detailed in this paper is the first to use archetype analysis to describe global spatio-temporal deforestation patterns in tropical moist forests (TMFs). It goes beyond analysing forest dynamics by incorporating a novel assessment of the current state of forests, including degradation levels, and examining the land-use conversions that drive deforestation (i.e., proximate drivers). We also analyse deforestation risk, offering important insights for the formulation of forest conservation policies.

The aim of this work is to (i) identify broad archetypes of forest state and changes in TMF landscapes over the past two decades (2000–2021); (ii) assess proximate drivers of deforestation, specifically the conversion of forests to other land uses in deforestation areas; and (iii) evaluate deforestation risk in TMF landscapes with high remaining forest cover and low historical deforestation.

2 Materials and methods

Archetype analysis used in sustainability sciences and environmental research generally works by identifying recurring patterns (i.e., 'archetypes') across various cases or datasets, helping to simplify complex systems while accounting for both commonalities and local variations.

In this study, the archetypes are derived through a structured, indicator-based classification scheme adapted from established approaches in earlier research on forest change monitoring (de Sy et al. 2012). We first define a set of spatially explicit metrics relevant to forest change – such as forest cover, rates of loss and indicators of degradation – based on available Earth Observation data and ancillary datasets. These metrics are aggregated into thematic typologies (e.g., severity, state, hotspots) using threshold values informed by statistical distribution properties and prior literature. Typologies are then combined to form broader archetypes, before being further refined into nested archetypes; this helps to capture both large-scale patterns and finer-grained, location-specific variations. This approach facilitates the identification of recurrent configurations of deforestation and land-use change and their associated drivers, thereby supporting the formulation of context-specific, actionable policy recommendations.

While our approach relies on a rule-based, expert-informed classification rather than statistical clustering, it shares the objective of other archetype derivation methods – such as statistical grouping, qualitative comparative analysis or mixed-method synthesis – in revealing recurrent system configurations that transcend single-case studies. The manual, threshold-based method has advantages for transparency, interpretability and replicability across different spatial and temporal contexts; it enables the incorporation of heterogeneous datasets and expert knowledge where purely statistical methods may be limited by data availability or comparability. Sensitivity of typology thresholds and validation of outputs against independent datasets are recognised as important future steps to further strengthen the robustness of the classification.

Specifically, our analytical framework (Figure 1) consists of four steps: (i) derive metrics to describe forest state and forest change; (ii) build thematic typologies; and use them to (iii) develop archetypes; with some archetypes then further developed into (iv) nested archetypes. The main structure of metrics, typologies and archetypes builds on the analytical framework of Buchadas et al. (2022). We adapted the specifics of their analytical framework to align with our aim of characterizing both forest state and forest change (versus only deforestation areas) in tropical moist forests (versus dry forests).

2.1 Main data source and study area

To characterize forest extent, forest state and forest change we used a global tropical moist forest (TMF) dataset (Vancutsem et al. 2021). This dataset provides detailed spatial (30 m resolution) and temporal (annual) information on long-term forest cover changes as well as detailed information on forest degradation and forest transition dynamics (e.g., forest regrowth, conversion to plantations). Metrics derived from the TMF dataset were aggregated from 30 m resolution pixels to 5 km resolution 'landscapes', our unit of analysis. Our study area consists of landscapes that had TMF present in 2000, the baseline year. A more detailed description of the TMF data and study area can be found in the supplementary information (SI)[1].

1 https://data.cifor.org/dataset.xhtml?persistentId=doi:10.17528/CIFOR/DATA.00318

2.2 Metrics and typologies

We derived five metrics that characterize both forest state and forest change processes within our study period from 2000 to 2021 (Table 1): (i) forest cover in 2000; (ii) forest cover in 2021; (iii) forest degradation in 2021; (iv) total deforestation from 2000 to 2021 relative to land area; and (v) activeness, which combines the magnitude (i.e., deforestation rate) and the timing of deforestation (Buchadas et al. 2022). The rate of deforestation was calculated as the annual rate of deforestation, averaged over three consecutive years, relative to the land area.

These five metrics were used to build the three typologies: state, severity and hotspots (Table 1). We haracterized the current **state** of TMFs within the 5x5 km landscape by combining forest cover in 2021 with forest degradation in 2021. The **severity** of deforestation in TMFs was characterized by combining our baseline forest cover in 2000 with total deforestation from 2000 to 2021. To build the state and severity typologies, the corresponding metrics were first classified into three categories (low, medium and high; Table 1). The thresholds were chosen based on the distribution of forest cover percentages across the 5x5 km landscapes (SI Figure S2) and the ability to distinguish between highly forested landscapes and sparsely forested landscapes in the context of TMFs. Similarly, forest degradation thresholds were based on the distribution of forest degradation percentages across landscapes (SI Appendix Figure S3). For the lower threshold of total deforestation across the studied period we selected a threshold (< 5%) close to the average total deforestation (4.2%) across all landscapes. The upper threshold was set to 20% as this aligns closely to an average annual deforestation rate of 1% which was used to calculate the activeness metric.

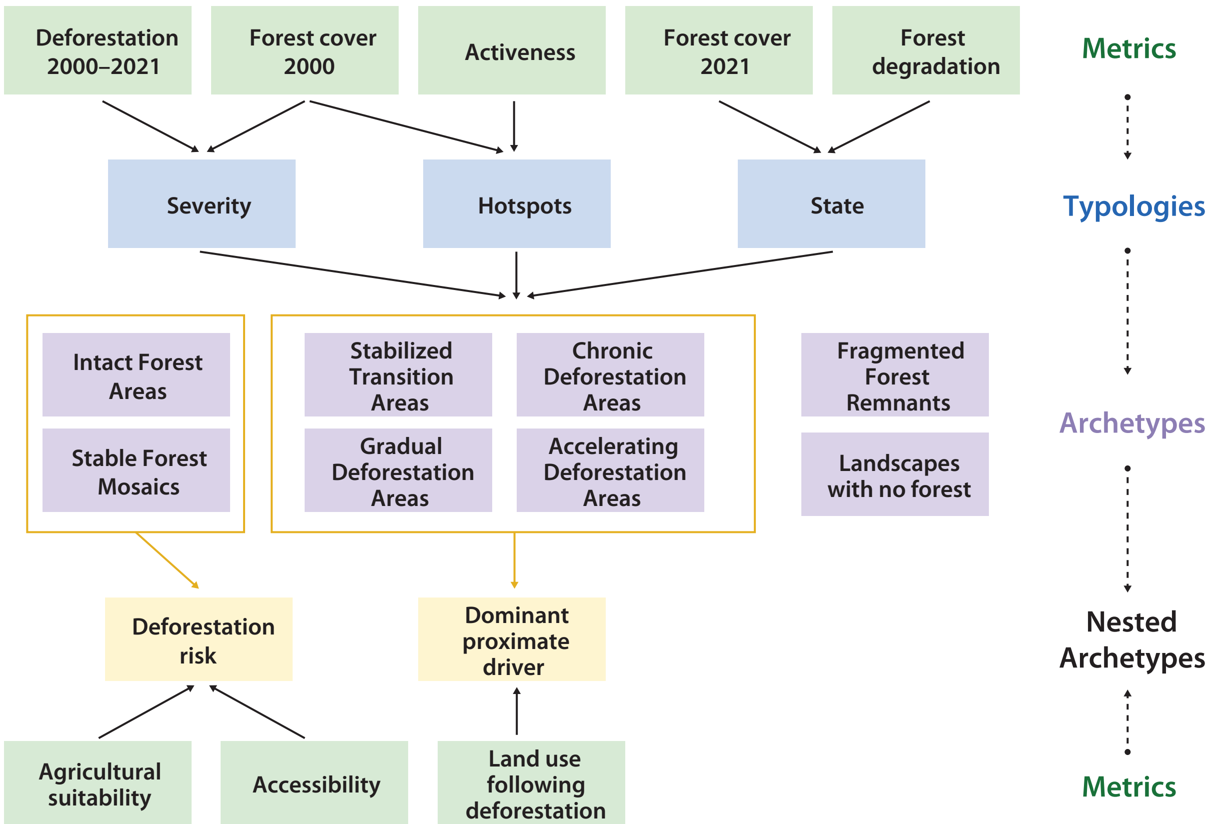

Figure 1. Overview of the analytical framework

Table 1. Metrics and thresholds used to define the typologies

Metric	Low		Medium	High
Forest cover 2000 and 2021 (% of land area)	0–25		25–75	75–100
Deforestation 2000–2021 (% of land area)	0–5		5–20	20–100
Forest degradation (% of forest)	0–20		20–65	65–100
	Inactive	**Old**	**Active**	**Emerging**
Activeness	Annual 3y loss rates < 1%	Annual 3y loss rate > 1%, only before 2015	Annual 3y loss rate > 1%, before and after 2015	Annual 3y loss rate > 1%, only after 2015

Nested archetypes allow the identification of finer-scale patterns within broader environmental classifications, facilitating more precise targeting of interventions. For example, Sietz et al. (2017) defined six nested archetypes within one broad vulnerability category in African drylands, enabling differentiation of governance quality, erosion risk and food security conditions. Similarly, Goodwin et al. (2022) implemented a multi-tier archetype framework in British agricultural landscapes, distinguishing patterns at three administrative and management scales. In our methodology, we adopt and extend the concept of nested archetypes by first identifying eight broad forest-landscape archetypes, then applying nested clustering to link subregional patterns (e.g., deforestation drivers, accessibility) within each broad archetype. This approach enhances both interpretability and policy relevance, by revealing heterogeneity that is obscured at the aggregated level.

To characterize **hotspots**, we combined two metrics: baseline forest cover (in 2000) and activeness of deforestation within a landscape. A landscape was considered active, i.e., a hotspot of deforestation, if the three-year averaged annual rate of deforestation was higher than 1%. We deviated from the thresholds proposed by Buchadas et al. (2022) to accommodate differences in our methods, such as deforestation rates relative to land area instead of forest area and a 5 km instead of a 3 km aggregation level. Hotspots were further classified (Table 1) based on their timing as old (only before 2015), active (both before and after 2015) or emerging (only after 2015) (Buchadas et al. 2022). This categorization allows us to assess if deforestation rates over time follow a pattern consistent with the forest transition theory (e.g., Mather 1992; Rudel et al. 2005). This theory proposes development over time, from high forest cover and low deforestation (intact forest areas) to accelerated deforestation and declining forest cover (deforestation areas), to a slowdown of deforestation and stabilisation of the forest cover (mosaics).

2.3 Archetypes of tropical moist forest state and change

From the state, severity and hotspot typologies, we developed seven main archetypes of forest state and forest change in TMF landscapes (Table 2), with an eighth category of non-forest land that is no proper forest or deforestation archetype. We categorised these archetypes based on how much certain combinations of typologies occur and how meaningful the categories are for policies and interventions. This resulted in the seven forest archetypes described and defined in Table 2. Two of these archetypes are characterized by low deforestation in landscapes with relatively high TMF forest cover (intact forest areas and stable forest mosaics), four archetypes are characterized as deforestation areas which are further defined by changes over time (stabilized transition areas and chronic, accelerating and gradual deforestation areas) and one archetype is characterized by low TMF cover (fragmented forest remnants).

2.4 Dominant land use following deforestation in deforestation areas

The four deforestation area archetypes (Table 2) were further characterized by a nested archetype focused on the dominant land use following deforestation within the 5x5 km landscape. Only the dominant land use in 2021 is considered for this analysis. Available global data does not currently allow for analysis of land-use trajectories after deforestation. We considered the following post-deforestation land uses/covers: tree plantations, forest regrowth, water, cropland, pastures, urban, bare soil, grassland and shrubland (descriptions in SI Table S1). Therefore, information on forest conversion to tree plantation, forest regrowth and water bodies is directly derived from the TMF dataset. The remaining forest-to-land-use conversions were derived from the 2021 ESA Worldcover dataset (Zanaga et al. 2022). To distinguish between managed (i.e., pastures or rangelands) and unmanaged grassland, we overlaid the grassland pixels (representing both managed and unmanaged grassland) from the 2021 ESA Worldcover dataset with the 2019 land-use map of Wrinkler et al. (2019).

Table 2. Archetypes of deforestation in tropical moist forest

Name	Description	Definition	Grouping	Nested archetype
Intact Forest Areas	High forest cover, low deforestation and generally low forest degradation. These landscapes are mostly undisturbed primary forests, such as the Amazon and Congo Basin.	High forest cover (>75% in 2021), low deforestation (<5% from 2000–2021) and low forest degradation (<20% in 2021).	Low deforestation area	Deforestation risk
Stable Forest Mosaics	Medium forest cover, low deforestation and higher levels of forest degradation, often found on the edges of intact forest areas.	Medium forest cover (25–75% in 2021), low deforestation (<5% from 2000–2021) and medium degradation (20–65% in 2021).	Low deforestation area	Deforestation risk
Stabilized Transition Areas	Areas with deforestation that peaked before 2015 but have since slowed down.	Hotspot identified by deforestation activity (>1% annual 3-year loss rates) only before 2015.	Deforestation areas	Land use following deforestation
Chronic Deforestation Areas	Areas with ongoing, active deforestation both before and after 2015.	Hotspot identified by deforestation activity (>1% annual 3-year loss rates) both before and after 2015.	Deforestation areas	Land use following deforestation
Accelerating Deforestation Areas	Areas where deforestation activity has intensified only after 2015.	Hotspot identified by deforestation activity (>1% annual 3-year loss rates) only after 2015.	Deforestation areas	Land use following deforestation
Gradual Deforestation Areas	Areas with medium to high forest loss (5–20% or >20% of land area) over the entire period (2000–2021), but without identified hotspots of activity.	Medium (5–20%) or high (>20%) deforestation between 2000–2021, with no hotspots.	Deforestation areas	Land use following deforestation
Fragmented Forest Remnants	Landscapes with low initial forest cover that either remained low or disappeared entirely by 2021.	Low forest cover (0–25%) in both 2000 and 2021, with variable deforestation rates.	Low TMF cover	—

2.5 Deforestation risk in intact and stable tropical moist forest landscapes

The intact forest areas and stable forest mosaics archetypes were further characterized by another nested archetype focused on their deforestation risk (Figure 1). As a proxy for deforestation risk, we combined metrics representing accessibility and agricultural suitability to derive five risk categories (see SI Table S2). We used agricultural suitability because agriculture is the most common driver of deforestation (De Sy et al. 2019; Jayathilake et al. 2021; Penderil et al. 2022). Agricultural suitability was derived from the GAEZ 3.0 dataset (IIASA and FAO 2012). In line with Buchadas et al. (2022), we summed up and standardised the agro-climatic potential for low-input, rainfed agriculture. Accessibility is also considered an important factor in deforestation (Ernst et al. 2013; Jayathilake et al. 2021; Kleinschroth et al. 2019; Sandker et al. 2017). We used a 1 km resolution dataset on travel time to cities (Weiss et al. 2018) as a proxy for accessibility.

3 Results

3.1 Typologies: Severity, state and hotspots

First, we investigated the *severity* of deforestation by comparing total deforestation between 2000 and 2021 to the baseline forest cover percentage in 2000.

Our analysis covers approximately 2.8 billion hectares of land area in the tropics that contained tropical moist forest in 2000 (Table 3) – equivalent to about three quarters of the world's tropical moist forest landscapes – and therefore includes both forest and non-forest areas within those units.[2]

Of these, 46% (1,297.5 Mha) had low forest cover in 2000, and 39% had high forest cover. Most deforestation over the next 20 years was 'low' (74%), but a substantial area experienced medium to high deforestation rates (together, approximately 26%), almost corresponding to the land area of Australia (768 Mha). We found that 40.5% of the landscapes had low forest cover and low deforestation (1,138.8 Mha) while only 30.1% of high forest cover landscapes had low deforestation (846.8 Mha) (Table 3 and SI Figure S4).

A larger proportion of high forest cover landscapes in Southeast Asia experienced medium to high deforestation (31.4% of high forest cover landscapes) when compared to similar landscapes in Central and South America (19.1%) and sub-Saharan Africa (23.4%) (SI Table S3–S5).

Next, we analysed the current *state* (2021) of forest cover within a landscape related to forest cover in 2021. Our findings (Table 3 and SI Figure S5) show that in high forest cover landscapes are found both, large areas of low degradation (37%) as well as large areas of high deforestation. Medium and high degradation levels taken together, across all forest densities, were seen in two thirds of all landscapes.

In Southeast Asia (for example, Borneo, Figure 2), a larger proportion of medium to high forest cover landscapes have high forest degradation levels (13.2% of the area with medium to high forest cover), compared to sub-Saharan Africa (8.0%) and Central and South America (3.5%) (SI Table S6–S8).

We assessed deforestation *hotspots* by combining 2000 forest cover with 'activeness', defined as the rate and timing of forest loss. Most of the study area – 2,233.5 Mha (79.4%) – did not meet the hotspot criteria and was classified as 'inactive' or experiencing 'gradual change' (Table 3; SI Figure S6). The most common hotspot typologies are old hotspots in medium forest cover landscapes (121.4 Mha, 4.3%), and active hotspots in both medium (130.7 Mha, 4.6%) and high (126.9 Mha, 4.5%) forest cover landscapes. Because hotspots are defined by change dynamics rather than extent, their significance cannot be judged by area alone. For countries aiming to halt deforestation, emerging hotspots are of particular concern – covering 52 Mha, roughly the size of Thailand.

In Southeast Asia, both old and active hotspots (respectively 14.4% and 11.9% of the study area on this continent) are more prevalent than in sub-Saharan Africa (respectively 5.4% and 11.5%) and Central and South America (respectively 8.5% and 7.7%) (SI, Table S9–S11). The share of emerging hotspots is slightly higher in Central and South America (2%) than in the other two continents (1.6% and 1.7%, respectively).

2 Note that the reported 2.8 billion hectares refers to the total area of all 5 × 5 km landscapes that contained tropical moist forest in 2000, and therefore includes both forest and non-forest land within those units; the actual extent of tropical moist forests is substantially smaller, in the order of ~1 billion hectares globally.

Table 3. Areas of typology classes in the study sample, with share of occurrence (percentage of study area)

Forest cover 2000	Deforestation 2001–2021							
	Low		Medium		High		Total	
	Mha	Percent	Mha	Percent	Mha	Percent	Mha	Percent
Low	1,138.8	40.5	155.4	5.5	3.3	0.1	1,297.5	46.1
Medium	103.1	3.7	194.7	6.9	121.8	4.3	419.6	14.9
High	846.8	30.1	148.9	5.3	102.3	3.6	1098.0	39.0
Total	2,088.7	74.2	499.0	17.7	227.4	8.1	2,815.1	100

Forest cover 2001	Forest degradation 2021							
	Low		Medium		High		Total	
	Mha	Percent	Mha	Percent	Mha	Percent	Mha	Percent
Low	15.6	0.6	272.6	10.5	962.1	37.0	1,250.3	48.1
Medium	73.3	2.8	245.0	9.4	82.3	3.2	400.6	15.4
High	827.2	31.8	112.9	4.3	10.7	0.4	950.8	36.5
Total	916.1	35.2	630.5	24.2	1,055.1	40.6	2,601.7	100

Forest cover 2000	Activeness of deforestation									
	Inactive/ gradual		Old		Active		Emerging		Total	
	Mha	Percent	Mha	Percent	Mha	Percent	Mha	Percent	Mha	Percent
Low	1,196.2	42.5	75.3	2.7	17.2	0.6	8.8	0.3	1,297.5	46.1
Medium	153,8	5.5	121,4	4.3	130,7	4.6	13,6	0.5	419,5	14.9
High	883,4	31.4	57,8	2.1	126,9	4.5	29,9	1.1	1,098,0	39.0
Total	2,233,4	79.3	254,5	9.0	274,8	9.8	52,3	1.9	2,815,0	100

Table 3. Areas of typology classes in the study sample, with share of occurrence (percentage of study area)

		Deforestation 2001–2021 (Mha)			
		Low	**Medium**	**High**	**Total**
Forest cover 2000	Low	1,138.8	155.4	3.3	1,297.5
	Medium	103.1	194.7	121.8	419.6
	High	846.8	148.9	102.3	1098.0
	Total	2,088.7	499.0	227.4	2,815.1

		Deforestation 2001–2021 (percent)			
		Low	**Medium**	**High**	**Total**
Forest cover 2000	Low	40.5	5.5	0.1	46.1
	Medium	3.7	6.9	4.3	14.9
	High	30.1	5.3	3.6	39.0
	Total	74.2	17.7	8.1	100

		Forest degradation 2021 (Mha)			
		Low	**Medium**	**High**	**Total**
Forest cover 2021	Low	15.6	272.6	962.1	1,250.3
	Medium	73.3	245.0	82.3	400.6
	High	827.2	112.9	10.7	950.8
	Total	916.1	630.5	1,055.1	2,601.7

		Forest degradation 2021 (percent)			
		Low	**Medium**	**High**	**Total**
Forest cover 2021	Low	0.6	10.5	37.0	48.1
	Medium	2.8	9.4	3.2	15.4
	High	31.8	4.3	0.4	36.5
	Total	35.2	24.2	40.6	100

		Activeness of deforestation (Mha)				
		Inactive/ gradual	**Old**	**Active**	**Emerging**	**Total**
Forest cover 2000	Low	1,196.2	75.3	17.2	8.8	1,297.5
	Medium	153,8	121,4	130,7	13,6	419,5
	High	883,4	57,8	126,9	29,9	1,098,0
	Total	2,233,4	254,5	274,8	52,3	2,815,0

		Activeness of deforestation (percent)				
		Inactive/ gradual	**Old**	**Active**	**Emerging**	**Total**
Forest cover 2000	Low	42.5	2.7	0.6	0.3	46.1
	Medium	5.5	4.3	4.6	0.5	14.9
	High	31.4	2.1	4.5	1.1	39.0
	Total	79.3	9.0	9.8	1.9	100

Table 4. Area (in Mha) of archetypes per continent and for the dataset, and share (percentage) of occurrence

Archetypes	Central & South America (Mha)	Sub-Saharan Africa (Mha)	Southeast Asia (Mha)	Total (Mha)	Central & South America (%)	Sub-Saharan Africa (%)	Southeast Asia (%)	Total (%)
Intact forest areas	493,7	170	172,9	836,6	35.9	22.0	25.9	29.7
Stable forest mosaics	45,7	33	27,8	106,4	3.3	4.3	4.2	3.8
Stabilized transition areas	115,9	40,9	94,9	251,7	8.4	5.3	14.2	8.9
Chronic deforestation areas	105,8	88,4	79,2	273,5	7.7	11.4	11.9	9.7
Accelerating deforestation areas	29,6	12,4	11,3	53,3	2.2	1.6	1.7	1.9
Gradual deforestation areas	67,9	35,4	52,8	156,1	4.9	4.6	7.9	5.5
Fragmented forest remnants	516,3	392	229,1	1137,4	37.6	50.8	34.3	40.4
Totals	**1374,9**	**772,1**	**668**	**2815**	**100**	**100**	**100**	**100**

3.2 Archetypes of tropical moist forest state and change

We identified seven archetypes based on our typologies (Table 4, Figure 2 and SI Table S12).

Intact forest areas (836.6 Mha, 29.7 % of study area) are characterized by high forest cover in 2021, low deforestation and generally low forest degradation. This archetype corresponds to about two thirds of the study sample, mostly linking to relatively undisturbed primary forests of the Amazon, the Congo Basin, Borneo and New Guinea. Smaller continuous areas of intact forest areas can still be found in Central America, the coastal forests of Brazil, in Liberia, Nigeria, Madagascar, Myanmar, Cambodia and the Philippines. This archetype is more prevalent in Central and South America (493.7 Mha, 35.9% of continental area) than in Southeast Asia (172.9 Mha, 25.9%) and sub-Saharan Africa (170.0 Mha, 22.0%).

Stable forest mosaics (106.4 Mha, 3.8% of study area) are also characterized by low deforestation, but these areas had medium forest cover in 2021, and generally have higher levels of forest degradation. These landscapes mainly occur at the edge of intact forest areas, with substantial areas in Cameroon, Central African Republic, Republic of the Congo, Democratic Republic of Congo (DRC) and Bhutan.

We distinguished four archetypes of deforestation areas. Stabilized transition areas and chronic, accelerating and gradual deforestation areas are associated with areas where deforestation hotspots were detected. The gradual deforestation area archetype refers to areas not identified as hotspots, but that experienced medium to high forest loss from 2000 to 2021 (>5% of land). Chronic deforestation areas are most common in medium forest-cover landscapes (20.2%; SI Table S13). Accelerating deforestation areas occur more frequently in high forest-cover landscapes (3.2%) than in medium (2.2%) or low (1.8%) forest cover, whereas stabilized transition areas and gradual deforestation areas show the opposite pattern.

Stabilized transition areas (251.7 Mha, 8.9%), with hotspots occurring before 2015 (i.e., old hotspots), are often present at the outer edge of chronic deforestation areas, for example on the West and South side of the arc of deforestation in Brazil, as well as in Sumatra, Borneo and Malaysia. Regions with a relatively large presence of stabilized transition areas are the Bahia interior forests and Araucaria moist forests ecoregion in Eastern Brazil, northern Guatemala, the northern East coast of Myanmar,

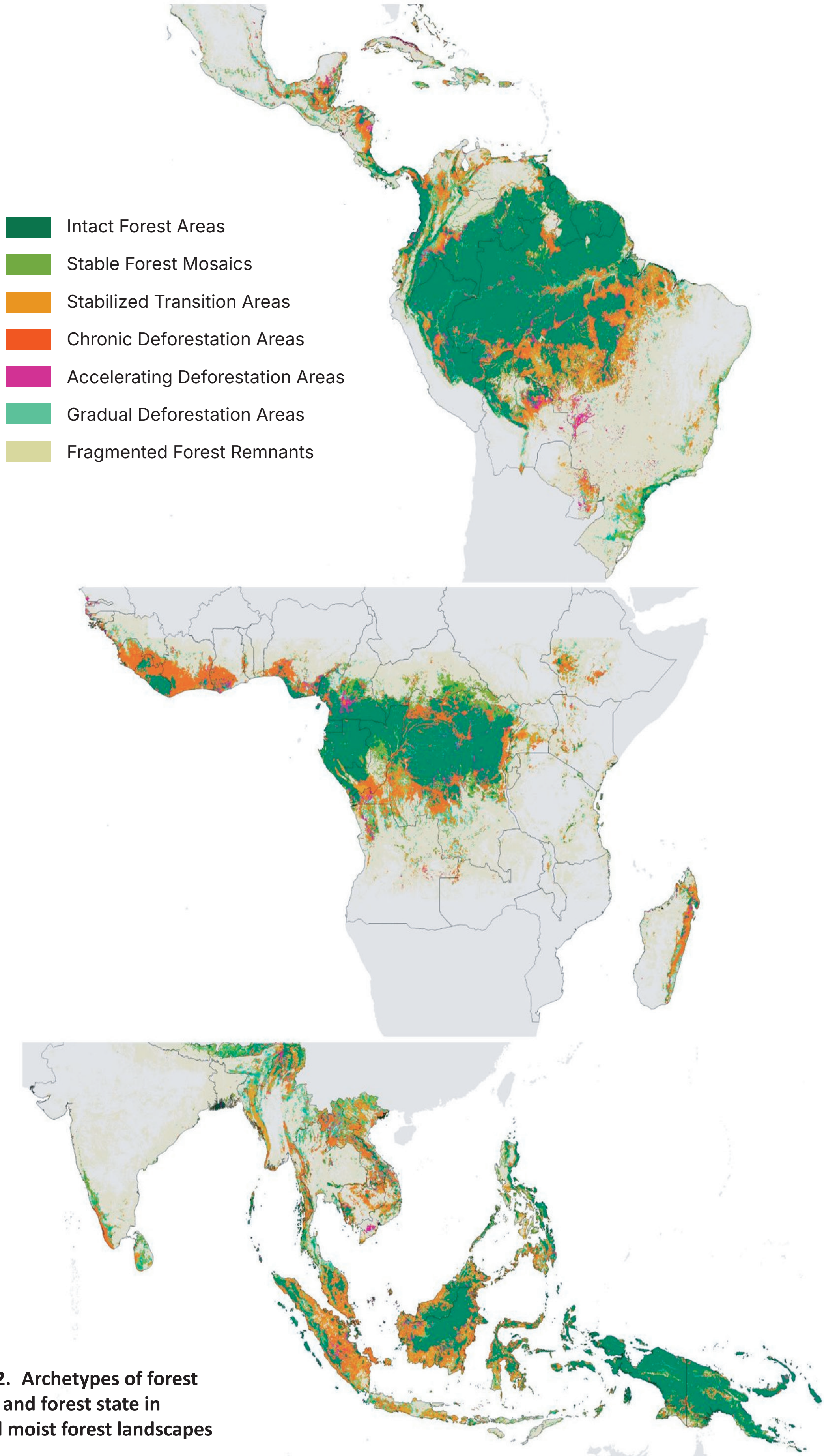

Figure 2. Archetypes of forest change and forest state in tropical moist forest landscapes

northern Vietnam and Java. Sub-Saharan Africa meanwhile contains relatively few stabilized transition areas (40.9 Mha, 5.3% of continental area), yet some larger stabilized transition areas can be found in Uganda, Ethiopia and the western regions of the Republic of the Congo and DRC.

Gradual deforestation areas (156.1 Mha, 5.5% of study area) are comparatively more common in Southeast Asia (7.9% of the continental area), particularly on the mainland, than in Central and South America (4.9%) and sub-Saharan Africa (4.6%). They occur in a more dispersed spatial pattern, with notable clusters in eastern Brazil, northeastern and southern India and Sri Lanka.

Chronic deforestation areas (273.5 Mha, 9.7% of study area), characterized by active deforestation occurring both before and after 2015, are widespread along the Amazonian arc of deforestation in Brazil, in West Africa, on the edges of the intact forest areas in the Congo Basin, in Indonesia and Malaysia. Other regions where larger continuous areas of chronic deforestation areas occur are Central America (e.g., Honduras and Nicaragua) and the Amazonian forests of Bolivia, Peru and Colombia. Chronic deforestation areas can also be found in Nigeria, Ethiopia, Madagascar, Laos, Cambodia, Vietnam and Myanmar.

Accelerating deforestation areas (53.3 Mha, 1.9% of study area), defined as hotspots emerging after 2015, can often be found near chronic deforestation areas and intact forest areas, notably in the Amazon region, the Congo Basin, Indonesia and Malaysia. Extensive accelerating deforestation areas also occur in the Brazilian Pantanal, Bolivia's Santa Cruz province, central Cameroon and the Mekong Delta in Vietnam.

Finally, fragmented forest remnants archetypes – the largest archetype, covering 1,137.4 Mha (40.4% of the study sample) – are those with low forest cover in 2000 that either remained low or were completely lost (no TMF remaining).

3.3 Dominant land use following deforestation in deforestation areas

Conversion to pasture is the dominant proximate driver in a large share of landscapes in Central and South America and sub-Saharan Africa (Figure 3, Figure 4).

In contrast, crop expansion is the main driver of forest loss in several other regions. In South America, this is particularly evident in Mato Grosso (Brazil) and around Santa Cruz (Bolivia). In Africa, crop-driven deforestation areas occur in Uganda, Ethiopia, and around Lake Kivu in Rwanda and the DRC. In Southeast Asia, cropland expansion dominates in Laos, Cambodia, northern Vietnam, South Sulawesi in Indonesia, and the Philippines.

Plantation expansion is another major driver. This dominates in Ecuador and eastern Brazil, in West Africa and to a lesser extent Central Africa, and in much of Southeast Asia, especially Indonesia (Sumatra, Kalimantan), Malaysia, and the Mekong Delta in southern Vietnam.

Across all continents, substantial areas show forest regrowth as the dominant land use following deforestation, with the highest shares in Asia, notably in Vietnam, Myanmar and Sri Lanka.

Conversion to grassland also contributes to deforestation areas throughout the tropics, while conversion to shrubland is particularly significant in sub-Saharan Africa.

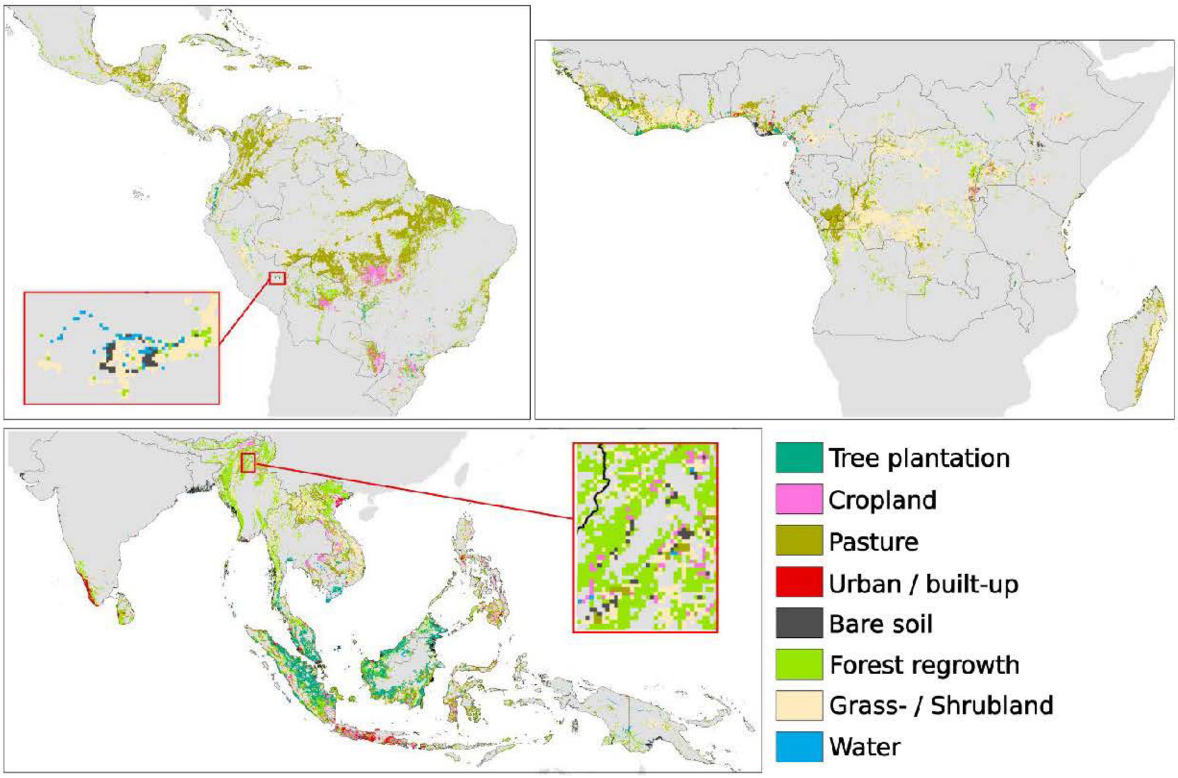

Figure 3. Dominant land use following deforestation in deforestation areas. The inserts show mining regions in Peru and Myanmar

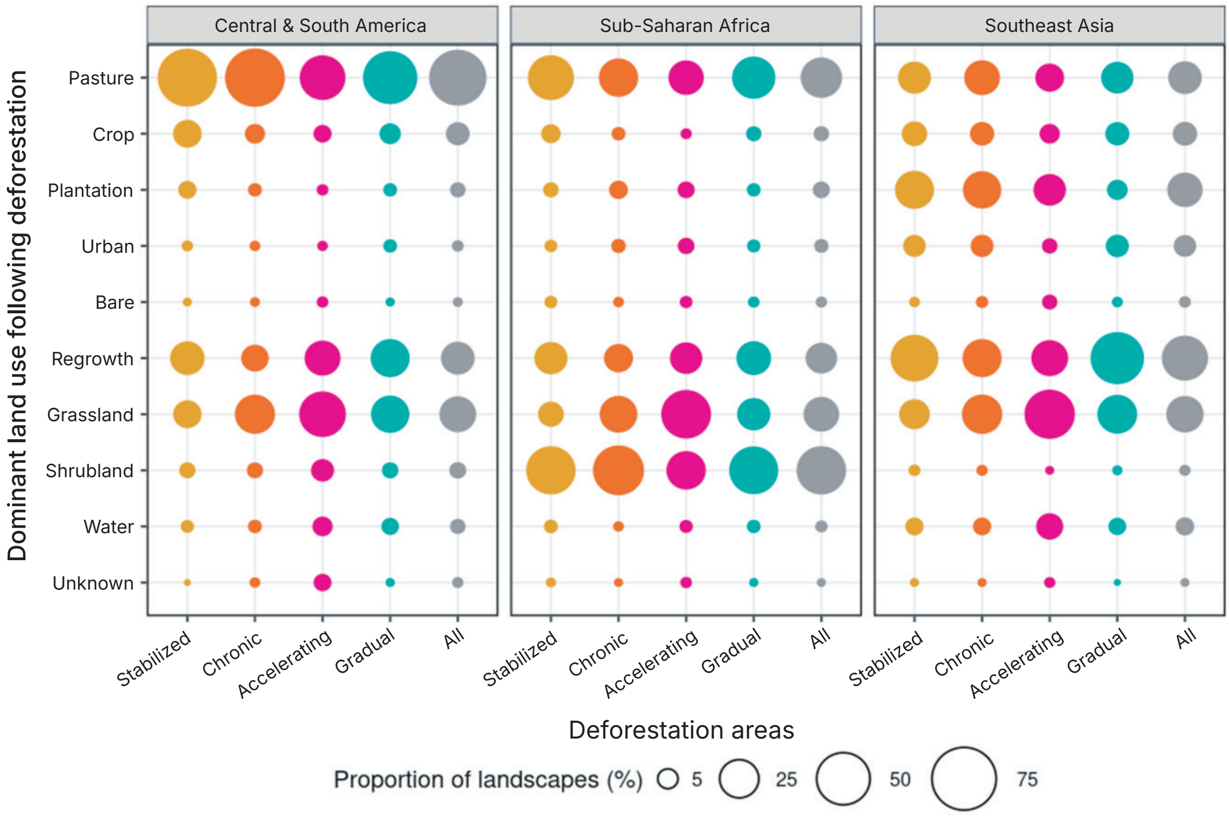

Figure 4. Continental proportions of dominant land use following deforestation (in percentage of landscapes) for stabilized transition areas, chronic, accelerating and gradual deforestation areas, and across all deforestation areas

Landscapes where forest conversion to urban area is dominant are most common in Southeast Asia (Figure 4), particularly in Java, Indonesia, and around Hanoi in northern Vietnam (Figure 2). Outside this region, such landscapes are also prominent in Nigeria.

Forest conversion to bare soil is dominant only in a small proportion of landscapes. Importantly, this can be an indication of mining activities, and as such be an important form of conversion in certain regions (the inserts in Figure 3 show examples in Peru and Myanmar). Similarly, forest conversion to water is locally important, occurring along coastlines, large meandering rivers such as in the Amazon Basin, and around new dams, for example in Venezuela.

We also examined the dominant processes of forest conversion across deforestation areas on each continent (Figure 4). In Central and South America, stabilized transition areas are characterized by conversion of forests to agriculture, while conversion to grassland plays a smaller role than in the other areas. Forest regrowth is less common in chronic deforestation areas, but more frequent in gradual deforestation areas. In sub-Saharan Africa, similar dynamics are observed, but conversion to shrubland has a stronger role. Here, chronic and accelerating deforestation areas are marked by more conversions to plantations and to urban areas. In Southeast Asia, stabilized transition areas and chronic deforestation areas are dominated to an equal extent by conversion to agriculture, while gradual deforestation areas show reduced conversion to plantations and more extensive forest regrowth. Gradual deforestation areas show a lower proportion of conversion to plantation and a high proportion of forest regrowth. Across all continents, accelerating deforestation areas tend to involve less conversion to agriculture and urban areas, with a greater share of regrowth.

3.4 Deforestation risk in intact forest areas and stable forest mosaics

We found considerably more intact forest areas and stable forest mosaics at high to very high deforestation risk in sub-Saharan Africa (43.3%) compared to Central and South America (7.6%) and Southeast Asia (8.0%) (SI Table S14). Particularly in the Congo Basin and the coastal region of West Africa, these forests show high to very high deforestation risk (Figure 5). In contrast, most of the intact forest areas and stable forest mosaics in South America (e.g., parts of Amazon Basin) and Southeast Asia (e.g., Borneo) show very low to low deforestation risk (68.4% and 66.2%, respectively). Patterns of accessibility and agricultural suitability are different on the three continents. Intact forest areas and stable forest mosaics in Central and South America are predominantly characterized by low accessibility (74.7%) while in Southeast Asia they are more characterized by low agricultural suitability (74.9%). In contrast, in sub-Saharan Africa, most of these landscapes are characterized by high agricultural suitability (63.1%).

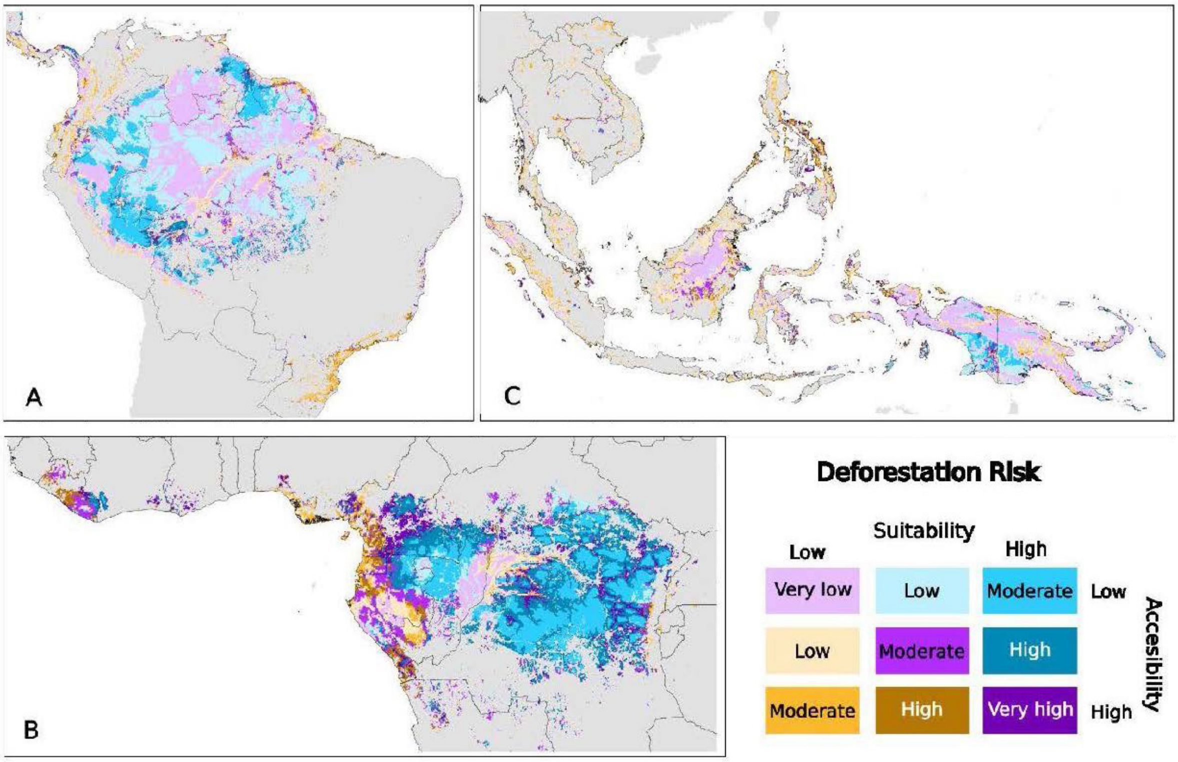

Figure 5. Deforestation risk in intact forest areas and stable forest mosaics

Note: Darker shades indicate higher risk; blue shows risk mainly limited by accessibility, brown by agricultural suitability, and purple by both factors equally.

4 Discussion

This study presents a global comparative overview of the extent to which tropical moist forest landscapes have experienced changes in the last 20 years. Less than a third of the study area is classified as intact forest area, with South and Central America hosting the largest area. Approximately a quarter of the study area was classified as a deforestation area. The identified deforestation areas align with those found in previous studies (e.g., Pacheco et al. 2021) but they also point to new areas to watch (e.g., the Brazilian Pantanal and the Vietnamese Mekong Delta). Our results indicate that TMFs in Southeast Asia have been most affected over the last twenty years with a higher proportion of deforestation areas and degraded forests. However, Central and South America has the largest absolute area of deforestation areas. While deforestation rates in sub-Saharan Africa have historically been lower (Achard et al. 2014; Vancutsem et al. 2021), we found that chronic, accelerating and gradual deforestation areas are as high as on the other continents.

Intact forest areas and stable forest mosaics represent landscapes with high forest cover and low forest cover change (Popatov et al. 2017). Protecting these landscapes is critical. Importantly, our results suggest that low accessibility provides passive protection to a substantial part (34%) of the landscapes with medium to high agricultural suitability. This is particularly true for the larger intact forests of the Amazon, the Congo Basin and the southern part of New Guinea (Indonesia and Papua New Guinea). Other regions are more protected by low agricultural suitability, e.g., due to slopes, poor soils and climate. We looked only at the agro-climatic suitability for low input agriculture, which means that these areas might be made more suitable through capital investments and technological investments (fertilizer, drainage of peatlands, terracing, irrigation).

While accessibility and agricultural suitability were used here as proxies to differentiate risk within archetypes, their relative influence likely varies across regions and interacts with other factors such as tenure insecurity, commodity demand or infrastructure investment. A more systematic analysis of these interactions – potentially using regression or machine learning models – could help quantify how these drivers jointly shape deforestation risk. Both accessibility and suitability are dynamic: road expansion, market integration or climate-driven changes in agroecological potential may shift risk landscapes over time. Anticipating such changes would support more forward-looking and adaptive conservation strategies tailored to context-specific deforestation dynamics.

Forest transition theory suggests that as forest cover declines, deforestation rates tend to slow, eventually giving way to a phase of net forest gain (Mather 1992). In light of this, one would expect to see more stabilized transition areas in low forest cover landscapes, and more accelerating deforestation areas in high forest cover landscapes. Our results broadly reflect this pattern as more accelerating deforestation areas occur in high forest cover landscapes. However, a substantial part of landscapes with low forest cover are situated in currently active deforestation areas, while stabilized transition areas occur also in medium to high forest cover landscapes. The reasons for this are hard to assess without further analysis, but possible explanations may relate to continued high accessibility or agricultural suitability of remaining forests in low-cover areas, continued pressure from commodity cycles, and weak or absent governance that allows clearing to persist. Conversely, some medium- and high-cover landscapes may have become 'stabilized' transition areas due to policy interventions, changing market dynamics, or social factors such as migration and conflict that reduce deforestation pressure despite substantial forest remaining.

The high proportion of stabilized transition areas, combined with the prevalence of forest regrowth as a subsequent land use in Southeast Asia, could signal the early stages of a forest transition. Yet it remains uncertain whether such regrowth reflects a genuine transition toward net forest recovery, or instead results from other land-use dynamics such as shifting cultivation or plantation expansion. Other studies have reported substantial gross tree cover gains in the region (Potapov et al. 2022; Song et al. 2018), but these coexist with persistent high levels of forest loss, as confirmed by our results. Vietnam illustrates this duality: deforestation rates have declined in recent decades (Meyfroidt and Lambin 2009), yet 18.5% of its landscapes are still classified as active deforestation areas. By contrast, the Amazon region shows little evidence of an ongoing forest transition, with active deforestation areas more widespread than stabilized transition areas in Brazil, Colombia and Peru.

In our deforestation areas, the dominant land use following deforestation demonstrates strong regional patterns, which is consistent with earlier pantropical research (Curtis et al. 2018; De Sy et al. 2019). We found a large proportion of forest conversion to grasslands in all continents, and to shrublands in Africa. There are three possible explanations for this. First, because data on managed versus unmanaged grassland are limited and datasets differ in scale and detail (Winkler et al. 2021), our analysis can distinguish the management type in well-established pasture areas, but may overestimate conversion to unmanaged grassland in smaller or more recently deforested areas. Second, more complex land-use dynamics might be at play when forests are converted to grassland and shrublands. There is evidence that agriculture-driven deforestation also occurs without being followed by a clear expansion of managed, productive agricultural land due to speculative land clearing, short-lived and abandoned agriculture, and uncontrolled agriculture-related fires (Pendrill et al. 2022). Third, small-scale or extensive land uses affecting forest cover may escape detection in medium resolution satellite imagery. Using deep learning with high-resolution data, a recent study in Africa (Masolele et al. 2024) produced more detailed land-use classifications, suggesting that many areas we identified as grassland or shrubland could in fact be small-scale cropland, cashew or cacao.

We found no consistent continental patterns linking deforestation areas to dominant follow-up land uses. This suggests that local context, rather than specific land-use conversions, plays the stronger role in shaping the spatio-temporal dynamics of deforestation. However, future research should include more thematically and temporally detailed land-use change data to provide better insight into this relationship. Characterization of specific commodities (Masolele et al. 2024) and complex land-use trajectories (Meyfroidt et al. 2022) would help to identify direct and underlying drivers, eventually leading to better theoretical underpinnings of the archetype analysis.

5 Conclusions

Our data-driven archetype analysis proves useful for the understanding of complex spatio-temporal dynamics of tropical moist forests. Our results show that these forests are under continued pressure and that deforestation is chronic; once high deforestation rates are reached, the process is difficult to slow down. The comparative overview of forest change archetypes can be used to pinpoint globally or nationally important hotspots (e.g., chronic or accelerating deforestation areas) or intact forests under threat. This can then support targeted policy intervention, allowing to target scarce resources to where they can be used more efficiently and effectively, such as in hotspots, where contextualized local responses might prove more efficient. Intact forests at risk need preventive policies (e.g., legal protection) to avoid the emergence of new deforestation areas; existing deforestation areas need reactive conservation policies to halt the deforestation dynamics that are ongoing there.

Our results also highlight clear regional contrasts: Southeast Asia has experienced the greatest proportion of degraded forests and deforestation areas, Central and South America contain the largest absolute deforestation areas, and sub-Saharan Africa, while historically less affected, now shows similar proportions of chronic and accelerating deforestation areas. In addition, analysis of dominant land uses following deforestation underscores how different processes prevail across regions, from pasture and cropland expansion in the Americas, to plantation establishment in Southeast Asia, and extensive grass- and shrubland conversions in Africa.

Further versions of archetype analysis should integrate contextual factors – such as underlying drivers, protection status and land ownership – to explain why some areas fade while others remain active despite low forest cover. Identifying these causal mechanisms would enable archetype analysis to evolve into a diagnostic tool – one that not only classifies recurrent patterns, but also supports comparative policy assessment of which interventions are most effective across different contexts.

These conclusions are intentionally kept general, as the primary aim of this paper is not to deliver any policy analysis, but rather to establish a robust, spatially explicit data foundation. This will then serve as the analytical basis for a forthcoming application of the deforestation diagnostics framework to assess the effectiveness and targeting of forest policy interventions. The deforestation diagnostics framework was outlined by Chervier et al. (2022) and combines context-specific archetypes, a typology of forest policies and measures and evidence-based evaluation of their effectiveness.

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Despite growing commitment for tropical forest conservation, the understanding of complex spatio-temporal deforestation patterns and their underlying drivers remains limited. This study uses archetype analysis to examine global spatio-temporal deforestation patterns in tropical moist forests (TMFs) over the last two decades. This work underpins our attempt to develop a systematized diagnostic of tropical forest policies, aimed at stemming deforestation and forest degradation. We identify seven archetypes of forest state and its change in tropical moist forests, assess conversion from forest to other land uses in deforestation areas, and evaluate deforestation risk in landscapes with high remaining forest cover and low historical deforestation. Our analysis covers approximately 2.8 billion hectares of land area in the tropics that contained tropical moist forest in 2000 – equivalent to about three quarters of the world's TMF landscapes – and thus includes both forest and non-forest areas within those units. Only less than a third of TMFs were classified as intact forest areas (i.e., high forest cover, low deforestation), while approximately a quarter were classified as deforestation areas (i.e., high deforestation). TMFs in Southeast Asia are showing higher proportions of deforestation areas and degraded forests than other regions. Central and South America has the largest absolute area of deforestation areas. While deforestation rates in sub-Saharan Africa have historically been lower, the proportion of deforestation areas is similar to that in the other continents. We could not discern clear patterns linking deforestation areas to specific types of land-use conversion, which suggests that local context plays a more significant role in shaping deforestation patterns. Low accessibility provides passive protection to a substantial part (34%) of intact forest landscapes with good agricultural suitability, particularly in the Amazon, the Congo Basin and southern New Guinea. These results indicate that tropical moist forests remain under continued pressure, with deforestation persisting at high rates. Once elevated deforestation levels are reached, they become difficult to reduce. The archetypes approach is a pragmatic tool to classify tropical deforestation, identify important hotspots under threat, and support spatially targeted policy interventions.

The present paper provides the analytical foundation for four country reports, each examining deforestation policies through the lens of deforestation archetypes in a specific national context: Brazil, the Democratic Republic of the Congo (DRC), Indonesia, and Peru. Together, these five papers introduce the deforestation diagnostic framework.

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