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1 **Title**

2 Reduced deforestation and degradation in Indigenous Lands pan-
3 tropically

4

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13 **Abstract**

14 Area-based protection is the cornerstone of international conservation policy. The
15 contribution of Indigenous Lands (ILs)—areas traditionally owned, managed, used, or
16 occupied by Indigenous Peoples—is increasingly viewed as critical in delivering on
17 international goals. A key question is whether deforestation and degradation is reduced on
18 ILs pan-tropically and their effectiveness relative to Protected Areas (PAs). We estimate
19 deforestation and degradation rates from 2010 to 2018 across 3.4 Mkm² ILs, 2 Mkm² of
20 PAs, and 1.7 Mkm² of overlapped Protected-Indigenous Areas (PIAs) relative to matched
21 counterfactual non-protected areas. Deforestation is reduced in ILs relative to non-
22 protected areas across the tropics, avoiding deforestation comparably to PAs and PIAs
23 except in Africa, where they avoid more. Similarly, degradation is reduced in ILs relative to
24 non-protected areas, broadly performing comparably to PAs and PIAs. Indigenous support

25 is central to forest conservation plans, underscoring the need for conservation to support
26 their rights and recognise their contributions.

27 **Main text**

28 Despite international commitments to protect forests under the New York Declaration on
29 Forests and United Nations Sustainable Development Goal 15 (Life on Land), tropical
30 deforestation continues unabated, with primary forest loss in 2019 up 2.8% from the
31 previous year¹. Tropical forests are central in preserving global biodiversity and retain
32 ~55% of global terrestrial carbon stocks^{2,3}. They are also essential to the biocultural
33 identities and livelihoods of Indigenous forest peoples⁴. Alongside increasing amounts of
34 forest lost through commodity frontier expansions for agribusiness, particularly in
35 Southeast Asia, Central and South America, and West Africa⁵, there is a lack of legal
36 recognition of Indigenous rights and respect for customary tenure in many countries⁴. This
37 has resulted in land grabs, violence and killings of Indigenous and local peoples defending
38 their land and forests⁶.

39 Area-based protection is a cornerstone in biodiversity conservation policy. These
40 encompass both traditional state-managed protected areas and ‘Other Effective area-based
41 Conservation Measures’ (OECMs), as defined by the Convention of Biological Diversity. The
42 addition of OECMs partly reflect increasing acknowledgment of the injustice caused by PA
43 expansions, resulting in human evictions, killings, loss of traditional livelihoods and
44 cultural identity, and increased conflicts⁷. The upcoming post-2020 global biodiversity
45 framework incorporates proposals to increase targets of the terrestrial surface area under
46 protection, with multiple ambitious visions of where, how, and how much to protect
47 (e.g. 30 by 30, Half-Earth, rights-based approaches)^{7,8}.

48 The role of Indigenous Lands (ILs), which include areas and territories conserved by
49 Indigenous peoples and local communities (ICCAs; or ‘territories of life’), is increasingly
50 highlighted as key to achieving these targets^{9,10}. Although there are concerns that
51 expanding area-based targets will further the injustices experienced by Indigenous Peoples
52 and local communities^{7,11}, it is also a transformative opportunity¹². By increasing

53 recognition and support for Indigenous peoples to secure their land rights and tenure,
54 Indigenous peoples may be able to further contribute to conservation, while retaining their
55 autonomy and land management practices^{12,13}.

56 ILs carry significant potential to reduce deforestation and degradation and protect
57 biodiversity at resource frontiers. At least 370 million people who self-identify as
58 Indigenous safeguard and manage or have tenure rights to more than a quarter of the
59 Earth's land surface, intersecting with ~40% of protected areas¹⁴ and at least 36% of Intact
60 Forest Landscapes¹⁵. In Latin America, ILs have reduced deforestation and degradation
61 rates¹⁶⁻¹⁸, often more so than in state-managed protected areas (PAs)¹⁹⁻²¹. For instance, in
62 Bolivia, Brazil, and Colombia, deforestation rates were lower on titled Indigenous
63 territories compared to matched areas outside by 3 to 88% between 2001 and 2013¹⁷.
64 However, these studies focused on countries where strong Indigenous movements
65 influenced constitutional reforms, resulting in greater governmental and legal recognition
66 and protection of Indigenous rights and land titling^{22,23}. In much of Africa and Asia,
67 enhanced recognition and protection is at best nascent or, at worst, governance and law
68 work against Indigenous land rights⁴.

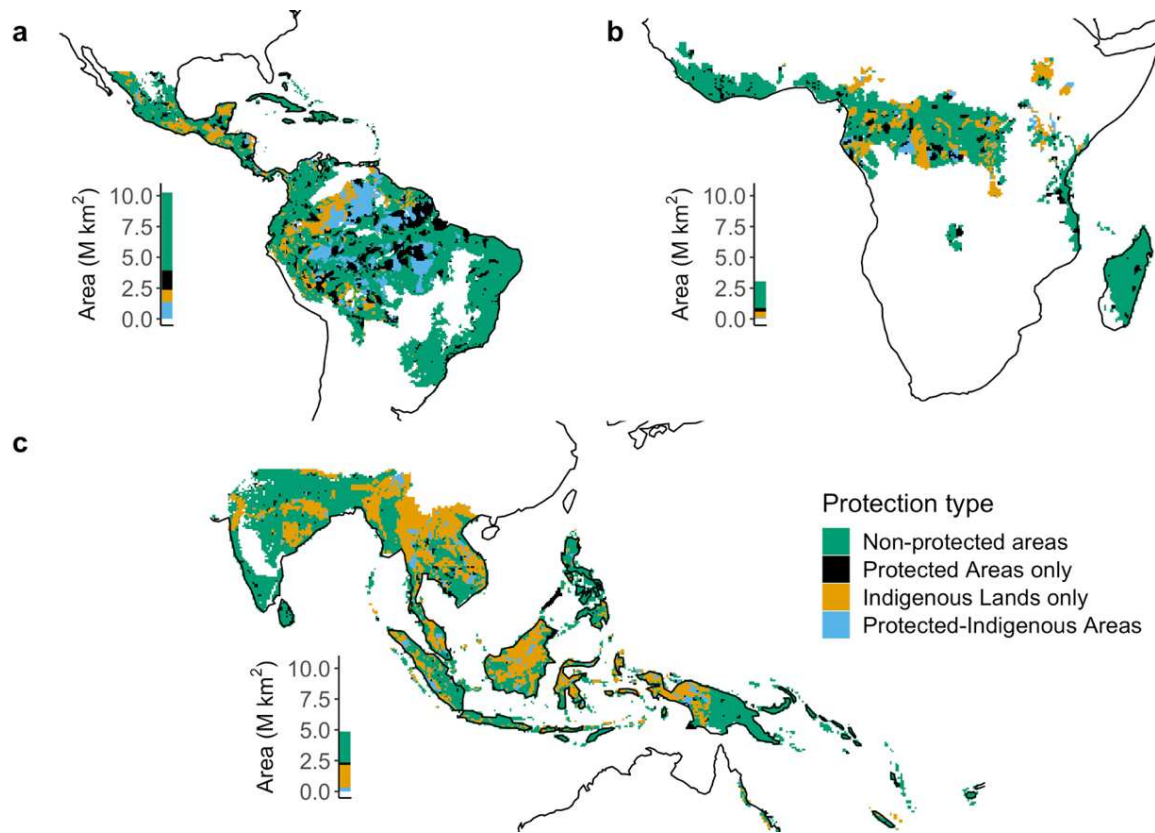
69 A critical knowledge gap for international policy is the effectiveness of ILs in reducing
70 deforestation and degradation pan-tropically, and whether they perform as effectively as
71 PAs. The lack of understanding of the amount of forest loss within ILs pan-tropically limits
72 the capacity of conservation to appropriately support ILs as a central component of
73 emerging policies and goals for area-based protection. Here, we uniquely quantify
74 deforestation and degradation rates in ILs using recently published geospatial data of
75 where Indigenous peoples have land tenure or *de facto* management of the land globally¹⁴.
76 The data were obtained from cadastral records for state-recognised Indigenous lands,
77 publicly available participatory mapping, models from census data and maps published in
78 scholarly articles.

79 To estimate deforestation and degradation rates across the tropics, we used two global
80 datasets. One, the European Commission's Joint Research Centre (ECJRC) dataset on forest
81 cover change in Tropical Moist Forest²⁴, which defines degradation as short-term (less than

82 2.5 years) disturbance in tree cover canopy, and deforestation as long-term (more than 2.5
83 years) conversion to non-forest land. Two, the Global Forest Watch²⁵ tree cover and loss
84 data, which defines deforestation as a stand-replacement disturbance, or a change from a
85 forest to non-forest state.

86 We compared tropical moist forest loss and degradation from 2010 to 2019 in 3.4 Mkm² of
87 ILs, 2 Mkm² of PAs, and 1.7 Mkm² of overlapping Protected-Indigenous Areas (PIAs; i.e. PAs
88 on Indigenous lands) relative to matched non-protected areas (Figure 1). We included PAs
89 of all management categories that were designated, inscribed, or established by 2010 and
90 masked out known areas of tree plantations from our analysis (see Methods). Using
91 statistical matching and regression adjustment with the matched samples, we obtain
92 robust estimates of deforestation and degradation under the different protection types²⁶,
93 whilst accounting for confounding factors including location and accessibility, that affect
94 deforestation and PA establishment and can overestimate intervention effectiveness^{19,27}.

95 We conducted the analysis at the 1 km pixel-level for the Americas (33 countries), Africa
96 (26), and Asia-Pacific (23), controlling for country-level effects (see Methods). The
97 Americas have the largest area of tropical moist forests in our study (10.3 Mkm²), followed
98 by Asia-Pacific (4.9 Mkm²) and Africa (3 Mkm²) (Figure 1; Supplementary Table 1). The
99 largest area of PAs and PIAs are in the Americas (1.5 Mkm² and 1.4 Mkm² respectively),
100 while Asia-Pacific has the largest area of ILs (1.9 Mkm²).



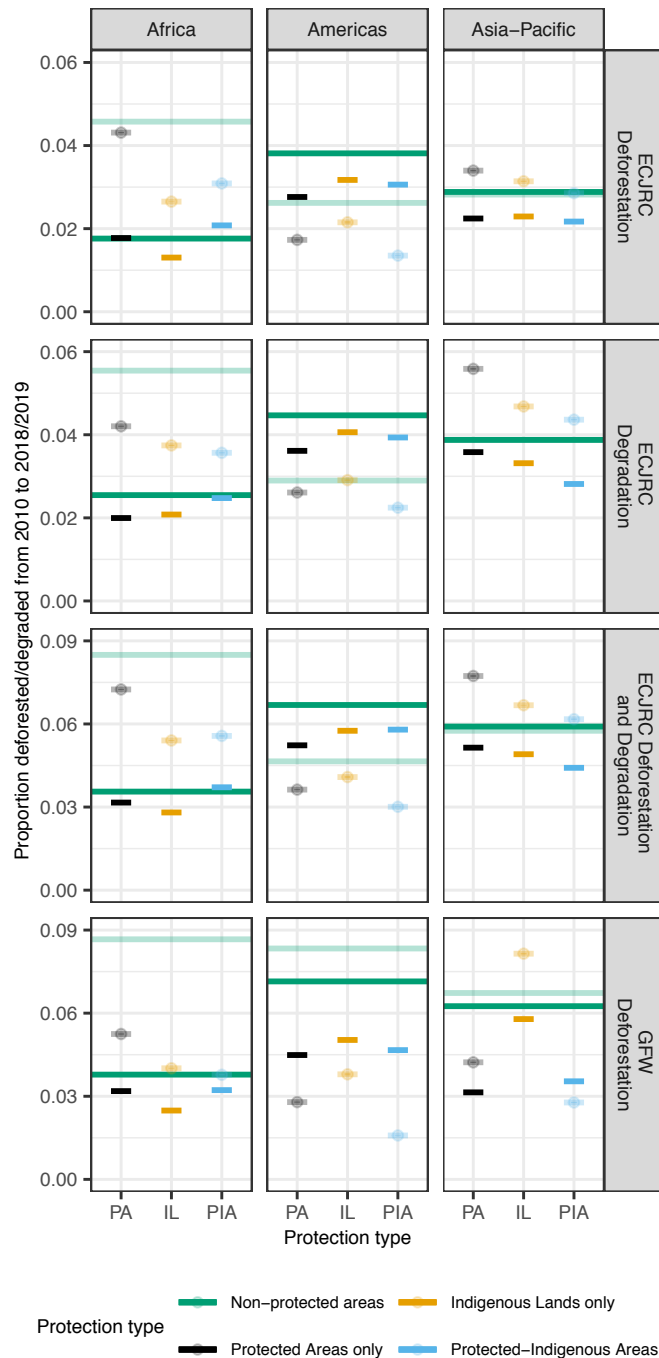
101
 102 *Figure 1. Indicative map of the different protection types across tropical moist forests within*
 103 *our analysis, coarsened to 30 km resolution where each pixel represents the dominant type.*
 104 *The resolution is intentionally coarsened so that boundaries are imprecise, as boundaries of*
 105 *Indigenous territories are often under dispute. A, the Americas. B, Africa. C, Asia-Pacific. See*
 106 *Supplementary Figure 1 for a map of the matched data.*

107

108 **Results**

109 We found that across the tropics, deforestation and degradation rates in ILs were less than
 110 in non-protected areas by 16.8-25.9% and 9.1-18.4% respectively (Figure 2;
 111 Supplementary Table 2). These rates are broadly comparable to those in PAs, except in
 112 Africa, where PAs and PIAs avoid little deforestation and/or degradation. Matching for
 113 comparable sites showed the greatest difference in Africa where deforestation and
 114 degradation rates were naively overestimated before matching (translucent lines in Figure
 115 2), while they were naively underestimated before matching in the Americas, and in Asia-
 116 Pacific, matching and regression showed that protection had reduced forest loss and
 117 degradation relative to non-protected areas.

118 ECJRC deforestation rates were about half that of GFW, though when we combine data on
119 deforested and degraded pixels, the deforestation rates between ECJRC and GFW are more
120 comparable, indicating that GFW considers a lot of short-term degradation as
121 deforestation. Estimated deforestation rates using GFW and ECJRC combined deforestation
122 and degradation data both show that ILs avoid deforestation, though the GFW data
123 estimates greater avoided deforestation in Africa and the Americas ($34.3 \pm 1.1\%$ avoided in
124 Africa using GFW data versus $21.2 \pm 1.3\%$ with ECJRC data, and $29.6 \pm 1.5\%$ avoided in the
125 Americas versus $13.9 \pm 1.4\%$ respectively) and less in Asia-Pacific ($7.5 \pm 2\%$ avoided using
126 GFW data versus $16.9 \pm 0.7\%$ with ECJRC data).



127

128 *Figure 2. Mean estimated deforestation rates from 2010 to 2019 (or 2018 for GFW data)*
 129 *predicted from GAMM regional models of protection types for ECJRC deforestation rates,*
 130 *degradation rates, combined deforestation and degradation rates, and GFW deforestation*
 131 *rates across tropical moist forest extents, before matching (in translucent colours) and after*
 132 *regression (in solid colours). Vertical lines show standard errors from calculating mean*
 133 *values, which may not be visible at the plotted scale. Values below the solid green horizontal*
 134 *line represent avoided deforestation relative to non-protected areas.*

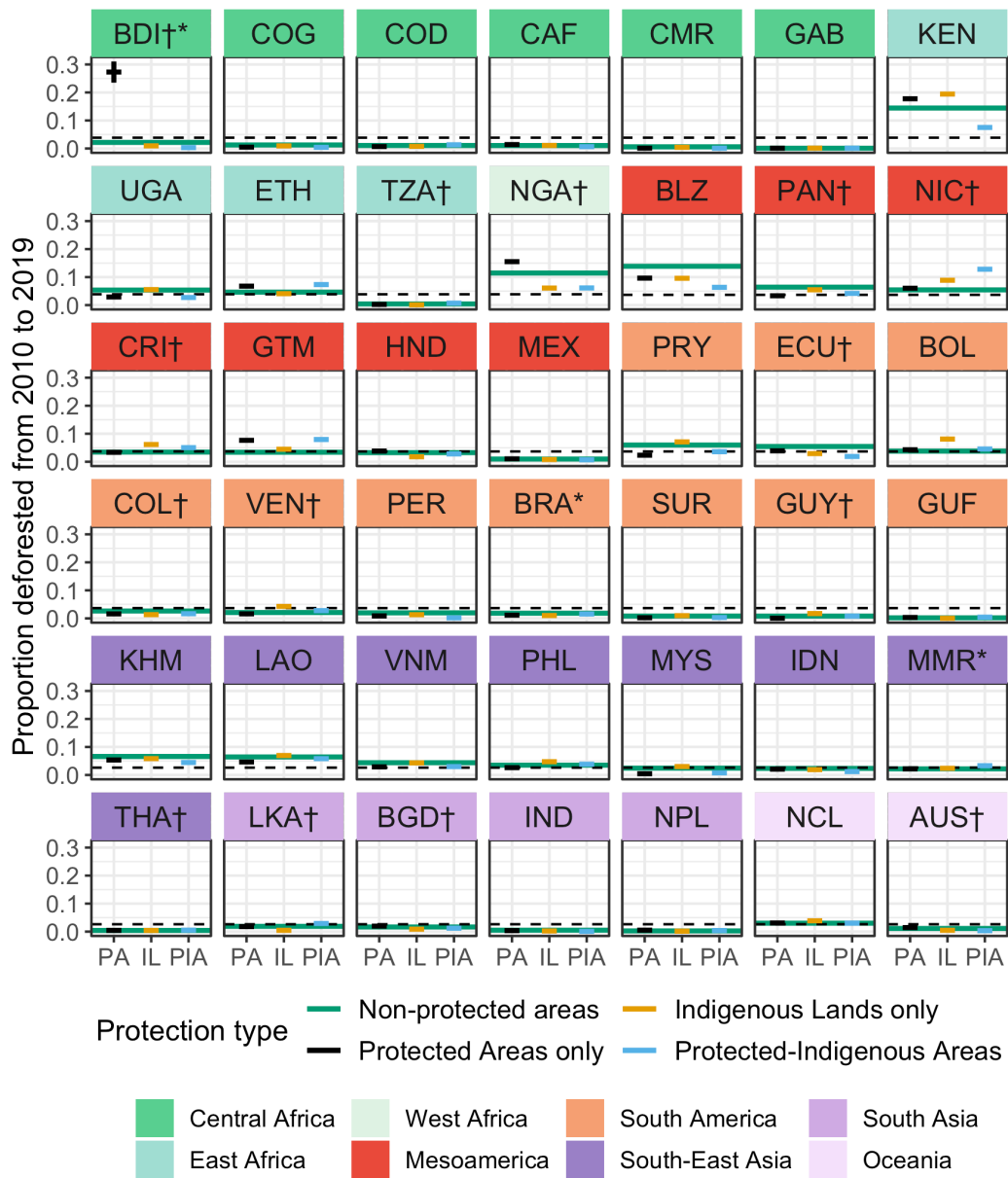
135

136 Forest use in ILs may be more similar to that of multi-use PAs (IUCN management
137 categories V and VI), where local forest use is permitted and deforestation rates are higher
138 than strict PAs²⁸. Thus, we repeated our analysis including only multi-use PAs and found
139 that ILs still avoid deforestation (21-34.9% for ECJRC data and 11.8-43.3% for GFW data;
140 Supplementary Figures 2 and 3 respectively; Supplementary Table 2). However, focusing
141 on the ECJRC deforestation data, multi-use PAs and ILs in the Americas avoid comparable
142 amounts of deforestation ($28.6 \pm 0.3\%$ and $21.0 \pm 0.4\%$, respectively) while in Africa and
143 Asia-Pacific, ILs avoid more deforestation than multi-use PAs (by 24.5 percentage points
144 and 11.9 percentage points, respectively). It can take time to develop effective governance
145 and management of PAs²⁹. We thus ran a precautionary analysis for PAs that have been
146 established for at least 10 years before our study period (i.e. before 2001), finding broadly
147 similar results to our main analysis that included all PAs established up to 2010 that ILs
148 have reduced deforestation by 14.8-29.8% (Supplementary Figure 2; Supplementary Table
149 2). However, PAs and PIAs in Africa have higher deforestation rates than non-protected
150 areas, which is in part due to the reduced area of analysis when PAs established between
151 2000 and 2010 were omitted, such that overall estimated deforestation rates are lower.

152 To better understand variation in performance across protection types and regions, we
153 performed two further analyses. First, we overlaid classified drivers of forest loss data from
154 Curtis *et al.*⁵ on our matched data (Supplementary Figure 1). This revealed that
155 deforestation attributed to commodities and forestry was highest in Asia-Pacific (60-64%
156 of all deforestation in ILs, PAs and PIAs), while in Africa, this fraction was less than 3%
157 (most deforestation attributed to shifting agriculture) and between 41-53% in the
158 Americas, except in ILs where it was 20% (Supplementary Figure 4).

159 Second, we ran country-specific matching and regression models for 42 countries; these
160 are countries that have sufficient coverage of both PAs and ILs to conduct matching, which
161 omits most countries in West Africa, Caribbean and Oceania. We calculated the regional
162 mean of deforestation rates in non-protected areas and found that higher-than-regional-
163 average deforestation was concentrated in East Africa, Mesoamerica and Southeast Asia
164 (Figure 3; Supplementary Table 3). For these 42 countries, as an exploratory attempt to

165 examine any effect of Indigenous land recognition on deforestation, we identified countries
166 where state governments have recognised Indigenous land ownership or management
167 according to two databases^{30,31}. We visualised avoided deforestation in Indigenous lands
168 for the 28 countries that have some Indigenous recognition and those without, but find
169 little association between recognition and avoided deforestation (Supplementary Figures
170 7-8). We acknowledge that data on secure land tenure and ownership is limited and not
171 spatially explicit; for example, Ecuador is not listed as having any Indigenous ownership or
172 territory, yet in 2008 Ecuador passed a new constitution that recognises Indigenous
173 peoples' rights and ownership of their ancestral lands (Article 84, Constitution of the
174 Republic of Ecuador 2008). As such, we are cautious in interpreting these results.



175

176 *Figure 3. ECJRC deforestation rates predicted from GAMM models of protection types for each*
 177 *country. Dashed line refers to regional mean deforestation rate of non-protected areas,*
 178 *vertical line shows standard error. Values below the green line represent avoided*
 179 *deforestation relative to non-protected areas. † represent countries for which imbalance*
 180 *remained after matching, * represent countries for which regression residuals did not show*
 181 *any spatial autocorrelation. BDI Burundi; COG Republic of Congo; COD Democratic Republic*
 182 *of the Congo; CAF Central African Republic; CMR Cameroon; GAB Gabon; KEN Kenya; UGA*
 183 *Uganda; ETH Ethiopia; TZA Tanzania; NGA Nigeria; BLZ Belize; PAN Panama; NIC*
 184 *Nicaragua; CRI Costa Rica; GTM Guatemala; HND Honduras; MEX Mexico; PRY Paraguay;*
 185 *ECU Ecuador; BOL Bolivia; COL Colombia; VEN Venezuela; PER Peru; BRA Brazil; SUR*
 186 *Suriname; GUY Guyana; GUF French Guiana; KHM Cambodia; LAO Laos; VNM Vietnam; PHL*
 187 *Philippines; MYS Malaysia; IDN Indonesia; MMR Myanmar; THA Thailand; LKA Sri Lanka;*

188 *BGD Bangladesh; IND India; NPL Nepal; NCL New Caledonia; AUS Australia. See*
189 *Supplementary Figure 5 for plot with free y-axis scales and Supplementary Figure 6 for results*
190 *with GFW deforestation data.*

191

192 **Discussion**

193 Drawing on the recent ECJRC tropical moist forest data and widely used GFW global forest
194 change data, our novel analyses reveal that across the tropics, Indigenous Lands have
195 reduced deforestation and degradation rates relative to non-protected areas, despite
196 receiving a much smaller fraction of official conservation funding compared to Protected
197 Areas⁷. While our results reveal deforestation and degradation rates on ILs without
198 identifying causal mechanisms, they reflect the myriad claims by Indigenous peoples who
199 advocate for more recognition on their contributions to conservation and active
200 participation in environmental policy^{12,13}, and suggests the dovetailing of mainstream
201 conservation efforts and Indigenous protection is a plausible ambition.

202 *Deforestation and degradation on Indigenous Lands*

203 Despite ongoing encroachment on Indigenous Lands³², we found that ILs have reduced
204 deforestation relative to non-protected areas, performing comparably with PAs and PIAs in
205 the Americas and Asia-Pacific and better in Africa using ECJRC data, but lesser in Asia-
206 Pacific using GFW data (Figure 2). This echoes previous work done in the Amazon^{16,17},
207 though we find that across the Americas, PAs do avoid marginally more deforestation than
208 ILs. ILs in Africa avoid more deforestation than PAs or PIAs across all our scenarios. The
209 history of PA establishment in Africa goes back to the colonial era, where the model of
210 fortress conservation is widely applied³³. Of 34 PAs established in the Congo Basin, 26
211 resulted in the partial or complete displacement of local and Indigenous communities with
212 no evidence of compensation³⁴ (e.g., the Twa people and Kahuzi-Biega National Park,
213 Democratic Republic of Congo). In these high-conflict and contentious spaces, it might not
214 be surprising that deforestation rates are higher than in ILs.

215 While successes in avoided deforestation are a positive outcome, it is encouraging that we
216 found ILs also avoid degradation of the forest canopy. Such degradation is a major source of

217 greenhouse gas emissions³⁵ and doubles biodiversity losses from deforestation³⁶. A myriad
218 of other factors that we were unable to quantify in our analysis also contribute to losses in
219 forest integrity across tropical moist forests³⁷. These include alteration of microclimates,
220 proliferation of lianas, and the cascading ecological effects resulting from selective logging,
221 road edges, and reduced populations of large-bodied vertebrates^{38,39}. The complexities of
222 monitoring forest degradation using remote sensing notwithstanding⁴⁰, our finding that
223 short term tree cover loss is reduced relative to non-protected areas and comparably with
224 PAs is encouraging, since 45% of short-term degradation leads to deforestation,
225 particularly in Southeast Africa and Southeast Asia²⁴. Selective logging is a key driver of
226 degradation in Southeast Asia and Indigenous communities might be better able than PAs
227 to restrict access to (illegal) logging companies, as some have with oil palm companies⁴¹.

228 In many Indigenous communities across the world, there exists both formal and informal
229 institutions for governing forest commons and resources⁴² and monitoring forest access⁴³.
230 The customary forest tenure of Indigenous peoples in Seram island of the Moluccas,
231 Indonesia involve custodians who coordinate forest use, understand the history of forest
232 rights inheritance, and can impose temporary bans on forest access⁴⁴. Similarly, in Ghana,
233 the traditional beliefs and practices of the Ashantis prohibit overexploitation of their
234 forests⁴⁵, while the Indigenous peoples in the Xingu, Brazil, mobilise to keep out
235 intruders⁴⁶. Our findings that deforestation and forest degradation are reduced on
236 Indigenous Lands pan-tropically relative to non-protected areas suggest that Indigenous
237 communities and their customary practices do help forest conservation.

238 *Indigenous Rights, Tenure and Land Tenure Security*

239 Indigenous peoples are often invested in protecting their lands from external threats,
240 concurring with our finding that a greater proportion of deforestation is attributed to
241 commodities and forestry within PAs and PIAs than ILs in the Americas and Asia-Pacific
242 (Supplementary Figure 4). However, their ability to steward ecosystems are contingent on
243 state support and protection; even where Indigenous peoples are recognized by state
244 governments and have constitutional rights (e.g. Bolivia, Brazil, Ecuador, Colombia,
245 Republic of the Congo, the Philippines), these rights may not necessarily be implemented or

246 upheld⁴. Indeed, in our exploratory country-level analysis, which utilises the best available
247 information from community-contributed databases that we are aware of, we were unable
248 to discern any patterns between forest protection and countries that recognise Indigenous
249 management and/or ownership (Supplementary Figures 7-8). This may be due to a
250 combination of insufficient or incorrect information, lack of respect or support despite
251 state recognition, or a true lack of association.

252 Nonetheless, at the regional level, our results reveal that ILs, alongside PAs and PIAs, in the
253 Americas have consistent patterns of reduced deforestation or degradation across our
254 various scenarios (Figures 2 & Supplementary Figures 2-3), which we posit is due to the
255 more advanced legal recognition and protection of Indigenous peoples there compared to
256 other regions, although infringements still occur⁴. Titled Miskitu communities in Bosawas
257 Biosphere Reserve, Nicaragua, were better able to control agricultural expansion threat
258 from mestizo colonisers than were untitled Miskitu communities⁴⁷. However, increasing
259 encroachment and land grabs linked to illicit drug trafficking and the lack of state support
260 have increased deforestation pressure on Indigenous territories^{48,49}, underscoring the
261 importance of adequate and enforced legal protections, not just titling in name without
262 support.

263 Extensive global reviews on community management and forest outcomes are increasingly
264 converging on finding that communities with secure land tenure, local autonomy in
265 management, established internal institutions, and supportive national policies have lower
266 deforestation and deliver socio-economic, biodiversity, and climate benefits⁵⁰⁻⁵². Although
267 our analysis is unable to account for land tenure security, our results mostly echo previous
268 findings on titling Indigenous territories, where *de jure* titling helped Indigenous peoples
269 slow agricultural expansion and deforestation in their territories. Future research could
270 examine Indigenous recognition, protection, and secure land tenure and refine our work on
271 their impacts on forest protection. However, land tenure systems and their effectiveness
272 are often highly context-dependent and in-depth grounded case studies would be better
273 able to understand these linkages⁵³. The process of formalizing land tenure may also bring
274 additional problems⁵⁴, such as reducing community autonomy and security⁵⁵.

275 *Limitations*

276 There are difficulties in defining Indigeneity at the policy level especially in Africa and Asia-
277 Pacific, and we acknowledge that maps are subjective and partisan⁵⁶. Hence, knowing
278 whether Indigenous peoples are actually present and actively able or willing to conserve
279 their bio-cultural heritage is empirically difficult. In lieu of this, interpreting results remain
280 challenging, particularly in Africa and Asia-Pacific. Further, western-based conservation
281 organisations have often struggled to foster inclusive and equitable participation with
282 Indigenous peoples⁵⁷. Thus, enrolling Indigenous peoples to fulfil internationally set targets
283 raises important ethical and moral concerns; critics argue Indigenous peoples' perspectives
284 and ontologies should be given primacy whilst decentring western ideals⁵⁸. Moving beyond
285 tokenistic inclusion of Indigenous peoples is necessary and potential misalignments in
286 goals of Indigenous communities and conservation will need to be debated.

287 PAs have spillover effects of either leakage or blockage (i.e., higher or lower deforestation
288 in unprotected adjacent surroundings), and in the Brazilian Amazon, ILs increase leakage
289 while federal PAs increase blockage⁵⁹. However, we have not accounted for spillover effects
290 in our analysis, which would be a refinement for future research. Additionally, we matched
291 on variables that influence deforestation probabilities and biases in locating protected
292 areas, and assumed similar confounders for degradation. We used short-term tree cover
293 loss as a measure of forest degradation, which omits other definitions and measures of
294 forest degradation and losses in forest integrity³⁷. Future research could examine how PAs
295 and ILs avoid deforestation where threats are similar (i.e. matching for areas where
296 deforestation is mostly driven by commodities, forestry, wildfires, or shifting agriculture)
297 and consider other industrial pressures on tropical forests. Our overlay of deforestation
298 drivers showed that ILs across the tropics faced less deforestation from commodity and
299 forestry compared to PAs (Supplementary Figure 4), however, given the coarser resolution
300 of the data (~10 km) and difficulties in identifying deforestation drivers from satellite
301 imagery, a more focused analysis would provide further nuance to our understanding of
302 how different protection types help avoid deforestation and degradation, alongside
303 grounded case studies. Further, while forest protection is a key aspect of biodiversity

304 conservation, the human use of wildlife has resulted in local extirpations, affecting tree
305 dispersal and potentially the long-term survival of tropical forests³⁹.

306 *Conclusion*

307 Protected areas and Indigenous territories are often threatened by the same
308 macroeconomic political forces⁶⁰. Planned investment increases in agriculture, economic
309 growth-inducing infrastructure, and road networks will likely accelerate deforestation and
310 biodiversity loss in the coming decades⁶¹, further increasing pressures both inside and
311 outside protected zones. For instance, high deforestation rates in Cambodia linked to large-
312 scale land acquisitions⁶² meant that PA and IL deforestation rates were still higher than the
313 regional average (Figure 3 and Supplementary Figures 5-6), while the expansion of foreign
314 direct investments and large-scale land acquisitions in Africa⁶³ points towards possible
315 future incursions into Indigenous lands. Strengthening Indigenous Peoples' rights,
316 providing secure tenure and conservationists actively supporting environmental defenders
317 and Indigenous communities will be a vital component of the coordinated action necessary
318 to ensure the survival of tropical forests into the Anthropocene.

319 **Methods**

320 We defined the spatial extent of tropical moist forests as the study area for this analysis,
321 using the data available from ECJRC. See Supplementary Methods for more details. Spatial
322 data cleaning was done in R version 3.6.2, Python 3.7.0, QGIS version 3.4.6 and ArcGIS
323 Desktop 10.7.1 ArcMap, while statistical analyses were done in R version 3.6.3.

324 **Data**

325 *Deforestation and degradation from 2010 to 2019* Tropical Moist Forest Subtypes were
326 downloaded from the European Commission Joint Research Centre²⁴. We used classes
327 defined as deforestation from 2010 to 2016 and deforestation/degradation from 2016 to
328 2019, and classes defined as degradation from 2010 to 2016 and
329 deforestation/degradation from 2016 to 2019 to define deforestation and degradation
330 respectively. We additionally combined deforestation and degradation classes to compare
331 with GFW data. To improve computational tractability, we aggregated ~30 m pixels of the

332 original dataset to 1 km, using number of deforested and/or degraded forest pixels (out of
333 maximum of 961 pixels) to fit binomial models of probability of losing a 30 m pixel. This
334 was processed in R environment.

335 *Forest loss from 2010 to 2018* Tree cover 2010⁶⁴ and 2011 to 2018 forest loss data (v1.6)⁶⁵
336 were downloaded from Global Forest Watch²⁵. We defined pixels as being forested in 2010
337 using 25% tree canopy cover threshold, as recommended by Ref. ⁶⁶ to be the threshold
338 which can identify tall woody vegetation unambiguously. Forested pixels that were not lost
339 between 2011 and 2018 were considered to still be forested in 2018. To improve
340 computational tractability, we aggregated 30 m pixels of the original dataset to 1 km, using
341 the number of forested pixels in 2010 and 2018 (out of the maximum 1024 pixels) to fit
342 binomial models of probability of losing a 30 m pixel. This was processed in the Python
343 environment.

344 *World Database of Protected Areas* Jan 2020 version was obtained from UNEP-WCMC⁶⁷
345 using the R package wdpar⁶⁸ and cleaned according to the recommended protocol, omitting
346 point data due to lack of area information. The IUCN categorises PA based on management
347 objectives; we considered categories I-IV to be strict PAs and categories V and VI to be
348 multi-use PAs. We included all IUCN categories for PAs created before 2011 (including PAs
349 with no information on year of establishment). This resulted in 1740 strict PAs, 939 multi-
350 use PAs and 1276 uncategorised PAs (Supplementary Table 8). We conducted a separate
351 matching and regression analysis with only multi-use PAs, and including only PAs created
352 before 2001 (1279 strict PAs, 587 multi-use PAs and 995 uncategorised PAs), with similar
353 results (Supplementary Table 2).

354 *Indigenous Peoples Lands* was obtained from Garnett *et al.*¹⁴ We acknowledge that
355 Indigenous lands were mapped based on publicly available information¹⁴ and that land not
356 mapped as Indigenous are not necessarily non-Indigenous. We also realise that boundaries
357 may be under contestation, and we do not assert their use here as a political statement.

358 *Protected-Indigenous Areas* Where boundaries of Indigenous Peoples Lands and PAs
359 overlapped, the spatial intersection of the two layers were considered as Protected-
360 Indigenous Areas (PIAs). PAs that were listed as being 'governed by Indigenous People'

361 within the WDPA database were also considered under this category of protection (467
362 PAs). The PAs in this PIA layer (established before 2011) consisted of 722 strict PAs, 327
363 multi-use PAs and 713 uncategorised PAs (note as this layer includes the spatial intersect
364 of WDPAs and IPLs, some of the PAs counted may only be partially represented).

365 *Non-protected areas* consists of areas that do not fall under PA or IPL or both, up to January
366 2020; 1777 PAs created between 2011 and 2019 were excluded. To ensure that pixels were
367 100% either in a protected category or not protected, we omitted all border pixels from our
368 analyses. As forest loss data from Global Forest Watch include tree plantations, we also
369 masked out known tree plantations^{69,70} from our analysis.

370 **Matching covariates** Following previous studies (e.g. refs. ^{19,20,71,72}), we included variables
371 that affect deforestation and assignment of PAs; the nature of ILs being under the
372 ownership and/or management of Indigenous Peoples since before nation states were
373 formed and contemporary political economic factors that affect ILs are such that there are
374 numerous unobservables that cannot be controlled for. Nonetheless, we controlled for
375 confounding variables where possible in both our matching and regression analyses. See
376 Supplementary Table 4.

377 *Baseline forest cover* We used tree cover 2010⁶⁴ at 25% tree canopy cover threshold to
378 calculate the baseline forest cover in 2010 for matching with PAs established before 2011,
379 and tree cover 2000⁷³ at 25% tree canopy cover threshold to calculate the baseline forest
380 cover in 2000 for matching with PAs established before 2001.

381 *Slope and elevation* data were obtained from Amatulli *et al.*⁷⁴ These influence likelihood of
382 deforestation and PA locations⁷².

383 *Travel time* to nearest populated area with more than 5000 population in 2015 was
384 obtained from Nelson *et al.*⁷⁵. Access to markets and transport hubs influence land-use
385 change decisions.

386 *Distance to roads* was calculated from CIESIN SEDAC⁷⁶ gROADS dataset in ArcMap using
387 Euclidean distance, as proximity to roads is a major driver of deforestation.

388 *Population density* in 2010 from WorldPop⁷⁷ was included to control for forest pressure
389 from local human populations.

390 *Countries* from GADM⁷⁸ were included as an exact matching variable and random effect in
391 regression models to control for country-level factors such as legislation and political-
392 economic situations.

393 **Analysis**

394 All spatial data were gridded to 1 km resolution in EPSG 4326 coordinate reference system
395 and split by IPBES regions (Africa, Americas and Asia-Pacific) for matching and regression.
396 While matching for individual polygons of PAs, ILs and PIAs and comparably sized non-
397 protected areas would have been a refinement of our work that takes protection type sizes
398 into consideration, to protect Indigenous communities from possible unintended
399 consequences, individual IL polygons defining communities are not available. As such, we
400 opted to match at the pixel level. Considering the tropical moist forest extent for PAs
401 established before 2011, this resulted in the following numbers of 1 km pixels for: Africa –
402 2567650 non-protected, 352365 PA, 554076 IL, and 120799 PIA; Americas – 7579846
403 non-protected, 1814842 PA, 1222916 IL, and 1583040 PIA; Asia-Pacific – 3033714 non-
404 protected, 203194 PA, 2268545 IL, and 352750 PIA (Supplementary Table 5). For
405 countries where all three protection types were present (42 countries), we conducted
406 additional analyses matching and regressing at the country-level.

407 **Statistical matching** We used propensity score matching to select counterfactuals; the
408 propensity score is the probability of receiving the intervention given the baseline
409 covariates, and control observations are matched to treatment observations with the
410 closest propensity score. This reduces imbalance/bias between the covariates, measured
411 using the standardised difference in means (SMD) of the covariates. Matching is considered
412 to have improved balance if the SMD is less than 0.25²⁶.

413 Matching was conducted separately for each of the protection type for each IPBES region.
414 To keep analysis tractable, we took samples of the data to eventually yield ~100,000 pixels
415 post-matching (out of 2.7 to 9.4 million pixels for each type-region dataset); 100,000 was
416 the maximum eventual sample size to be able to carry out the matching process within a

417 reasonable time period. We used the MatchIt package in R⁷⁹ on the samples, with the
418 default logit method and 1:1 nearest neighbour match without replacement and caliper size
419 of 0.25 of the standard deviation of the estimated propensity score to ensure good matches.
420 We included all numeric covariates (slope, elevation, population density, travel time,
421 distance to roads, and forest area in 2000 or 2010), with exact matching for country. We
422 took 5 separate samples, yielding a total of 3.3 million pixels, and checked that balance was
423 improved from the matching (Supplementary Table 5); only IAs in Americas and PIAs in
424 Asia-Pacific did not have improved balance after matching. Matching at the country level
425 did not reduce imbalance in 20 instances (Supplementary Table 6).

426 **Regression adjustment** Matching alone does not completely eliminate imbalance in all
427 covariates across all observations, and the additional regression conducted sought to
428 resolve this. As such, we combined the matched datasets for the different protection types
429 for each region, removing duplicate observations (of non-protected pixels). There were no
430 strong correlations ($r > 0.7$) between the covariates of each region, apart from elevation
431 and slope in the Americas. At the country level, strong correlations were also observed
432 mostly between slope and elevation, which is expected.

433 We fitted Generalised Additive Mixed Models (GAMMs) for each region using the mgcv
434 package in R⁸⁰, including a parametric term for protection type, numeric covariates as cubic
435 regression smoothing splines and geographic coordinates as an additional spline to reduce
436 spatial autocorrelation (with default thin spline smoothing basis). We fit country-level
437 random slopes for 2010 forest area (for PAs established before 2011, or 2000 forest area
438 for PAs established before 2001), an interaction term between protection type and country,
439 and a random intercept for country. We used the bam function for large datasets, default
440 fREML method, binomial family with logit link, with the argument discrete=TRUE to ensure
441 model convergence. We examined autocorrelation plots of model residuals and no pattern
442 was observed. We also fitted models without geographic coordinates and examined model
443 residuals to check if possible confounding factors have been included and find our models
444 robust to endogeneity. We used the models to predict deforestation/degradation rates for
445 each region, holding numeric covariates constant at their means and the longitude and
446 latitude coordinates and countries from the input data. For the country models, we fitted

447 similar models, but used only data from each country and so did not include any country-
448 related random effects. Most model residuals showed some spatial autocorrelation.

449 **Data availability**

450 The data that support the findings of this study are all publicly available online (see
451 Supplementary Table 4 for full source details). The map of Indigenous Peoples Lands can
452 be obtained from the authors upon reasonable request (Garnett *et al.* 2018).

453 **Code availability**

454 Code used for the analysis can be found in the Supplementary Methods section.

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461 **Author contributions**

462 Correspondences and requests for materials should be addressed to JSS and DPE. All
463 authors contributed to the conceptualisation and design of the study. JSS processed and
464 analysed the data, and all authors interpreted the results. JSS led the writing of the
465 manuscript, and all co-authors contributed critically to the drafts.

466 **Competing interests**

467 The authors declare no competing interests.

468 **Figure Legends**

469 Figure 1. Indicative map of the different protection types across tropical moist forests
470 within our analysis, coarsened to 30 km resolution where each pixel represents the
471 dominant type. The resolution is intentionally coarsened so that boundaries are imprecise,
472 as boundaries of Indigenous territories are often under dispute. A, the Americas. B, Africa.
473 C, Asia-Pacific. See Supplementary Figure 1 for a map of the matched data.

474 Figure 2. Mean estimated deforestation rates from 2010 to 2019 (or 2018 for GFW data)
475 predicted from GAMM regional models of protection types for GFW deforestation rates,
476 combined ECJRC deforestation and degradation rates, and separate ECJRC deforestation
477 and degradation rates across tropical moist forest extents, before matching (in translucent
478 colours) and after regression (in solid colours). Vertical lines show standard errors from
479 calculating mean values, which may not be visible at the plotted scale. Values below the
480 solid green horizontal line represent avoided deforestation relative to non-protected areas.

481 Figure 3. ECJRC deforestation rates predicted from GAMM models of protection types for
482 each country. Dashed line refers to regional mean deforestation rate of non-protected
483 areas, vertical line shows standard error. Values below the green line represent avoided
484 deforestation relative to non-protected areas. † represent countries for which imbalance
485 remained after matching, * represent countries for which regression residuals did not show
486 any spatial autocorrelation. BDI Burundi; COG Republic of Congo; COD Democratic Republic
487 of the Congo; CAF Central African Republic; CMR Cameroon; GAB Gabon; KEN Kenya; UGA
488 Uganda; ETH Ethiopia; TZA Tanzania; NGA Nigeria; BLZ Belize; PAN Panama; NIC
489 Nicaragua; CRI Costa Rica; GTM Guatemala; HND Honduras; MEX Mexico; PRY Paraguay;
490 ECU Ecuador; BOL Bolivia; COL Colombia; VEN Venezuela; PER Peru; BRA Brazil; SUR
491 Suriname; GUY Guyana; GUF French Guiana; KHM Cambodia; LAO Laos; VNM Vietnam; PHL
492 Philippines; MYS Malaysia; IDN Indonesia; MMR Myanmar; THA Thailand; LKA Sri Lanka;
493 BGD Bangladesh; IND India; NPL Nepal; NCL New Caledonia; AUS Australia. See
494 Supplementary Figure 5 for plot with free y-axis scales and Supplementary Figure 6 for
495 results with GFW deforestation data.

496

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