

1 **Archetypes and Drivers of Deforestation in Central America's Tropical Moist**
2 **Forest Frontiers**

3 Santos Daniel Chicas^{1*}, Nobuya Mizoue¹, Helen Xiaohui Bao², Ana Buchadas³, Shizuka
4 Hashimoto⁴, Jaboury Ghazoul⁵, Tetsuji Ota¹, Jair Gaspar Valladarez⁶, Khin Thu Wint Kyaw¹,
5 Matthias Baumann⁷

6 ¹ Department of Agro-Environmental Science, Faculty of Agriculture, Kyushu University, 744
7 Motoooka, Nishi-ku, Fukuoka, Japan.

8 ² Department of Land Economy, University of Cambridge, Cambridgeshire, United Kingdom.

9 ³ Earth and Life Institute, UCLouvain, Louvain-la-Neuve 1348, Belgium.

10 ⁴ Graduate School of Agricultural and Life Sciences, The University of Tokyo, Tokyo, Japan.

11 ⁵ Ecosystem Management, Department of Environmental Systems Science, ETH Zurich,
12 Universitaetstrasse 16, 8092 Zurich, Switzerland.

13 ⁶ Faculty of Science and Technology, University of Belize, Belmopan, Belize.

14 ⁷ Geography Department, Humboldt-Universität zu Berlin, Berlin, Germany.

15 *Corresponding author: Email: chicas.daniel.santos.398@m.kyushu-u.ac.jp

16

17 **Abstract**

18 Deforestation assessments still treat tropical moist forest loss as a uniform process, and do not
19 distinguish the frontier dynamics that shape where and how forests are lost and the drivers
20 associated with them. Here, we develop a regional spatially explicit frontier classification for
21 Central America's tropical moist forest by combining annual 30-m forest-change data (1990-2023)
22 with a frontier-metrics framework aggregated to 1.5-km cells. We derive three frontier typologies

23 and five archetypes from six metrics. We then move beyond descriptive frontier mapping by using
24 non-parametric contrasts and a Bayesian multinomial logit model to understand the drivers
25 associated with different frontier archetypes. Region-wide, Consolidated (19.4%) accounts for the
26 largest share, but active-edge frontier types remain extensive (Critical 11.1%, Developing 9.2%)
27 alongside Fragmented (12.9%) and Dormant (11.7%) frontiers. The multivariate results show that
28 Critical, Developing and Dormant frontiers are systematically in more remote undisturbed forest
29 when compared to Consolidated and Fragmented frontiers. Protected-area associations differ by
30 archetype, with Critical less and Dormant more associated with protected areas. Our findings
31 demonstrate that deforestation drivers are frontier-process specific, and provide an actionable
32 framework for targeting archetype-specific conservation interventions rather than relying on
33 general regional strategies.

34 **Introduction**

35 Tropical forests are important in sustaining livelihoods, mitigating climate change, and preserving
36 biodiversity, yet they continue to be deforested and degraded. The majority of forest loss occurs
37 in frontier areas. In these areas extractive industries and agricultural expansion encroach on the
38 remaining forest, creating trade-off between conservation and economic development ¹⁻³. In these
39 regions, land use decisions, commodity markets and governance regimes influence the
40 spatiotemporal processes of deforestation and degradation ⁴⁻⁷. Therefore, a comprehensive
41 understanding of these processes across frontier regions is essential for designing policies that can
42 protect forest, promote inclusive conservation and development.

43 Frontier areas are defined as “places experiencing marked transformations owing to rapid resource
44 exploitation,” highlighting their distinct social-ecological changes and persistent inequalities ^{2,4}.
45 These transformations are driven by complex interactions among smallholders, agribusinesses, and
46 state actors, which often overlap with historical and ongoing processes such as waves of
47 colonization, land speculation and infrastructure investment ^{6,8}. However, only recently has
48 frontier theory been operationalized in spatially explicit frameworks. This operationalization is
49 crucial, as it allows for the precise identification of frontier archetypes and the specific conditions
50 that pose the greatest risks to both local communities and forest integrity ⁹⁻¹².

51 The reconstruction of land-cover change across entire continents and biomes at high spatial and
52 temporal resolution has been made possible by recent advances in remote sensing and time-series
53 analysis. Several studies have developed frontier metrics using these spatial datasets to measure
54 important aspects of frontier processes, including baseline forest cover, cumulative forest loss,
55 remaining forest, the speed and activity of deforestation and degradation, and post-deforestation
56 land use ^{9,11,13}. These metrics, which summarize the severity, spatiotemporal pattern, and
57 development stage of forest conversion, are used by archetype-based methods to classify
58 landscapes into recurrent frontier types, such as consolidated, degraded, or rampant frontiers ¹⁰.
59 These studies show that frontier metrics provide a diagnostic framework for identifying the variety
60 of deforestation processes and informing spatially targeted governance ¹⁴.

61 With only recent extensions to tropical moist forests (TMF) in Amazonian ¹¹, empirical
62 applications of frontier metrics and archetypes have mostly concentrated on tropical dry forest and
63 woodland frontiers particularly in South America Chaco, the Cerrado and other dry-forest regions
64 in South America, Africa and Southeast Asia ^{9,10}. These studies provide detailed descriptions of
65 frontier patterns and their overlap with protected areas or conservation-priority layers, and
66 qualitatively discuss how archetypes relate to colonization history, agricultural suitability and
67 governance. However, a significant gap remains frontier-metric applications have largely
68 remained descriptive, and no study has explicitly quantified how classic deforestation drivers
69 jointly shift the probability that a location belongs to one frontier archetype rather than another.
70 Moving toward such a process-oriented analysis is essential for identifying the specific driver
71 combinations of each frontier state, which in turn is crucial for designing effective conservation
72 strategies ^{2,4,5}.

73 Despite decades of conservation efforts, Central America has experienced substantial TMF
74 deforestation as a result of agricultural intensification, land reforms, migration, and global market
75 integration ^{15,16}. Protected areas (PAs) and community-based conservation initiatives have
76 emerged as regional strategies to halt deforestation and preserve remaining forests ¹⁷⁻¹⁹.
77 Nonetheless, deforestation has advanced into protected and unprotected TMF in northern
78 Guatemala and Belize, the Mosquitia region of Honduras and Nicaragua, and the Darién of eastern
79 Panama, caused by a mixture of cattle ranching, commercial agriculture, smallholder settlement
80 and associated road building ²⁰⁻²⁴. In these frontier regions, deforestation and degradation are

81 closely tied to land tenure insecurity, speculative clearing and conflicts between colonists and
82 indigenous communities, as well as uneven enforcement of conservation rules ^{20,23,25,26}.
83 Collectively, these diverse pressures create highly heterogeneous frontier dynamics that challenge
84 standardized conservation approaches and demand a more nuanced, archetype-based
85 understanding of the region.

86 Despite these frontier dynamics, regional assessments for Central America are lacking. Most
87 studies continue to describe forest change using aggregate deforestation rates, simple forest/non-
88 forest transitions ²⁷ or classic landscape metrics ^{22,28}, rather than multi-dimensional frontier
89 archetypes. For instance, early remote-sensing analyses in Honduras, Guatemala and Belize
90 assessed forest fragmentation and edge expansion in specific parks and buffer zones using patch-
91 based metrics, identifying roads and settlements as strong drivers of deforestation ²⁹⁻³¹. Later
92 research advances linked deforestation with environmental and socioeconomic factors by
93 combining remote sensing and household surveys ^{32,33}. More recent research has applied emerging
94 hotspot and time-series clustering methods to identify deforestation in protected-area systems, for
95 instance, in the Selva Maya and the Usumacinta watershed ^{17,34}. However, while recent analysis is
96 shifting toward time-series data, these approaches still fail to integrate multiple aspects of frontier
97 dynamics to develop a clear set of archetypes that can be compared across countries and
98 governance regimes. Consequently, this lack of a typological framework limits the capacity to
99 identify specific frontier states and prioritize appropriate policy tools like strict protection,
100 community forestry or sustainable intensification ³⁵.

101 Based on the preceding review four gaps emerge. First, there has been no regional, assessment of
102 deforestation frontiers in Central America. Second, most analyses characterize deforestation in
103 TMF either through aggregate rates or classic landscape metrics, without jointly integrating the
104 severity of forest loss, the spatial configuration of disturbance and the temporal stage or activeness
105 of the frontier, despite evidence from tropical dry woodland studies that these dimensions strongly
106 condition ecological impacts and governance options ¹⁰. Third, and most importantly, emerging
107 frontier-metric applications have yet to perform an explicit, multivariate analysis of how different
108 frontier archetypes are conditioned by classic deforestation drivers. While some studies
109 qualitatively interpret how archetypes relate to accessibility, agricultural suitability or governance,
110 they do not model how these covariates jointly shift the odds of belonging to one archetype versus

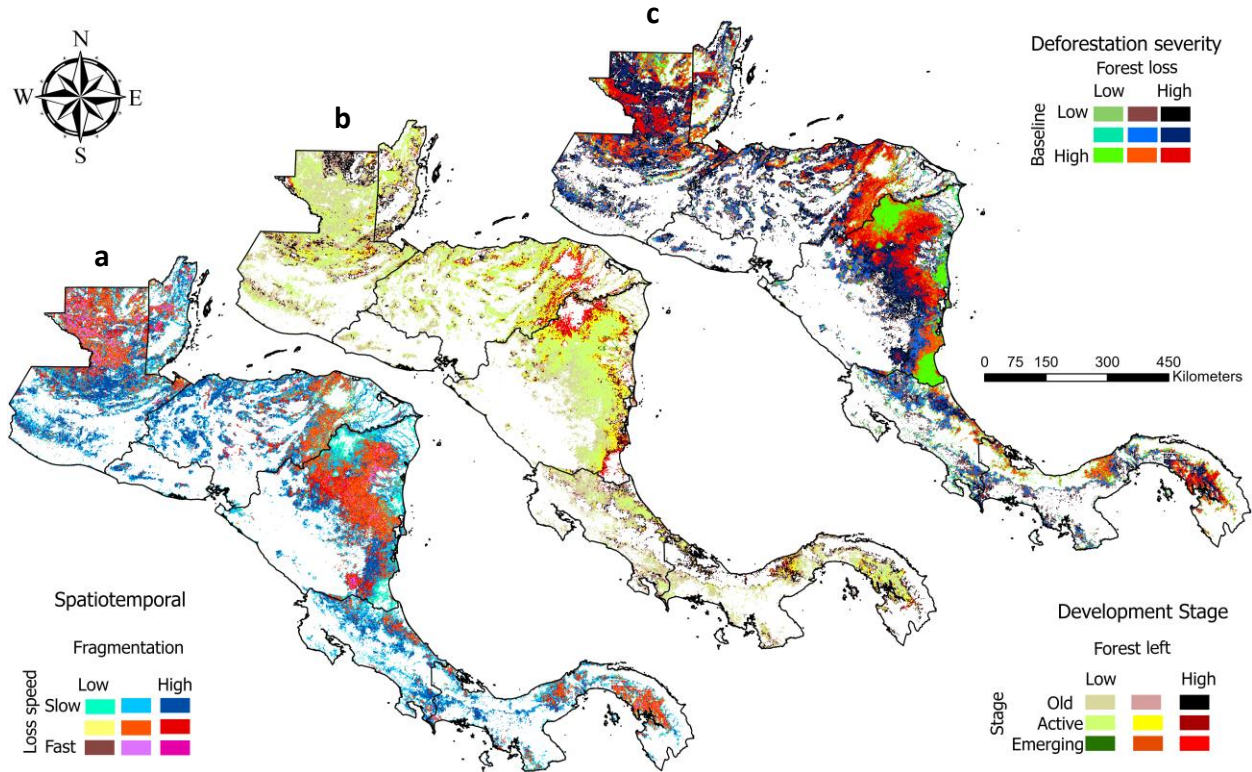
111 another⁹⁻¹¹. Fourth, the alignment between TMF frontier archetypes and conservation instruments
112 remains poorly understood. Specifically, there is limited information on how different IUCN
113 management categories, indigenous territories and other tenure regimes intersect with different
114 TMF frontier archetypes, despite the importance of such data for the debate of management and
115 the future of the forest frontier in TMF regions.

116 We address these gaps by developing and applying a frontier-metric approach specifically tailored
117 for Central America's tropical moist forests. Using the EU-TMF dataset, we derive six process-
118 based metrics: baseline forest, forest loss, loss speed, fragmentation, activity timing and remaining
119 forest. These metrics are calculated at a 1.5-km resolution across Belize, Guatemala, Honduras, El
120 Salvador, Nicaragua, Costa Rica and Panama. We then combined these metrics into three
121 typologies (severity, spatio-temporal pattern, development stage) which were further grouped into
122 five deforestation frontier archetypes: Consolidated, Critical, Developing, Dormant and
123 Fragmented. Beyond providing the first regional, quantitative classification of TMF frontiers in
124 Central America, our study provides an explicit multivariate framework that links archetype
125 membership to classic deforestation drivers. We used non-parametric statistics and an association-
126 focused Bayesian multinomial logit model to quantify how biophysical, accessibility, protection
127 status and land-use factors influence each archetype. In doing so, we show not only where frontier
128 archetypes occur, but also what differentiates them and how they align with existing conservation
129 regimes.

130 **Results**

131 Across Central America, the three landscape typologies indicate a consistent west-to-east gradient,
132 transitioning from long-settled, Fragmented landscapes on the Pacific slope to rapidly shifting
133 frontiers along the Caribbean lowlands. The spatiotemporal pattern typology characterizes the
134 Pacific regions, from Guatemala to Panama, as areas of high fragmentation but slow forest loss
135 (Fig. 1a). In contrast, the Caribbean flank is dominated by medium-to-fast loss with medium-high
136 fragmentation. Specific hotspots of intense, fast, and highly fragmented loss are identified in the
137 Petén basin (Guatemala), the Caribbean coasts of Honduras and Nicaragua, and the Darién region
138 of Panama.

139 The development-stage typology distinguishes Old fronts with low remaining forest, which prevail
 140 in the Pacific and central regions, from Active and Emerging fronts (Fig. 1b). Active and Emerging
 141 fronts with medium-to-high forest retention are concentrated along the Caribbean side of Honduras,
 142 Nicaragua, and central-eastern Panama. Nicaragua provides a distinct spatial progression
 143 beginning with Old fronts on the Pacific, transitioning through a central belt of Active fronts, and
 144 culminating in Emerging fronts at the northern and the Caribbean edges.

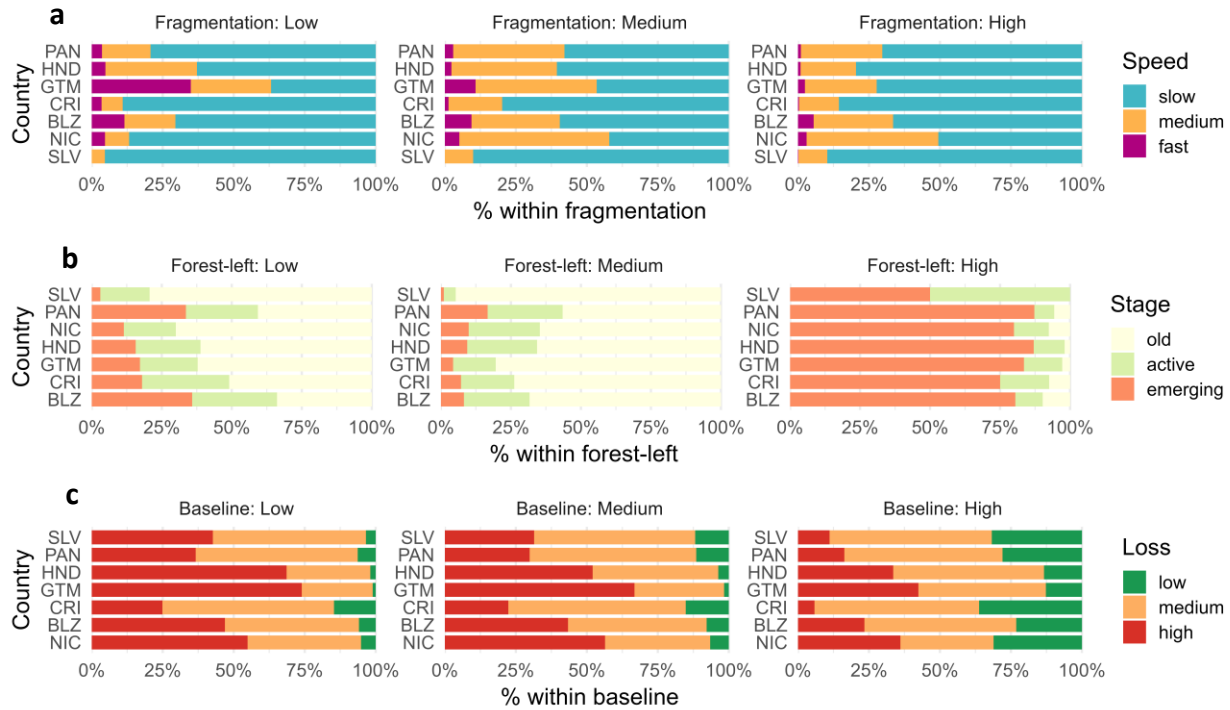


145

146 **Fig. 1| Spatial patterns of three deforestation-frontier typologies across Central America**
 147 **(1990–2023).** (a) *Spatiotemporal typology, combining loss speed (slow → fast) and fragmentation*
 148 *(low → high).* (b) *Development-stage typology, combining stage (emerging → active → old) and*
 149 *forest left (low → high).* (c) *Deforestation-severity typology, combining baseline condition (low*
 150 *→ high) and forest loss (low → high).* Each pixel is assigned to one of the nine class combinations
 151 *per typology.*

152 Finally, the deforestation severity typology pinpoints critical hotspots distinguished by high
 153 baseline forest cover and high subsequent loss (Fig. 1c). These clusters correspond to Active

154 frontier zones, particularly in the Petén, eastern Honduras, and the Darién. These severe-loss areas
 155 are frequently bordered by expanding edges of high-baseline medium-loss areas, contrasting the
 156 high-forest low loss areas found in Nicaragua.



157 **Fig. 2| Country-level composition of deforestation frontier typologies across Central America.**
 158 *Panels show (a) the spatiotemporal typology (loss speed) stratified by fragmentation class, (b) the*
 159 *development-stage typology (frontier stage) stratified by forest-left class, and (c) the severity*
 160 *typology (forest loss) stratified by baseline class. Stacked bars indicate the percentage share*
 161 *within each stratifying class for each country (i.e., bars sum to 100% within each fragmentation,*
 162 *forest-left or baseline tier).*

163 At the Central American scale, the spatiotemporal typology is dominated by slow loss, accounting
 164 for 59.8% of all loss, with medium loss as a consistent secondary mode (35.3%) and fast loss
 165 comprising a small fraction (4.9%) (Table S4). Under high fragmentation (31.2% of all loss), slow
 166 loss overwhelmingly prevails in most countries, such as Costa Rica (CRI, 85.6%). The clear
 167 exception is Nicaragua (NIC), where slow loss (50.6%) and medium loss (46.4%) are nearly equal
 168 (Fig. 2a). In the medium-fragmentation stratum (the largest, accounting for 60.9% of all loss),
 169 patterns diverge. While Costa Rica (79.8%) remains strongly slow-loss dominated, medium loss

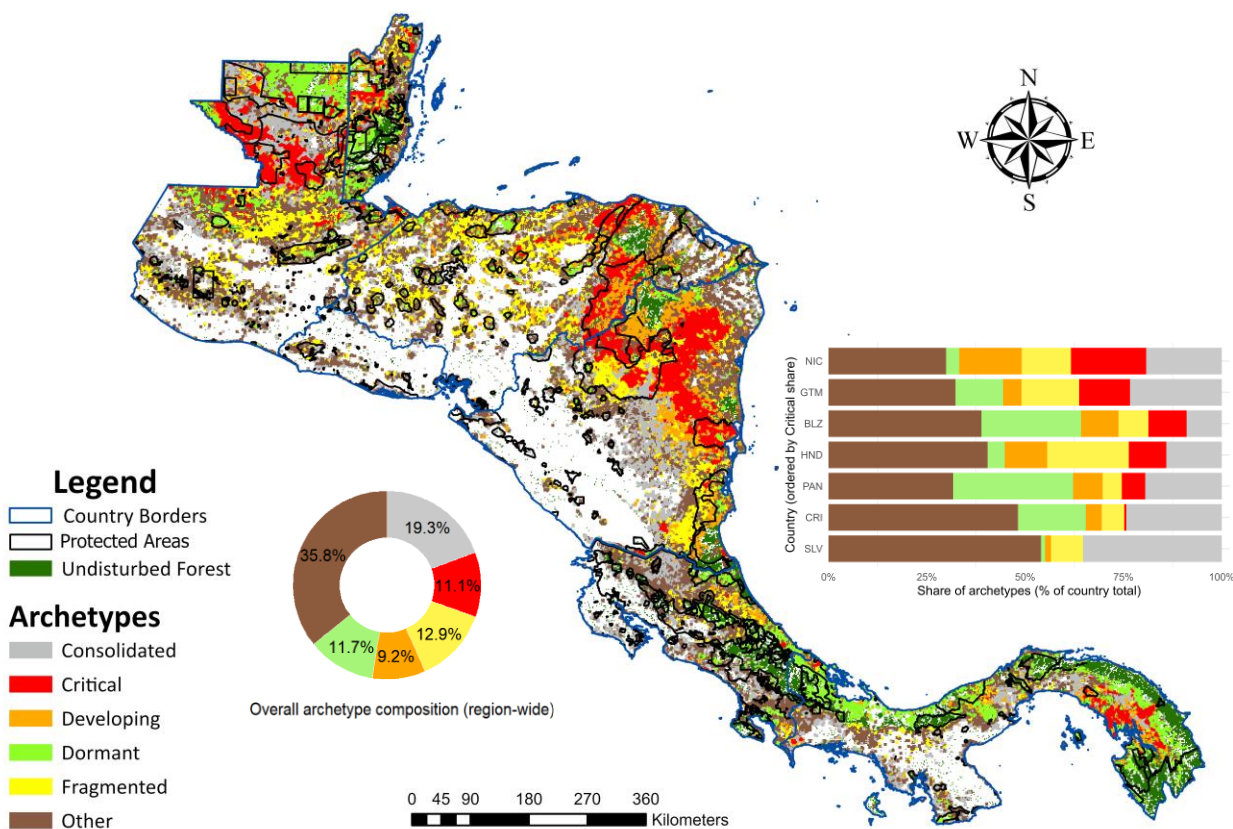
170 becomes the single largest category in Nicaragua (NIC, 52.8%). It is also highly prominent in
171 Guatemala (GTM, 42.7%) and Honduras (HND, 37.2%). The low-fragmentation frontiers (7.9%
172 of all loss) show the greatest contrast. Guatemala (GTM) has a considerable fast-loss component
173 (34.9%). Most other countries, including Costa Rica (89.1%), and Nicaragua (86.8%), remain
174 strongly slow-loss dominated. In this stratum, the most substantial medium-loss shares can be seen
175 in Honduras (32.2%) and Guatemala (28.3%).

176 Across Central America, the Development-stage typology is dominated by Old fronts (61.1% of
177 all area), followed by Active (22.6%) and Emerging (16.3%) fronts (Table S5). The landscape is
178 almost evenly split between low (47.8%) and medium (49.0%) forest-left strata, with high forest-
179 left areas being exceedingly rare (only 3.2% of the total area). The high forest-left stratum is
180 predominantly dominated by Emerging fronts, which cover 82.8% of its area. The medium forest-
181 left stratum is predominantly Old (68.6% of its area) with Active and Emerging fronts accounting
182 for 22.6% and 8.8% respectively. The low-forest-left stratum is dominated by Old fronts (57.2%),
183 with Active (23.3%) and Emerging (19.4%) fronts persisting as smaller, secondary components.
184 At the country level, for example, in Costa Rica the high-forest-left stratum is three-quarters
185 Emerging (75.0%), with 17.5% Active and just 7.5% Old; the medium-forest stratum is 73.81%
186 Old, 19.01% Active and 7.18% Emerging; and the low-forest stratum is split between Old
187 (50.91%), Active (31.14%) and Emerging (17.94%) (Fig. 2b). Guatemala exhibits the same pattern
188 even more strongly: the high-forest-left stratum is 83.52% Emerging (13.64% Active; 2.84% Old),
189 the medium-forest stratum is 80.43% Old (15.20% Active; 4.36% Emerging) and the low-forest
190 stratum 62.19% Old (20.61% Active; 17.20% Emerging).

191 At the regional level, the severity typology reveals that loss is predominantly medium (42.2%) or
192 high (44.9%). These most prevalent areas had high baseline forest cover (42.4% of the region)
193 followed by medium baseline forest cover (32.18%), with the single largest combination being
194 high baseline, medium loss (18.9%) (Table S6). Notably, low loss is rare, accounting for only
195 12.8% of the total area. Country-level analysis reveals individual regimes. Belize (25.9%),
196 Honduras (21.1%) and Panama (26.8%) are characterized by a high baseline and medium loss
197 pattern. Costa Rica (26.5%), Guatemala (24%) and Nicaragua (18%) are characterized by medium
198 baseline-medium loss, medium baseline -high loss and high baseline-high loss, respectively.
199 Within low-baseline strata, high-loss is overwhelmingly dominant for Guatemala (73.9%),

200 Honduras (68.6%) and Nicaragua (54.8%) (Fig. 2c). A similar pattern is observed in the medium-
 201 baseline strata for these countries where high loss exceeds 50%. In contrast, in the high-baseline
 202 strata high loss is below 50% for all countries. Honduras and Guatemala show the strongest high-
 203 baseline loss profiles, with medium-to-high loss jointly accounting for 86.1% and 87.2% of their
 204 high-baseline strata, respectively. This pattern is mirrored in Belize, where medium-to-high loss
 205 is the dominant category within its extensive high-baseline stratum (53.1% and 53.4%,
 206 respectively). However, this pattern is less pronounced in Costa Rica which exhibits 36.2% of slow
 207 loss and only 5.8 % of high loss.

208

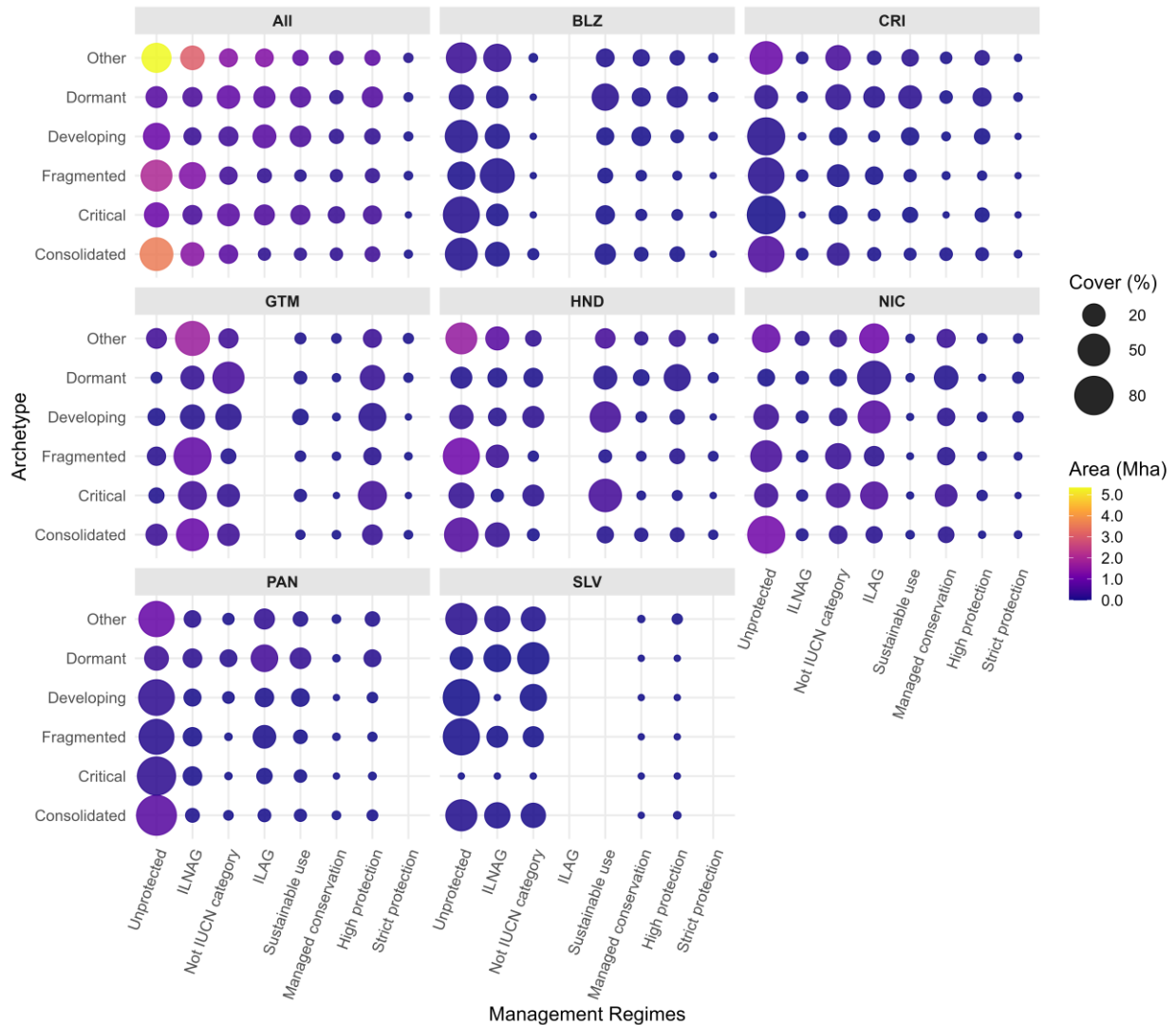


209

210 **Fig. 3| Frontier archetypes across Central America and country-level composition.** *The donut*
 211 *chart summarizes the region-wide archetype composition. The stacked bars show within-country*
 212 *archetype shares (percentage of each country's total archetype area; bars sum to 100%) and*
 213 *countries are ordered by the share of the Critical archetype.*

214 Regionally, the archetype mosaic shows a coherent progression from intact cores to post-frontier
215 landscapes. Quantitatively, the Other category accounts for the largest share of mapped area
216 (35.8%), followed by Consolidated post-frontier landscapes (19.4%), Fragmented frontiers
217 (12.9%), Dormant frontiers (11.7%), Critical frontiers (11.1%), and Developing frontiers (9.2%)
218 (Fig. 3). The map reveals that Developing frontiers form semi-continuous belts at the edges of
219 remaining intact forest, most prominently along the Mosquitia-Caribbean flank of Honduras-
220 Nicaragua and across south-western Petén in Guatemala with extensions into central Belize. These
221 belts border Critical frontiers, producing the expected sequence of active conversion that attenuates
222 into fragmented mosaics and then consolidated interiors. Dormant frontiers appear as enclaves
223 where clearing has slowed but substantial forest remains.

224 Country profiles mirror this continental gradient. Ordering countries by the proportion of Critical
225 area Nicaragua ranks highest, followed by Guatemala and Belize, then Honduras and Panama, with
226 Costa Rica and El Salvador ranking lowest. In Nicaragua, a broad Critical corridor runs from the
227 North Caribbean Autonomous Region into the central–eastern lowlands, with adjacent Developing
228 and Fragmented frontiers extending westward. Guatemala features a notable Critical belt along
229 southwest Petén; with consolidated areas in the middle and Dormant classes northeast. In Belize,
230 Critical and Developing frontiers cluster along the northern lowlands, while Dormant pockets
231 persist toward the Maya Mountains. Honduras shows a mixed portfolio: Critical and Developing
232 along the Caribbean, Fragmented interiors across valley bottoms, and localized Dormant areas in
233 the montane reserves. Panama’s Critical frontiers concentrate in Darién, with an extensive
234 Dormant belt that extends to Costa Rica. By contrast, El Salvador is dominated by Consolidated
235 and Other classes, reflecting long-standing settlement, limited remaining intact cores, and
236 widespread post-frontier land systems. This stratified view identifies where pressure is currently
237 greatest, where it is expanding into Fragmented frontiers, and where the frontier has largely
238 transitioned to post-frontier types.

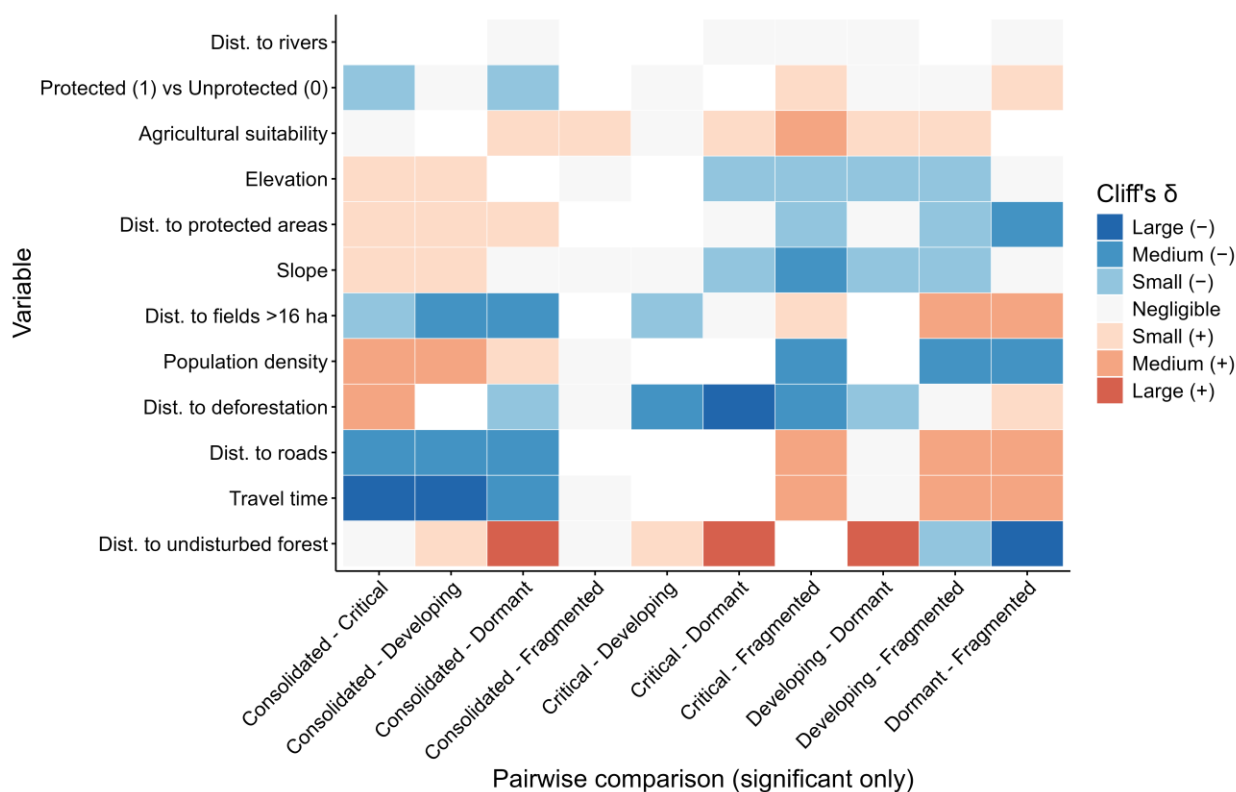


239

240 **Fig. 4| Distribution of deforestation archetypes across management regime classes to all**
 241 **Central America (all) and by country.** *Bubble size represents the cover (%) share of archetype*
 242 *area that falls into each protection class per country (i.e., for a given country and archetype row,*
 243 *percentages across protection classes sum to 100%). Bubble color represents the absolute areas*
 244 *of each country-archetype-protection combination expressed in million hectares (Mha).*

245 At the regional scale, the archetype areas are concentrated in unprotected and low-protection
 246 classes. For Central America, the largest within-archetype shares (bubble size) and the greatest
 247 absolute areas (color intensity) occur in unprotected lands for most archetypes, with ILNAG and
 248 not-IUCN category also accounting for substantial fractions (Fig. 4). By contrast, the strictest
 249 categories shown here contain only a small share of most archetypes at the regional scale (e.g.,

250 10% of Critical and 7% of Developing), showing that active frontier types are generally not
 251 embedded within strictly protected cores. Multiple-use categories (ILAG, sustainable use) include
 252 frontier types, but their importance varies widely by country. Country panels reveal distinct
 253 governance intersections. Guatemala is an exception to the regional pattern, with large shares of
 254 Critical (37%) and Developing (33%) occurring in highly protected areas. Honduras concentrates
 255 a large share of active frontier types in sustainable use (Critical 53%, Developing 44%), while
 256 Nicaragua shows a strong intersection with ILAG areas (Developing 51%; Dormant 55%). Panama
 257 and Costa Rica are dominated by unprotected or low-protection classes overall, while Belize shows
 258 visible shares of Fragmented, Critical and Developing archetypes across unprotected and ILNAG.
 259 El Salvador is almost entirely confined to the least-protected classes in this TMF-based domain,
 260 with negligible representation in the strictest categories.



261
 262 **Fig. 5| Effect-size heatmap (Cliff's δ) for significant pairwise differences in drivers across**
 263 **frontier archetypes.** Rows show standardized predictors and columns show pairwise archetype
 264 contrasts labeled as Group1 – Group2 (Group1 appears to the left of the dash; Group2 to the
 265 right). Each cell reports Cliff's delta (δ) for the predictor between the two archetypes and is
 266 shown only for contrasts that are significant in Dunn's post-hoc tests following a Kruskal–Wallis

267 screen (FDR-adjusted $p \leq 0.05$). Colors encode both direction and magnitude: warm colors ($\delta >$
 268 0) indicate higher predictor values in Group1 than Group2, whereas cool colors ($\delta < 0$) indicate
 269 higher values in Group2 than Group1. Color intensity reflects effect-size class (negligible, small,
 270 medium, large). For binary predictors (e.g., Protected = 1 vs Unprotected = 0), $\delta > 0$ indicates
 271 a higher probability of the value “1” in Group1 relative to Group2.

272 We summarized differences in covariates across archetypes using Cliff’s δ (Fig. 5), masking cells
 273 that were not significant after Benjamini–Hochberg correction ($\alpha=0.05$) (Fig. S1). Positive values
 274 indicate larger covariate values in the first archetype of each contrast, while negative values
 275 indicate the opposite. Across variables, the clearest, most consistent separations are observed along
 276 accessibility gradients and forest-edge proximity. Consolidated areas are more accessible than any
 277 other class. They have substantially shorter travel times and smaller distances to roads than Critical,
 278 Developing and Dormant. They also lie closer to large fields (>16 ha) while hosting higher
 279 population densities. At the same time, Consolidated pixels tend to be farther from undisturbed
 280 forest than Developing and Dormant pixels and farther from protected areas. Critical frontiers, in
 281 contrast, are closer to deforestation areas than all the other frontiers. Agricultural suitability is
 282 generally higher for Critical than for Dormant and Fragmented and Critical frontiers also occur at
 283 lower slopes and elevations. Dormant frontiers differ from Critical frontiers most strongly by
 284 proximity to undisturbed forest (and, similarly, by greater distance from prior deforestation),
 285 whereas Developing differs from Critical primarily by proximity to prior deforestation (with
 286 smaller differences in distance to undisturbed forest). Fragmented frontiers in general resemble
 287 Consolidated frontiers, except that agriculture suitability is higher for Consolidates frontiers.

288 **Table 1| Bayesian multinomial logit associations between covariates and archetype**
 289 **membership**

Predictor	Critical	Developing	Dormant	Fragmented
Fixed Effects	Est. [95% CI]	Est. [95% CI]	Est. [95% CI]	Est. [95% CI]
Intercept	-0.81 [-1.83, 0.16]	-0.39 [-1.45, 0.62]	-1.19 [-2.47, 0.26]	-0.17 [-1.09, 0.74]
		-0.37 (-0.58, -		
Elevation (z)	-0.36 (-0.62, -0.12)	0.16)	-0.00 (-0.18, 0.18)	-0.12 (-0.24, 0.01)
		-0.18 (-0.34, -		
Slope (z)	-0.40 (-0.59, -0.22)	0.02)	0.12 (-0.04, 0.27)	-0.09 (-0.20, 0.02)

Travel time (log1p, z)	1.18 (0.99, 1.37)	0.92 (0.74, 1.10)	1.09 (0.89, 1.30)	0.14 (0.01, 0.26)
Dist. to roads (log1p, z)	0.20 (0.08, 0.32)	0.05 (-0.06, 0.16)	0.19 (0.05, 0.34)	-0.08 (-0.16, 0.00)
Population (log1p, z)	0.18 (-0.03, 0.39)	0.27 (0.08, 0.45)	0.13 (-0.08, 0.34)	0.26 (0.12, 0.41)
Agricultural suitability (z)	-0.28 (-0.41, -0.15)	-0.25 (-0.37, -0.12)	-0.32 (-0.47, -0.16)	-0.28 (-0.40, -0.17)
Dist. to PAs (log1p, z)	-0.31 (-0.46, -0.16)	-0.21 (-0.35, -0.06)	-0.23 (-0.41, -0.06)	0.03 (-0.10, 0.16)
Dist. to prior defor. 1990–2010 (log1p, z)	-0.66 (-0.74, -0.58)	-0.11 (-0.20, -0.02)	0.31 (0.17, 0.45)	-0.12 (-0.21, -0.04)
Dist. to undisturbed forest 2023 (log1p, z)	-0.20 (-0.34, -0.06)	-0.67 (-0.79, -0.55)	-1.23 (-1.36, -1.11)	-0.27 (-0.39, -0.14)
Dist. to fields >16 ha (log1p, z)	0.14 (0.01, 0.26)	0.30 (0.18, 0.43)	0.30 (0.14, 0.46)	0.07 (-0.02, 0.16)
Protected (1) vs Unprotected (0)	-0.37 (-0.71, -0.05)	-0.02 (-0.33, 0.28)	0.49 (0.12, 0.87)	0.17 (-0.08, 0.43)

290 *The table presents the posterior mean estimates and 95% Credible Intervals (CIs). Estimated for which the 95% CI*
291 *excludes zero (indicating strong evidence of an effect) are highlighted in bold*

292 The multinomial logit model (reference = Consolidated) corroborates and sharpens the
293 distributional patterns seen with Cliff's δ by quantifying how accessibility, edge context, and land-
294 use setting shift the odds of each frontier state. Accessibility appears as the dominant separator. A
295 one standard deviation increase in travel time multiplies the odds of Critical by 3.3 (log-odds 1.18,
296 95% CrI 0.99-1.37), Developing by 2.5 (0.92, 0.74-1.10), and Dormant by 3.0 (1.09, 0.89-1.30)
297 relative to Consolidated. Distances to roads show a similar (though smaller) pattern, increasing the
298 odds of Critical (0.20, 0.08-0.32) and Dormant (0.19, 0.05-0.34), while being indistinguishable
299 from zero for Developing and Fragmented (Table 1). Furthermore, population density shifts the
300 odds away from Consolidated frontiers toward Developing (0.27, 0.08-0.45) and to Fragmented
301 (0.26, 0.12-0.41).

302 Deforestation shows strong, coherent signals. Greater distance from prior (1990-2010)
303 deforestation sharply lowers the odds of Critical (-0.66, -0.74 to -0.58; OR 0.52) and Fragmented
304 (-0.12, -0.21 to -0.04), while increasing the odds of Dormant (0.31, 0.17-0.45), aligning with a
305 legacy-clearing footprint around active fronts and waning pressure in older fronts. In contrast, a
306 greater distance from undisturbed forest strongly lowers the odds of Developing (-0.67, -0.79 to -
307 0.55; OR 0.51) and especially Dormant (-1.23, -1.36 to -1.11; OR 0.29), situating both along or
308 immediately exterior to remaining intact cores. More broadly, distance to undisturbed forest is
309 negative for all non-Consolidated classes (Critical -0.20, Fragmented -0.27), indicating that these
310 frontier types tend to occur closer to intact forest than the Consolidated reference, with the
311 strongest proximity signal for Dormant. These associations fit together with the effect-size results
312 where Critical concentrates near recent clearing, while Developing and Dormant border intact-
313 forest edges.

314 Signals tied to land-use intensity also differentiate types. Greater distance from large fields (>16
315 ha) increases the odds of Developing and Dormant (both 0.30), indicating that these types are more
316 prevalent away from large-field agriculture relative to Consolidated, whereas Fragmented shows
317 no clear contrast with Consolidated. Agricultural suitability is lower in all non-Consolidated types
318 (Critical -0.28, -0.41 to -0.15; Developing -0.25, -0.37 to -0.12; Dormant -0.32, -0.47 to -0.16;
319 Fragmented -0.28, -0.40 to -0.17), supporting the Cliff's δ pattern that high-suitability areas are
320 more often Consolidated or already converted. Protection status exhibits asymmetric associations.
321 Pixels in protected areas have lower odds of being Critical versus Consolidated (-0.37, -0.71 to -
322 0.05; OR 0.69), but higher odds of being Dormant (0.49, 0.12-0.87; OR 1.63), consistent with
323 slowed but not absent frontier activity within protected areas.

324 **Discussion**

325 **Interpretation of frontier metrics in Central America**

326 Our frontier metrics reveal a multi-dimensional gradient of tropical moist forest change across
327 Central America. This framework captures, with distinct combinations of how much forest has
328 been lost (severity), how loss unfolds in space (spatiotemporal pattern), and where landscapes sit
329 along a pre- to post-frontier trajectory (development stage). Collectively, these metrics
330 demonstrate variability in accessibility, land-use intensity, and governance context. This multi-

331 dimensional approach aligns with recent advances in defining diverse frontier typologies in other
332 global deforestation hotspots, such as the South American Chaco ⁹ and the dry woodlands of the
333 tropics ¹⁰.

334 At the regional scale, deforestation severity is dominated by medium-to-high cumulative loss
335 occurring in areas that initially had high baseline forest cover, while low-loss frontiers are
336 comparatively rare. This indicates that much of the multi-decadal conversion has occurred in once-
337 intact, high-biomass forest landscapes rather than being confined to already-open, heavily
338 modified mosaics. This finding is consistent with continent-scale evidence that recent tropical
339 forest loss has disproportionately affected remaining high-cover forest ^{36,37}.

340 The development-stage typology further clarifies that Central America is not defined by a single
341 frontier, but by the coexistence of long-established (Old) frontier landscapes, ongoing (Active)
342 conversion zones, and a distinct leading edge of Emerging frontiers. These Emerging frontiers are
343 probably caused by actors looking for new areas to establish themselves, a dynamic observed in
344 frontier emergence globally⁴. Notably, Emerging fronts cluster along the Caribbean-facing
345 escarpments and lowlands of Guatemala, Honduras and Nicaragua and in eastern Panama,
346 indicating that the contemporary expansion front is concentrated where relatively continuous moist
347 forest still remains.

348 The spatiotemporal typology indicates that the bulk of historical clearing has been relatively slow
349 but highly fragmented, consistent with land-use change dominated by smallholders and gradual
350 road extension, rather than by very large, abrupt clear-cuts alone ^{21,38,39}. However, our metrics also
351 capture pockets where loss is both fast and spatially aggregated especially within Critical frontiers
352 in northern Guatemala, the Honduran-Nicaraguan Mosquitia and Darién. These findings show
353 recent accelerations in commodity-driven or road-facilitated expansion ^{38,40,41}.

354 While our model did not explicitly test for illicit drivers, the spatial coincidence of these Critical
355 fast-loss clusters with known trafficking corridors strongly suggests a link to illicit capitalization
356 and narco-deforestation dynamics documented in these specific sub-regions ^{42,43}. As opposed to
357 traditional smallholder-driven deforestation, such processes are frequently characterized by
358 uncharacteristic capital injections that fuel rapid land clearing for territory control and money
359 laundering rather than productive agriculture alone. This phenomenon is becoming more widely
360 acknowledged in landscape suitability models for trafficking throughout the region ⁴⁴.

361 The distribution of frontier types throughout the region and their relationship to the gradient from
362 intact cores to post-frontier landscapes can be concisely understood by combining the three
363 typologies into archetypes^{9,11}. The regional mosaic is characterized by extensive Other and
364 Consolidated landscapes, with Fragmented frontiers widespread across long-settled agricultural
365 regions, consistent with Central America's long history of frontier expansion and in some areas
366 movement toward post-frontier transition dynamics^{45,46}. Dormant and Developing frontiers
367 frequently cluster near remaining forests, while Critical frontiers occur at the frontier edge of
368 forest-rich landscapes. This spatial edge-mediated pattern is consistent with frontier expansion
369 driven by improved access, land speculation and the progressive outward expansion of cattle^{20,47}.
370 Country profiles show that the frontier gradient differs markedly among countries, likely reflecting
371 distinctions in remaining forest extent and wider national land-use and governance contexts.
372 Nicaragua and Guatemala contain the largest proportions of Critical frontiers^{15,48}, while Panama,
373 Belize, and Costa Rica have substantial shares of Dormant frontiers^{49,50}. By contrast, Honduras
374 has comparatively large Fragmented frontiers, consistent with a more pervasive network of long-
375 settled agricultural landscapes alongside ongoing edge-mediated expansion¹⁵. These archetypes
376 highlight how divergent national trajectories have produced distinct patterns of forest loss across
377 Central America.

378 **Accessibility, edge dynamics, and protection shape frontier archetypes**

379 The covariate contrasts and multinomial logit model suggest that accessibility is the strongest
380 separator among frontier types relative to Consolidated, Critical, Developing, and Dormant
381 frontiers. Critical and Dormant frontiers are systematically more remote showing higher travel
382 times and further from roads. This is consistent with global mappings of travel time which
383 highlight how accessibility stratifies economic opportunity and human activity⁵¹, and with long-
384 standing evidence that transport costs are among the most robust proximate predictors of tropical
385 deforestation²¹. The most accessible areas tend to be cleared earlier, leaving later frontier activity
386 concentrated in remaining forest margins and newly accessible peripheries. The proximity of
387 Critical frontiers to prior deforestation footprints is consistent with stepwise, edge-mediated
388 expansion, in which earlier clearing creates local access, land markets, and spatial contagion
389 effects that increase the likelihood of subsequent clearing nearby⁵² and are theorized as a key
390 mechanism of frontier emergence globally⁴. Developing frontiers are also more likely to be closer

391 to prior deforestation and to remaining undisturbed forest, consistent with active expansion along
392 existing forest-edge interfaces. In contrast, Dormant frontiers are concentrated near undisturbed
393 forest yet occur farther from historical deforestation footprints, aligning with potential pioneer
394 efforts. More broadly, distance to undisturbed forest is negatively associated with all non-
395 Consolidated frontier types (with the strongest effect in Dormant).

396 The land-use intensity proxies further suggest that Central American frontiers are determined by
397 interactions between smallholder mosaics, and more capitalized agriculture. Greater distance from
398 large fields (>16 ha) is associated with higher odds of Critical, Developing and Dormant relative
399 to Consolidated, implying that large-field, capital-intensive agriculture is most characteristic of
400 consolidated landscapes. This pattern is consistent with the idea that much of the remaining Active
401 frontier in Central America is unfolding away from established mechanized-agriculture cores, in
402 more remote forest margins and mixed-use landscapes. It also suggests that large-field expansion
403 may be more characteristic of later-stage consolidation than of the leading edge captured by our
404 Critical and Emerging fronts. This stands in contrast to several South American frontiers, where
405 rapid large-scale expansion often occurs at much earlier stages of frontier advance⁹. At the same
406 time, agricultural suitability is lower in all non-Consolidated types relative to Consolidated,
407 implying that the highest-suitability lowlands have already been disproportionately converted,
408 while remaining frontier advance is increasingly pushed into less favorable or more weakly
409 governed settings⁵³.

410 Protection status shows an asymmetric association, protected pixels are less likely to be Critical
411 than Consolidated, but more likely to be Dormant. This is consistent with the interpretation that
412 protection often slows frontier advance without necessarily eliminating pressure, and that
413 protected landscapes may include substantial areas where conversion is reduced or displaced
414 toward edges rather than absent altogether⁵⁴. Several frontier states are notably situated in
415 proximity to protected areas, indicating a tendency to cluster around protected-area boundaries,
416 even in regions where critical conversion is less probable within protected lands. This pattern
417 aligns with evidence indicating that the effects of protected areas are heterogeneous, influenced
418 not only by formal designation but also by location, accessibility, and local enforcement capacity
419 ^{55,56}. It also implies that varying results throughout the region may indicate disparities in the
420 intensity of underlying frontier pressures rather than solely differences in management. In the

421 Costa Rican context, PAs have reduced deforestation largely due to long-standing state policies
422 and institutionalized conservation programs^{57,58} and the placement of PAs in lower-pressure areas
423⁵⁵. In Guatemala, on the other hand, protected areas have been heavily encroached upon as a result
424 of colonization, land speculation, illegal cattle ranching, and drug-trafficking-linked land use
425 change^{47,59,60}. However, in Guatemala's Maya Biosphere Reserve, community-managed
426 concessions have historically outperformed strictly protected areas in limiting forest loss^{61,62}. This
427 indicates that in some Active frontiers, well-secured and enforceable community tenure can be
428 highly effective, but the persistence of Critical and Developing frontiers in ILAG areas (e.g.
429 Nicaragua) indicates that tenure recognition alone does not guarantee protection.

430 **Relevance to conservation and land-use policy**

431 Our archetypes indicate that the region's highest near-term leverage for avoided deforestation lies
432 in Critical and Developing frontier belts that are still forest-rich yet comparatively more remote
433 and close to remaining intact forest. In these settings, relatively small changes in access (e.g., road
434 upgrading and travel-time reductions) and land-market dynamics can trigger rapid, edge-mediated
435 expansion, implying high additionality for interventions that strengthen tenure security, reduce
436 incentives for speculative clearing and anticipate and manage new access before forest loss
437 accelerates⁵.

438 Most Critical and Developing frontiers lie outside the strictest categories. However, this pattern is
439 not uniform. For example, Guatemala is a clear exception, where a substantial fraction of Critical
440 and Developing frontiers occurs within high-protection categories, alongside large shares in
441 ILNAG and non-IUCN category. Across the region, strict categories contain a higher relative
442 representation of Dormant than Developing, but also a non-trivial Critical area in specific national
443 contexts. Importantly, this overlap analysis is not a counterfactual estimate of protected-area
444 effectiveness; rather, it is consistent with evaluation evidence that protected-area outcomes vary
445 with placement and management capacity. Country contrasts suggest different policy entry points
446 for similar frontier types. In Guatemala, the prominence of Critical and Developing archetypes
447 within strict protection categories aligns with concerns about encroachment pressures in parts of
448 the protected-area system⁴⁷. In Nicaragua, Active frontier archetypes show a strong intersection
449 with the ILAG category, consistent with the central role of tenure and governance dynamics in
450 frontier expansion²⁰. Honduras, by contrast, concentrates much of its Critical and Developing

451 frontier signals in sustainable use and unprotected areas, highlighting multi-use landscapes as key
452 arenas for managing frontier advance. Finally, in Costa Rica most frontier archetypes intersect
453 with unprotected areas with the exception of Dormant, consistent with the country's longstanding
454 focus on environmental protection measures.

455 These results imply that a single frontier response, such as simply expanding protected area
456 coverage, will be insufficient. Instead, an archetype-informed strategy suggests different
457 instrument mixes. In Critical frontiers, the priority is speed and credibility because the land system
458 is changing quickly and local environmental governance is being outpaced. These areas are located
459 in the Caribbean-facing frontier belts (e.g. Honduras and Nicaragua) where loss is relatively fast
460 and increasingly fragmented. In these areas mitigation cannot be limited to a new plan on paper.
461 These areas require near real-time monitoring tied to rapid-response enforcement and very
462 practical tenure actions such as accelerating titling or co-titling in places where land claims are
463 being contested, particularly to secure and protect Indigenous peoples' land rights. Developing
464 frontiers, in contrast, are found where conversion pressure is expanding outward from an already
465 active edge into adjacent higher forested areas. That pattern is visible in zones around remaining
466 intact cores, where medium-to-fast loss is present but not yet fully converted into a high-
467 fragmentation end state. These areas are where supply-chain and land-use planning tools can be
468 effective. For instance, targeted zero-deforestation procurement, zoning that explicitly sets no use
469 buffers around the intact core, and road planning that treats new access as a land-use decision
470 rather than a neutral infrastructure upgrade may be especially valuable.

471 Dormant frontiers in our results look more like landscapes where clearing has slowed and the
472 pattern is comparatively stable, often away from the main expansion front. These areas offer
473 opportunities for ensuring forest stability. In these areas, co-management agreements, restoration
474 incentives, and community-based governance can be used to prevent re-acceleration when
475 commodity prices rise or a new access route appears. For example, this could include restoration
476 payments to verifiable regeneration in previously disturbed zones, along with empowering local
477 enforcement authorities with genuine jurisdictional power and resources (for example, allowing
478 community forest guards to issue legally binding citations), rather than just assigning them
479 monitoring responsibilities without the legal backing to act.

480 In Fragmented mosaics, which are prominent in the long-settled Pacific-slope landscapes, the
481 problem is less the presence of a single advancing edge and more the slow advancement of
482 degradation and connectivity loss. Therefore, the intervention logic shifts toward landscape-scale
483 design. For instance, priorities include maintaining functional corridors between remnant patches,
484 reducing chronic degradation, and making regeneration financially rational inside these landscapes.
485 This is where strategies such as riparian buffer enforcement, agroforestry incentives, and corridor-
486 focused restoration are needed because connectivity is already the scarce resource.

487 Finally, Consolidated interiors are areas where most conversion is already historical. Therefore,
488 the remaining leverage here is about how production systems operate and how restoration is
489 targeted. In these landscapes, prevention is no longer the main policy margin. The more realistic
490 strategy is long-term. For example, it may involve sustainable intensification where agriculture is
491 entrenched, restoration corridors that reconnect higher-value patches, and demand-side policies
492 that reduce incentives for land-intensive production.

493 **Limitations and future research**

494 Several limitations qualify our findings. First, all frontier metrics ultimately inherit the
495 uncertainties of the underlying TMF dataset. While we partially mitigate this by focusing on broad
496 tiers (low/medium/high) and by interpreting patterns at 1.5-km resolution, some fine-scale mosaics
497 and smallholder dynamics will be under-represented. Second, our typology is static over the
498 analysis period each pixel is assigned to a single archetype summarizing its 1990-2023 trajectory.
499 This is appropriate for identifying long-term frontier types, but it cannot capture within-class
500 dynamics such as transitions from Developing to Critical or from Fragmented towards
501 Consolidated. Third, the covariates we analyze are predominantly biophysical and infrastructural
502 proxies. We do not explicitly model actor types, commodity supply networks or land-tenure
503 categories, which are known to be decisive for frontier behavior in Latin America. Nor do we
504 consider telecoupled feedbacks whereby policies or market shocks in one country displace
505 deforestation to another. Finally, our governance analysis simplifies the diversity of protection
506 status into seven classes and does not explicitly consider management effectiveness, enforcement
507 capacity or Indigenous and community land rights beyond the ILAG and ILNAG categories.
508 However, comparative research suggests that official protection status is often a poor proxy for
509 actual conservation outcomes ⁶³. In many cases, Indigenous territories provide robust forest

510 safeguards that equal or exceed those of formal IUCN-designated areas, although they may lack a
511 legal conservation mandate ^{64,65}.

512 Future work could address these limitations in several ways. Temporal archetype analysis or
513 Markov models could capture path dependencies more explicitly by tracing shifts between frontier
514 types over time. Integrating actor-specific data, such as cattle versus oil-palm expansion or
515 smallholder versus agribusiness clearing, would sharpen the policy relevance of particular
516 archetypes and help distinguish national from transnational drivers. Research could also examine
517 telecoupled feedbacks, where policies or market shocks in one country displace deforestation to
518 another. A further priority is to connect our frontier typology to independent indicators of
519 governance quality and formal rights recognition, which would better reflect the realities of forest
520 conservation on the ground.

521 **Conclusion**

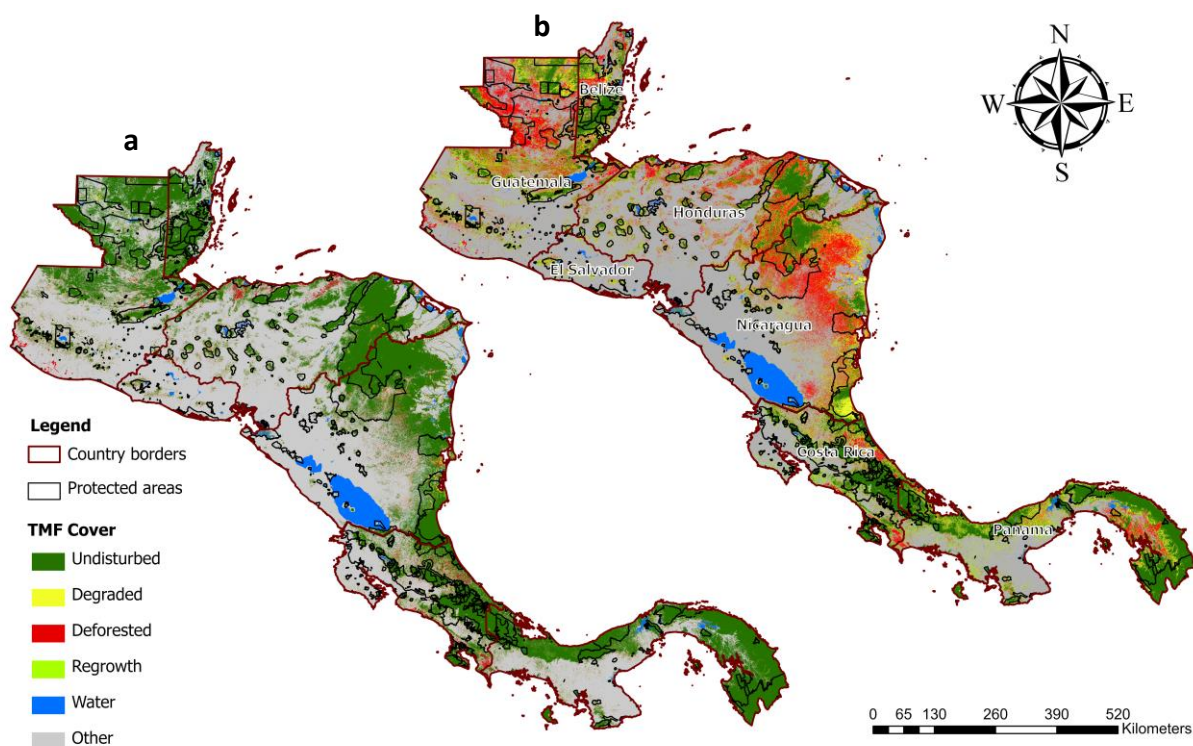
522 This study moves beyond aggregate deforestation rates to reveal, in a process-based and spatially
523 explicit way, how tropical moist forest frontiers unfold across Central America. Using frontier
524 metrics, archetype classification, and multivariate modeling, we provide the first regional
525 quantitative framework that maps where frontier types occur and identify the combinations of
526 drivers associated with each frontier type. The results show that Central American deforestation is
527 not a single regional process, but a mosaic of distinct frontier types distributed along a broad west
528 to east gradient, from long-settled, Fragmented and Consolidated Pacific landscapes to active,
529 forest-rich frontier belts concentrated in Petén, central Belize, the Mosquitia corridor, and Darién.
530 These Active frontiers remain extensive and are systematically more remote, closer to undisturbed
531 forest, and more tightly linked to frontier-edge expansion than Consolidated post-frontier
532 landscapes. Our findings also show that frontier drivers and governance relationships are archetype
533 specific. By identifying where different frontier processes occur and what distinguishes them, our
534 study provides an actionable basis for targeting conservation policy where it can have the greatest
535 ecological and governance impact.

536

537 **Methods**

538 **Study Region**

539 Our study centers on the tropical moist forest (TMF) of Central America, spanning Belize,
540 Guatemala, Honduras, El Salvador, Nicaragua, Costa Rica and Panama (Fig. 6), where TMF is
541 defined as closed forests in the humid tropics, including tropical rain forests, moist deciduous
542 forest, and mangroves. In this region, TMF extends from the Selva Maya and lowland Petén basin
543 in the north through the Honduran and Nicaraguan Caribbean lowlands to the Darién in eastern
544 Panama, with fragmented TMF on the Pacific slope and interior uplands. The TMF in
545 Mesoamerica is a biodiversity hotspot and forms a corridor between the tropical forests of southern
546 Mexico and north-western South America providing critical habitat connectivity and protecting
547 biodiversity¹⁵. Climatically, the region is characterized by humid tropical conditions, with annual
548 rainfall exceeding 2,000 mm on the Caribbean coast and declining toward the Pacific⁶⁶. The steep
549 changes in elevation caused by terrain create mosaics of lowland, premontane and montane forest
550 formations, interspersed with mangroves and riparian systems along both coasts⁶⁷.



551 **Fig. 6 | Central America’s Tropical Moist Forest Cover (a) 1990 and (b) 2023**

552 Central America’s TMFs have undergone rapid and spatially heterogeneous changes over the past
553 four decades. Land-use frontiers have advanced into lowland moist forests in northern Guatemala

554 and Belize, across the Mosquitia of Honduras and Nicaragua, and into the Darién of eastern
555 Panama. These shifts are driven by a dynamic combination of cattle ranching, commercial crops,
556 smallholder colonization, road building and, in some areas, extractive and illicit economies^{20,43,68}.
557 Deforestation continues in Petén and Belize where land speculation, and agricultural expansion
558 have turned forested areas into pasture and cropland^{22,31,41}. In Honduras and Nicaragua,
559 deforestation increasingly affects Indigenous territories and community lands. For example, in the
560 Caribbean region, land tenure disputes and speculative clearing interact with unequal access to
561 infrastructure and markets^{20,69}. Furthermore although, deforestation has decreased nationally,
562 mature forests in Panama are still being cleared along road corridors and within frontier
563 municipalities, most notably in Darién^{63,70}.

564 The rural communities in this region are reliant on land and forest-based livelihoods. However,
565 deforestation has impacted their well-being, by reducing ecosystem services and endangering
566 biodiversity. Significant differences in human development and governance capacity, both
567 between countries and among subnational units, exacerbate these pressures^{15,71}. As a result, the
568 region has implemented governance regimes such as community forests and protected areas to
569 address deforestation and improve livelihoods. Nevertheless, the implementation of these
570 governance regimes varies spatially. For example, community territories are important in the
571 northern Guatemalan lowlands and the Caribbean regions of Honduras and Nicaragua, whereas in
572 Costa Rica, Belize, and parts of Guatemala and Panama protected-area networks are more
573 prevalent^{19,20,72}. Despite these efforts, research shows ongoing deforestation and degradation in
574 buffer zones, isolated border interiors, and the margins of protected areas. These processes are
575 frequently linked to weak enforcement, insecure tenure, cattle ranching, logging and drug-
576 trafficking interests.

577 **Frontier delineation, metric derivation, and archetype classification from the Tropical Moist** 578 **Forest dataset**

579 We used the Tropical Moist Forests dataset TMF v2024 (1990-2023, 30 m resolution, with an
580 overall accuracy of 91.4%)⁷³. This dataset maps tropical rainforest and tropical moist deciduous
581 forest characterized by low annual temperature variability and high rainfall (>200 cm yr⁻¹). TMF
582 labels each 30 m pixel as undisturbed forest, degraded forest, deforested, regrowth, water, or other

583 land cover. In this dataset, undisturbed forest is described as closed evergreen or semi-evergreen
 584 forest with no observed disturbance across the Landsat record and degradation is defined as short-
 585 duration canopy disturbance (<2.5 years) after which the pixel remains forested. The TMF dataset
 586 does not attribute drivers or disturbance intensity, therefore we defined baseline forest as the
 587 combination of undisturbed and degraded TMF in 1990. Using Google Earth Engine, we extracted
 588 two layers for Central America the annual change collection between 1990 and 2023 and the
 589 deforestation year layer between 1991 and 2023. We then aggregated baseline forest and the annual
 590 deforestation time series from 30 m to a 1.5×1.5 km grid. In order to identify frontier cells, we
 591 excluded grid cells with less than 10% baseline forest, eliminating areas with little initial forest.
 592 Next, we selected cells that had an average annual loss of at least 0.5% over any consecutive 5-
 593 year interval between 1990 and 2023¹⁰. This process defines frontiers as areas where forest loss
 594 is persistent and significant.

595 Following Buchadas et al. (2022), we computed six metrics for every 1.5 km cell: (a) baseline
 596 forest; (b) forest loss; (c) speed; (d) fragmentation; (e) activeness; and (f) forest left (Table 2). To
 597 ensure that the classification was appropriate for tropical moist forests in Central America, metric
 598 thresholds were adapted from Buchadas et al. (2022) and adjusted to the distribution of values
 599 observed in our dataset, while maintaining the conceptual interpretation of each metric.

600 Table 2| Definition and Classification for the six land-cover metrics

Metric	Definition	Classification
Baseline forest	Forest area in 1990 within each 1.5 km cell	Low: <0.68 km ² ; Medium: 0.68–1.58 km ² ; High: >1.58 km ²
Forest loss	Cumulative forest loss relative to the 1990 baseline	Low: <10% of baseline; Medium: 10–50%; High: >50%
Speed	Maximum annual rate of forest loss over 1990–2023, estimated as the peak first derivative of a LOESS fit to the annual loss time series	Slow: <0.03 km ² yr ⁻¹ ; Medium: 0.03–0.12 km ² yr ⁻¹ ; Fast: >0.12 km ² yr ⁻¹

Fragmentation	Maximum edge density of the evolving forest-loss pattern across the study period, computed from yearly cumulative loss maps	Low: <23 m m ⁻² ; Medium: 23–45 m m ⁻² ; High: >45 m m ⁻²
Activeness	Timing of frontier activity within 1990–2023, derived from five-year rolling means of annual loss rates using a $\geq 0.5\%$ yr ⁻¹ threshold	Old: activity only in early windows (1991–2016); Emerging: activity only in recent windows (2018–2023); Active: activity in both early and late windows, or concentrated in mid-period windows
Forest left	Forest area remaining in 2023 within each 1.5 km cell	Low: <0.75 km ² ; Medium: 0.75–1.5 km ² ; High: >1.5 km ²

601

602 These pairs of metrics were then combined to form three 3×3 typologies: Deforestation Severity
603 (Baseline × Loss), Spatiotemporal Pattern (Speed × Fragmentation), and Development Stage
604 (Activeness × Forest-left), resulting in nine classes in each typology which represent, respectively,
605 accumulated pressure, spatial progression mode, and development stage along a pre- to post-
606 frontier gradient. Finally, we consolidated selected type combinations into six archetype categories
607 (Tables S1): Consolidated, Critical, Developing, Dormant, Fragmented and Other based on the
608 most prevalent patterns and on combinations that offered particular analytical insight, potentially
609 reflecting distinct mechanisms of frontier development consistent with theory-driven typology
610 construction ¹⁰.

611 **Spatial covariates, data preprocessing, and archetype comparisons**

612 Based on the deforestation literature in Central America ^{21,30,46,48,74,75}, we identified the region’s
613 main deforestation drivers. We represented terrain using slope and elevation (DEM), which
614 influence accessibility and cultivation costs. In Costa Rica and Panama, for instance, steeper slopes
615 have been shown to significantly deter clearing due to their low suitability for mechanized

616 agriculture ^{49,56}. We used distance to roads and travel time to cities as proxies for landscape
617 accessibility. Roads are the primary channel for deforestation frontiers in Petén (Guatemala) and
618 Bosawás (Nicaragua), facilitating the influx of colonists and cattle ^{20,47}. Prior deforestation (1990-
619 2010) was included as a legacy indicator of land-use pressure and edge creation, highlighting
620 places where clearing has already occurred and may propagate. Additionally, since frontiers nearer
621 perennial water often experience higher levels of human use and in-forest mobility, we used
622 distance to streams to capture proximity to water and riparian corridors.

623 Distance to undisturbed forest (2023) measures edge effects, shorter distances indicate areas where
624 spillover clearing can advance more easily into the undisturbed forest. In situations where other
625 constraints are minimal, population density frequently increases conversion risk because it reflects
626 both local human pressure and market demand. Agricultural suitability (agro-climatic potential)
627 serves as a proxy for expected agricultural returns, with higher suitability generally increasing the
628 opportunity cost of forest retention. We used protected areas as a proxy for governance. Their
629 performance varies by region. For example, they are relatively effective in Costa Rica ⁵⁵, PAs
630 commonly experience encroachment in Guatemala and Honduras ^{48,59}. Finally, we used distance
631 to large fields (>16 ha) as a proxy for adjacency to capital-intensive, mechanized agriculture.
632 Shorter distances indicate exposure to commodity-driven frontiers which can facilitate further
633 expansion.

634 All covariates were resampled to 1.5 km to match the analysis grid. Elevation and slope were
635 derived from SRTM. Roads and streams were derived from OpenStreetMap, and travel time to
636 cities was obtained from the European Commission global accessibility surface ⁵¹. Population
637 density (2020) was sourced from CIESIN. Protected areas were obtained from the World Database
638 on Protected Areas (WDPA), while Indigenous lands (Indicative indigenous areas not
639 acknowledged by government (ILNAG) and Indigenous territories acknowledged by government
640 (ILAG)) were obtained from the LandMark database. Prior deforestation was the aggregated area
641 of TMF deforestation from 1990–2010, and undisturbed forest was the remaining TMF forest in
642 2023. Agricultural suitability was taken from GAEZ v4.0 (summed agro-climatic potential for
643 low-input, rain-fed crops/commodities). Large field size was obtained from Lesiv, M. *et al.*
644 (2019)⁷⁶. For all distance-to variables (roads, protected areas, prior deforestation, undisturbed
645 forest, large fields, streams), we computed Euclidean distance rasters.

646 Cell-level covariates were extracted for the six archetypes ($n = 105,045$), and records with missing
647 attributes were removed (remaining: $n = 104,213$). We also excluded the category Other from the
648 analysis (remaining $n = 73,705$) and all archetype cells in El Salvador (remaining: $n = 67,746$),
649 due to the low frequency of some archetype categories in that region. To stabilize scales and
650 comparability, distance variables were log1p-transformed, and all continuous predictors were z-
651 standardized (mean = 0, s.d. = 1). The binary factor (unprotected vs protected) was coded as 0–1.

652 We applied a two-stage collinearity screen to the z-standardized covariates to limit redundancy
653 and unstable estimates. First, we computed the Pearson correlation matrix and then performed
654 iterative correlation pruning when a pair exceeded $|r| > 0.85$, we removed the covariate with the
655 larger mean absolute correlation to all other variables and recomputed correlations. This process
656 was repeated until no pairs exceeded the threshold. Second, on the remaining set we calculated
657 variance inflation factors (VIFs) using auxiliary OLS regressions and dropped variables with VIF
658 > 8 , recalculating VIFs after each removal (Table S2). Finally, a stratified sample (by country and
659 archetype), representing 10% of sample of the filtered dataset ($n = 6,762$) was used for the non-
660 parametric characterization and for the Bayesian model.

661 We applied non-parametric contrasts to the dataset to characterize distributional differences in
662 covariates across frontier archetypes. For each covariate we ran a Kruskal–Wallis (KW) test across
663 the five remaining archetype categories. When the KW test indicated significant heterogeneity, we
664 conducted Dunn’s post-hoc pairwise comparisons with Benjamini–Hochberg false-discovery-rate
665 control across predictors and pairs⁷⁷ (Fig. S1). To convey magnitude and direction rather than p-
666 values alone, we computed Cliff’s δ for each archetype pair and variable, retaining the sign
667 (indicating which group tends to be higher) and classifying $|\delta|$ as *negligible* (< 0.147), *small* (0.147 –
668 0.33), *medium* (0.33 – 0.474) or *large* (≥ 0.474)⁷⁸. These KW/Dunn results are reported as
669 descriptive distributional fingerprints of the archetypes; they were not used to select predictors for
670 the multivariate model.

671 **Bayesian multinomial analysis of archetype covariate associations, model diagnostics, and** 672 **prior sensitivity**

673 We quantified adjusted associations between spatial covariates and frontier archetype using an
674 association-focused Bayesian multinomial logit model (fitted via brms with the cmdstanr/Stan

675 backend)⁷⁹. The outcome was the five-level archetype factor, including Critical (n = 1,396),
676 Developing (n = 1,198), Dormant (n = 967), Fragmented (n = 1,565), Consolidated (n = 1,636)) as
677 the reference category. Continuous covariates were entered in their pre-processed form distance-
678 like variables were log1p-transformed and all continuous predictors were z-standardized (mean 0,
679 s.d. 1). To absorb contextual heterogeneity, we included a country-level random intercept, and to
680 capture broad residual spatial structure we added a bivariate thin-plate spline over scaled
681 coordinates, $s(x_z, y_z; k = 30)$, with x_z and y_z expressed in kilometers and z-scaled. To
682 mitigate pseudoreplication and keep computation tractable for intensive diagnostics, the model
683 was estimated on the stratified 10% sample (n = 6,762).

684 We ran four chains (4,000 iterations per chain; 1,500 warm-up) with $\text{adapt_delta} = 0.995$ and
685 $\text{max_treedepth} = 15$. For the primary model we used brms defaults flat priors: flat priors for fixed-
686 effect slopes (class “b”), Student-t (3, 0, 2.5) for category-specific intercepts, and half-Student-t
687 (3, 0, 2.5) for standard deviation parameters (country-level random-effect SDs and spline SDs).
688 We compared $k \in \{10, 30, 50\}$ using PSIS-LOO. Both spatial models ($k = 10$ and $k = 30$)
689 substantially out-performed the non-spatial baseline, and $k = 50$ yielded the highest ELPD overall.
690 However, the $k = 50$ fit exhibited a persistent influential observation (Pareto- $k > 0.7$) even after
691 moment matching, whereas $k = 30$ had all Pareto- $k < 0.7$ and provided a strong improvement over
692 $k = 10$. We therefore retained $k = 30$. Convergence and sampler behavior were assessed via split-
693 \hat{R} (< 1.01), effective sample sizes, absence of divergent transitions, and no treedepth saturation.
694 Posterior predictive checks (overall bars and country-grouped bars) indicated good reproduction
695 of observed class frequencies.

696 Model adequacy and comparisons relied on leave-one-out cross validation (PSIS-LOO) with
697 Pareto- k diagnostics; for $k = 30$ all $k < 0.7$. As a prior-sensitivity check, we refit the $k = 30$ spatial
698 model with stronger regularizing priors (Normal (0,1) on slopes; Student-t (3,0,2.5) on intercepts;
699 Exponential (1) on country and spline SDs). Out-of-sample fit was worse relative to the default-
700 prior model ($\Delta\text{ELPD} = -15.5$, $\text{SE} = 6.0$); thus, the default priors were used. Even though our model
701 is association-focused rather than predictive, we summarized classification using overall accuracy
702 (0.54), balanced accuracy (0.545), macro-F1 (0.537) and macro-AUC (0.824), computed from
703 posterior mean class probabilities. Fixed-effect coefficients of the selected model are presented as

704 odds ratios (OR) with 95% credible intervals (CrI); we consider evidence strong when the 95%
705 CrI excludes zero.

706 **Protected area and Indigenous land overlap analysis**

707 We quantified the overlap between frontier archetype classes, protected area IUCN management
708 categories (PIUCN) and indigenous lands (IL) using the tabulate area tool in ArcGIS Pro (Esri).
709 For each country, we ran a tabulate area with the PIUCN and IL layer as the zone dataset and the
710 categorical archetype raster as the class dataset. We calculated the area of overlap between
711 archetypes, PIUCN and IL, and the area of the country overlapped by PIUCN and IL. We
712 harmonized PIUCN categories into five analytical classes based on similarities in IUCN
713 management objectives (Table S3): Strict protection (Ia/Ib), High protection (II/III), Managed
714 conservation (IV), Sustainable use (V/VI), and Not an IUCN category. We separately classified
715 LandMark Indigenous and community lands by recognition status as acknowledged by
716 government (ILAG) or not acknowledged by government (ILNAG), following LandMark's
717 definitions of formal state recognition. Finally, we mapped archetype for each country, PIUCN
718 and IL class, and computed: (1) the percentage cover % within each country, (2) the archetype's
719 share of its total archetype area that falls into each protection class and (3) the absolute area of that
720 country-archetype protection combination.

721

722

723

724

725

726

727

728

References

- 730 1 Blum, D. *et al.* Subnational institutions and power of landholders drive illegal deforestation in a
731 major commodity production frontier. *Global Environmental Change* **74** (2022).
732 <https://doi.org/10.1016/j.gloenvcha.2022.102511>
- 733 2 Brockhaus, M. *et al.* The forest frontier in the Global South: Climate change policies and the
734 promise of development and equity. *Ambio* **50**, 2238-2255 (2021).
735 <https://doi.org/10.1007/s13280-021-01602-1>
- 736 3 Miranda, J., Britz, W. & Börner, J. Impacts of commodity prices and governance on the expansion
737 of tropical agricultural frontiers. *Scientific Reports* **14** (2024). <https://doi.org/10.1038/s41598-024-59446-0>
- 738
- 739 4 Meyfroidt, P. *et al.* Explaining the emergence of land-use frontiers. *Royal Society Open Science* **11**
740 (2024). <https://doi.org/10.1098/rsos.240295>
- 741 5 Meyfroidt, P. *et al.* Middle-range theories of land system change. *Global Environmental Change*
742 **53**, 52-67 (2018). <https://doi.org/10.1016/j.gloenvcha.2018.08.006>
- 743 6 Pacheco, P. Actor and frontier types in the Brazilian Amazon: Assessing interactions and outcomes
744 associated with frontier expansion. *Geoforum* **43**, 864-874 (2012).
745 <https://doi.org/10.1016/j.geoforum.2012.02.003>
- 746 7 Mastrángelo, M. E., Sun, Z., Seghezze, L. & Müller, D. Survey-based modeling of land-use intensity
747 in agricultural frontiers of the Argentine dry Chaco. *Land Use Policy* **88** (2019).
748 <https://doi.org/10.1016/j.landusepol.2019.104183>
- 749 8 Magliocca, N. R. *et al.* Two of a kind? Large-scale land acquisitions and commodity frontier
750 expansion in Argentina's Dry Chaco. *Ecology and Society* **27** (2022). <https://doi.org/10.5751/ES-13103-270225>
- 751
- 752 9 Baumann, M. *et al.* Frontier metrics for a process-based understanding of deforestation dynamics.
753 *Environmental Research Letters* **17** (2022). <https://doi.org/10.1088/1748-9326/ac8b9a>
- 754 10 Buchadas, A., Baumann, M., Meyfroidt, P. & Kuemmerle, T. Uncovering major types of
755 deforestation frontiers across the world's tropical dry woodlands. *Nature Sustainability* **5**, 619-
756 627 (2022). <https://doi.org/10.1038/s41893-022-00886-9>
- 757 11 Briceño, G. *et al.* Diversity of frontier processes in Amazonian subnational jurisdictions: Frontier
758 metrics reveal major patterns of human–nature interactions. *Ecological Indicators* **171** (2025).
759 <https://doi.org/10.1016/j.ecolind.2025.113198>
- 760 12 Eigenbrod, F. *et al.* Identifying Agricultural Frontiers for Modeling Global Cropland Expansion. *One*
761 *Earth* **3**, 504-514 (2020). <https://doi.org/10.1016/j.oneear.2020.09.006>
- 762 13 Lukman Alage, I., Tan, Y., Wasiu Akande, A. & Suprijanto, A. Advanced characterization of
763 deforestation frontiers in Nigeria utilizing deep learning and Bayesian approaches with sentinel-1
764 SAR imagery. *Geocarto International* **40** (2025).
765 <https://doi.org/10.1080/10106049.2025.2451164>
- 766 14 Buchadas, A. *et al.* Tropical dry woodland loss occurs disproportionately in areas of highest
767 conservation value. *Glob Chang Biol* **29**, 4880-4897 (2023). <https://doi.org/10.1111/gcb.16832>
- 768 15 Redo, D. J., Grau, H. R., Aide, T. M. & Clark, M. L. Asymmetric forest transition driven by the
769 interaction of socioeconomic development and environmental heterogeneity in Central America.
770 *Proceedings of the National Academy of Sciences of the United States of America* **109**, 8839-8844
771 (2012). <https://doi.org/10.1073/pnas.1201664109>
- 772 16 Howard, P. Cattle and crisis: the genesis of unsustainable development in Central America. *Land*
773 *Reform, Land Settlement and Cooperatives* **1995**, 89-116 (1995).

- 774 17 Gallardo-Cruz, J. A. *et al.* Deforestation and trends of change in protected areas of the Usumacinta
775 River basin (2000–2018), Mexico and Guatemala. *Regional Environmental Change* **21** (2021).
776 <https://doi.org/10.1007/s10113-021-01833-8>
- 777 18 Tafoya, K. A. *et al.* Effectiveness of Costa Rica's Conservation Portfolio to Lower Deforestation,
778 Protect Primates, and Increase Community Participation. *Frontiers in Environmental Science* **8**
779 (2020). <https://doi.org/10.3389/fenvs.2020.580724>
- 780 19 Chicas, S. D. *et al.* Mixed results on the conservation effectiveness of long-term community forest
781 enterprises in tropical moist forests: Insights from Honduras. *Journal of Environmental*
782 *Management* **391** (2025). <https://doi.org/10.1016/j.jenvman.2025.126580>
- 783 20 Stocks, A., McMahan, B. & Taber, P. Indigenous, colonist, and government impacts on Nicaragua's
784 Bosawas reserve. *Conservation Biology* **21**, 1495-1505 (2007). <https://doi.org/10.1111/j.1523-1739.2007.00793.x>
- 786 21 Chomitz, K. M. & Gray, D. A. Roads, land use, and deforestation: a spatial model applied to Belize.
787 *World Bank Economic Review* **10**, 487-512 (1996). <https://doi.org/10.1093/wber/10.3.487>
- 788 22 Chicas, S. D., Omine, K., Ford, J. B., Sugimura, K. & Yoshida, K. Using spatial metrics and surveys
789 for the assessment of trans-boundary deforestation in protected areas of the Maya Mountain
790 Massif: Belize-Guatemala border. *Journal of Environmental Management* **187**, 320-329 (2017).
791 <https://doi.org/10.1016/j.jenvman.2016.11.063>
- 792 23 Mateo-Vega, J., Spalding, A. K., Hickey, G. M. & Potvin, C. Deforestation, territorial conflicts, and
793 pluralism in the forests of eastern Panama: A place for reducing emissions from deforestation and
794 forest degradation? *Case Studies in the Environment* **2** (2018).
795 <https://doi.org/10.1525/cse.2017.000562>
- 796 24 Sunderlin, W. D. Deforestation, livelihoods, and the preconditions for sustainable management in
797 Olancho, Honduras. *Agriculture and Human Values* **14**, 373-386 (1997).
798 <https://doi.org/10.1023/A:1007306202212>
- 799 25 Hayes, T. M. & Murtinho, F. Are indigenous forest reserves sustainable? An analysis of present
800 and future land-use trends in Bosawas, Nicaragua. *International Journal of Sustainable*
801 *Development and World Ecology* **15**, 497-511 (2008).
802 <https://doi.org/10.1080/13504500809469845>
- 803 26 Milian, B. Poverty, deforestation, and land tenure institutions: The case of the communities living
804 in Guatemala's Maya Biosphere Reserve. *Journal of Planning Literature* **26**, 187 (2011).
805 <https://doi.org/10.1177/0885412211400979>
- 806 27 Jiménez, A., Hernández, A. J. & Rodríguez-Espinosa, V. M. Integration of Geospatial Tools and
807 Multi-source Geospatial Data to Evaluate the Tropical Forest Cover Change in Central America and
808 Its Methodological Replicability in Brazil and the DRC. *Remote Sensing* **12** (2020).
809 <https://doi.org/10.3390/rs12172705>
- 810 28 Southworth, J., Nagendra, H. & Tucker, C. Fragmentation of a landscape: Incorporating landscape
811 metrics into satellite analyses of land-cover change. *Landscape Research* **27**, 253-269 (2002).
812 <https://doi.org/10.1080/01426390220149511>
- 813 29 Southworth, J. & Tucker, C. The influence of accessibility, local institutions, and socioeconomic
814 factors on forest cover change in the mountains of western Honduras. *Mountain Research and*
815 *Development* **21**, 276-283 (2001). [https://doi.org/10.1659/0276-4741\(2001\)021\[0276:TIOALI\]2.0.CO;2](https://doi.org/10.1659/0276-4741(2001)021[0276:TIOALI]2.0.CO;2)
- 817 30 Southworth, J., Nagendra, H., Carlson, L. A. & Tucker, C. Assessing the impact of Celaque National
818 Park on forest fragmentation in western Honduras. *Applied Geography* **24**, 303-322 (2004).
819 <https://doi.org/10.1016/j.apgeog.2004.07.003>

820 31 Emch, M., Quinn, J. W., Peterson, M. & Alexander, M. Forest cover change in the Toledo District,
821 Belize from 1975 to 1999: A remote sensing approach. *Professional Geographer* **57**, 256-267
822 (2005). https://doi.org/10.1111/j.0033-0124.2005.476_1.x

823 32 Monzón-Alvarado, C. *et al.* Land-use decision-making after large-scale forest fires: Analyzing fires
824 as a driver of deforestation in Laguna del Tigre National Park, Guatemala. *Applied Geography* **35**,
825 43-52 (2012). <https://doi.org/10.1016/j.apgeog.2012.04.008>

826 33 Chicas, S. D., Omine, K. & Saqui, P. CLASlite algorithms and social surveys to assess and identify
827 deforestation and forest degradation in Toledo's protected areas and forest ecosystems, Belize.
828 *Applied Geography* **75**, 144-155 (2016). <https://doi.org/10.1016/j.apgeog.2016.08.012>

829 34 Cuba, N. *et al.* Emerging hot spot analysis to indicate forest conservation priorities and efficacy on
830 regional to continental scales: a study of forest change in Selva Maya 2000-2020. *Environmental*
831 *Research Communications* **4** (2022). <https://doi.org/10.1088/2515-7620/ac82de>

832 35 Min-Venditti, A. A., Moore, G. W. & Fleischman, F. What policies improve forest cover? A
833 systematic review of research from Mesoamerica. *Global Environmental Change* **47**, 21-27 (2017).
834 <https://doi.org/10.1016/j.gloenvcha.2017.08.010>

835 36 Hansen, M. C. *et al.* High-Resolution Global Maps of 21st-Century Forest Cover Change. *Science*
836 **342**, 850–853 (2013).

837 37 Potapov, P. *et al.* The last frontiers of wilderness: Tracking loss of intact forest landscapes from
838 2000 to 2013. *Science Advances* **3** (2017).

839 38 Curtis, P. G., Slay, C. M., Harris, N. L., Tyukavina, A. & Hansen, M. C. Classifying drivers of global
840 forest loss. *Science* **361**, 113–113 (2018).

841 39 Geist, H. J. & Lambin, E. F. Proximate causes and underlying driving forces of tropical deforestation.
842 *BioScience* **52**, 143–150 (2002).

843 40 Shriar, A. J. Economic integration, rural hardship, and conservation on Guatemala's agricultural
844 frontier. *Journal of Sustainable Forestry* **30**, 133-157 (2011).
845 <https://doi.org/10.1080/10549811003738777>

846 41 Shriar, A. J. Theory and context in analyzing livelihoods, land use, and land cover: Lessons from
847 Petén, Guatemala. *Geoforum* **55**, 152-163 (2014).
848 <https://doi.org/10.1016/j.geoforum.2014.06.002>

849 42 Tellman, B. *et al.* Illicit Drivers of Land Use Change: Narcotrafficking and Forest Loss in Central
850 America. *Global Environmental Change* **63** (2020).
851 <https://doi.org/10.1016/j.gloenvcha.2020.102092>

852 43 Wrathall, D. J. *et al.* The impacts of cocaine-trafficking on conservation governance in Central
853 America. *Global Environmental Change* **63** (2020).
854 <https://doi.org/10.1016/j.gloenvcha.2020.102098>

855 44 Magliocca, N. R., Summers, D. S., Curtin, K. M., McSweeney, K. & Price, A. N. Shifting landscape
856 suitability for cocaine trafficking through Central America in response to counterdrug interdiction.
857 *Landscape and Urban Planning* **221** (2022). <https://doi.org/10.1016/j.landurbplan.2022.104359>

858 45 Lambin, E. F. & Meyfroidt, P. Global land use change, economic globalization, and the looming
859 land scarcity. *Proc Natl Acad Sci U S A* **108**, 3465-3472 (2011).
860 <https://doi.org/10.1073/pnas.1100480108>

861 46 Kaimowitz, D. Livestock and deforestation in Central America in the 1980s and 1990s: A policy
862 perspective. *Center for International Forestry Research (CIFOR)* (1996).

863 47 Devine, J. A., Currit, N., Reygadas, Y., Liller, L. I. & Allen, G. Drug trafficking, cattle ranching and
864 Land use and Land cover change in Guatemala's Maya Biosphere Reserve. *Land Use Policy* **95**
865 (2020). <https://doi.org/10.1016/j.landusepol.2020.104578>

866 48 Sesnie, S. E. *et al.* A spatio-temporal analysis of forest loss related to cocaine trafficking in Central
867 America. *Environmental Research Letters*. *Environmental Research Letters* **12** (2017).

868 49 Sloan, S. Reforestation amidst deforestation: Simultaneity and succession. *Global Environmental*
869 *Change* **18**, 425-441 (2008). <https://doi.org/10.1016/j.gloenvcha.2008.04.009>

870 50 Calvo-Alvarado, J., McLennan, B., Sánchez-Azofeifa, A. & Garvin, T. Deforestation and forest
871 restoration in Guanacaste, Costa Rica: Putting conservation policies in context. *Forest Ecology and*
872 *Management* **258**, 931-940 (2009). <https://doi.org/10.1016/j.foreco.2008.10.035>

873 51 Weiss, D. J. *et al.* A global map of travel time to cities to assess inequalities in accessibility in 2015.
874 *Nature* **553**, 333-336 (2018). <https://doi.org/10.1038/nature25181>

875 52 Silva, V. V. D. & da Costa Silva, R. G. D. C. Amazon, Frontier and Protected Areas: dialectic between
876 economic expansion and nature conservation. *Ambiente e Sociedade* **25**, 1-21 (2022).
877 <https://doi.org/10.1590/1809-4422ASOC20200224R1VU2022L3OA>

878 53 Laurance, W. F., Sayer, J. & Cassman, K. G. Agricultural expansion and its impacts on tropical
879 nature. *Trends Ecol Evol* **29**, 107-116 (2014). <https://doi.org/10.1016/j.tree.2013.12.001>

880 54 Ford, S. A. *et al.* Deforestation leakage undermines conservation value of tropical and subtropical
881 forest protected areas. *Global Ecology and Biogeography* **29**, 2014-2024 (2020).
882 <https://doi.org/10.1111/geb.13172>

883 55 Andam, K. S., Ferraro, P. J., Pfaff, A., Sánchez-Azofeifa, G. A. & Robalino, J. A. Measuring the
884 effectiveness of protected area networks in reducing deforestation. *Proceedings of the National*
885 *Academy of Sciences of the United States of America* **105**, 16089-16094 (2008).
886 <https://doi.org/10.1073/pnas.0800437105>

887 56 Pfaff, A., Robalino, J., Sanchez-Azofeifa, G. A., Andam, K. S. & Ferraro, P. J. Park location affects
888 forest protection: Land characteristics cause differences in park impacts across Costa Rica. *The*
889 *B.E. Journal of Economic Analysis & Policy* **9** (2009).

890 57 Pagiola, S. Payments for environmental services in Costa Rica. *Ecological Economics* **65**, 712-724
891 (2008). <https://doi.org/10.1016/j.ecolecon.2007.07.033>

892 58 Brockett, C. D. & Gottfried, R. R. State Policies and the Preservation of Forest Cover: Lessons from
893 Contrasting Public-Policy Regimes in Costa Rica. *Latin American Research Review* **37**, 7-40 (2022).
894 <https://doi.org/10.1017/s0023879100019348>

895 59 Radachowsky, J., Ramos, V. H., McNab, R., Baur, E. H. & Kazakov, N. Forest concessions in the
896 Maya Biosphere Reserve, Guatemala: A decade later. *Forest Ecology and Management* **268**, 18-
897 28 (2012). <https://doi.org/10.1016/j.foreco.2011.08.043>

898 60 Bullock, E. L., Nolte, C., Segovia, A. R. & Woodcock, C. E. Ongoing forest disturbance in Guatemala's
899 protected areas. *Remote Sensing in Ecology and Conservation* **6**, 141-152 (2020).
900 <https://doi.org/10.1002/rse2.130>

901 61 Bray, D. B. *et al.* Tropical deforestation, community forests, and protected areas in the Maya
902 Forest. *Ecology and Society* **13** (2008). <https://doi.org/10.5751/ES-02593-130256>

903 62 Blackman, A. Strict versus mixed-use protected areas: Guatemala's Maya Biosphere Reserve.
904 *Ecological Economics* **112**, 14-24 (2015). <https://doi.org/10.1016/j.ecolecon.2015.01.009>

905 63 Walker, K. L. Effect of land tenure on forest cover and the paradox of private titling in Panama.
906 *Land Use Policy* **109** (2021). <https://doi.org/10.1016/j.landusepol.2021.105632>

907 64 Garnett, S. T. *et al.* A spatial overview of the global importance of Indigenous lands for
908 conservation. *Nature Sustainability* **1**, 369-374 (2018). <https://doi.org/10.1038/s41893-018-0100-6>

909

910 65 Sze, J. S., Carrasco, L. R., Childs, D. & Edwards, D. P. Reduced deforestation and degradation in
911 Indigenous Lands pan-tropically. *Nature Sustainability* **5**, 123-130 (2021).
912 <https://doi.org/10.1038/s41893-021-00815-2>

913 66 Taylor, M. A. & Alfaro, E. J. in *Encyclopedia of World Climatology* (ed J.E. Oliver) (Springer, 2005).
914 67 Corrales, L., Bouroncle, C. & Zamora, J. C. in *Climate Change Impacts on Tropical Forests in Central*
915 *America* 22 (Routledge, 2015).

- 916 68 Quezada, M. L., Arroyo-Rodríguez, V., Pérez-Silva, E. & Aide, T. M. Land cover changes in the
917 Lachuá region, Guatemala: Patterns, proximate causes, and underlying driving forces over the last
918 50 years. *Regional Environmental Change* **14**, 1139-1149 (2014). [https://doi.org/10.1007/s10113-](https://doi.org/10.1007/s10113-013-0548-x)
919 [013-0548-x](https://doi.org/10.1007/s10113-013-0548-x)
- 920 69 Hayes, T. M. Does tenure matter? A comparative analysis of agricultural expansion in the
921 Mosquitia Forest Corridor. *Human Ecology* **35**, 733-747 (2007). [https://doi.org/10.1007/s10745-](https://doi.org/10.1007/s10745-007-9117-6)
922 [007-9117-6](https://doi.org/10.1007/s10745-007-9117-6)
- 923 70 Wright, S. J. & Samaniego, M. J. Historical, demographic, and economic correlates of land-use
924 change in the Republic of Panama. *Ecology and Society* **13** (2008). [https://doi.org/10.5751/ES-](https://doi.org/10.5751/ES-02459-130217)
925 [02459-130217](https://doi.org/10.5751/ES-02459-130217)
- 926 71 Richards, M. Protected areas, people and incentives in the search for sustainable forest
927 conservation in Honduras. *Environmental Conservation* **23**, 207-217 (1996).
928 <https://doi.org/10.1017/s0376892900038820>
- 929 72 Bocci, C. & Fortmann, L. Community and industrial forest concessions: Are they effective at
930 reducing forest loss and does FSC certification play a role? *World Development* **170** (2023).
931 <https://doi.org/10.1016/j.worlddev.2023.106315>
- 932 73 Vancutsem, C. *et al.* Long-term (1990–2019) monitoring of forest cover changes in the humid
933 tropics. *Science Advances* **7** (2021).
- 934 74 Schmitt-Harsh, M. Landscape change in Guatemala: Driving forces of forest and coffee agroforest
935 expansion and contraction from 1990 to 2010. *Applied Geography* **40**, 40-50 (2013).
936 <https://doi.org/10.1016/j.apgeog.2013.01.007>
- 937 75 Sánchez-Azofeifa, G., Daily, G. C., Pfaff, A. S. P. & Busch, C. Integrity and isolation of Costa Rica's
938 national parks and biological reserves: Examining the dynamics of land-cover change. *Biological*
939 *Conservation* **109**, 123-135 (2002). [https://doi.org/10.1016/S0006-3207\(02\)00145-3](https://doi.org/10.1016/S0006-3207(02)00145-3)
- 940 76 Lesiv, M. *et al.* Estimating the global distribution of field size using crowdsourcing. *Glob Chang Biol*
941 **25**, 174-186 (2019). <https://doi.org/10.1111/gcb.14492>
- 942 77 Dunn, O. J. Multiple Comparisons Using Rank Sums. *Technometrics* **6**, 241-252 (1964).
943 <https://doi.org/10.1080/00401706.1964.10490181>
- 944 78 Cliff, N. Dominance statistics: Ordinal analyses to answer ordinal questions. *Psychological Bulletin*
945 **114**, 494–509 (1993).
- 946 79 Bürkner, P.-C. brms: An R Package for Bayesian Multilevel Models Using Stan. *Journal of Statistical*
947 *Software* **80** (2017). <https://doi.org/10.18637/jss.v080.i01>

948 Data availability

949 The tropical moist forest data used to derive baseline forest, prior deforestation (1990–2010), and
950 undisturbed forest (2023) were obtained from the European Commission Joint Research Centre
951 Tropical Moist Forest product, available at <https://forobs.jrc.ec.europa.eu/TMF>. Elevation data
952 used to derive elevation and slope were obtained from the Shuttle Radar Topography Mission
953 (SRTM), available via EarthExplorer at <https://earthexplorer.usgs.gov/>. Road and stream layers
954 were derived from OpenStreetMap data, available from <https://planet.openstreetmap.org/>. Travel
955 time to cities was obtained from the European Commission Global Accessibility Map, available at
956 <https://forobs.jrc.ec.europa.eu/gam>. Population density (2020) was obtained from the Gridded
957 Population of the World, Version 4 (GPWv4): Population Density, Revision 11, distributed by the

958 NASA Socioeconomic Data and Applications Center (SEDAC), available at
959 <https://www.earthdata.nasa.gov/data/catalog/sedac-ciesin-sedac-gpww4-popdens-r11-4.11>.

960 Protected areas were obtained from the World Database on Protected Areas (WDPA) via Protected
961 Planet, available at <https://www.protectedplanet.net/en/thematic-areas/wdpa>. Indigenous lands
962 were obtained from the LandMark global platform, available at <https://www.landmarkmap.org/>.
963 Agricultural suitability was obtained from the Global Agro-Ecological Zoning (GAEZ) v4 data
964 portal, available at <https://gaez.fao.org/pages/data-access-download>. The global field-size layer
965 used to identify large fields (>16 ha) was obtained from the Geo-Wiki agricultural field-size
966 dataset, available from IIASA at [https://iiasa.ac.at/models-tools-data/data-from-geo-wiki-](https://iiasa.ac.at/models-tools-data/data-from-geo-wiki-campaigns-on-agricultural-field-size)
967 [campaigns-on-agricultural-field-size](https://iiasa.ac.at/models-tools-data/data-from-geo-wiki-campaigns-on-agricultural-field-size).

968 Code availability

969 The workflow used to generate the frontier metrics, typologies, and archetypes for Central America
970 was adapted, see methods, from the Frontiermetrics_Code archived by Buchadas et al., available
971 on Zenodo at <https://doi.org/10.5281/zenodo.6141799>. The derived typologies and archetypes for
972 Central America are available on Zenodo at <https://doi.org/10.5281/zenodo.19103981>

973 Acknowledgements

974 This work was supported by the Kyushu University Institute for Advanced Study through the
975 World-leading Researchers Training Program.

976 Author contributions

977 S.D.C. conceived the study, designed the methodology, compiled and processed the data,
978 implemented the analysis, interpreted the results, and wrote the first draft of the manuscript. N.M.
979 supervised the research, interpretation of the results, and manuscript revision. A.B. and M.B
980 contributed to the adaptation of the frontier-metrics framework and to interpretation of the results.
981 H.X.B., S.H., J.G., T.O., J.G.V., and K.T.W.K. contributed to interpretation of the results,
982 discussion of the findings, and improvement of the manuscript.

983 Competing interests

984 The authors declare no competing interests.