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Restoring logged tropical forests: the removal of woody, climbing plants

by

CATHERINE FINLAYSON

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AUTHOR'S DECLARATION

I, the author, confirm that the thesis is my own work and has not previously been presented for an award at this, or any other, university. This thesis is a collaborative piece of research from myself (C.F) and several other researchers: Robert P Freckleton (R.P.F), David P Edwards (D.P.E), Anand Roopsind (A.R), Bronson W Griscom (B.W.G), Matthew G Hethcoat (M.G.H), Patrick G Cannon (P.G.C), Robert G Bryant (R.G.B), and Kalsum M Yusah (K.M.Y). I am aware of the University's Guidance on the Use of Unfair Means (www.sheffield.ac.uk/ssid/unfair-means).

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1 ABSTRACT

2 In a world facing twin climate and biodiversity crises, the protection and restoration of logged tropical
3 forests is pivotal. Woody, climbing plants (lianas) restrict the recovery of logged tropical forests, but
4 their removal can restore timber and carbon value. While liana removal is employed to restore logged
5 forests in several tropical countries, the efficacy, application, and monitoring of this technique to track
6 the outcome for timber and carbon require further consideration before it can be rolled out widely. In
7 this thesis I, firstly, use meta-analytic techniques to quantify the overall effect of liana removal on the
8 growth of trees and aboveground biomass, and to explore the drivers of variation in efficacy. I find
9 that liana removal significantly enhances tree growth and nearly doubles aboveground biomass
10 accumulation, but the Neotropical bias in liana removal studies prevents me from drawing meaningful
11 conclusions about the causes of variation in liana removal efficacy. Secondly, I conduct a novel liana
12 removal experiment across 320 ha of logged forest in Sabah, Malaysian Borneo, in which I remove
13 varying proportions of lianas. I acquire satellite data across this experiment and find that liana
14 removal can be detected using Normalized Burn Ratio – a vegetation index based on spectral
15 reflectance that differentiates leaf from non-photosynthesising material. In this chapter I also provide
16 the first experimental evidence that partial removal has a smaller impact on the canopy, potentially
17 minimising negative impacts on biodiversity. Finally, I find that satellite data can also detect
18 commercial-scale liana removal (applied across 17,000 ha in Sabah). Overall, my thesis demonstrates
19 the significant potential of liana removal as a restoration action to enhance timber and carbon in
20 logged tropical forests and develops a simple remote sensing method to validate the application and
21 monitor the influence of large-scale liana removal on the canopy. However, much is yet unknown
22 about liana ecology and the myriad impacts of liana removal on biodiversity and forest function, so I
23 urge further research into these questions and strongly recommend that at least 20% of lianas are
24 retained if liana removal is rolled out to restore logged forests across the tropics. Further work should
25 also focus on operationalizing the use of remote sensing for monitoring.

26

27 CHAPTER 1: General introduction

28 **Global importance and degradation of tropical forests**

29 Tropical forests present a dilemma: they are fundamental to the functioning of our planet (Bruijnzeel,
30 2004; Devaraju et al., 2015), yet their future is seriously threatened (Malhi et al., 2014). Covering just
31 10% of global land area, tropical forests hold over half of the world's biodiversity (Barlow et al.,
32 2018; Pillay et al., 2022) and over half of the carbon stored in the world's forests (Pan et al., 2011).
33 Hence, these forests hold even greater value today in a world that is facing both the climate change
34 crisis (Solomon et al., 2009) and catastrophic rates of biodiversity loss (Ceballos et al., 2015).
35 Tropical forests are also a quandary as they provide natural resources and ecosystem services that
36 support over a billion people worldwide (Lewis et al., 2015), yet humans are the key driver of
37 declines in this ecosystem (Asner et al., 2009; Gibbs et al., 2010; Malhi et al., 2014). Despite their
38 importance, in 2017 it was estimated that only 20% of tropical forests remain intact (Potapov et al.,
39 2017), and the over-exploitation for natural resources and loss and fragmentation of tropical forests
40 does not seem set to change (Lewis et al., 2015).

41 Human activities have myriad impacts on tropical forests, and land-use change is the biggest
42 threat (Asner et al., 2009; Hansen et al., 2013). Agricultural expansion is the leading driver of tropical
43 deforestation, causing the loss of 0.4% of forests per year between 1980 and 2020 (Gibbs et al., 2010),
44 but this thesis studies the insidious impact of selective logging that degraded roughly 14 times the
45 area deforested between 2000 and 2005 (Asner et al., 2009). In this thesis, I define forest degradation
46 as activities that change the structure, faunal and floral composition, or function (such as tree growth
47 or carbon storage) of a forest away from old-growth conditions, but do not necessarily deforest an
48 area. Timber harvesting is no new phenomenon, but industrialized, large-scale logging has engulfed
49 tropical forests over the past century (Edwards et al., 2014; Shearman et al., 2012). In 2011, 400
50 million ha of tropical forests were classed as production forests (Blaser et al., 2011), and this is likely
51 to increase with the growing global demand for timber (Malhi et al., 2014).

52

53 Selective logging and the value of logged forests

54 Selective logging is one of the most common land-uses in the tropics, affecting 20% of the humid
55 tropical forests – ‘rainforests’ that represent over half of all tropical forests – between 2000 and 2005
56 (Asner et al., 2009). Selective logging is the harvest of stems from particular tree species and that are
57 above a minimum cutting diameter, rather than the removal of all stems that is carried out in clear-
58 cutting (Edwards et al., 2014). While selective logging allows forest cover to remain, there is still a
59 substantial impact on the plant and faunal communities and timber and carbon storage (Baraloto et al.,
60 2012; Edwards et al., 2011; Putz et al., 2012a). Modifications to selective logging, such as lower
61 harvest volumes (Burivalova et al., 2014) and reduced impact logging practices (Bicknell et al., 2014;
62 Griscom et al., 2019; Miller et al., 2011; Pereira Jr et al., 2002), can minimise these impacts, but
63 logging practices are still largely unsustainable since successive rounds of logging are too quick for
64 full timber recovery (Putz et al., 2022; Shearman et al., 2012). Consequently, timber harvesting is
65 often a “boom and bust” process, where-by logged forests eventually become financially unviable,
66 leading logging companies to expand timber harvesting into pristine forests and leaving an expanding
67 scar of environmental destruction in their wake (Shearman et al., 2012). Reducing the contribution of
68 timber harvesting to environmental issues including the biodiversity and climate crises, therefore,
69 requires improved sustainability of logging practices that will increase timber recovery and decrease
70 the area of land degraded by timber harvesting (Cerullo and Edwards, 2019; Gibson et al., 2011; Putz
71 et al., 2022).

72 While reducing the area of land affected by logging is important, the huge area of forests that
73 have already been degraded by logging (i.e. that have altered structure, composition, or function) also
74 represents a significant opportunity to protect biodiversity and address global carbon emissions
75 (Edwards et al., 2014; Philipson et al., 2020). Pristine forests are irreplaceable in terms of biodiversity
76 and carbon (Gibson et al., 2011; Pan et al., 2011), but logged forests have substantial recovery
77 capacity (Cook-Patton et al., 2020; Gourlet-Fleury et al., 2013; Rutishauser et al., 2015) and still

78 retain crucial biodiversity and ecosystem services (Edwards et al., 2011; Putz et al., 2012b). Despite
79 this, logged forests are threatened with conversion to non-forest land-uses that have greater financial
80 value (Burivalova et al., 2020) but far worse consequences for biodiversity and carbon (Edwards et
81 al., 2014; Lewis et al., 2015). Consequently, restoring logged tropical forests towards pre-logging
82 structure, faunal and floral composition, and function may prevent the rampant conversion of logged
83 tropical forests, protecting and enhancing the biodiversity and ecosystem services of logged tropical
84 forests (Burivalova et al., 2020; Cerullo and Edwards, 2019; Harrison et al., 2020).

85

86 **Restoration of logged tropical forests**

87 Concerns about ecosystem degradation and its consequences have prompted an era of ecosystem
88 restoration. This is exemplified by numerous global restoration initiatives, including the UN declaring
89 2021-2030 as the Decade on Ecosystem Restoration (United Nations Environment Agency, 2019).
90 Programs exist to restore ecosystems ranging from freshwater to grassland (Harper et al., 2021; Török
91 et al., 2021), including the Bonn Challenge and REDD+ that focus specifically on restoring hundreds
92 of millions of hectares of forests in the coming years (Strassburg et al., 2020).

93 Restoration is generally defined as assisting the recovery of an ecosystem that has been
94 degraded and often relates to bringing functions back to the land, such as biodiversity or other
95 ecosystem services (Benayas et al., 2009; Martin, 2017). In the context of tropical forests, restoration
96 often aims to restore the characteristics of old-growth forest – the condition of the forest prior to
97 human disturbance (Crouzeilles et al., 2016). However, there are multiple ways to define old-growth
98 forests, such as by forest structure or species diversity, multiple ways to restore degraded forests, and
99 the full restoration of all ecological attributes of pre-disturbed forests is difficult (Crouzeilles et al.,
100 2016; Lamb et al., 2005). Passive restoration, for example, allows degraded forests to recover forest
101 structure and biodiversity naturally, but can be slow, requires specific conditions that allow for the
102 recruitment of old-growth species, and may have limited success if perceived as land abandonment
103 (Cerullo and Edwards, 2019; Ren et al., 2017; Zahawi et al., 2014). Active restoration methods, on the

104 other hand, such as planting seedlings of old-growth tree species into logged forests, can enhance the
105 speed and chance of reaching pre-logging floral composition, but can be prohibitively expensive
106 (Benayas et al., 2009; Cerullo and Edwards, 2019; Ren et al., 2017).

107 In selectively logged forests, restoration could alternatively aim to restore timber and carbon
108 stocks (Cerullo and Edwards, 2019; Philipson et al., 2020). While this does not explicitly focus on
109 recovering old growth species composition, this could restore vegetation structure while the enhanced
110 timber and carbon value of the forest could provide a reason to maintain the land as forest and reduce
111 the expansion of logging into pristine forests, both of which ultimately benefit biodiversity (Edwards
112 et al., 2014). Enhancing tree growth and carbon storage in selectively logged forests is the primary
113 aim of restoration throughout this thesis. Post-logging silvicultural practices, such as removing
114 competing trees, can be employed to encourage the growth of commercial timber species (Peña-
115 Claros et al., 2008a) and an emerging method with huge potential to enhance timber growth and
116 carbon storage in logged tropical forests is the removal of woody climbing plants (referred to herein
117 as lianas or climbers) (Cerullo and Edwards, 2019; César et al., 2016; Marshall et al., 2016)..

118

119 **Liana-tree competition and liana removal**

120 Lianas, defined in the section above as woody, climbing plants, are often described as structural
121 parasites (Visser et al., 2018) as they exploit the trunks of trees to reach sunlight in the canopy rather
122 than investing in their own supportive tissue (Schnitzer and Bongers, 2002). Because they do not form
123 thick trunks, lianas grow much faster than trees, especially in the increased light environment created
124 by logging and other disturbances (Schnitzer and Bongers, 2002; Schnitzer and van der Heijden,
125 2019). Lianas quickly reach the canopy and allocate more resources into producing large quantities of
126 leaves, competing heavily with trees for light as a result (Putz, 1983; Song et al., n.d.). Research also
127 shows that lianas have alternative water use strategies to trees, allowing them to continue growing in
128 drier conditions during which trees tend to have lower growth rates (Schnitzer and van der Heijden,
129 2019), resulting in greater liana abundance in seasonally dry tropical forests (Toledo-Aceves, 2014).

130 Given their biology, it is no surprise that lianas negatively impact numerous aspects of tree
131 performance, including tree growth and fruit production (Estrada-Villegas and Schnitzer, 2018;
132 Grauel and Putz, 2004; Kainer et al., 2014; Schnitzer and Carson, 2010). When they reach high
133 abundances, for example after logging activity, lianas ultimately stunt forest recovery (Marshall et al.,
134 2020; Tymen et al., 2016). Moreover, lianas contribute less to forest carbon stocks than trees since
135 they invest more in foliage than carbon-dense stems, meaning that lianas also reduce the recovery of
136 carbon in logged forests (van der Heijden et al., 2015). Removing lianas, therefore, has potential as a
137 restoration technique in logged tropical forests by enhancing tree growth, timber volume, and carbon
138 stocks towards pre-disturbed level.

139 Aside from the ecological effects of liana removal, this method has strong restoration
140 potential since cutting lianas is low-cost, does not require specialised skills or equipment, and is
141 already implemented as part of reduced impact logging (RIL), albeit inconsistently (Marshall et al.,
142 2016; Mills et al., 2019; Philipson et al., 2020; Sist, 2000). Hence, liana removal has the potential to
143 be applied quickly to restore timber and carbon stocks across logged tropical forests, and is being
144 trialled and implemented in various countries (Mills et al., 2019; Peña-Claros et al., 2008a; Sabah
145 Forestry Department, 2020). However, refinement of liana removal treatment, consideration of
146 potential negative consequences of removing lianas, and development of methods to monitor the
147 impact of liana removal on carbon sequestration and timber growth are required before this method
148 can be operationalized to restore large expanses of tropical forests.

149

150 **Refining liana removal**

151 Lianas are undoubtedly problematic to adult trees, but they are also a critical component of the highly
152 complex tropical forest system: something that should be considered when implementing liana
153 removal. Lianas produce large quantities of leaves and fruits that are an important food source, for
154 example, whilst their leaves can be used as nesting resources (Arroyo-Rodriguez et al., 2015;
155 Odegaard, 2000; Putz et al., 2001). The woody stems of lianas also assist animal locomotion and, in

156 the context of degraded forests, could connect faunal species to less disturbed forests (Arroyo-
157 Rodriguez et al., 2015). Lianas also help to maintain a closed canopy, buffering against extreme
158 temperatures that is crucial for species that rely on a dark and cool understory microclimate (Meunier
159 et al., 2021c; O'Brien et al., 2019; Rodríguez-Ronderos et al., 2016; Scheffers et al., 2014). Moreover,
160 lianas are a highly biodiverse group of plants, contributing around 20% of the rich biodiversity of
161 tropical woody plants (Schnitzer and Bongers, 2002). The complete removal of lianas, therefore,
162 could have catastrophic consequences for biodiversity in the tropical forest biome that is crucial for
163 conservation. The only direct evidence of the effect of liana removal on faunal diversity found that
164 insectivorous birds had lower abundance for 20-months post-liana removal, and some studies surmise
165 that lianas could aid restoration through reducing edge effects or aiding faunal dispersal (Campbell et
166 al., 2015; Magnago et al., 2017). To ensure that liana removal synergistically restores carbon and
167 timber stocks and benefits biodiversity (a crucial step for policy as discussed in Pettorelli et al., 2021),
168 the technique needs to be refined to ensure that an ecologically functional subset of lianas remain in
169 the forest.

170 The adoption of liana removal as a restoration technique is also partly limited by variability in
171 the efficacy of the technique. A recent review found that liana removal increased the growth of adult
172 trees by between a quarter and three times (Estrada-Villegas and Schnitzer, 2018), while a study in
173 Malaysian Borneo showed a decrease in tree growth (O'Brien et al., 2019). This variability is perhaps
174 unsurprising given the complex ecology of lianas, for example that the competition between lianas
175 and trees can vary with climate, season, and species (Schnitzer and van der Heijden, 2019; Venegas-
176 Gonzalez et al., 2020), but there is currently no consensus as to what drives the variation in removal
177 efficacy. Individual studies that are conducted in different field sites using an array of liana removal
178 methods will struggle to ascertain the causes of variation in liana removal efficacy, but it is crucial to
179 know the circumstances under which liana removal is most (or not) effective.

180

181 **Remote sensing and liana removal**

182 Another challenge facing the wide-spread adoption of liana removal, and ecosystem restoration in
183 general, is how to validate and monitor actions applied over large scales (Murcia et al., 2016). Here, I
184 define “validation” as a process to verify that liana removal, or other methods, has been applied, and
185 “monitoring” as a process to assess the impact of liana removal on the canopy, carbon sequestration,
186 and timber growth. While commitments to restore hundreds of millions of hectares of forests
187 (Strassburg et al., 2020) and providing payments for the resulting additional carbon storage (GOFC-
188 GOLD, 2016) are highly commendable, accessing these payments, tracking progress towards
189 restoration targets, and determining restoration efficacy all require validation and monitoring across
190 large areas (Deluca et al., 2010; Holl and Cairns, 2010; Murcia et al., 2016). Studies have developed
191 optimal field sampling designs to monitor restoration projects (Londe et al., 2022; Viani et al., 2018)
192 but this only monitors a sample of the total treated area and, given the vast expanse of degraded
193 tropical forests that are targeted for restoration, conventional field methods still present logistical
194 challenges.

195 Remote sensing, defined as the acquisition of data via non-contact recording (Wang et al.,
196 2010), has become increasingly linked with conservation over the past few decades (Pettorelli et al.,
197 2014; Turner et al., 2003), and recent advances show its potential for restoration monitoring (de
198 Almeida et al., 2020). For example, satellite data, which can be acquired across the entire globe up to
199 several times per day at 3 m resolution (Shendryk et al., 2019), has been used to detect selective
200 logging (Hethcoat et al., 2020), track land-use change (Vancutsem et al., 2021), and assess the impact
201 of logged forest restoration (Wu et al., 2020), evidencing that forest management can be monitored
202 using such data.

203 There have been simultaneous advances in the use of remote sensing to study lianas, largely
204 based on the light reflectance properties of this plant group (Castro-Esau et al., 2004; Chandler et al.,
205 2021b; Meunier et al., 2021c; Waite et al., 2019), and a recent review calls for further use of remote
206 sensing to study lianas (van der Heijden et al., 2022). Consequently, there is clear potential for

207 satellite imagery to facilitate low-cost, temporally and spatially detailed monitoring of large-scale
208 restoration of logged tropical forests through the removal of over-abundant lianas. Validating the
209 large-scale application of liana removal would be particularly useful, facilitating the inclusion of liana
210 removal projects in schemes that provide payments for restoration, such as REDD+ (GOFC-GOLD,
211 2016). The enhanced monitoring capacity provided by remote sensing could also further evidence the
212 beneficial impacts of liana removal and improve the efficacy and application of the treatment,
213 ultimately encouraging more land managers to adopt liana removal as a sustainable logging and
214 restoration practice. Remote sensing could also reveal information about liana ecology, addressing
215 some of the many unanswered questions about lianas that we need to consider before large-scale liana
216 removal can be rolled out widely.

217

218 **Thesis aims and objectives**

219 The overarching aim of this thesis is to improve our understanding, the application, and the
220 monitoring of liana removal in logged tropical forests, demonstrating the potential for liana removal
221 in sustainable logging and the restoration of carbon storage and timber growth in huge expanses of
222 critically important logged tropical forests. Specifically, I aim to a) quantify the overall efficacy and
223 variability of liana removal for enhancing timber and aboveground biomass growth, b) assess a novel
224 liana removal method that could minimise the detrimental impacts on biodiversity, and c) develop a
225 remote-sensing method that can detect and monitor large-scale liana removal.

226

227 **Chapter 2 – Removing climbers more than doubles tree growth and biomass in degraded** 228 **tropical forests**

229 Huge expanses of tropical forests have been degraded and the recovery of these forests can be
230 inhibited by super-abundant woody climbing plants, also known as lianas or climbers. While
231 experimental evidence shows that climber removal largely increases tree and aboveground biomass

232 growth, there is substantial variation in the efficacy of this method. This chapter uses meta-analytic
233 techniques to determine the magnitude and variation in the efficacy of climber removal. I quantify the
234 overall effect of climber removal on enhancing tree growth and biomass accumulation, estimate the
235 potential contribution of climber removal to global carbon sequestration, and explore the drivers of
236 variation in climber removal efficacy.

237

238 **Chapter 3 – Monitoring lianas from space: Using Sentinel-2 imagery to detect liana removal in** 239 **logged tropical forests**

240 Ecosystem restoration is recognised as a key global priority and logged tropical forests represent a
241 huge area with restoration potential. Liana removal could be introduced widely to restore tree growth
242 and carbon sequestration in such forests but validating and monitoring large-scale restoration is
243 difficult and liana removal could have negative consequences for biodiversity. In this chapter I
244 combined a novel field experiment, removing varying intensities of lianas, with Sentinel-2-derived
245 vegetation indices to determine whether varying intensities of liana removal can be detected with
246 satellite data and to ascertain whether partial removal minimises the impact of this technique on the
247 canopy.

248

249 **Chapter 4 – Commercial-scale liana removal detected using satellite data**

250 Improving the sustainability of logging has the potential to address both the climate and biodiversity
251 crises. Enhancing timber recovery through the removal of lianas presents one opportunity to achieve
252 this, but monitoring application over vast areas is a challenge. This chapter builds on the results of
253 Chapter 3, aiming to determine whether commercial-scale liana removal can be detected using
254 satellite data and to identify any drivers of variation in this signal.

255 CHAPTER 2: Removing climbers more than doubles tree growth and
256 biomass in degraded tropical forests

257 This thesis chapter has been published as:

258 Finlayson, C., Roopsind, A., Griscom, B.W., Edwards, D.P, Freckleton, R.P. (2022) ‘Removing
259 climbers more than doubles tree growth and biomass in degraded tropical forests’, *Ecology and*
260 *Evolution*, 12(3), pp. 1–13. doi: 10.1002/ece3.8758

261

262 *A correction to this chapter has been published at <https://doi.org/10.1002/ece3.9917> and is copied*
263 *below. Please consider this when reading the original chapter as I have not amended the original*
264 *chapter to avoid discrepancies with the published article. In particular, please note the updated*
265 *interpretation of the SMD effect size, the new log response ratio method used to calculate the*
266 *percentage effect of liana removal on carbon sequestration, and the resulting updated global*
267 *potential of liana removal for biomass accumulation.*

268

269 **CORRECTION:**

270 In the article by Finlayson et al. (2022), titled “Removing climbers more than doubles tree growth and
271 biomass in degraded tropical forests”, the authors note an error. The paper misinterprets the
272 standardized mean difference (SMD) summary effect size, resulting in an overestimation of the effect
273 of climber removal on tree growth and biomass and an overestimation of the global carbon
274 sequestration potential of climber removal. This correction finds that climber removal almost doubles
275 aboveground biomass (AGB) accumulation in degraded tropical forests rather than tripling AGB.

276 Throughout the article, SMD should be interpreted as the number of standard deviations
277 difference between the tree growth and AGB in treated and control forest plots rather than the

278 proportional effect of climber removal. For example, the summary SMD for tree growth of 1.56
279 means tree growth is 1.56 standard deviations higher in treated than control plots, rather than a 2.56-
280 fold (or 256%) increase in tree growth, and the summary SMD for AGB of 2.09 means AGB is 2.09
281 standard deviations higher in treated than control plots, rather than a 3.09-fold (or 309%) increase.

282 In this correction, we use the log response ratio (logRR) between climber removal treated and
283 control plots rather than the SMD to calculate the proportional effect of climber removal on biomass
284 accumulation and the global carbon sequestration potential of climber removal. We calculate a
285 summary log response ratio (logRR) of 0.63, equating to an 88% increase in biomass accumulation
286 (95% CI = 40%–145%) in climber removal relative to control plots once logRR is transformed back
287 to a normal scale. Extrapolating this proportional effect to timber production and secondary forests
288 across the tropics, we find that climber removal could sequester an additional 7.4 Gigatons of CO₂
289 over a decade (4.1 in production forest and 3.3 in secondary forest) at a cost of US\$0.59 and US\$0.08
290 per Mg (metric ton) of CO₂ sequestered over 10 years, respectively (range: US\$0.01–US\$ 1.19).

291 The overall conclusion of the paper remains the same: There is a significant and substantial
292 positive effect of climber removal on tree growth and aboveground biomass compared with untreated
293 forest stands.

294 **Abstract**

295 Huge areas of tropical forests are degraded, reducing their biodiversity, carbon, and timber value. The
296 recovery of these degraded forests can be significantly inhibited by climbing plants such as lianas.
297 Removal of super-abundant climbers thus represents a restoration action with huge potential for
298 application across the tropics. While experimental studies largely report positive impacts of climber
299 removal on tree growth and biomass accumulation, the efficacy of climber removal varies widely,
300 with high uncertainty as to where and how to apply the technique. Using meta-analytic techniques, we
301 synthesise results from 26 studies to quantify the efficacy of climber removal for promoting tree
302 growth and biomass accumulation. We find that climber removal increases tree growth by 156% and
303 biomass accumulation by 209% compared to untreated forest, and that efficacy remains for at least 19
304 years. Extrapolating from these results, climber removal could sequester an additional 32 Gigatons of
305 CO₂ over 10 years, at low cost, across regrowth and production forests. Our analysis also revealed that
306 climber removal studies are concentrated in the Neotropics (N=22), relative to Africa (N=2) and Asia
307 (N=2), preventing our study from assessing the influence of region on removal efficacy. While we
308 found some evidence that enhancement of tree growth and AGB accumulation varies across
309 disturbance context and removal method, but not across climate, the number and geographical
310 distribution of studies limits the strength of these conclusions. Climber removal could contribute
311 significantly to reducing global carbon emissions and enhancing the timber and biomass stocks of
312 degraded forests, ultimately protecting them from conversion. However, we urgently need to assess
313 the efficacy of removal outside the Neotropics, and consider the potential negative consequences of
314 climber removal under drought conditions and for biodiversity.

315 **Introduction**

316 Around 300 million hectares of moist tropical forest were deforested or degraded between 1990-2020
317 (Vancutsem et al., 2021). Both forms of disturbance threaten biodiversity, erode carbon stocks in a
318 biome that contributes 55% of the global forest carbon sink, and reduce future timber yield, the main
319 economic incentive for maintaining managed forests (Fisher et al., 2011b; Gibson et al., 2011; Pan et
320 al., 2011; Putz et al., 2012b). While the protection of pristine ecosystems remains vital (Gibson et al.,
321 2011), the enduring biological value of degraded forests emphasises the critical role of restoration in
322 conserving biodiversity, reducing atmospheric CO₂, and supporting livelihoods (Edwards et al., 2014;
323 Moomaw et al., 2019; Strassburg et al., 2020).

324 Various global initiatives, including the UN Decade on Ecosystem Restoration, the Bonn
325 Challenge, and REDD+, recognise the benefits of restoration, with ambitions to restore hundreds of
326 millions of hectares of degraded land (Cerullo and Edwards, 2019; Strassburg et al., 2020). However,
327 ‘restoration’ encompasses different strategies with varying potential, from converting agricultural land
328 back to forest, to enhancing the state of degraded forests, such as those produced by selective logging
329 (Moomaw et al., 2019; Strassburg et al., 2020). While restoring forests to currently non-forested land
330 has huge potential (Strassburg et al., 2020), this is unlikely to yield the carbon sequestration required
331 in the immediate future to meet global goals. Reforestation can also compete with food production
332 and urban expansion (Moomaw et al., 2019). Alternatively, restoring degraded tropical forests to help
333 them achieve their full ecological potential could remove approximately 350 PgCO₂ from the
334 atmosphere (Erb et al., 2018), recover timber stocks that prevents the expansion of ‘boom-and-bust’
335 timber harvesting into pristine forests (Burivalova et al., 2020), and reduce the risk of degraded land
336 being converted to more lucrative, but lower carbon and biodiversity value agricultural plantations
337 (Cerullo and Edwards, 2019).

338 A key remaining question is how best to restore degraded forests (Coleman et al., 2019), and how
339 much climate mitigation potential can be delivered, given large uncertainty in existing estimates
340 (Griscom et al., 2017). A variety of methods have been developed for overall restoration of

341 biodiversity and productivity in degraded forests, from ‘natural restoration’ where human activity is
342 simply removed, to enrichment planting where trees are planted to enhance natural restoration
343 (Cerullo and Edwards, 2019). However, especially for enrichment planting, success and carbon gains
344 can be limited, and interventions expensive (Burivalova et al., 2020; Philipson et al., 2020). An
345 alternative solution is climber cutting. This method targets climbing plants such as lianas (woody,
346 climbing plants) bamboo, and rattan that limit forest recovery. It is already widely recommended as
347 part of reduced impact logging (RIL) practices, and is legally required but poorly implemented post-
348 logging in Indonesia and other countries (Griscom et al., 2014; Putz et al., 2008; Ruslandi et al.,
349 2017). Furthermore, climber cutting is relatively affordable (~ \$8.64 ha⁻¹ across Africa and the
350 Americas [see additional data] compared to enrichment planting (~\$1500-\$2500 ha⁻¹ in Malaysian
351 Borneo (Philipson et al., 2020)), requires limited expertise, can be easily integrated with forest
352 inventories, and has potential to enhance forest restoration and carbon sequestration on a faster
353 timescale (Cerullo and Edwards, 2019).

354 Climbing plants tend to proliferate extensively after disturbance and compete strongly with trees
355 for light, water, and other resources, limiting tree growth, survival, recruitment and aboveground
356 biomass sequestration (Meunier et al., 2021b; Schnitzer and Bongers, 2002). Estrada-Villegas and
357 Schnitzer (2018) conclude that lianas have a negative impact on all metrics of tree performance, and it
358 has been estimated that removing climbers in tropical forests enhances tree growth up to 372%,
359 timber yield by 1.51 m³ per tree over 40 years, and aboveground biomass by ~76% per year compared
360 to untreated forest (Estrada-Villegas and Schnitzer, 2018; Mills et al., 2019; van der Heijden et al.,
361 2015). However, these are site and region-specific studies that report varying climber cutting efficacy.

362 Compared to untreated controls, the efficacy of climber cutting ranges from reducing tree growth
363 by 20-90%, depending on size class (O’Brien et al., 2019), to more than doubling it (Gerwing, 2001;
364 Grauel and Putz, 2004), with little consensus on what drives this variation. Marshall *et al* (2017) noted
365 that, across continents, tree growth after climber removal was enhanced by between 41-122%
366 compared to control forest, but there is conflicting evidence regarding whether the outcome of climber
367 removal on tree growth and carbon sequestration are influenced by region and climate. For example,

368 two studies in SE Asia and Central America conclude that efficacy of cutting varies with total annual
369 rainfall and between wet and dry seasons, while other studies find similar efficacy in wet and dry
370 seasons (Álvarez-Cansino et al., 2015; O'Brien et al., 2019; van der Heijden et al., 2019; Venegas-
371 Gonzalez et al., 2020).

372 Climber removal is also applied in various intensities and across different forest types, spanning
373 old growth, selectively logged, and secondary forests of various ages, with no 'best-practice'
374 procedures yet defined. In some cases, climber removal is applied just once to selected focal trees
375 (Grogan and Landis, 2009), while in others removal is applied to the entire stand with repeated
376 treatments (van der Heijden et al., 2019). Again, results are conflicting: some studies find a greater
377 impact of climber removal on tree growth in younger forest, in earlier successional species, and on
378 larger trees as climber load tends to be greater in these contexts (De Lombaerde et al., 2021; Duncan
379 and Chapman, 2003; Estrada-Villegas et al., 2020). Conversely, a recent study found no effect of liana
380 removal on AGB accumulation across varying successional ages and tree sizes in a tropical dry forest
381 (Estrada-Villegas et al., 2021).

382 Due to the range in efficacy, breadth of climber removal contexts, and limited systematic attempt
383 to understand drivers of variation in treatment efficacy, it is difficult to anticipate the outcome of
384 climber removal with accuracy. Not only is this problematic for land managers, but it also limits our
385 ability to estimate the contribution that climber removal could have to global restoration and carbon
386 sequestration goals.

387 In this study, we use meta-analytic techniques to determine the overall magnitude of climber
388 removal efficacy in tropical forests, and to understand the potential drivers of variation in efficacy.
389 We focus on tree growth and AGB accumulation as they contribute substantially to forest commercial
390 value and productivity. We first synthesise existing experimental climber removal studies to quantify
391 the effect of climber removal on enhancing tree growth and AGB accumulation, taking study context
392 into account (Objective 1). We use this to estimate the potential contribution of climber removal to
393 global carbon sequestration through restoration of degraded forests. Second, we exploit the breadth of

394 study contexts to investigate whether region, climate, and forest disturbance context influence the
395 efficacy of removal, to determine the best method of application, and to assess the longevity of
396 treatment efficacy (Objective 2). Overall, this study determines whether climber removal can be
397 applied to enhance aboveground biomass and timber stocks globally and, ultimately, restore function
398 and economic value to degraded tropical forests.

399 **Methods**

400 *1. Literature search and screening*

401 We conducted literature searches in Web of Science (WoS), SCOPUS and Google Scholar, the latest
402 search completed in March 2021. Author C.F. ran two search strings in each database: to find all
403 studies that applied climber removal in tropical forests with any type of disturbance (none, regrowth
404 after deforestation, and selectively logged), and to find studies that applied climber removal before
405 disturbance (Table S4). We also conducted searches in the E-Theses online Service (EThOS)
406 database, contacted academics known to work on climber removal, and contacted organisations
407 including national forestry departments and the Centre for International Forestry Research (CIFOR).
408 This yielded a further 8 studies. Due to the high number of irrelevant results returned by Google
409 Scholar, we screened results for relevance against inclusion criteria set a priori (Table S5) directly
410 from the webpage. We stopped searching Google Scholar when we reached 100 consecutive
411 irrelevant results. All WoS and SCOPUS search results were screened.

412 The WoS, SCOPUS, relevant Google Scholar results, and the eight studies from other sources,
413 yielded 5304 unique results. These were screened against the inclusion criteria, resulting in 65 studies
414 (Figure S12). We then excluded 13 results that combined climber removal with another vegetation
415 management, seven results that reused data from another publication, and six results that did not have
416 a relevant tree growth or biomass metric (Table S6). A further 13 were excluded because mean tree
417 growth, aboveground biomass (AGB), or control data were unavailable; authors were contacted for
418 missing data before being excluded from the dataset. This resulted in 26 controlled experimental
419 studies that assess the impact of climber removal on tree growth (Figure S12 and Table S7). For the

420 AGB analysis, we only included a subset of the 26 studies which measured the effect of climber
421 removal on trees ≥ 5 cm dbh, resulting in 12 studies. To quantify removal efficacy we require
422 treatment and control results for each study, contrasting to Estrada-Villegas and Schnitzer (2018) that
423 qualitatively summarises 64 studies including non-controlled studies and other responses to climber
424 removal, such as tree mortality and canopy openness.

425 *2. Data extraction*

426 Author C.F. recorded data to calculate effect size (mean tree growth or AGB accumulation across all
427 trees measured in treatment and control plots, variation around the mean, sample size [number of
428 treatment and control plots], and tree growth response metric), study details (e.g., sampling effort and
429 experimental design), and explanatory variables relating to region and climate, forest disturbance
430 context, and method of removal that could influence climber removal. C.F. verified data at the time of
431 extraction for accuracy. See Supplementary Information, Appendix B for details of tree growth and
432 AGB response data collection, and details of how missing data were handled, and Table S7 and our
433 published additional data for metadata of each study included in the analyses.

434 *3. Meta-analysis*

435 *3.1 Calculating individual effect sizes*

436 We calculated the individual effect sizes (ES) (and variance) for each study using the standardised
437 mean difference (SMD; Hedges g) in RGR or AGB between treatment and control sites using the
438 *metafor* and *compute.es* R packages (Del Re, 2013; Viechtbauer, 2010). Multiple effect sizes were
439 calculated per study if there were treatment vs control comparisons measured at more than one
440 timepoint, or on different size classes of trees. SMD is less biased by small sample sizes than mean
441 difference (MD) and there was no difference in the results using either method (Figure S17). See Del
442 Re (2015) for equations to calculate SMD and variance.

443 A value of SMD greater than zero indicates greater growth or biomass accumulation in trees in
444 plots that had climbers removed compared to trees in control plots: the larger the positive number the

445 greater the impact of climber removal. A value of SMD not significantly different from zero indicates
446 equal tree growth or biomass accumulation in treated and control plots, meaning that climber removal
447 has no significant effect.

448 *3.2 Assessing the magnitude of climber removal efficacy*

449 To assess the magnitude of the effect of climber removal on promoting growth or biomass
450 accumulation of trees (Objective 1), we fitted mixed-effects linear models (using *lme4* and *lmerTest* R
451 packages: (Bates et al., 2015; Kuznetsova et al., 2017)). One model was fitted to the 103 individual
452 effect sizes from the 26 studies in the analysis of tree growth, and another to the 69 individual effect
453 sizes from 12 studies in the analysis of biomass (Table S10). The models were run on each of the 10
454 datasets generated from imputing missing variances for growth and biomass (see Supplementary
455 Information, Appendix B ‘Missing data’ for details). The model results presented in the manuscript
456 are the average parameter coefficients (including intercept), standard error of the coefficient, degrees
457 of freedom, coefficient confidence intervals, and p-values (based on these averaged values) from the
458 10 models. The models were weighted by the inverse SMD variance.

459 A unique study identifier was included as a random effect in both models to account for non-
460 independence when there were multiple effect sizes from each study. Time of measurement after
461 treatment, number of species measured in mean growth rate, and study quality were included as fixed
462 effects to capture known sources of variation between effect sizes or studies (Spake et al., 2020).
463 Study quality is an ordinal scale (“high”, “medium”, or “low” quality), assigned based on study
464 design, sample size, sampling effort (sampling area or number of trees measured), whether the tree
465 growth was relative (RGR), how far the treatment site was from control plot, and whether there were
466 any disturbance differences between treatment and control forests (Table S8). Study quality was
467 included as a fixed effect as it only has three categories, and allows us to account for the variation
468 between studies in terms of their design and rigour. The ‘number of species’ variable accounts for
469 variation caused by different studies measuring a different number of species, see Supplementary
470 Information, Appendix B for more details.

471 We assessed the level of variation (heterogeneity) in the efficacy of climber removal using Q
472 statistics and I^2 values. A significant Q statistic indicates significant heterogeneity, meaning that effect
473 sizes from different studies vary more than would be expected by chance (Del Re, 2015; Harrison,
474 2011). The I^2 value indicates the extent of the heterogeneity, with 25% considered low, 50%
475 considered moderate and 75% considered a high amount of heterogeneity (Del Re, 2015).

476 *3.3 Assessing drivers of variation in climber removal efficacy*

477 To determine whether region and climate, forest disturbance, or removal method were causing
478 variation in climber removal efficacy (Objective 2), we added explanatory variables to the two models
479 described previously. For the tree growth analysis, we included variables with the greatest theoretical
480 impact on the outcome of climber removal (Table S10). The direction and size of the coefficient for
481 each variable indicated its influence on climber removal efficacy. Several parameters could not be
482 assessed (Table S9), or were assessed in supplementary models (Table S11), due to data constraints.

483 For the analysis of AGB, we were only able to assess the influence of a few parameters relating to
484 removal method and disturbance context due to data constraints, and used three separate models to do
485 so. We present all three models in the main text (see details in Table S10). Objective 2 models for tree
486 growth and biomass accumulation were run for all imputed datasets (see Supplementary Information,
487 Appendix B ‘Missing data’ for details), and model results herein show the average parameter
488 coefficients, standard error of the coefficient, degrees of freedom, coefficient confidence intervals,
489 and p-values (based on these averaged values). We assessed the heterogeneity of the objective 2
490 models using Q and I^2 statistics.

491 *4. Sensitivity analysis and assessing publication bias*

492 We tested for publication bias in several ways. Firstly, we analysed the relationship between
493 publication year and effect size to infer whether datasets with results opposing that of the first
494 published paper remain unpublished. Secondly, we tested for asymmetry in funnel plots with Eggers
495 test, using the *metafor* R package (Viechtbauer, 2010).

496 To test the robustness of the results, we calculated fail-safe numbers following the Rosenthal,
497 Rosenberg and Orwin methods, using the *metafor* R package (Viechtbauer, 2010). These indicate how
498 many studies with null results would need to be added to the analysis to reduce the significance level
499 of the summary effect size so that it was no longer significant, or to reduce the effect size by half.
500 Larger numbers indicate the effect size is robust.

501 *5. Global carbon sequestration potential*

502 To determine the potential contribution of climber removal to global carbon sequestration, we
503 extrapolated the effect of climber removal on AGB accumulation (intercept of model for objective
504 1.2) to an assumed maximum scenario. This includes: a) the area of natural tropical forest managed
505 for selective timber harvest with a valid concession license (FAO, 2020), and b) the area of moist
506 tropical forest regrowing >3 years after deforestation (Vancutsem et al., 2021). We calculated the
507 difference between the baseline AGB growth rate for the forest type and the climber removal
508 enhanced AGB growth rate. We then subtracted the AGB lost in removed climbing plants and their
509 annual biomass growth, and converted the final difference in AGB to tons of CO₂ (IPCC, 2003). See
510 Table 3 and additional published data for full details.

511 All analyses were conducted in R (R Core Team, 2020) and figures produced using the R package
512 *ggplot* (Wickham, 2016).

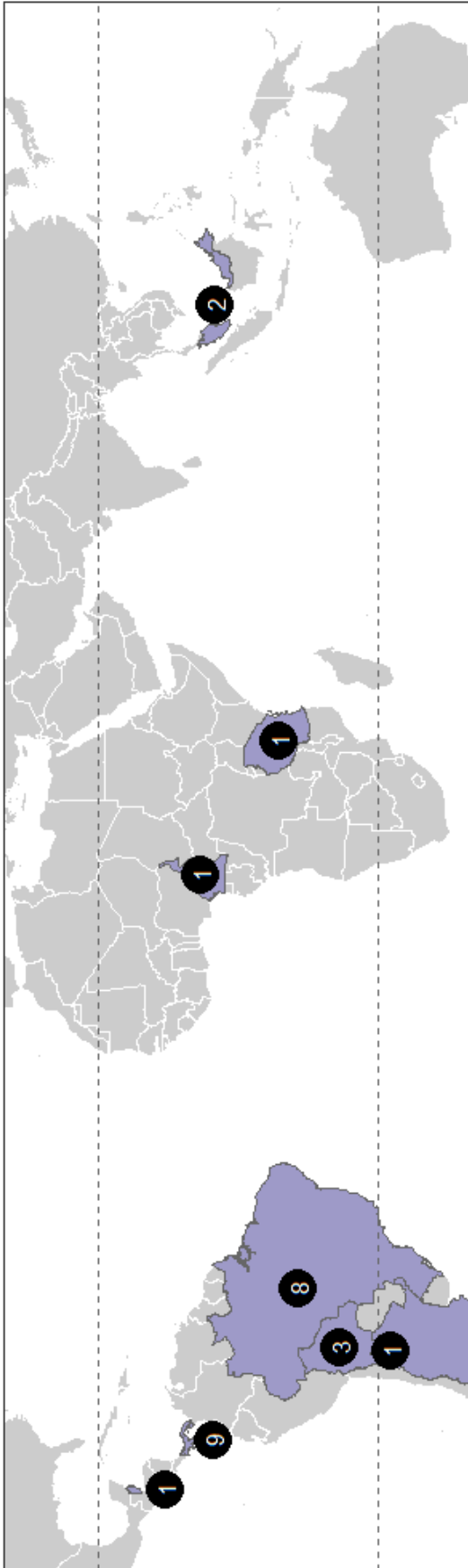
513

514 **Results**

515 *Global distribution and details of study sites*

516 The 26 studies included in the analysis of tree growth are distributed across eight countries in the
517 tropics, plus one in subtropical Argentina (-26 degrees latitude) (Figure 1). While there is good
518 representation in Central and South America (22 studies), there were limited studies from Asia (2) and
519 Africa (2). The 12 studies in the biomass analysis are from five countries, mainly in Central and South
520 America (11 studies), plus Asia (1), with none in Africa.

521 The studies cover a range of elevations (range: 13-776 m.a.s.l), and gradients of precipitation
522 (1144-2964 mm year⁻¹), temperature (21.2-27.7°C), and dry season length (0-7 months). There were
523 three studies in sites without any disturbance, 13 had been selectively logged, seven were forests
524 regrowing after being cleared (secondary forest), and three were forests regrowing after being cleared
525 that had also been selectively logged. Cutting was applied 1-720 months after disturbance in studies
526 removing climbers post disturbance, and 1-12 months before removal for studies applying climber
527 removal pre disturbance. Study monitoring duration ranged from 12-228 months post treatment.
528 Studies repeated climber removal between 0-27 times, and across entire plots or just on focal trees.
529 See Table S7 and additional published data for full study metadata.



531 **Figure 1:** Geographical distribution of the 26 studies across the tropics included in the meta-analysis
532 literature search. A subset of these is included in the biomass analysis. Black circles indicate number
533 of studies in each country. Dashed horizontal lines indicate the Tropic of Cancer (23° N) and the
534 Tropic of Capricorn at (23° S).

535

536 *Effect of climber removal on tree growth*

537 We find that the results of our meta-analysis are robust, even though there is some evidence of
538 publication bias (see Figures S13-S16 and Supplementary Information, Appendix D for details). Trees
539 in plots from which climbers were removed experienced a 2.56-fold increase in growth (summary
540 effect size 156%; 95% CI = 109-203%) compared to those in untreated control plots (Figure 2, Table
541 1) across all tree size classes and various growth metrics combined. This represents the tree growth
542 enhancement resulting from climber removal at the stand level. There was substantial variation in the
543 effect on tree growth: the lowest individual effect size across studies showed a -36% decrease in tree
544 growth, whereas the highest showed a 409% increase in growth. African studies had effect sizes of -
545 36% and 12%, and Asian studies had effect sizes of 56% and 179% compared to untreated controls
546 (Lussetti et al., 2016; Marshall et al., 2016; O'Brien et al., 2019; Parren, 2003), respectively; Figure
547 2). The median effect size outside the Neotropics (29%) is much lower than the overall tree growth
548 effect size (156%), but we could not directly assess the influence of region due to insufficient studies
549 located in Asia and Africa (see Methods section 3.3).

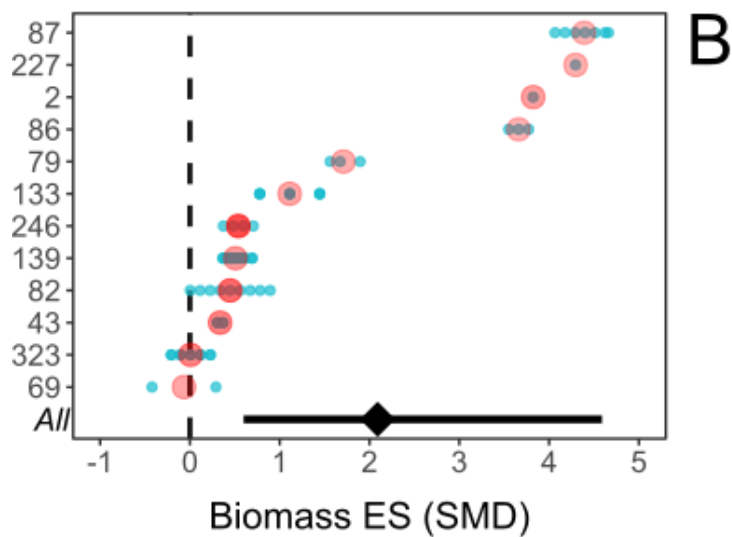
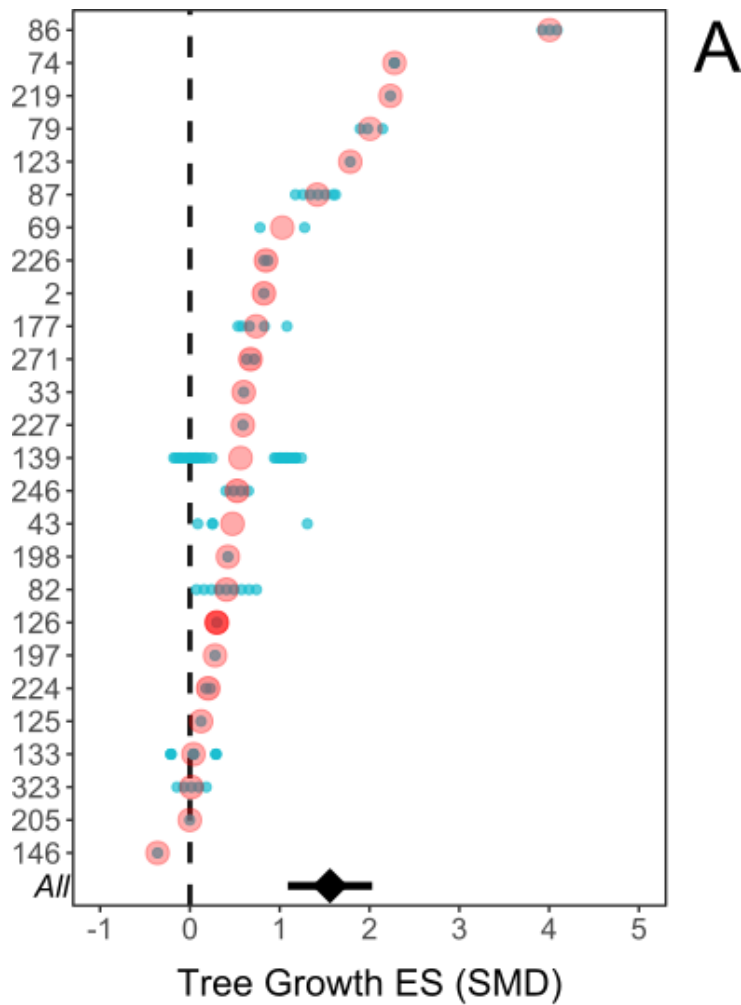
550 Q statistics and I^2 values indicate that the magnitude of the positive effect of climber removal on
551 enhancing tree growth is expected to vary, but only by a small amount ($Q = 164$, 95 CI = [121-218],
552 $p\text{-val} < 0.001$; $I^2 = 38\%$, 95% CI = [16-53%]). Model results did not differ substantially if we excluded
553 imputed data, if we calculated effect sizes using MD rather than SMD (Figure S17), nor if we
554 removed van der Heijden et al (2015) that had an effect size almost double those of the other studies
555 (Table S12).

556 The efficacy of climber removal for enhancing tree growth varied with quality of study: efficacy
557 was 122% greater (95% CI = [44, 201]) in high- than low-quality studies, and 118% greater (95% CI
558 = [88, 149%]) in high- than medium-quality studies (Table 1). We observed that the efficacy of
559 climber removal for enhancing tree growth did not vary with the number of species in the mean
560 growth rate (Table 1).

561

562 *Effect of climber removal on AGB accumulation*

563 Climber removal increased total aboveground biomass storage of all trees in treated plots by 3.09
564 times (summary effect size 209%; 95% CI = [60, 359 %]) compared to untreated controls. This
565 represents the increased AGB accumulation resulting from climber removal at the stand level. Again,
566 there was substantial variation, with the individual effect size sizes across studies ranging from -42 to
567 466% (Figure 2, Table 1). The only study outside the Neotropics (in Malaysia) experienced 51%
568 increase in tree growth compared to untreated controls. The effect size was much lower and the
569 credible intervals cross zero when imputed data is not included (N=9) (Figure S18), but only one
570 study of nine had a negative effect of climber removal on biomass, confirming the overall positive
571 effect of climber removal on biomass accumulation. Q statistics and I^2 values indicate that, while we
572 expect a positive effect of climber removal, the magnitude of the effect of climber removal on AGB
573 accumulation is likely to vary substantially (Q = 257, 95 CI = [150, 371], p-val <0.001; (I^2 = 74%,
574 95% CI = [55, 82 %]).



● Individual ES Study ES Precision
● Study ES ● low ● high

575

576 **Figure 2:** Overall, individual, and study average effect sizes (ES) of climber removal for promoting
 577 tree growth (Panel A) and AGB accumulation (Panel B). Numbers on the y-axis represent study ID, as
 578 given in Table S7, and metadata spreadsheet in our published additional data. Blue dots are individual

579 effect sizes within a study, predicted from the models for Objective 1.1 and 1.2 and averaged for all
 580 imputed datasets. Red circles are the study ES (the average of the individual ES for each study); the
 581 shade of the circle represents precision of the study ES and is proportional to the inverse of the
 582 variance of the individual effect sizes, averaged by study. The black diamond at the bottom of each
 583 figure is the overall summary effect size of climber removal for promoting tree growth and biomass,
 584 taken from the intercept of the models for Objective 1.1 and 1.2 when continuous covariates are at
 585 their mean value and study quality reference level is “high”; error bar shows 95% credible intervals.

586 **Table 1: Magnitude and direction of climber removal efficacy on tree growth and biomass**
 587 **accumulation.** Results of models for Objective 1.1 (tree growth) and Objective 1.2 (AGB). ‘Tree
 588 growth Effect Size (ES)’ and ‘AGB Effect Size (ES)’ are the intercept of each model and show the
 589 number of times greater tree growth or biomass accumulation with climber removal versus untreated
 590 control plots. Results are the average of 10 Linear Mixed Models using 10 datasets imputed using
 591 linear regression, including the study with just post-treatment data (Tree growth N=26 studies,
 592 Biomass N=12 studies). See Supplementary Information, Appendix C for full description of models.
 593 Bolded effect sizes indicate level of significance at either 0.05,0.01, or 0.001.

<i>Objective</i>	<i>Fixed effect</i>	<i>Estimate (SE)</i>	<i>Degrees of Freedom</i>
<i>Objective 1.1: Tree growth</i>	<u>Tree growth ES</u>	1.56 (0.23)***	32
	<i>Study quality High:Low</i>	-1.22 (0.40)**	81
	<i>Study quality High:Med</i>	-1.18 (0.15)***	86
	<i>Number of species</i>	0.00 (0.00)	89
	<i>Time elapsed since removal</i>	0.01 (0.00)***	90
	<u>AGB ES</u>	2.09 (0.67)*	11

<i>Objective 1.2:</i> <i>AGB</i> <i>accumulation</i>	<i>Study quality High:Low</i>	-1.97 (1.76)	7
	<i>Study quality High:Med</i>	-0.23 (0.41)	61
	<i>Number of species</i>	-0.00 (0.01)	8
	<i>Time elapsed since removal</i>	0.01 (0.00) *	54

594 * < 0.05, ** < 0.01, *** < 0.001

595

596 *Drivers of variation in efficacy for tree growth*

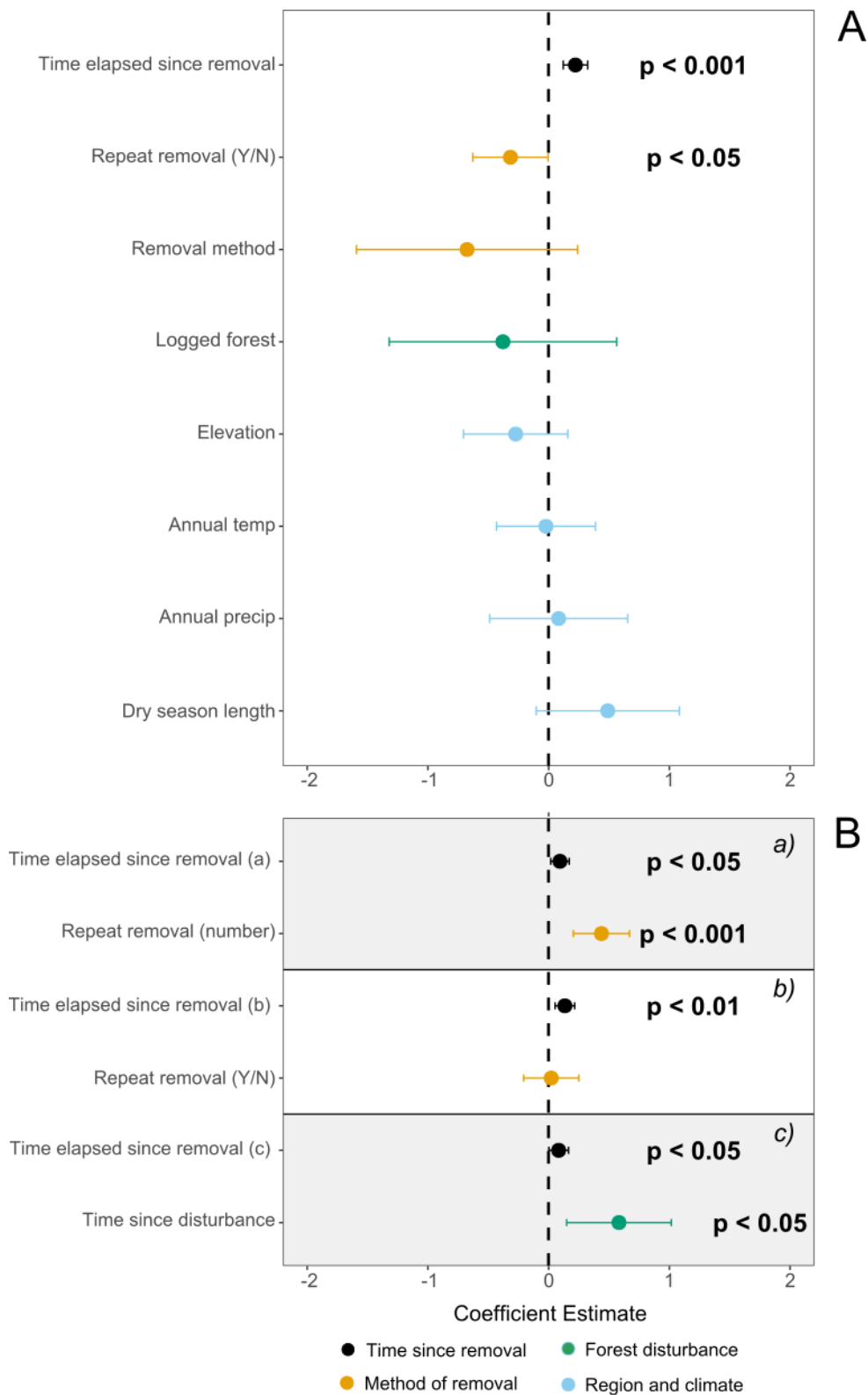
597 Explanatory variables relating to climate, region, and forest disturbance did not influence the efficacy
598 of climber removal for enhancing the growth of trees (Figure 3, Table 2). However, efficacy did
599 increase, marginally, per month since treatment (1% greater effect on tree growth per month in
600 objective 1.1 and 2.1 models (95% CI = [0, 1%]); Table 1 and 2). This shows that climber removal
601 enhances tree growth for at least the maximum study monitoring period of studies in this analysis: 19
602 years. The model for objective 2.1 found that studies which repeated removal had 41% less tree
603 growth enhancement compared to studies which did not repeat removal (95 % CI = [1, 82 %]; Table
604 2). However, the confidence intervals are very close to zero and the supplementary models suggest
605 that repeating removal does not significantly influence the efficacy of climber removal for enhancing
606 tree growth (Table S13). Supplementary models also found no effect of latitude, time between
607 disturbance and removal, and dry season temperature and precipitation on the efficacy of climber
608 removal for promoting tree growth.

609 As with objective 1.1, the Q statistics and I² values indicate that the positive effect of climber
610 removal on tree growth is still likely to vary by a small amount, even when accounting for variation
611 due to parameters included in the model for objective 2.1 (Q = 177, 95 CI = [132, 232], all p-values
612 <0.001; I² 42%, 95% CI = [23, 56%]).

613 *Drivers of variation in efficacy for AGB accumulation*

614 The AGB accumulated in treated plots relative to untreated plots increased with the time elapsed since
615 removal, the number of times the treatment was applied, and the amount of time between disturbance
616 and initial application of removal (Table 1 and 2, Figure 3). The efficacy of climber removal for
617 enhancing AGB increased 0.1% (95% CI = [0.0, 1.2%]) with each month elapsed since removal. This
618 shows that climber removal enhances AGB for at least 10 years: the maximum study monitoring
619 period of studies in the biomass analysis. We also found that removal more greatly enhanced biomass
620 accumulation in older secondary forest and forests logged longer ago: efficacy increased by 115.9%
621 (95% CI = [29.7, 202.0%]) with each additional year between disturbance and treatment (maximum
622 60 years between disturbance and treatment). Efficacy also increased by 18% with each removal
623 repetition (95% CI = [9, 28%]).

624 According to the Q statistics and I^2 values, the positive effect of climber removal on AGB
625 accumulation is still expected to vary substantially, even when accounting for variation due to
626 parameters included in the models for objective 2.2 (Q = 239-269, 95 CI = [132-383], p-val <0.001;
627 I^2 = 65-68%, 95% CI = [41, 84%]; across objective 2.2 a, b, and c models).



628

629 **Figure 3:** Influence of region and climate, disturbance context, and method of removal (whole plot vs
 630 focal tree removal and whether removal was repeated) on the efficacy of climber removal for
 631 promoting tree growth and AGB accumulation. Panel A shows coefficient estimates for the objective

632 2.1 (tree growth) model and Panel B shows estimates for the objective 2.2 (AGB) models a), b) and
 633 c). The coefficient for the repeat removal (number) is excluded from model 2.2 c) as it was no
 634 different from model a). Centred and scaled parameter estimates are shown for continuous variables
 635 with error bars indicating 95% CI. For categorical variables, the figure shows the fitted mean value
 636 with 95% CI between the reference level and the other categorical level. The reference level for the
 637 ‘Logged forest’ variable is ‘logged’, ‘Repeat removal (Y/N)’ variable is ‘no repeated removal’, and
 638 ‘Removal method’ variable is the whole plot removal method. Significant parameter estimates are
 639 shown with p-values. Colour indicates the parameter category.

640 **Table 2: Drivers of variation in the efficacy of climber removal for tree growth and AGB**
 641 **accumulation.** Results for objective 2.1 and 2.2 models, averaged from 10 Linear Mixed Models
 642 using 10 imputed datasets (imputed using linear regression), and including one study with just post-
 643 treatment data (tree growth N=26 studies, biomass N=12). Response variable is tree growth for
 644 Objective 2.1 and AGB change for Objective 2.2, see full model details in Supplementary
 645 Information, Appendix C. Bolded explanatory parameters indicate level of significance at either
 646 0.05,0.01, or 0.001.

<i>Objective</i>	<i>Explanatory parameter</i>	<i>Estimate (SE)</i>	<i>Degrees of Freedom</i>
Objective 2.1 (Tree growth)	<i>Time elapsed since removal</i>	0.01 (0.00)***	86
	<i>Repeat removal (Y/N)</i>	-0.41 (0.20)*	91
	<i>Removal method (whole plot / focal tree)</i>	-0.88 (0.57)	21
	<i>Logged forest</i>	-0.49 (0.58)	17
	<i>Dry season length</i>	0.30 (0.17)	17
	<i>Annual precipitation</i>	0.00 (0.00)	16
	<i>Annual temperature</i>	-0.02 (0.19)	19
	<i>Elevation</i>	-0.00 (0.00)	23

647

Objective 2.2 (AGB accumulation)	a)	<i>Time elapsed since removal</i>	0.01 (0.00)*	54
		<i>Repeat removal (number)</i>	0.18 (0.05)***	62
	b)	<i>Time elapsed since removal</i>	0.01 (0.00)**	54
		<i>Repeat removal (Y/N)</i>	0.04 (0.27)	56
	c)	<i>Time elapsed since removal</i>	0.01 (0.00)*	48
		<i>Repeat removal (number)^a</i>	0.17 (0.05)***	51
		<i>Time since disturbance</i>	1.16 (0.40)*	13

648 * $p < 0.05$, ** $p < 0.01$. *** $p < 0.001$

649 ^a Excluded from Figure 3 as the same result as model a).

650

651 *Global carbon sequestration potential*

652 Extrapolating the 209% increase in AGB accumulation resulting from climber removal to our
653 assumed maximum application scenario (timber production and secondary forest), we find that
654 climber removal could sequester an additional 32 Gigatons of CO₂ over a decade (22.9 in production
655 forest and 9.2 in secondary forest; Table 3). With the mean reported cost of climber removal as
656 US\$8.64 ha⁻¹ (see additional published data), we calculate the cost of climber removal as US\$0.11 and
657 US\$0.03 per Mg (metric ton) of CO₂ sequestered over 10 years for selectively logged and secondary
658 forests, respectively (range: US\$0.003-US\$0.22; Table 3).

659 **Table 3: Global carbon sequestration potential of climber removal.** Extrapolating the
 660 enhancement of AGB accumulation through climber removal (intercept of the model for Objective
 661 1.2) to calculate the carbon sequestration that could be provided by climber removal in production and
 662 secondary tropical forests. See published additional data for full calculation.

Forest Classification	AGBg ₀ (Mg C ha ⁻¹ yr ⁻¹) ^a	AGBg _{CR} (Mg C ha ⁻¹ yr ⁻¹) ^b	Area of forest (ha yr ⁻¹) ^c	Additional carbon sequestration with climber removal over 10 years (Mg C ₀₂) ^d	Cost of climber removal per CO ₂ sequestered over a decade (US\$ Mg C ₀₂ ⁻¹) (min/max) ^e
<i>Production forests</i>	1.49	4.61	282,879,090	22,862,805,785.40	0.11 (0.01,0.22)
<i>Secondary Forests >3 years since deforestation</i>	4.49	13.87	29,500,000	9,163,581,171.56	0.03 (0.003,0.06)
Total			312,379,090.00	32,026,386,956.95	

^a $AGBg_0$ is the baseline biomass growth (in metric tons [Mg] of carbon per hectare per year): for production forest this is the mean biomass growth rate from (Butarbutar et al., 2019; Gourlet-Fleury et al., 2013; Rutishauser et al., 2015); for secondary forest this is the mean from Cook-Patton *et al* (2020).

^b $AGBg_{CR}$ is the climber removal enhanced biomass growth rate:

$AGBg_0 + (AGBg_0 * 2.09)$ [effect of climber removal on AGB accumulation; intercept of model for objective 1.2].

^c Forest area classified as production forests with a valid concession license (designated management objective or production forests;(FAO, 2020); Area of moist tropical forest that is classified as regrowing >3 years post deforestation event (Vancutsem et al., 2021).

^d Difference in baseline and enhanced AGB growth for 10 years in each area of forest, accounting for biomass lost from removing climbers ($AGB_{climber}$) and converted to CO_2 as per IPCC 2003 guidelines: $((AGBg_{CR} * Area * 10) - (AGBg_0 * Area * 10) - (AGB_{climber} * Area * 10)) * 44/12$.

^e Cost of climber removal per each additional metric ton of CO_2 sequestered in a decade:

$$\text{Cost climber removal for area} / \text{Additional } CO_2 \text{ sequestered over 10 years}$$

See additional published data for total cost of climber removal in production and secondary forests.

663

664 Discussion

665 Quantifying the benefits of climber removal for tree growth and AGB is crucial for deciding whether
 666 removal should be implemented. We find that climber removal more than doubles tree growth and
 667 roughly triples AGB accumulation compared to untreated forests, and that efficacy is sustained for at
 668 least 19 years. We also quantify the potential of implementing climber removal for global carbon
 669 sequestration and provide recommendations for applying climber removal in certain regions, but note
 670 the lack of evidence outside the Neotropics and highlight urgent areas for research.

671 *Climber removal substantially enhances tree growth and AGB accumulation*

672 Our results confirm the findings of individual studies that climber removal has an overall positive
 673 effect on tree growth and AGB accumulation (Estrada-Villegas and Schnitzer, 2018), plus emphasise
 674 the dramatic role of climbers in tropical forest growth dynamics, carbon sequestration, and forest
 675 management. Our approach builds on the largely qualitative Estrada-Villegas *et al* (2018) review by
 676 calculating the size of the effect of climber removal and uncertainty in efficacy, whilst methodically
 677 accounting for study context. We also estimate the potential contribution of climber removal to global
 678 carbon sequestration: sequestering 32 Gigatons of CO_2 in a decade at relatively low cost if applied to
 679 secondary forests and production forests across the tropics.

680 The global carbon sequestration potential is not surprising given the unrealized carbon potential
681 of degraded tropical forests (350 Gigatons CO₂) identified by Erb *et al.* (2018). However, our
682 extrapolation may be influenced by (i) selection bias for studies occurring in locations with high
683 climber density, (ii) our inclusion of a few studies that only measure the efficacy of removal on trees
684 directly infested with climbing plants (rather than all trees in a given plot), and (iii) extrapolating to
685 the total area of secondary forests >3 years old while our analysis only included studies conducted in
686 secondary forests 20-60 years old. On the other hand, climbers do influence entire plots, not just the
687 tree they infest (van der Heijden *et al.*, 2015), and climber infestation in degraded forests tends to be
688 high (Schnitzer and Bongers, 2002); up to 80% trees infested in selectively logged forest in Malaysian
689 Borneo [unpublished data]). Moreover, secondary forests only contribute a third of the total calculated
690 sequestration potential of climber removal, and we do not account for the reduced tree mortality and
691 enhanced seedling recruitment associated with climber removal (O'Brien *et al.*, 2019; Philipson *et al.*,
692 2020; van der Heijden *et al.*, 2015). For these reasons we anticipate that any over-estimate of the
693 climate mitigation potential of climber removal is limited. Nevertheless, more research and more
694 detailed data, such as climber abundance and individual tree-level data, are needed to further refine
695 our global estimates of the stand-level impact of climber removal on tree carbon sequestration rates.

696 This study demonstrates how to extrapolate our results to the extent of tropical forest in two
697 scenarios. Our estimate assumes that the maximum extent where climber removal is appropriate is
698 312.4 million ha (tropical timber production natural forest and secondary forest). While it will not be
699 feasible in every hectare in these landscapes, and many logging concessions are not yet logged nor
700 will see the benefit of climber removal for some time, we consider this a conservative estimate. We
701 restrict our tropical timber production forest to areas under valid timber concession licences (282.9
702 million ha), while noting there is a larger area reported as production forest (~400 million ha
703 according to FAO (2020)). Further, (Potapov *et al.*, 2017) estimate ~1.4 billion ha is non-intact
704 tropical forest, indicating considerably larger maximum extent for implementing climber removal.
705 Using our study as an example, extrapolations could be made for alternative forest extents, at scales
706 relevant to individual countries or landowners, and regarding timber rather than carbon stocks.

707 *Influence of region and climate remains unclear*

708 Though our results give no indication that the efficacy of climber removal on tree growth and biomass
709 accumulation is influenced by elevation, latitude, presence and length of dry season, precipitation, and
710 temperature, the poor distribution of study sites means there is insufficient evidence to conclude that
711 region and climate have no effect. There are very few studies outside the Neotropics, none in the
712 montane tropics and forests with the highest annual rainfall (e.g., the Chocó, Colombia), and very few
713 studies considered the influence of drought, despite their increasing frequency and concerns that
714 climber removal may be detrimental in drought conditions (Berenguer et al., 2021; IPCC, 2021;
715 O'Brien et al., 2019). The scarcity of climber removal studies outside the Neotropics represents a
716 major gap in our knowledge: particularly troubling as climber removal is increasingly prescribed as a
717 restoration intervention (Cerullo and Edwards, 2019; Philipson et al., 2020).

718 Climber removal, nonetheless, remains an important potential restoration action, especially in
719 Africa and Asia where forest disturbance is widespread and climber abundance is high (DeWalt et al.,
720 2015; Hansen et al., 2013). Removal studies in these regions and across wider climatic gradients are
721 urgently required so that evidence-based climber removal can be rolled out pan-tropically. Beyond the
722 tropics, and outside the scope of this meta-analysis, climber removal could also be important in
723 temperate regions, where competing vegetation and climber abundance can hinder growth and
724 biomass accumulation (De Lombaerde et al., 2021; Smith, 1984).

725 *Efficacy of climber removal is similar across disturbance history and methods of removal*

726 Overall, we find limited evidence that the efficacy of removal is influenced by forest disturbance
727 context or method of removal. Climber removal enhances tree growth to a similar extent in selectively
728 logged and secondary forests disturbed up to 60 years previously. This confirms that climber
729 competitive advantage is similar in both selectively logged and secondary forests, and sustained long
730 after disturbance (Schnitzer and Bongers, 2002). Furthermore, our results suggest that sufficient
731 climbers are removed to enhance tree growth with a single intervention and when limited to focal
732 trees. The number of removal interventions and intensity of removal (focal tree or whole plot

733 removal) are key considerations when applying climber removal (Gerwing, 2001; Grogan and Landis,
734 2009; Mills et al., 2019).

735 While our biomass analysis found that AGB accumulation was more enhanced by climber
736 removal in forests disturbed longer ago and when removal is repeated, the strength of our conclusions
737 is limited by the number of studies (N=12). However, given that the abundance of larger trees
738 increases with age of forest, and that only trees > 5cm dbh were included in the biomass analysis, this
739 result could indicate that larger trees benefit more from climber removal, potentially due to higher
740 climber loads (Estrada-Villegas et al., 2020). Moreover, the four studies with higher biomass effect
741 sizes in Fig 2 all experienced disturbance at least 55 years ago, or were undisturbed, highlighting the
742 need to corroborate the influence of time since disturbance on removal efficacy.

743 *Recommendations for application and conclusions*

744 We identify two key climber removal scenarios for timber and carbon benefits in the Neotropics.
745 Firstly, in timber production forests, forestry personnel could apply removal to just focal trees, during
746 pre-harvest inventory and timber cruising for greatest efficiency. This is especially significant
747 considering the huge area of production forests (FAO, 2020). Secondly, a single application of
748 ‘whole-plot’ climber removal could be conducted by unskilled labour in degraded forests (regrowing
749 or already selectively logged). Edges of forests could be specifically targeted as they have low value
750 and are easy to access (Ordway and Asner, 2020; Poor et al., 2019), though the important role of
751 climbing plants in edge forests should not be jeopardised (Magnago et al., 2017). Moreover,
752 prioritising removal in older regrowth forests would yield the highest AGB accumulation rates as
753 regrowing forests have higher baseline sequestration rates than selectively logged forests (Butarbutar
754 et al., 2019; Cook-Patton et al., 2020; Gourlet-Fleury et al., 2013; Rutishauser et al., 2015).

755 The expected gains in growth rates in these scenarios will ultimately contribute to climate
756 mitigation, enhance sustainable timber yields, potentially limit the expansion of timber harvesting into
757 primary forest (Burivalova et al., 2020), and enhance the economic value and function of degraded
758 forests that may prevent their conversion (Cerullo and Edwards, 2019). However, while preventing

759 degraded forests from conversion could protect biodiversity, this study only considers the impact of
760 climber removal on tree and AGB growth. Climbing plants have various functions in tropical forests
761 and their removal can have negative consequences for biodiversity by reducing the species richness of
762 climbing plants, removing food and locomotion resources, and influencing the microclimate (Addo-
763 Fordjour et al., 2020; Arroyo-Rodriguez et al., 2015; Campbell et al., 2015; Cosset and Edwards,
764 2017; Magnago et al., 2017; Putz et al., 2001; Schnitzer et al., 2020), though see (Cerullo et al., 2019).
765 Our study finds that applying removal just to focal trees and not repeating treatment yield growth
766 benefits while giving climbers greater chance to recover, but this will not be enough to prevent
767 biodiversity losses from climber removal. Additional best-practice guidelines, such as leaving areas of
768 forest untreated and avoiding certain climber species, are critical to safeguard the functional role of
769 climbing plants and minimise negative impacts on biodiversity.

770 While it may not be feasible, nor advisable, to apply climber removal across the entire tropics,
771 this action clearly presents a major climate mitigation opportunity: one that has not been accounted
772 for in prior estimates of natural climate solutions (Griscom et al., 2020, 2017; Roe et al., 2021). We
773 recommend that climber removal is implemented to some extent as part of restoration and carbon
774 sequestration programmes in the Neotropics, specifically as part of forest management in logging
775 concessions, pre- and post-harvest, and in already degraded forests. However, further studies are
776 urgently required to confirm treatment efficacy in Africa and Asia, and to minimise negative
777 biodiversity implications of climber removal. With climber removal, we have the potential to greatly
778 improve the value of degraded tropical forests, and the future of global biodiversity and carbon

779 CHAPTER 3: Monitoring lianas from space: Using Sentinel-2
780 imagery to detect liana removal in logged tropical forests

781

782 **Abstract**

783 Liana removal – the cutting of over-abundant woody climbing plants (lianas) and bamboos – has the
784 potential to substantially increase tree growth and biomass accumulation across millions of hectares of
785 degraded tropical forest. Satellite imagery could provide data capable of detecting the effect of liana
786 removal on the forest canopy, enabling the large-scale monitoring and validation of liana removal,
787 which remains a key hurdle to its widespread implementation. Using a 320-ha liana removal
788 experiment in Sabah, Malaysian Borneo, we tested whether a time series of Sentinel-2 imagery could
789 detect the canopy signature of liana removal. Calculating a range of metrics derived from the
790 Normalized Burn Ratio – a vegetation index based on spectral reflectance that differentiates leaf from
791 non-leaf – we quantified satellite derived canopy disturbance and fragmentation across a range of
792 liana removal intensities and examined how canopy effects changed in the 12-months following
793 removal treatments. We find that liana removal significantly increases canopy disturbance and
794 fragmentation one month after removal, with partial removal having a smaller effect than complete
795 removal. The impact of liana removal on the canopy declined over time, with measures of canopy
796 disturbance and fragmentation largely indistinguishable from control plots within 12-months of
797 treatment. Our findings provide the first evidence that freely available satellite imagery can
798 effectively detect and monitor large-scale liana removal at a range of intensities. Additionally, we find
799 evidence that partial liana removal could be used to significantly reduce initial canopy disturbance
800 during forest restoration programs.

801 **Introduction**

802 Logging has a profound impact on tropical forests globally. Over 400 million ha of the world's forest
803 are currently designated as timber production forests (FAO, 2020) and global timber demand is only
804 increasing (Malhi et al., 2014). While logging threatens biodiversity (Gibson et al., 2011), alters forest
805 structure (Gatti et al., 2014), and reduces carbon stocks (Pan et al., 2011), logged forests are still
806 instrumental in biodiversity conservation (Edwards et al., 2011; Fisher et al., 2011b; Gilroy et al.,
807 2014), carbon sequestration (Erb et al., 2018; Putz et al., 2012b), and for local economies (Edwards et
808 al., 2021). Protection of logged forests from conversion to non-forest uses is therefore a global
809 priority (Edwards et al., 2014, 2011).

810 One option to protect logged forests from conversion is to enhance forest function and value
811 (Cerullo and Edwards, 2019). This can include restoring tree composition, timber volumes, or carbon
812 stocks in logged forest towards that of primary forests (Putz et al., 2023; Toledo-Aceves et al., 2021).
813 Such restoration methods include enrichment planting, which aims to replenish tree seedling stocks,
814 and interventions that enable the passive recovery of forests (Cerullo and Edwards, 2019). Large-scale
815 implementation of planting initiatives, however, can be costly, requiring significant increases in
816 global carbon payments to off-set such initial costs (Philipson et al., 2020), and the success of passive
817 restoration depends on particular environmental conditions and protection of recovering forest from
818 human activities (Zahawi et al., 2014).

819 An alternative solution is the removal of woody, climbing plants (called lianas) that
820 proliferate in logged forests and limit their recovery. Lianas compete intensely with trees and are
821 sometimes referred to as “structural parasites”, climbing the stems of trees to reach the canopy rather
822 than investing in their own supportive trunk. Liana removal, therefore, accelerates forest recovery
823 (César et al., 2016; Marshall et al., 2016) by substantially enhancing tree growth, carbon stocks
824 (Estrada-Villegas et al., 2022; Finlayson et al., 2022), and other tree-based metrics including tree
825 reproduction and survival (Estrada-Villegas and Schnitzer, 2018). Restoration in this study is
826 therefore focussed on restoring tree growth and carbon stocks. Liana removal also has substantial

827 potential as a natural climate solution, with one study finding that liana removal could sequester up to
828 7.4 Gt CO₂ per decade across the tropics at comparatively low cost (Finlayson et al., 2022). However,
829 this is an emerging technique and there are several barriers to its widespread implementation.

830 Liana removal is already applied over large swathes of logged forest in Malaysian Borneo
831 (Sabah Forestry Department, 2020) and is poised to be rolled out across millions more hectares
832 globally (Finlayson et al., 2022; Putz et al., 2023). Verifying removal extent and monitoring forest
833 responses to liana removal are vital for land managers to accurately track treatment application and
834 efficacy, quantify carbon or tree growth responses, and secure carbon credits and payments from
835 initiatives such as REDD+ and Verra (GOFC-GOLD, 2016). However, monitoring such responses
836 over large and often remote areas of forest using traditional field-based methods requires a lot of
837 labour hours and is logistically problematic (Camarretta et al., 2020; Murcia et al., 2016). Remotely
838 sensed data, which can now be accessed freely at high spatial and temporal resolutions, could be the
839 solution to large scale restoration monitoring and may be particularly relevant to liana management
840 (de Almeida et al., 2020; van der Heijden et al., 2022).

841 Previous studies have already demonstrated the ability of remote sensing products to
842 differentiate between tree crowns and over-topping lianas based on distinct spectral reflectance
843 (Chandler et al., 2021b; Meunier et al., 2021c; van der Heijden et al., 2022), and to detect decreases in
844 canopy vegetation one year after combinations of enrichment planting and liana removal (Wu et al.,
845 2020). These studies evidence the utility of remote sensing imagery to observe lianas, but do not
846 determine the satellite signal of purely liana removal, nor the spatial or temporal nuances in this signal
847 that could help develop remote sensing tools to monitor treatment. For example, a time-series of
848 satellite images could detect the initial loss and browning of canopy leaves after liana removal and
849 track the recovery of the canopy (Martínez-Izquierdo et al., 2016; Perez-Salicrup, 2001). Moreover,
850 assessing the spatial pattern of changes in the canopy, which is expected due to the variable
851 abundance of lianas within a forest (Campanello et al., 2007; Campbell et al., 2018), could quantify
852 the extent of canopy disturbance and fragmentation (here defined as the process by which a closed
853 canopy becomes disturbed, resulting in smaller patches of contiguous closed canopy) caused by liana

854 removal. As well as aiding with detection and monitoring, temporal and spatial analyses of remote
855 sensing imagery could reveal information about the role of lianas in canopy structure and dynamics.

856 Remote sensing data could also help to refine the application of liana removal. Lianas are a
857 key component of tropical forest systems: constituting 20% of the woody plant diversity in tropical
858 forests, providing food and nesting resources, facilitating arboreal animal locomotion, and buffering
859 the understory from extreme temperatures (Arroyo-Rodriguez et al., 2015; Magnago et al., 2017;
860 O'Brien et al., 2019; Putz et al., 2001; Schnitzer and Bongers, 2002). Hence, there are serious
861 concerns about the unintended negative consequences of large-scale liana removal, with many
862 recommending that a proportion of lianas should be retained in a target area (here-in termed “partial
863 removal”) (Estrada-Villegas and Schnitzer, 2018; Finlayson et al., 2022). However, the trade-offs of
864 partial removal between carbon and timber recovery and wider biodiversity and ecosystem
865 functioning have yet to be experimentally tested. Satellite data could be used to compare the extent of
866 canopy disturbance and fragmentation after partial and complete removal, evidencing whether partial
867 liana removal minimises damage to the forest, and potentially has fewer negative consequences. A
868 less fragmented canopy after partial removal, for example, could indicate that the movement of
869 arboreal animals will be less restricted by this form of removal treatment.

870 Different satellite signals for partial compared to complete removal would also suggest that
871 satellite data could detect areas where liana removal has missed some liana individuals. This issue has
872 been identified in commercial liana removal – for example in Belize where Mills *et al* (2019) found
873 that 30% of climbers were missed during commercial liana removal – and could reduce the tree
874 growth and carbon sequestration achieved by liana removal. Consequently, satellite data could be
875 used to identify where liana removal crews need to re-visit, or to adjust the expected outcomes of
876 removal treatment.

877 Here, we experimentally applied varying intensities of liana removal to 320 ha of logged
878 forest in Malaysian Borneo and used a time series of satellite images to determine whether Sentinel-2
879 can monitor and detect this emerging restoration activity. Specifically, we test: (1) whether satellite

880 imagery can be used to detect canopy degradation and fragmentation caused by liana removal; (2)
 881 whether the effects of liana removal differ between varying intensities of removal; and (3) how long
 882 the signal of liana removal remained detectable post-treatment.

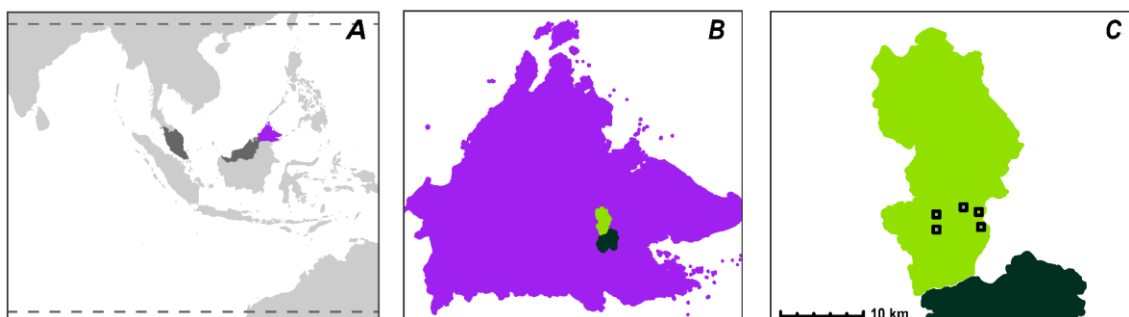
883

884 **Methods**

885 *Study area*

886 We set up the liana removal experiment in the Ulu Segama-Malua Forest Reserve (USMFR), within
 887 the Yayasan Sabah (YS) logging concession, Sabah, north-eastern Malaysian Borneo (Figure 4). The
 888 study site is defined as an aseasonal lowland dipterocarp forest, with mean annual rainfall of 2651 mm
 889 year⁻¹ and a mean maximum temperature was 29.1°C between 2018-2020 (SEARRP, 2020).

890 The USMFR forest reserve was selectively logged twice using a modern uniform system,
 891 employing tractors and high-lead cable extraction techniques. The area was first logged between 1976
 892 and 1991 when ~120 m³ ha⁻¹ of timber was extracted, and then again between 2001 and 2007 when an
 893 additional 15-72 m³ ha⁻¹ of timber was extracted (Edwards et al., 2011). Tree basal area at the site
 894 averaged 4.85 m³ ha⁻¹ (± 1.56) with tree composition dominated by fast-growing, early successional
 895 species. Liana infestation was high, with 82% of adult trees infested with lianas, and lianas covering
 896 an average of 50% of infested trees' crowns (Cannon et al., 2023).



897

898 **Figure 4: Study site location.** Map of SE Asia with Malaysia highlighted in dark grey and Sabah in
 899 purple (A), map of Sabah with Danum Valley Conservation Area in dark green and Malua Forest

900 Reserve in light green (B), locations of the five 800 x 800 m experimental sites within the Malua
901 Forest Reserve (C).

902 *Liana removal experiment and field data*

903 In 2019, we established five independent 800 x 800 m sites at least 1 km apart and 100 m from the
904 nearest logging road (Figure 4C). We divided each site into sixteen 200 x 200 m treatment blocks (80
905 blocks in total) (Figure 5A). Between September and November 2019, we applied one of three liana
906 removal treatments or a control to each treatment block. The treatments represent varying intensities
907 of liana removal, achieved by leaving different proportions of the block with uncut lianas: 0% area
908 treated (control), 60% area treated (two 40 m strips uncut), 80% area treated (two 20 m strips uncut),
909 and 100% area treated (complete removal across whole block). We kept the number of uncut strips
910 consistent between intermediate treatments, thus limiting difference in the amount of uncut edge
911 between blocks. Cutting in strips aligned with the methods used by commercial liana removal teams
912 in the region. We arranged treatments in a 4 x 4 Latin square design with all four treatments
913 represented in each row and column (Figure 5A), totalling 20 replicates of each treatment across the
914 five sites.

915 A team of local contractors with experience of liana removal and forest management within
916 USMFR carried out the liana removal treatments. Climbing plant stems (including lianas, climbing
917 bamboo, and rattan) were cut near to the floor and at shoulder height using machetes to prevent stems
918 from re-connecting (Putz et al., 2023). Cut climbers were not physically removed and were allowed to
919 decompose in situ to avoid damaging tree crowns.

920 To account for variation in initial liana abundance, we recorded pre-treatment canopy liana
921 load in two to five 20 x 20 m subplots randomly located in the central 100 m² of each treatment block
922 (Cannon et al., 2023). Canopy liana load estimates the proportion of liana coverage in each adult tree
923 crown (Muller-Landau and Visser, 2019), following a five-point ordinal scale (0 = no lianas in the
924 canopy, 1 = 1-25% coverage, 2 = 26-50% coverage, 3 = 51-75% coverage, 4 = 76-100% coverage).
925 Canopy liana load was averaged for all trees within each subplot, and then averaged across all

926 subplots within each treatment block. Rainfall data were collected at the Malua Forest Research site,
927 twice daily where possible (accessible at: <http://www.searrp.org/scientists/available-data/>).

928 *Remote sensing data*

929 In order to detect potentially fine-scale and temporally dynamic changes in canopy structure following
930 liana removal, we used high spatial (10 x 10 m) and temporal (every 5 days) resolution imagery from
931 the Sentinel-2 (S2) MultiSpectral Instrument (Level 2A data). Imagery is orthorectified and
932 atmospherically corrected to surface reflectance. This instrument acquires reflectance data in 12
933 spectral bands, ranging from aerosols (443.9 nm) to short-wave infrared (2202.4 nm).

934 We used all S2 images acquired across our experimental sites from December 2018 (the first
935 surface reflectance corrected images available over the study region) to November 2020, totalling 78
936 images spanning nearly one year before and one year after treatment (Table S14). As Borneo is
937 among the cloudiest places on Earth (Wilson and Jetz, 2016) and to minimise noise from atmospheric
938 effects obscuring subtle canopy disturbances, clouds, cloud shadows, and non-forest artefacts were
939 removed from all images using the in-built S2 cloud mask, which determines presence of clouds
940 based on several bands (European Space Agency, 2023), and fine-tuned thresholds in the aerosol,
941 blue, red, and green bands.

942 *Quantifying canopy disturbance and fragmentation*

943 To quantify canopy disturbance and fragmentation resulting from liana removal, we derived the
944 Normalized Burn Ratio (NBR) from the Sentinel-2 images in Google Earth Engine. We used NBR as
945 it detects a loss of photosynthetically active leaves, directly quantifies canopy openness and
946 disturbance, and has recently been used to detect small-scale canopy disturbance (Langner et al.,
947 2018). Initial data exploration also demonstrated that liana removal treatment blocks were more
948 clearly distinguishable using NBR than Normalized Difference Vegetation Index (NDVI), Enhanced
949 Vegetation Index (EVI), and Greenness Index (GI) (see Supplementary Information section '*Other
950 satellite imagery and metrics*'). The equation for NBR is as follows:

$$951 \quad \text{NBR} = (\text{N-SWIR2})/(\text{N+SWIR2}) \quad (1)$$

952 *Letters indicate spectral reflectance bands: N = near-infrared (835.1 nm); SWIR2 = short-wave*
 953 *infrared 2 (2202.4 nm).*

954 We calculated NBR for each pixel in each S2 image one year before and one year post-
 955 treatment and summarised the NBR values in each treatment block using four metrics indicating the
 956 level of canopy disturbance and fragmentation. We excluded pixels within 5 m of the edge of each
 957 block to account for GPS error and excluded data when more than 15% of pixels in a treatment block
 958 were masked due to clouds or other artefacts. We calculate two metrics of canopy disturbance and
 959 fragmentation for each treatment block:

- 960 1. Median NBR: lower NBR suggests fewer photosynthetically active leaves in the canopy,
 961 more bare earth, or greater canopy openness.
- 962 2. Proportion of canopy disturbed: we quantified the proportion of S2 pixels in each treatment
 963 block that had > 5% reduction in NBR compared to the median NBR value for each pixel
 964 during the year pre-treatment.
- 965 3. Mean area of intact canopy patches: we classed pixels as ‘intact’ when they had < 5%
 966 reduction in NBR compared to the median value for the pixel for a year pre-treatment. We
 967 then calculated the mean area of ‘intact patches’ in each treatment block, defined as an area of
 968 adjoining intact pixels (the minimum patch size is one pixel).
- 969 4. Aggregation of intact canopy patches: we quantified how aggregated (or clumped together)
 970 intact canopy patches were, using the definition of an intact canopy patch from metric 3.

971

972 Metrics 2-4 were devised following landscape ecology theory (Hesselbarth et al., 2019;
 973 Senior et al., 2019) and calculated using *landscapemetrics* and *landscapetools* packages in R
 974 (Hesselbarth et al., 2019; Sciaini et al., 2018). The 5% change in NBR was an arbitrary threshold that
 975 aimed to differentiate between changes in NBR caused by liana removal and naturally expected
 976 variation in NBR. Since this paper aimed to test whether satellite data can detect liana removal, the

977 ecological meaning of the 5% change is less important. To test whether metrics 2-4 were impacted by
978 different NBR reduction thresholds, we also calculated these metrics with a 10% change in NBR
979 threshold. To verify conclusions about the influence of liana removal on canopy disturbance based on
980 NBR we also calculated metrics 1 and 2 using NDVI, EVI, and GI (Zeng et al., 2022). See
981 Supplementary Information section *Other satellite imagery and metrics* for details of other satellite-
982 derived metrics that we explored but do not present in this manuscript.

983

984 *Statistical tests*

985 To test whether liana removal caused canopy disturbance that could be detected by satellite (objective
986 1), we initially visualised the pixel-level NBR and percentage change in NBR compared to the year
987 pre-treatment for one S2 scene in which one experimental site had no cloud-masked pixels. To
988 confirm any visual signal of liana removal – suggesting a significant effect on canopy degradation and
989 fragmentation – we analysed the difference between the median NBR in treated blocks compared to
990 control and pre-treatment, and the difference between the proportion of pixels with decreased NBR,
991 mean area of intact patches, and aggregation of intact patches in treated compared to control blocks.
992 We ran statistical analyses for all images within one-month, when we expect the impact of liana
993 removal to be largest (O’Brien et al., 2019), and all images within 12-months post-treatment to
994 determine if there was a significant satellite signal across both time series.

995 The one-month time-series was analysed using linear fixed effects models, with canopy
996 disturbance and fragmentation metrics for each treatment block as the response variables, treatment
997 (0, 60, 80, or 100% liana removal) and experimental design (row and column of treatment blocks) as
998 fixed effects, and rainfall and mean liana load for the treatment block as fixed effects when
999 significant. The models were run using the *nlme* package in R (Pinheiro et al., 2018). The 12-month
1000 time series was analysed using generalized additive models (GAMs) to account for seasonality and
1001 temporal non-independence in the time-series. These models followed the same model structure as the
1002 one-month models, included a smoothing term of the image date * site interaction, and were run using

1003 the *mgcv* package in R (Wood, 2011). The reference treatment level in all models was 0% removal
1004 (control), meaning that a significant positive coefficient for 60, 80, or 100% removal treatment
1005 indicated that liana removal significantly increased the disturbance or fragmentation metric compared
1006 to control and showing that liana removal could be detected using the response variable metric. To
1007 determine whether canopy disturbance and fragmentation metrics differed significantly between
1008 removal intensities (objective 2), we also calculated the estimated marginal means for all
1009 combinations of removal intensities (i.e., 60% vs 100% removal) from the one-month and 12-month
1010 models.

1011 To determine whether the canopy degradation and fragmentation caused by liana removal
1012 varied across a year post-treatment (objective 3), we compared the coefficients for liana removal
1013 treatments between the one-month and 12-month analyses. We also plotted the canopy disturbance
1014 and fragmentation metrics in the treated blocks relative to control blocks for each month in the year
1015 post-treatment. This showed the change in NBR metrics caused by liana removal relative to control
1016 blocks throughout the year. All analyses and figures were produced using R statistical software (R
1017 Core Team, 2020).

1018

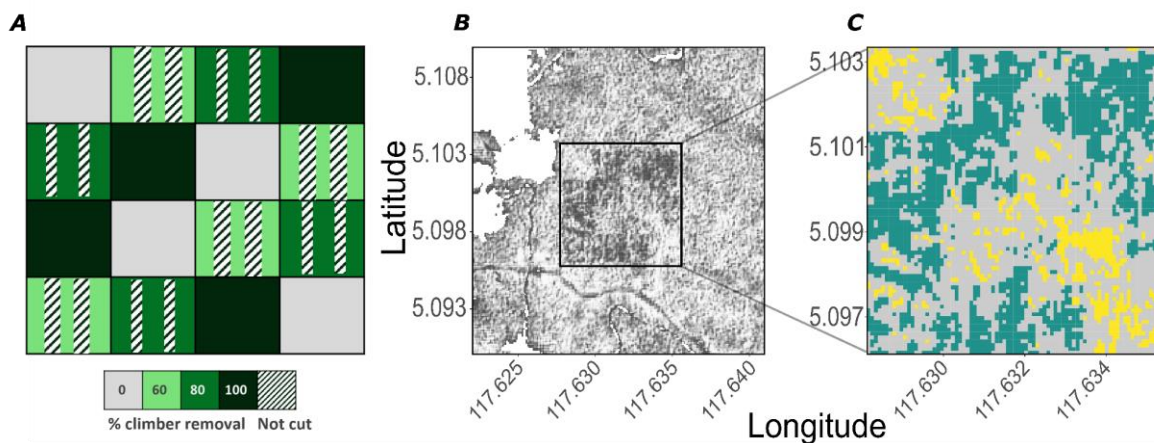
1019 **Results**

1020 *Canopy disturbance and fragmentation detected by Sentinel-2*

1021 We found that liana removal caused canopy disturbances that were clearly detectable using Sentinel-2
1022 (S2) imagery. Liana removal treatment blocks with any level of liana removal (60, 80, or 100%) were
1023 visually distinct from surrounding forest and control blocks when using raw NBR (Fig 5B) and the
1024 change in NBR compared to pre-treatment (Fig 5C) at one-month post-treatment. Moreover, we found
1025 that liana removal caused significant canopy disturbance when examining all NBR metrics from all
1026 five experimental sites and all S2 images within a month post-treatment. Specifically, all liana
1027 removal intensities (60, 80, and 100%) significantly reduced median NBR compared to control blocks

1028 and pre-treatment levels and increased the proportion of the canopy that was disturbed (the proportion
 1029 of the canopy with decreased NBR) compared to control blocks (Fig 6A; p-values < 0.01; Table S16).
 1030 On average across 12-months post-treatment there was also a significant increase in canopy
 1031 disturbance according to these metrics (Fig 6B, p-values < 0.001, Table S16). Liana abundance had no
 1032 influence on the level of canopy disturbance across either time series (Table S16).

1033 Additional analyses corroborated these results. We found that liana removal affected canopy
 1034 disturbance across one-month and 12-months post-treatment similarly irrespective of whether the
 1035 proportion of the canopy with decreased NBR was calculated using a 5% or 10% reduction threshold
 1036 (Table S17). The canopy disturbance caused by liana removal was also detected when using minimum
 1037 NBR, median GI, NDVI, and EVI, and the proportion of the canopy with a decrease in these
 1038 vegetation indices across 12-months post-treatment (p-values < 0.05), with one exception, and across
 1039 many of these metrics when we only analysed images from one-month post-treatment (Table S18; Fig
 1040 S19).



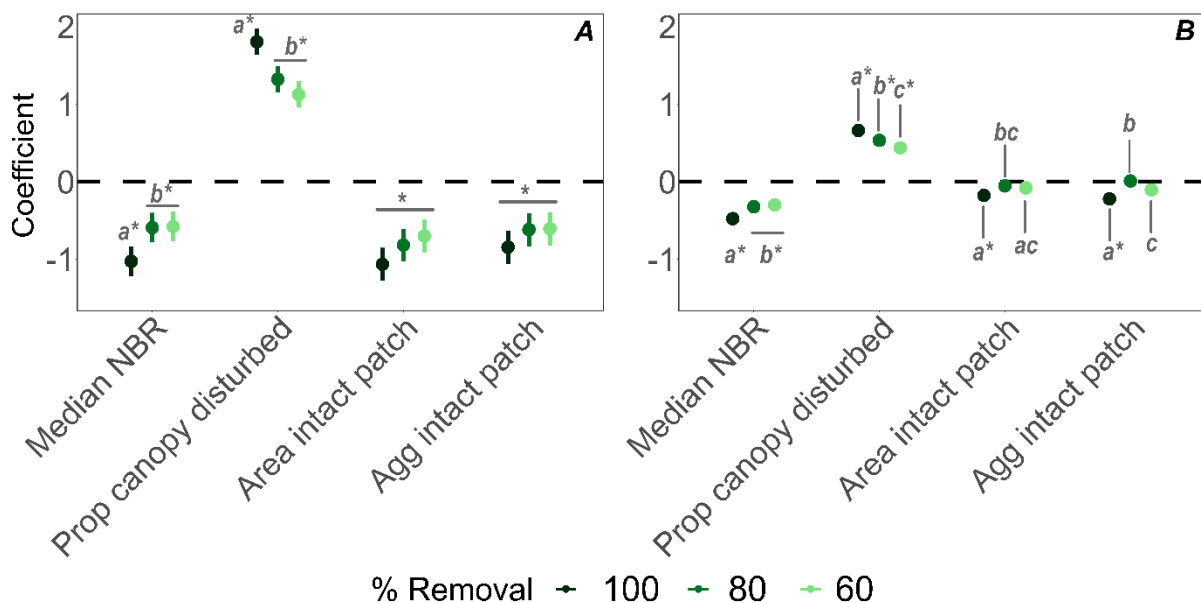
1041

1042 **Figure 5: Impact of liana removal on Sentinel 2- derived NBR in one experimental site four**
 1043 **weeks post-treatment.** Layout of liana cutting treatments for each of the five sites using a Latin-
 1044 Square design (A), raw NBR values across one experimental site (inside the black square) and the
 1045 surrounding forest (B), change in pixel-level NBR values compared to median for the year pre-
 1046 treatment (C). Darker pixels in (B) represent lower NBR values (minimum -1), lighter colour
 1047 represents higher NBR values (maximum 1), and white patch is a cloud that has been masked. Yellow

1048 pixels in (C) indicate those with > 5% increase in NBR compared to pixel-level median NBR for one
 1049 year pre-treatment, blue indicates pixels with > 5% decrease in NBR, and grey indicate < 5% change
 1050 in NBR.

1051 We also detected a significant increase in canopy fragmentation after liana removal treatment.
 1052 Intact canopy patches were significantly smaller and less aggregated in all liana removal treated
 1053 blocks than control blocks during the first-month post-treatment, irrespective of removal intensity (Fig
 1054 6A, p-values <0.01, Table S16). However, only 100% removal blocks had significantly higher canopy
 1055 fragmentation than control blocks across 12-months of treatment (p-values < 0.001, Fig 6B, Table
 1056 S16). Liana removal increased canopy fragmentation similarly irrespective of whether intact canopy
 1057 was defined as less than 5% or 10% reduction in NBR (p-values < 0.001, Table S17). Again, the
 1058 impact of liana removal on forest fragmentation was not influenced by initial liana load.

1059



1060

1061 **Figure 6: Effects of different intensities of liana removal (60, 80, and 100% removal) on canopy**
 1062 **disturbance and fragmentation based on S2 images acquired during one-month (A) and 12-**
 1063 **months (B) post-treatment.** Points show coefficients of treatment intensities from linear models in

1064 (A), and from GAMs in (B); response variables are normalized before running models. The dotted
1065 line shows control (0% removal), coefficients below the line indicate a decrease compared to control,
1066 and above the line indicate an increase compared to control. Different grey letters indicate a
1067 significant difference between percentage removal treatments, calculated using the estimates marginal
1068 means, and “*” indicates removal treatments that are significantly different from control (zero). Error
1069 bars show standard error.

1070

1071 *Higher intensity liana removal causes greater canopy disturbance and fragmentation*

1072 We were able to differentiate between the effects of some intensities of removal (60, 80, and 100%)
1073 on the forest canopy using Sentinel-2 imagery. Blocks treated with complete (100%) removal had
1074 greater canopy disturbance (lower median NBR and greater proportion of the canopy with decreased
1075 NBR) compared to control blocks than partial (60 and 80%) removal treatments during the first month
1076 and one-year post-treatment (Fig 6, p-values < 0.05, Table S16). There was also greater canopy
1077 fragmentation (smaller and less aggregated intact patches) after complete removal than partial
1078 removal, but this was only significant when assessing all S2 images within 12-months of treatment
1079 (Fig 6B, p values <0.06, Table S16). Greater canopy disturbance and fragmentation in complete than
1080 partial removal blocks was also observed when metrics were calculated using a 10% rather than a 5%
1081 reduction in NBR threshold (p-values < 0.05, Table S17).

1082 We were generally unable to differentiate between partial removal treatments (60 and 80%
1083 removal) using canopy disturbance and fragmentation metrics. Exceptions to this did not conclusively
1084 indicate whether 60 or 80% removal had a greater impact on the canopy. While 80% removal caused
1085 a greater proportion of the canopy to be disturbed than 60% across 12-months post-treatment, 80%
1086 removal had a smaller effect on the aggregation of intact canopy patches (Fig 6B, p-values <0.05,
1087 Table S16) and caused a smaller reduction in EVI compared than 60% (Fig S19B, p-value = 0.001,
1088 Table S18). Moreover, partial removal treatments were indistinguishable when disturbance and
1089 fragmentation metrics were calculated using 10% rather than 5% reduction in NBR (Table S17).

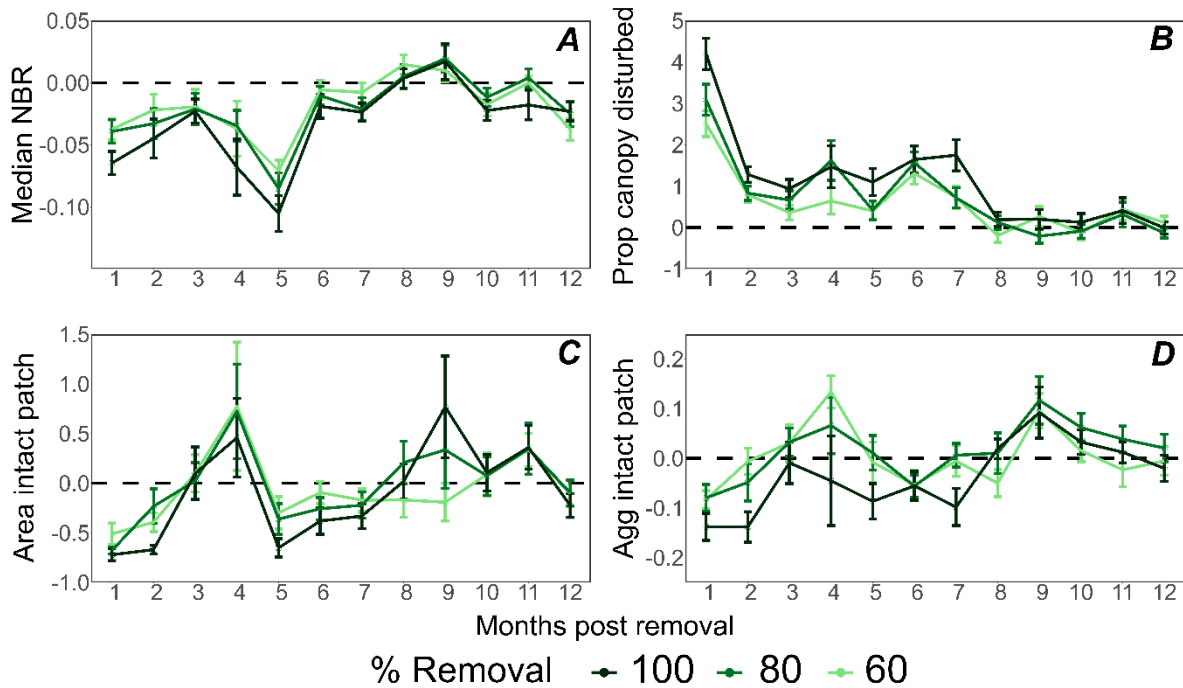
1090 Overall, these results suggest there is a difference in canopy disturbance and fragmentation when
1091 decreasing the proportion of lianas removed from 100 to 80% but no difference between partial liana
1092 removal treatments.

1093

1094 *Canopy disturbance and fragmentation decline over a year post-liana removal*

1095 The impact of liana removal on the canopy reduced over a year post-treatment – there was a greater
1096 average effect of liana removal in the one-month time-series compared to 12-months for all metrics
1097 (represented by larger coefficients in Fig 6A than 6B). By month 12 post-treatment, minimum NBR,
1098 proportion of canopy disturbed, and fragmentation metrics had returned to being similar in treated and
1099 control blocks (Figure 7), indicating substantial canopy recovery within a year of liana removal.
1100 These results are consistent across additional canopy metrics (GI, NDVI, EVI, minimum NBR
1101 indices), and when using a 10% threshold for calculating the proportion of disturbed canopy and
1102 fragmentation metrics (Tables S17-S18 & Fig S19). Also, the large drop in median NBR in treated
1103 compared to control blocks at month five (Fig 7A) results from a sharp increase in the median NBR in
1104 control blocks (Fig S20), likely caused by an artefact in the imagery and fewer images in this month
1105 due to cloud cover.

1106 The proportion of the canopy with decreased NBR had the clearest recovery across 12-months
1107 (Fig 7B), with all intensities of removal increasing the proportion of disturbed canopy compared to
1108 control blocks until 8-months post-treatment. Conversely, in terms of median NBR, treated blocks
1109 became indistinguishable from control blocks by month six (Fig 7A) and much sooner in terms of the
1110 area and aggregation of intact pixels (Fig 7C & D). Supplementary analyses showed that median and
1111 minimum NBR had similar trends over 12-months post-treatment (Fig S21), but the trend is more
1112 variable and treated blocks become indistinguishable from control sooner with metrics based on GI,
1113 NDVI, and EVI (Fig S22). In general, complete removal had a larger influence on canopy disturbance
1114 and fragmentation than partial removal throughout 12-months post-treatment (Fig 7), but all
1115 intensities of removal became indistinguishable from control at a similar time for each metric.



1116

1117 **Figure 7: Effect of liana removal on canopy degradation and fragmentation over 12-months**

1118 **post-treatment.** Lines in shades of green represent the mean degradation and fragmentation metric

1119 value at each month post-treatment for each treatment intensity, relative to the mean control value at

1120 each month (dotted black line at zero). Values above the dotted line indicate that in that month, the

1121 metric was higher in treated than control blocks, and vice versa. (A) Shows median NBR, (B) shows

1122 the level of canopy degradation, defined as the proportion of the canopy with more than a 5%

1123 decreased NBR, (C) shows the mean area of undisturbed canopy patches, and (D) shows the

1124 aggregation of undisturbed canopy patches. Error bars show standard error.

1125 **Discussion**

1126 The ability to detect and quantify the effects of liana removal via remote sensing is key to its large-

1127 scale monitoring and validation. We show, for the first time, that remote sensing data can detect the

1128 impact of varying intensities of liana removal on the canopy over large spatial and temporal scales.

1129 Specifically, we find that: liana removal fragments and disturbs the canopy, these impacts are

1130 minimised with partial removal, and the canopy largely recovers within a year of treatment. Below,

1131 we discuss what our work reveals about liana ecology and tropical forests and outline the implications
1132 of our results for enhancing tree growth and biomass accumulation in logging concessions.

1133

1134 *Liana removal and canopy dynamics*

1135 Studying the satellite signal of liana removal provides insight into the influence of lianas on the
1136 canopy and their role in tropical forests. Consistent with other studies, our results indicate that liana
1137 removal increases canopy browning or openness (O'Brien et al., 2019; Perez-Salicrup, 2001; Wu et
1138 al., 2020). Detecting these canopy changes using 10 m resolution imagery evidences that lianas are a
1139 substantial component of the canopy, supporting literature showing that lianas maintain cool, low-
1140 light, and low-wind understory conditions (Meunier et al., 2021c). Hence, our results emphasise that
1141 liana removal could reduce the survival of shade-tolerant tree species (O'Brien et al., 2019) and
1142 subject fauna and flora to more extreme conditions (Scheffers et al., 2014). The fragmentation of the
1143 canopy after liana removal also exemplifies that lianas help to connect across the canopy, without
1144 which arboreal animals may become isolated and have fewer modes of movement (Benjamin J.
1145 Adams et al., 2019; Putz et al., 2001). While further field data is required to directly explore how liana
1146 removal influences these factors and the response of faunal taxa, the substantial impact of liana
1147 removal on the canopy is likely to have myriad knock-on effects, emphasising that safeguarding the
1148 functional role of lianas is critical when implementing liana removal in tropical forests.

1149 Partial removal has been suggested as a safeguard against the potential negative consequences
1150 mentioned above (Estrada-Villegas and Schnitzer, 2018; Finlayson et al., 2022), and this study is the
1151 first experimental comparison between complete and partial removal. As anticipated, partial removal
1152 significantly reduced canopy disturbance, but, interestingly, our results suggest that 60% and 80%
1153 liana removal release trees from lianas to a similar extent. Evidently, further research is required to
1154 explicitly measure the impact of partial removal on biodiversity, forest function, and tree growth and
1155 biomass accumulation, but this is the first evidence that leaving 20-40% of the target area untreated
1156 could substantially reduce canopy openness, fragmentation and their harmful consequences. The

1157 relative impact of alternative configurations of partial removal on tree and carbon benefits and
1158 biodiversity should also be tested. For example, could treating a proportion of future crop trees, as
1159 proposed by Putz *et al* 2023, preserve some of the connectivity and resource functions of lianas
1160 throughout a treated area?

1161 The recovery of the canopy within 12-months of treatment, consistent with field-based data
1162 from the same region (O'Brien *et al.*, 2019), shows that the canopy is highly dynamic, but it is
1163 difficult to determine whether this recovery is driven by trees or lianas. While other studies quantify
1164 liana abundance using airborne hyper-spectral and trained satellite data (Chandler *et al.*, 2021),
1165 Sentinel-2 imagery alone is too coarse resolution so we cannot use this data to determine the relative
1166 proportion of trees and lianas in the canopy (van der Heijden *et al.*, 2022). Lianas are known to
1167 recover after liana removal treatment (Alvira *et al.*, 2004; Campanello *et al.*, 2012) and are generally
1168 thought to have faster growth rates than trees due to lower investment in woody stems (Phillips *et al.*,
1169 2005; Schnitzer *et al.*, 2014), suggesting that canopy recovery could be driven but lianas, but a recent
1170 study found that leaf turnover in aseasonal forests is similar between lianas and trees (Medina-Vega *et*
1171 *al.*, 2021). There was a significant positive correlation between pre-treatment liana load and median
1172 NBR, but the relationship was relatively weak (Fig S23; $R^2 = 5\%$) so we cannot use NBR values post-
1173 treatment to accurately estimate the liana load. Ground data and higher resolution imagery, such as
1174 from Unmanned Aerial Vehicles (UAVs) (van der Heijden *et al.*, 2022; Waite *et al.*, 2019), are
1175 required to elucidate whether canopy closure in our study is due to tree or liana growth. In either case,
1176 the closure of canopy gaps caused by liana removal implies that the microclimate buffer recovers
1177 within a year, benefitting shade-tolerant tree species and understory fauna. If further research finds
1178 that canopy closure is driven by lianas, this could suggest that the negative impacts of liana removal
1179 on food, nesting, and locomotion resources are temporary.

1180

1181 *Detecting and monitoring liana removal*

1182 This study presents a method for using Sentinel-2 imagery – a freely available remote sensing product
1183 – to detect liana removal. We build on work by Wu *et al* (2020), showing that liana removal increased
1184 overall canopy disturbance, the proportion of the canopy that is disturbed, and the mean area and
1185 aggregation of intact patches. Combining these four metrics may differentiate liana removal from
1186 other disturbances that can be detected with Normalized Burn Ratio (Langner et al., 2018), but further
1187 work is needed to compare the signal of liana removal to other disturbances. Our study shows that,
1188 once operationalised, quantifying NBR within a few months post-treatment could evidence that liana
1189 removal activities have taken place, helping land managers to earn payments from schemes such as
1190 REDD+ (Sirro et al., 2018). Compared to collecting similar verification evidence from the ground,
1191 using S2 imagery will be faster, cheaper, and be able to cover the entire area treated rather than a
1192 subsample of the area (Camarretta et al., 2020; Murcia et al., 2016; Zahawi et al., 2015).

1193 Our results also support the use of Sentinel-2 imagery to monitor application efficacy and
1194 forest changes following liana removal treatments over large areas. The clear recovery of the canopy
1195 within 12-months suggests that NBR metrics could be used to determine when the effect of liana
1196 removal for enhancing tree growth or carbon accumulation has diminished, potentially indicating
1197 when removal should be repeated, if desired. Moreover, since we were able to differentiate between
1198 partial and complete removal, Sentinel-2 imagery could be used to identify areas where lower
1199 intensity liana removal has been applied. This could direct further removal applications to solve the
1200 issue of incomplete liana removal in large-scale implementation (as seen in Mills et al., 2019) that
1201 reduces the tree growth and carbon sequestration enhancement that can be achieved.

1202

1203 *Operationalising large-scale monitoring of liana removal*

1204 While our study takes the first steps towards using Sentinel-2 imagery for verifying and monitoring
1205 large-scale liana removal, further work is necessary to check the generalisability of our results and for
1206 the method to be operational. Firstly, the satellite signals of liana removal that we have identified
1207 should be tested across larger, non-experimental areas of liana removal, such as logging concessions

1208 in Malaysian Borneo (Sabah Forestry Department, 2020). Commercial treatments may use different
1209 methods and intensities of removal that could influence the magnitude and spatial arrangement of the
1210 satellite signal, such as the tree-centred approach used in Belize that achieved 70% removal (Mills et
1211 al., 2019).

1212 Secondly, forest structure may influence the detectability of liana removal. Since liana
1213 abundance had limited effect on the NBR metrics in this study, and this study was conducted in the
1214 Asian tropics that are thought to have lower liana abundance than the American and African tropics
1215 (DeWalt et al., 2015), we anticipate that liana removal will cause some level of canopy changes
1216 detectable by satellite in all tropical regions. However, it may still be harder to detect liana removal
1217 with Sentinel-2 imagery when there is lower liana abundance, such as areas with less intense or less
1218 recent disturbance (Schnitzer et al., 2014; Yorke et al., 2013). Moreover, the canopy fragmentation
1219 found in this study may be specific to forests of the Asian tropics that are dominated by Dipterocarps
1220 (Brearley et al., 2016). This family of tree species tends to be less infested with lianas than other tree
1221 species, potentially giving rise to the patchy influence of liana removal on the canopy (Wright et al.,
1222 2015). Expanding our work to other global regions and forest types may identify common liana
1223 removal signals or indicate that calibrating the signal is required in each site.

1224 Finally, while the high spatial and temporal resolution and free access to Sentinel 2 are huge
1225 benefits of this imagery source, it is worth exploring whether other remote sensing tools and products,
1226 such as GEDI (Dubayah et al., 2022), Planet (Roy et al., 2021), or drone imagery (Waite et al., 2019),
1227 find alternative signals of liana removal that could be used to detect and monitor the application of
1228 this restoration technique. Notably, GEDI is also freely available and has been used to quantify carbon
1229 stored in forests (Ngo et al., 2023; Potapov et al., 2021), so it is worth exploring whether GEDI data
1230 can calculate the additional carbon storage achieved by liana removal, facilitating access to Verra
1231 carbon credits (GOFC-GOLD, 2016) without extensive ground data collection.

1232 Conclusion

1233 Liana removal causes disturbances to the canopy that can be detected using Sentinel-2-derived NBR.
1234 Further work is required to determine whether partial liana removal reduces the negative impacts of
1235 the technique, but we recommend leaving at least 20% of target forests untreated to safeguard the
1236 various roles lianas have for faunal communities and forest function. Once operationalized, satellite-
1237 based detection of liana removal could be employed by land managers to validate and monitor the
1238 efficacy of liana removal, assisting the widespread application of the technique to restore tree growth
1239 and carbon sequestration in logged tropical forests.

1240

1241 CHAPTER 4: Commercial-scale liana removal detected using satellite
1242 data

1243 **Abstract**

1244 There is growing need for logging practices to become more sustainable to reduce the negative
1245 impacts on biodiversity, carbon stocks, and local livelihoods. Lianas (woody climbing plants) grow
1246 extensively after logging, becoming a barrier to forest recovery and logging sustainability. While
1247 removing lianas significantly enhances timber recovery and is a powerful restoration tool, monitoring
1248 the effectiveness of liana removal over vast areas is a challenge. Local-scale liana removal can be
1249 detected using satellite data, but it is not known whether this approach can be deployed at greater
1250 spatial scales. This study aimed to determine whether commercial-scale liana removal – applied
1251 across 17,000 ha of selectively logged forest in Malaysian Borneo – could be detected using satellite-
1252 derived data. We also aimed to assess the drivers of variation in the satellite signal of commercial
1253 liana removal. We analysed two metrics based on Sentinel-2-derived Normalized Burn Ratio (NBR):
1254 minimum NBR and the proportion of the canopy with decreased NBR compared to pre-treatment.
1255 These were calculated for one year pre- and post-treatment in logging compartments in which liana
1256 removal had been applied, and reference compartments. We ran generalized additive models and
1257 mixed effects linear models to determine the effect of commercial liana removal on these metrics. In
1258 the year post-treatment, commercial liana removal significantly increased minimum NBR. There was
1259 also a negative impact of removal on the proportion of the canopy with decreased NBR that became
1260 more negative at higher daily rainfall. The signal of liana removal on NBR metrics was also
1261 influenced by terrain and distance from roads. Overall, our study shows the potential for using remote
1262 sensing to monitor commercial liana removal and variation in removal intensity, reducing the need for
1263 costly on-the-ground quality assessments.

1264 **Introduction**

1265 Logging is one of the biggest causes of tropical forest loss and degradation globally (Hosonuma et al.,
1266 2012), with myriad detrimental impacts on biodiversity, carbon, and timber value (Gibson et al., 2011;
1267 Pan et al., 2011; Putz et al., 2012b). Although the expanse of logging is concerning, with recent
1268 estimates suggesting that 25% of forests across the globe are subjected to selective logging (Putz et
1269 al., 2022), forest management has become increasingly sustainable over the past several decades in
1270 many regions (Putz et al., 2008). Sustainable forestry practices are essential to managing increasing
1271 timber demand (Malhi et al., 2014), have the potential to reduce the damage to forest ecosystems
1272 (Putz et al., 2008), and are being adopted to address biodiversity and climate crises (Betts et al., 2021;
1273 Griscom et al., 2020). However, for the most part, logging practices still deplete timber yields over
1274 time and truly sustainable logging practices are still lacking (Putz et al., 2022).

1275 One way to improve the sustainability of selective logging is to enhance timber recovery. This
1276 can be achieved in various ways, from removing trees that are competing with those of commercial
1277 value (Peña-Claros et al., 2008a) to re-planting commercially viable trees (Philipson et al., 2020).
1278 Timber enhancement also increases carbon storage in previously-logged areas (Erb et al., 2018),
1279 which enhances the economic value of the forest while combating global carbon emissions, and
1280 reduces the expansion of timber harvesting into undisturbed areas of forest (Cerullo and Edwards,
1281 2019), which ultimately protects pristine forests that are critical for biodiversity (Gibson et al., 2011).
1282 However, timber enhancement can be intensive and expensive (Finlayson et al., 2022).

1283 An emerging, relatively inexpensive method to increase timber recovery is the removal of
1284 woody climbing plants such as lianas and bamboos (Finlayson et al., 2022). Lianas become
1285 problematic after logging as they grow rapidly in the increased light conditions (Schnitzer and
1286 Bongers, 2002), and their removal substantially enhances tree growth and nearly doubles
1287 aboveground carbon storage (Finlayson et al., 2022), amongst other benefits for trees (Estrada-
1288 Villegas and Schnitzer, 2018). Consequently, liana removal (LR) has been advocated to restore timber
1289 and carbon stocks in huge expanses of logged tropical forests and is already being implemented and

1290 trialled in countries including Malaysia, Belize, and Bolivia (Mills et al., 2019; Peña-Claros et al.,
1291 2008b; Reynolds et al., 2011; Sabah Forestry Department, 2020). However, monitoring the
1292 implementation of liana removal over vast areas and validating its application to access carbon
1293 sequestration payment schemes, such as REDD+, are critical to deriving the greatest benefit from
1294 liana removal.

1295 Satellite-derived vegetation indices have been used to detect small-scale liana removal
1296 (Finlayson et al., 2022; Wu et al., 2020), suggesting that remote sensing data could be used to validate
1297 and monitor the intervention. Using a field experiment, Finlayson and Hethcoat *et al* (2022) found
1298 that Normalized Burn Ratio (NBR) can be used to detect changes in canopy greenness and gaps in
1299 forest plots that were subject to liana removal. However, LR was applied at a small spatial scale in
1300 this experiment (in 200 x 200 m forest blocks) compared to the several thousand hectares over which
1301 LR has been applied in commercial logging sites (Sabah Forestry Department, 2020). A key step
1302 towards operationalising the use of remote sensing for large-scale monitoring, therefore, is to
1303 determine whether commercial-scale liana removal can be similarly detected using satellite-derived
1304 indices.

1305 One issue with liana removal that may influence its detectability over large areas is that
1306 achieving complete removal is difficult. For example, 30% of climbing plants were missed during
1307 commercial LR in Belize (Mills et al., 2019) and 13% were missed during reduced impact logging
1308 practices across 1400 ha in Malaysian Borneo (Pinard and Putz, 1997). Incomplete removal of lianas
1309 could reduce disturbance to the canopy and thus make this intervention harder to detect by satellite
1310 than the careful experimental cutting of lianas across 300 ha in Finlayson et al (2022). Consequently,
1311 this could make validating treatment to acquire carbon credits using remote sensing more difficult.
1312 Finlayson and Hethcoat *et al* 2022 also found that NBR could differentiate between low intensity and
1313 complete LR, suggesting that remote sensing could help to identify areas where a proportion of lianas
1314 have been missed, directing where crews need to revisit, or quantifying the completeness of removal
1315 to generate better estimates of the resulting timber growth and carbon sequestration enhancement.

1316 Variation in liana removal completeness could be due to crew fatigue. Mills et al (2019)
1317 found that most lianas were missed due to distance from tree targeted for liana removal, and difficulty
1318 finding all lianas entering a tree's canopy, but crews missed treating 6% of trees entirely. While there
1319 is no direct evidence that crew fatigue reduces liana removal efficacy, liana removal is physically
1320 demanding. Hence, we posit that the accuracy of removal crews (and signal of liana removal) may
1321 diminish with larger treatment areas or with increased crew exertion due to further distance walked
1322 from the access road and steeper terrain. Building on the work by Finlayson and Hethcoat *et al*
1323 (2022), in addition to quantifying and detecting incomplete removal, satellite-derived NBR could be
1324 used to determine what drives variation in LR completeness, indicated by the strength of satellite
1325 signal.

1326 The signal of LR, in terms of changes in NBR, may also differ at the commercial compared to
1327 the experimental scale due to the variable distribution of lianas and competition with trees. For
1328 example, studies have shown that competition between lianas and trees varies with precipitation, as
1329 does the relative growth of the two groups (O'Brien et al., 2019; Schnitzer and van der Heijden, 2019;
1330 Venegas-Gonzalez et al., 2020). Consequently, the impact of LR on NBR, or the 'detectability' of LR,
1331 may be greater with lower precipitation – when lianas would be growing fastest relative to tree growth
1332 and potentially be at higher abundance. Moreover, the effect of liana removal on the canopy is likely
1333 to vary with pre-treatment liana abundance. While Finlayson and Hethcoat *et al* (2022 did not find a
1334 consistent effect of pre-treatment liana abundance on the canopy disturbance caused by liana removal,
1335 liana abundance is likely to vary to a greater extent across larger areas, altering the signal of liana
1336 removal across space and potentially revealing information about the ecology of lianas. Areas of a
1337 forest with higher liana abundance, due to factors such as higher timber extraction (Addo-Fordjour
1338 and Rahmad, 2015a; Putz et al., 2019; Schnitzer and Bongers, 2002), greater time since logging
1339 (Yorke et al., 2013), or shallower terrain (Addo-Fordjour et al., 2014; Dalling et al., 2012), may see a
1340 greater reduction in NBR after liana removal, for example. Yet, variation in the impact and
1341 detectability of liana removal in satellite data remains unexplored as the only other remote sensing LR

1342 studies applied removal to a small area of forest within a few months of a single year (Finlayson et al.,
1343 2022; Wu et al., 2020).

1344 In this study, we extend our previous experimental work to ask whether commercial-scale
1345 liana removal can be monitored using satellite-derived data, and to investigate factors that could
1346 influence the detectability or efficacy of the treatment. We explore two core objectives: 1) determine
1347 whether commercial-scale LR can be detected using satellite-derived NBR; and 2) assess whether the
1348 impact of liana removal on NBR metrics varies due to factors relating to crew fatigue or liana
1349 abundance (treatment year, precipitation, size of compartment, terrain, or distance from the road).

1350

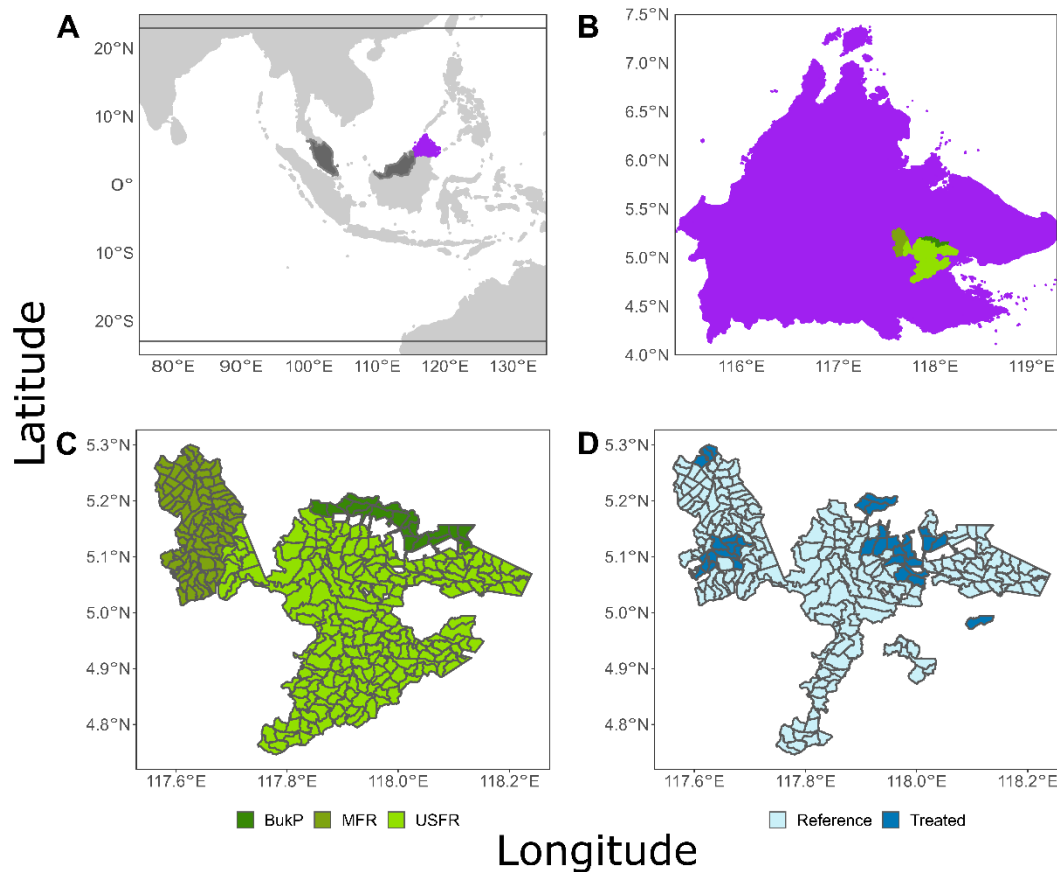
1351 **Methods**

1352 *Study area and commercial liana removal*

1353 Commercial liana removal was applied in three forest reserves in Sabah, Malaysian Borneo (Fig 8)
1354 between 2007 and 2021: Ulu-Segama (USFR), Malua (MFR), and Bukit Piton (BPFR) Forest
1355 Reserves (Fig 8B and C). The reserves are dipterocarp forests that tend to have higher rainfall from
1356 December to March (Ancrenaz et al., 2010). From 2017 to 2021, the mean annual rainfall was 2908
1357 mm year⁻¹ and the mean maximum temperature was 31.6°C (SEARRP, 2022). Annual rainfall was
1358 lowest in 2020 (2373 mm year⁻¹, respectively), with a peak in annual rainfall in 2017 (2992 mm year⁻¹).
1359 There was a very strong El Nino in 2015-2016 and a weak El Nino in 2018-2019. All reserves were
1360 selectively logged twice between 1960 and 2013, using a variety of harvest methods including
1361 conventional logging, logging using a log-fisher or crawler tractor, and heli-logging (Sabah Forestry
1362 Department, 2020). The volume of extracted timber was 117 m³ ha⁻¹ in the first round of logging and
1363 34.70 m³ ha⁻¹ in the second round of logging (Fisher et al., 2011a).

1364 We analysed satellite imagery across 34 compartments, ranging between 200 ha and 840 ha in
1365 size, that had greater than 90% of their area treated with liana removal within 12 months between
1366 2017 and 2021 (Fig 8D). In 2017, 13 compartments were treated in USFR; in 2019, three

1367 compartments were treated in MFR and six in BPFR; in 2020, nine compartments were treated in
 1368 MFR; and in 2021, three compartments were treated in MFR. A team of contractors cut liana stems in
 1369 each compartment using machetes and allowed them to decompose in situ. Untreated compartments
 1370 from these three reserves were used as reference forests (Fig 8D).



1371

1372 **Figure 8:** Map of South East Asia showing Malaysia in dark grey and Sabah in purple (A); the
 1373 location of the three forest reserves in Sabah (B); the three forest reserves in which liana removal was
 1374 applied between 2017 and 2021: BukP = Bukit Piton Forest Reserve, MFR = Malua Forest Reserve,
 1375 USFR = Ulu Segama Forest Reserve (C); the logging compartments in which more than 90% of the
 1376 area was treated with liana removal within 12 months, and compartments used as reference (D).

1377

1378 *Remote-sensing data and NBR metrics*

1379 We used Level 2A data from the Sentinel-2 (S2) MultiSpectral Instrument, which is orthorectified and
 1380 atmospherically corrected to surface reflectance (S2-SR), to detect commercial liana removal in
 1381 compartments treated between 2020 and 2021, following Finlayson and Hethcoat *et al* (2022). Level
 1382 2A data (S2-SR) was only available from December 2018 for our study region, so, to detect
 1383 commercial liana removal treatments conducted between 2017 and 2019, we used Level 1C data from
 1384 S2, which records top-of-atmosphere reflectance (S2-TOA). We used the in-built S2 quality band and
 1385 fine-tuned thresholds of aerosol, blue, red, and green bands to remove cloud-affected and non-forest
 1386 pixels, as per Finlayson and Hethcoat *et al* (2022).

1387 We calculated the Normalized Burn Ratio (NBR) vegetation index (see Equation 1) for each
 1388 S2 image one-year pre and one-year post-liana removal (from the first day of the first annual quarter
 1389 in which liana removal was applied to the last day of the last annual quarter in which removal was
 1390 applied). We used NBR because it is calculated from wavelengths that relate to leaf pigments and can
 1391 differentiate between leaf and non-leaf material (such as bare ground or wood) (Langner et al., 2018).
 1392 Finlayson and Hethcoat *et al* (2022) also found that NBR showed the strongest response to
 1393 experimental liana removal compared to a suite of other vegetation indices.

$$1394 \quad NBR = \frac{N-SWIR}{N+SWIR} \quad (1)$$

1395 *Letters indicate spectral reflectance bands: N = near-infrared (835.1 nm); SWIR2 = short-wave*
 1396 *infrared 2 (2202.4 nm).*

1397 From the raw NBR values, we derived two summary metrics for each treated and reference
 1398 compartment at each S2 image date, following Finlayson and Hethcoat *et al* (2022):

- 1399 1. Minimum NBR: We extracted the minimum NBR value across each compartment, indicating the
 1400 overall change in canopy greenness.
- 1401 2. Proportion of the canopy with decreased NBR: We calculated the percentage difference between
 1402 the median NBR for each pixel one-year pre-treatment and the NBR value for each pixel in each
 1403 S2 image post-treatment. We summarised this as the proportion of the pixels in each compartment

1404 that had greater than 5% decrease in NBR compared to pre-treatment, hereafter referred to as the
1405 proportion of the canopy with decreased NBR. This metric showed the proportion of the canopy
1406 in which greenness had decreased in treated and reference compartments.

1407

1408 *Statistical analyses*

1409 To answer our first objective, asking whether commercial-scale LR can be detected by assessing
1410 changes in minimum NBR or the proportion of the canopy with decreased NBR, we used the two
1411 NBR metrics as response variables in generalized additive models (GAMs). GAMs were used to
1412 account for seasonality and temporal non-independence in the time-series data (Simpson, 2018).
1413 These models included LR treatment (treated or reference) as a fixed effect to determine if LR could
1414 be differentiated from reference compartments. Coefficients for LR treatment significantly above zero
1415 indicated that commercial LR significantly increased the minimum NBR value or the proportion of
1416 the canopy with a decrease in NBR compared to reference logging compartments, and vice versa. We
1417 ran additional models to account for error in the treatment dates as we only knew the annual quarter in
1418 which liana removal treatment started and ended: firstly, we ran the above models with compartments
1419 in which liana removal was completed in the fewest months (within 3 months in 2017, 2019, and
1420 2020, and within 6 months for 2021), and, secondly, excluded S2 images acquired during treatment
1421 applications.

1422 To reduce the noise in the data that could be masking the effect of LR on NBR metrics, this
1423 model also included compartment size, daily rainfall, and treatment year as fixed effects,
1424 compartment ID and forest reserve as random effects, and month as a smooth term with 12 knots. We
1425 also included the interaction between LR treatment and compartment size, rainfall, treatment year,
1426 and forest reserve, where possible, to answer part of our second objective: examining the causes of
1427 variation in liana removal signal at the compartment level, potentially due to crew fatigue or liana
1428 abundance. A significant compartment ID term indicated that there was significant variation in the
1429 NBR metrics between compartments, and significant interactions between the LR treatment term and

1430 compartment size, rainfall, treatment year, or forest reserve indicated that these variables influenced
1431 the signal of liana removal on NBR metrics.

1432 To further assess the causes of variation in the signal of liana removal, this time within
1433 compartments, we split treated and reference compartments into 200 m x 200 m sub-compartments.
1434 We calculated the minimum NBR and proportion of pixels with a decrease in NBR for each sub-
1435 compartment in each S2 image. Sub-compartment models included NBR metrics as the response
1436 variables, LR treatment, month, daily rainfall, forest reserve, and treatment year as fixed effects, and
1437 compartment ID as a random effect. To test whether NBR metrics varied substantially *within*
1438 compartments we compared the conditional R^2 values between models with and without sub-
1439 compartment ID as a random effect. A higher R^2 in the model with sub-compartment ID indicated that
1440 there was variation in the NBR metrics within compartments. We used mixed effects models instead
1441 of GAMs due to the size of the sub-compartment dataset and computational limitations.

1442 Lastly, to assess whether terrain steepness or distance from road (factors that could influence
1443 crew fatigue and completeness of removal or liana abundance) influenced the signal of LR on NBR
1444 metrics, we ran the above sub-compartment models with the interaction between liana removal
1445 treatment and maximum terrain steepness and minimum distance from main roads or roads used for
1446 some activities (hereafter called “secondary roads”). Terrain steepness was obtained for each sub-
1447 compartment using the 90 m resolution digital elevation dataset from the Centre for Tropical
1448 Agriculture (CIAT) (Jarvis et al., 2008), and the minimum distance of each sub-compartment from
1449 roads was calculate using a road network provided by the Sabah Forestry Department. Significant
1450 coefficients for these interaction terms would suggest that the impact of liana removal on minimum
1451 NBR or the proportion of the canopy with decreased NBR were influenced by terrain and distance
1452 from roads, potentially indicating variation in completeness of liana removal or liana abundance.

1453 We used a subset of 51 reference logging compartments (representing all three forest
1454 reserves) for the sub-compartment analyses due to excessive time to extract the minimum NBR per
1455 sub-compartment in Google Earth Engine. All analyses based on the proportion of the canopy with

1456 decreased NBR excluded S2 data when more than 15% of the compartment was affected by cloud
1457 cover. GAMs were run using the *mgcv* R package (Wood, 2011) and linear mixed effects models were
1458 run using the *lme4* R package (Bates et al., 2015). All analyses and figures were produced using R
1459 statistical software (R Core Team, 2020).

1460

1461 **Results**

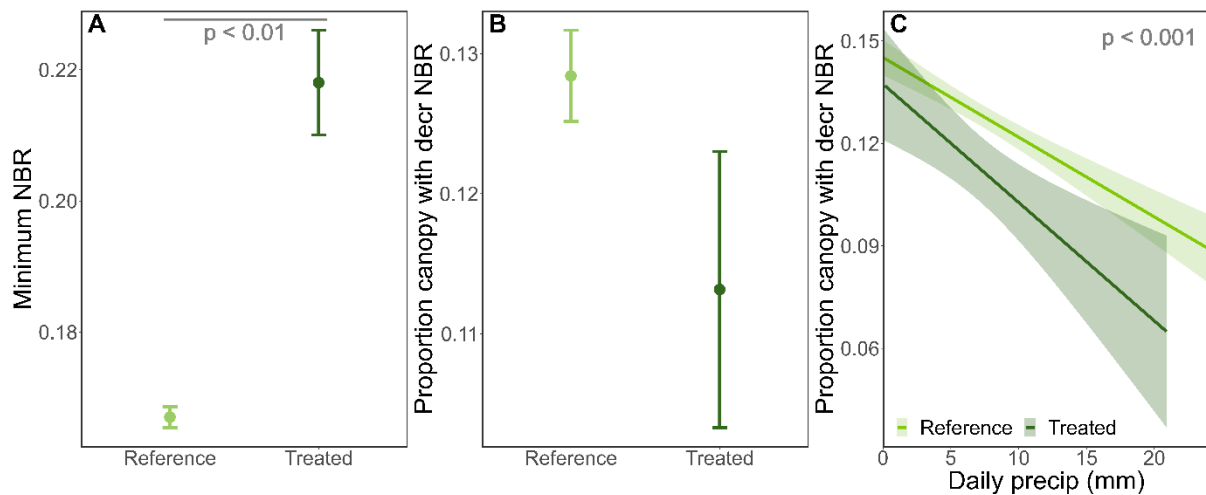
1462 *Effect of commercial liana removal on NBR*

1463 Commercial liana removal caused changes to the forest canopy that were visible with satellite-derived
1464 NBR. There was a significant increase in minimum NBR in treated compared to untreated
1465 compartments across a year post-treatment (coefficient = 0.08, $p < 0.01$, Figure 9A, Table S19),
1466 meaning that liana removal increased canopy greenness. Supplementary analyses also found a
1467 significant positive effect of commercial liana removal on minimum NBR when the analysis was
1468 constrained to compartments treated within a shorter time-frame, but the positive effect was no longer
1469 significant when the analyses only included Sentinel-2 images that were captured after the annual
1470 quarter in which treatment was completed (Table S19).

1471 The signal of commercial liana removal on the proportion of the canopy with decreased NBR
1472 was less clear. Commercial liana removal reduced this NBR metric compared to reference
1473 compartments within a year of treatment (9B), but this was non-significant potentially due to the
1474 interaction of treatment with daily rainfall (coefficient = -0.04, $p < 0.001$, Figs 9C & 10B, Table S19).
1475 Below 5 mm of rain per day similar proportions of the canopy had decreased NBR in reference and
1476 treated compartments, but as rainfall increased, treated compartments had an increasingly smaller
1477 proportion of the canopy with decreased NBR compared to reference compartments (Fig 9C). These
1478 results suggest that commercial liana removal causes a slight reduction in the proportion of the canopy
1479 which is open or dominated by non-photosynthetic material. Results were similar in supplementary

1480 analyses constrained to compartments with shorter treatment lengths and excluding S2 images during
 1481 treatment (Table S19).

1482



1483

1484 **Figure 9:** Effect of commercial liana removal on (A) minimum NBR, (B) the proportion of canopy
 1485 with a decrease in NBR compared to pre-treatment, and (C) the interaction between the effect of
 1486 commercial liana removal on the proportion of the canopy with decreased NBR and daily
 1487 precipitation. Points in (A) and (B) show average NBR metrics for reference compartments and all
 1488 compartments pre-liana removal (“Reference”), and average NBR metrics in treated compartments
 1489 during 12 months post-liana removal (“Treated”). P-value in (A) is the level of statistical difference in
 1490 minimum NBR between treated and reference, taken from the GAMs, and error bars indicate the 95%
 1491 confidence interval. Lines in (C) show the relationship between the proportion of the canopy with
 1492 decreased NBR and daily precipitation, separated by treated and reference compartment. The lighter
 1493 band around each line shows the SE of the relationship and the p-value in (C) is taken from the GAM,
 1494 indicating the significant effect that daily rainfall had on impact of treatment on the proportion of the
 1495 canopy with decreased NBR.

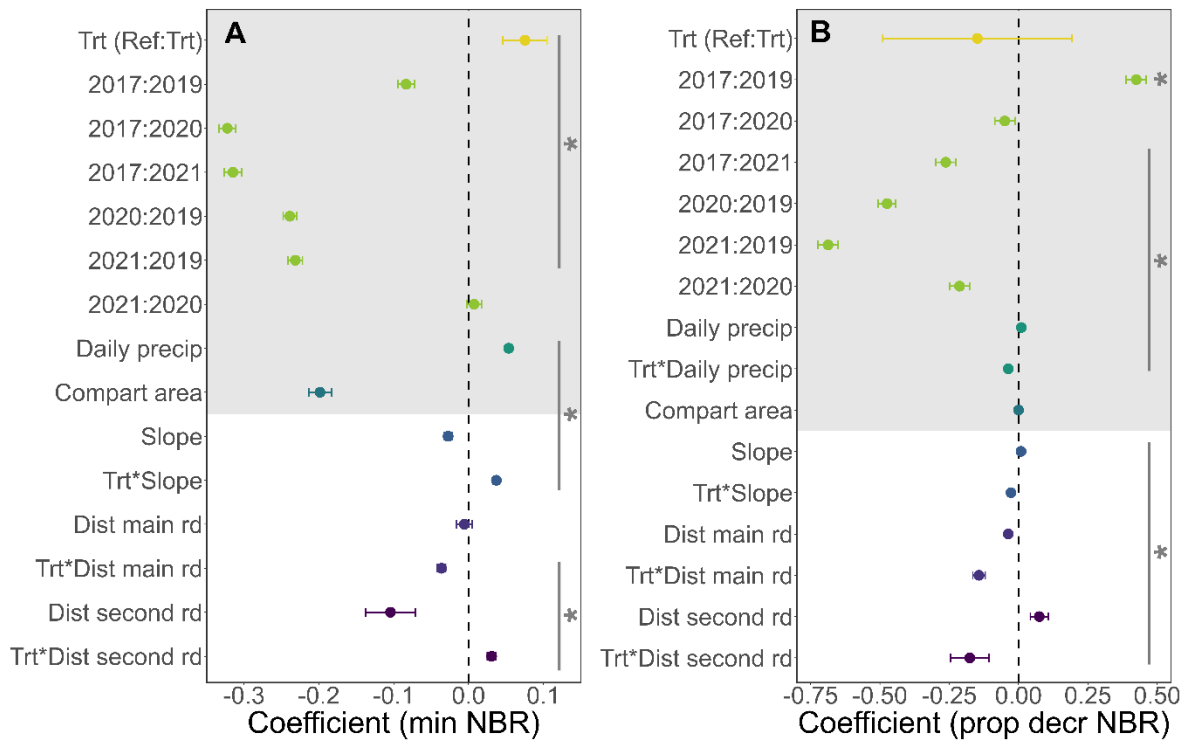
1496

1497 *Variation in the signal of liana removal on NBR*

1498 There was substantial variation in NBR metrics between and within compartments. This is shown by
1499 the significant compartment ID smooth terms in the GAMs (EDF: 123-200, p-values < 0.001, Table
1500 S19) and the roughly doubling of conditional R^2 values when including sub-compartment ID in the
1501 linear mixed effect models (increasing from 0.256 to 0.419 and from 0.077 to 0.143 in the minimum
1502 NBR and proportion of canopy with decreased NBR models, respectively).

1503 We also found several variables that caused significant variation in the impact of commercial
1504 liana removal on NBR metrics (i.e., the signal of liana removal), potentially indicating that crew
1505 fatigue or liana abundance influenced the outcome of commercial liana removal. There were
1506 significant interactions between LR treatment and precipitation, terrain steepness, and distance from
1507 main and secondary roads (Fig 9C, 10 & 11, Tables S19 & S20). Distance from main and secondary
1508 roads had the largest effect, reducing the proportion of the canopy with decreased NBR in treated
1509 compared to reference compartments by 14-18% as distance from road increased (Fig 10B, 11D & F).

1510 —



1511

1512 **Figure 10:** Effect of covariates on minimum NBR (A) and the proportion of the canopy with
 1513 decreased NBR (B), and the interaction between liana removal treatment and covariates. Points
 1514 represent the coefficient for different covariates or interactions, taken from whole compartment
 1515 GAMs for the coefficients in the grey panel and the sub-compartment linear mixed effect models for
 1516 the coefficients in the white panel. Slope is terrain steepness in degrees. Continuous covariates are
 1517 scaled in the models and the part of the name before the colon shows the reference level in categorical
 1518 covariates. Coefficients that interact with treatment are indicated by “Trt*” in the covariate name.
 1519 Dotted lines at zero indicate where there is no effect of the covariate on the NBR metric and a grey
 1520 star indicates covariates that significantly increase or decrease the NBR metrics (actual p-values in
 1521 Table S19 and S20). Error bars indicate standard error.

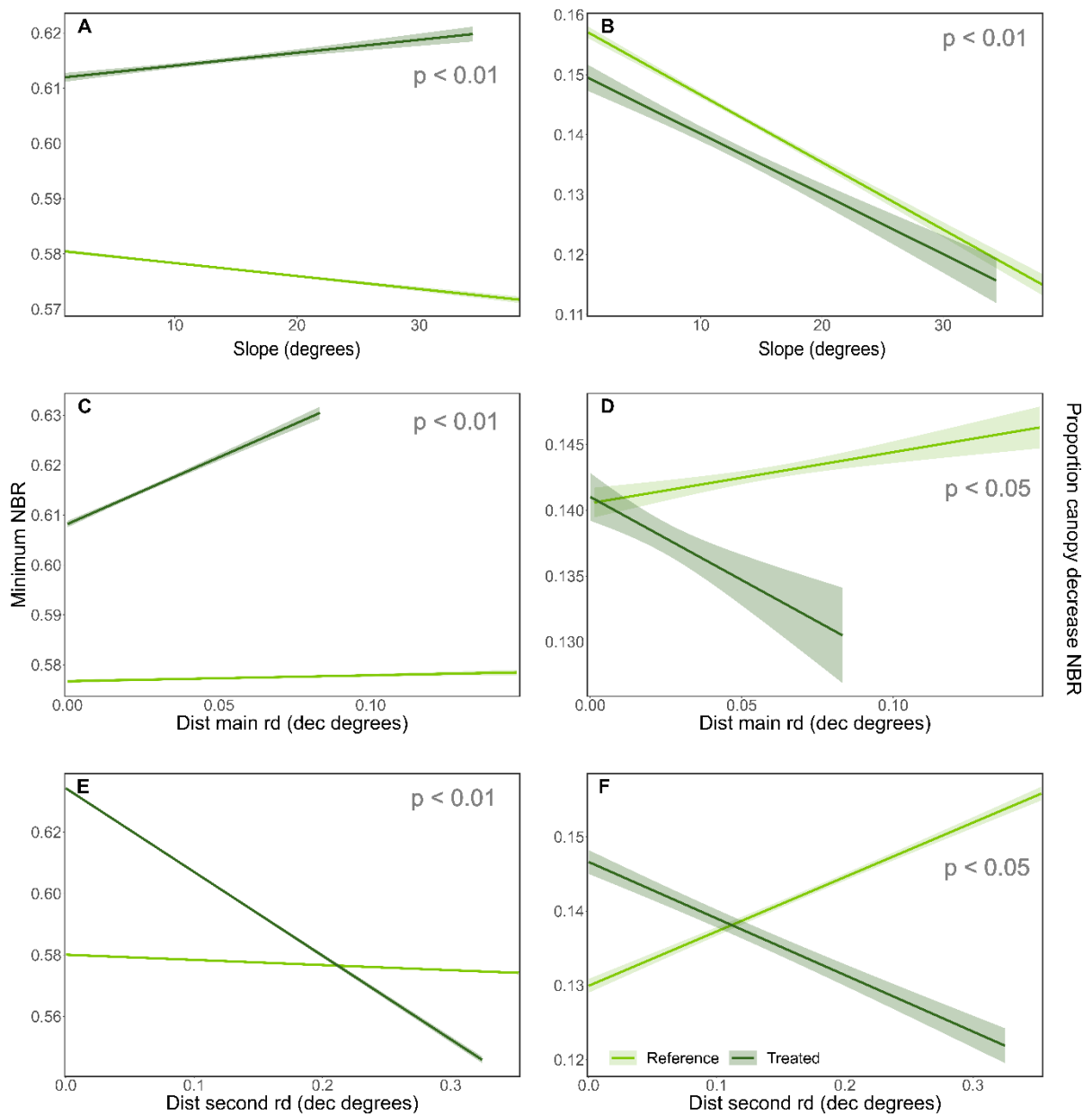
1522 The significant interactions of covariates with the effect of commercial LR treatment on NBR
 1523 metrics reveal the conditions in which the signal of liana removal is likely to be largest, potentially
 1524 indicating where removal crews removed the greatest proportion of lianas, or where liana abundance
 1525 was highest. For example, the difference in minimum NBR between treated and reference

1526 compartments was greatest in steeper sub-compartments and those further from main roads (Fig
1527 11A&C), but the difference diminished in sub-compartments further from secondary roads (Fig 11E).
1528 In fact, the positive effect of liana removal on minimum NBR was reversed at the furthest distances
1529 from secondary roads, with liana removal reducing minimum NBR compared to reference
1530 compartments.

1531 The strength of the signal of commercial liana removal in terms of the proportion of the
1532 canopy with decreased NBR was also context dependent. Firstly, as shown in Fig 9C, the reduction in
1533 the proportion of the canopy with decreased NBR in treated compared to reference compartments was
1534 most pronounced with higher rainfall. This lower proportion of canopy with reduced NBR after
1535 treatment was also clearest further from main and secondary roads (Fig 11D & F), and the proportion
1536 of the canopy with reduced NBR was actually higher in liana removal than reference compartments
1537 when close to secondary roads. There was also a very small influence of terrain steepness on the
1538 difference between the proportion of the canopy with reduced NBR in treated and reference
1539 compartments (Fig 11B).

1540

1541



1542

1543 **Figure 11:** Variation in the effect of commercial liana removal on NBR metrics. Panels A, C, and E
 1544 show the interaction between steepness of terrain (slope), distance from main and secondary roads and
 1545 the effect of liana removal on minimum NBR, while panels B, D, and F show the interaction of these
 1546 variables with the effect of liana removal on the proportion of the canopy with decreased NBR. Lines
 1547 show the linear relationship for treated and reference compartments separately and the lighter band

1548 around each line shows the SE of the relationship. P-values indicate the level of significance for the
1549 coefficient of the interaction, taken from the mixed effects models.

1550

1551 **Discussion**

1552 This study finds that satellite imagery can detect commercial scale liana removal, but that the signal of
1553 commercial liana removal is context dependent. While we detect significant variation in the signal of
1554 commercial liana removal, our analyses are unable to determine if liana abundance and crew fatigue
1555 are driving this variation. We propose further work to operationalise the use of satellite imagery to
1556 validate and monitor this emerging method to restore timber and carbon stocks in large areas of
1557 logged tropical forests.

1558 *Commercial liana removal can be detected using Sentinel-2 data*

1559 Our study provides the first evidence that logged tropical forests treated with liana removal at the
1560 commercial scale can be distinguished from untreated forests using satellite-derived data. This
1561 supports the conclusion of Finlayson and Hethcoat *et al* (2022) that remote sensing could be an
1562 important tool for validating the application of liana removal and monitoring the outcome of the
1563 intervention. To detect commercial liana removal, we recommend comparing minimum NBR in
1564 treated and reference forest for the year post-treatment. While there was variation in minimum NBR
1565 between compartments, likely due to differences in liana abundance, forest structure, and other factors
1566 (Finlayson et al., 2022; Putz et al., 2019; Schnitzer and van der Heijden, 2019; Venegas-Gonzalez et
1567 al., 2020), the signal of liana removal on minimum NBR was consistent across daily rainfall. Our
1568 results also show that liana removal can be detected using the proportion of the canopy with decreased
1569 NBR, but this may not be visible when there is less than 5 mm of rainfall daily. These results are a
1570 key step in operationalizing the use of satellite data to validate the proposed widespread
1571 implementation of liana removal (Finlayson et al., 2022), and could facilitate access to schemes that
1572 pay for restoration, enhanced logging sustainability, and carbon sequestration (GOF-C-GOLD, 2016).

1573 While our results agree with studies that found a change in the canopy after climber removal
1574 (César et al., 2016; Finlayson et al., 2022; O'Brien et al., 2019; Wu et al., 2020), contrary to previous
1575 studies we found that commercial liana removal *increases* rather than decreases canopy greenness.
1576 The difference in these results could arise from this study assessing a longer period post-removal than
1577 in Finlayson and Hethcoat *et al* (2022). Since we only know the annual quarter in which removal
1578 occurred, the post-treatment period analysed in this study could be up to 18 months post-treatment if
1579 liana removal started at the beginning of a quarter and ended at the end of a quarter. However, an
1580 additional analysis of the liana removal experiment in Finlayson and Hethcoat *et al* (2022) shows no
1581 increase in canopy greenness in treated compared to untreated forest between 12 to 24-months of
1582 treatment (Fig S24).

1583 Alternatively, the increase in canopy greenness could indicate that commercial liana removal
1584 achieved lower removal intensity than the 60-100% removal in Finlayson and Hethcoat *et al* (2022).
1585 Rather than creating canopy gaps, less intense removal could have promoted quicker re-infestation of
1586 lianas or greater growth of new leaves in liberated canopy trees, both of which have high green light
1587 reflectance and could influence NBR (Chandler et al., 2021a; Wu et al., 2017). Increased greenness
1588 could also occur if fewer canopy gaps arise post liana removal due to a lower abundance of lianas
1589 resulting in reduced damage to trees (Estrada-Villegas and Schnitzer, 2018; Garrido-Pérez et al.,
1590 2008). Equally, the removal applied to the forests in this study could have promoted the growth of
1591 plant species that have higher green reflectance (Taddeo et al., 2019), but such changes to
1592 composition and gap formation would take several years to manifest, longer than the study period in
1593 this paper. With more precise treatment dates we could observe the temporal changes in canopy
1594 greenness post commercial liana removal, determining whether the expected dip in greenness after
1595 treatment did occur. Higher resolution imagery, such as from UAVs, could also allow us to determine
1596 canopy plant composition (Waite et al., 2019), helping to determine the precise impact of commercial
1597 liana removal on the forest canopy.

1598 *Satellite imagery detects variation in commercial liana removal signal*

1599 We identified several factors that drive variation in the satellite signal of commercial liana removal.
1600 Consequently, this study shows that remote sensing could be used to monitor *how* liana removal is
1601 applied across large scales such as entire logging concessions, agreeing with the results of Finlayson
1602 and Hethcoat *et al* (2022) who found that NBR could differentiate between liana removal that was
1603 applied at different intensities. We found that the signal of liana removal can vary at the compartment
1604 (200-840 ha) and sub-compartment (4 ha) scale, showing the utility of satellite data to observe the
1605 impact and application of liana removal across spatial scales that would be hard to achieve with field
1606 surveys (de Almeida et al., 2020; Deluca et al., 2010). Detecting variation in liana removal signal may
1607 be particularly useful to identify areas where the removal of all lianas has not been achieved,
1608 something which may be important for forest managers seeking to maximise the timber and carbon
1609 stocks of logged forests (Finlayson et al., 2022) or to better estimate the expected outcome of the
1610 intervention.

1611 While we observed a variable signal of liana removal, it is unclear whether this supports our
1612 hypothesis that crew fatigue or liana abundance influence the signal of liana removal. We anticipated
1613 that larger compartments, steeper terrain, and greater distance from road would increase crew fatigue
1614 and reduce removal completeness (Mills et al., 2019), leading to a smaller signal of liana removal.
1615 However, the results tell a mixed story: the most convincing results suggested that steeper terrain and
1616 distance from main roads increased the signal of liana removal, potentially indicating higher removal
1617 completeness and lower crew fatigue in these contexts, while distance from secondary roads appeared
1618 to reduce the liana removal signal. Combined with the fact that compartment size did not influence
1619 liana removal signal, this suggests that crew fatigue is not a main driver of variation in removal signal
1620 and intensity. Alternatively, since we cannot directly link crew activity to terrain and distance to main
1621 or secondary roads, these may be poor proxies of crew fatigue and therefore tell us little about the
1622 impact of crew fatigue on liana removal signal.

1623 We also proposed that variation in the satellite signal of commercial liana removal could be
1624 due to variation in liana abundance, but we again find minimal support for this. While the lack of
1625 impact of liana abundance agrees with Finlayson and Hethcoat *et al* (2022), we expected liana

1626 abundance to vary to a greater extent in this larger study area due to greater variation in terrain, edge
1627 effects, logging activity, and composition of tree and liana species that influence liana abundance
1628 (Addo-Fordjour and Rahmad, 2015a; Campbell et al., 2018; Putz et al., 2019; Schnitzer and Bongers,
1629 2002). However, we found that there was a smaller signal of liana removal on flatter terrain (where
1630 some studies report higher liana abundance (Addo-Fordjour and Rahmad, 2015b)) and further from
1631 main roads (which create edges that tend to have higher liana abundance (Campbell et al., 2018)).
1632 Without direct liana abundance data from the logging compartments in this study, we cannot fully test
1633 the influence of liana abundance on the strength of the liana removal signal.

1634 We recommend further studies with detailed information on removal crew activity and liana
1635 abundance to determine the causes of variation in satellite-derived-NBR after liana removal.
1636 Ultimately, this would reveal the utility of satellite data for detecting commercial liana removal in
1637 varying circumstances and for determining removal completeness. Commercial liana removal is
1638 poised to enhance selective logging sustainability and restore logged tropical forests globally and our
1639 work shows that large-scale monitoring of such interventions could be assisted by remote sensing
1640 tools.

1641 CHAPTER 5: General Discussion

1642 **Summary**

1643 My thesis focusses on developing our understanding, the application, and the monitoring of liana (or
1644 climber) removal – an emerging technique that can restore the tree growth and carbon stocks of
1645 logged forests towards pre-disturbance levels and enhance the sustainability of selective logging.
1646 Conducting a meta-analysis of global liana removal papers (Chapter 2), I found that liana removal
1647 vastly enhances timber recovery and carbon sequestration in logged tropical forests – potentially
1648 sequestering 7.4 Gigatons of CO₂ over 10 years at less than \$1 MgCO₂⁻¹ if applied to logged and
1649 secondary forests globally. However, there was poor representation of studies outside the Neotropics.
1650 Following this, Chapters 3 and 4 present the first steps for using freely available satellite data to detect
1651 and monitor large-scale liana removal in logged tropical forests. I find that both experimental and
1652 commercial-scale liana removal cause changes to the canopy that are detectable with satellite data,
1653 and that this method can monitor the intensity of liana removal. In Chapter 3, I also provide the first
1654 experimental evidence of partial liana removal, showing that leaving 20 or 40% of the forest untreated
1655 reduced the canopy disturbance caused by liana removal, and tentatively suggesting that partial
1656 removal could reduce the harmful impacts on biodiversity. Ultimately, I conclude that liana removal
1657 could be a cost-effective and powerful tool to restore the carbon and timber value of logged tropical
1658 forests and find that it can be detected and monitored using a simple remote sensing method based on
1659 freely available data. However, serious caution should be taken to preserve the biodiversity value of
1660 lianas and forest functions that they provide.

1661 In the following sections I will discuss how findings from this thesis contribute to our
1662 understanding of liana ecology, outline the issue of regional bias in tropical ecology research, and
1663 detail the next steps for monitoring forest restoration and liana removal research. I will also outline
1664 some of the important concerns about liana removal and provide some recommendations for using
1665 liana removal to protect and enhance logged tropical forests.

1666

1667 **Liana ecology**

1668 In addition to developing our understanding of liana removal, my analyses reveal information about
1669 the impact of lianas on tropical forests, both confirming the intense burden that lianas have on trees
1670 (Schnitzer and Bongers, 2002), but also evidencing the beneficial roles that lianas have. The
1671 overwhelmingly positive impact of liana removal on tree growth in Chapter 2 agrees with another
1672 meta-analysis on the topic (Estrada-Villegas et al., 2022), and evidences the substantial influence of
1673 lianas in terms of timber recovery and aboveground carbon dynamics. Chapter 3 and 4 further
1674 demonstrate the impact of lianas, showing that, while liana removal may be thought of as causing
1675 relatively minimal canopy disturbance compared to logging, the removal of lianas has an impact on
1676 the canopy that is visible from space. This emphasises the high occupancy of lianas in the canopy of
1677 logged tropical forests, but also the critical part that lianas play in forest structure and light
1678 interception (Meunier et al., 2021c) and the impact that liana removal could have on the survival of
1679 fauna and flora that rely on the microclimate buffering provided by a closed canopy (O'Brien et al.,
1680 2019; Scheffers et al., 2014). This thesis clearly evidences the substantial impact that lianas have on
1681 tropical forests, supporting recent calls to stop this plant group from being overlooked in field and
1682 modelling studies (di Porcia e Brugnera et al., 2019), and to retain a proportion of lianas in restoration
1683 treatments (Putz et al., 2023).

1684 While experimental and commercial liana removal lead to changes in canopy greenness, the
1685 remote sensing methods that I used in this thesis were unable to determine the precise causes of this. I
1686 posit that the recovery of the canopy in Chapter 3 could be due to lianas given their documented re-
1687 growth after disturbance (Addo-Fordjour et al., 2016; Rocha et al., 2020) and faster growth rate than
1688 trees (Schnitzer and Bongers, 2002). However, the growth rate of trees and lianas may be more
1689 similar in aseasonal forests (Medina-Vega et al., 2021), such as the forests in Chapter 3 and 4, so it is
1690 hard to infer what was driving the recovery of the canopy post liana removal. Better inference about
1691 the post-treatment canopy composition using Sentinel-2 imagery could be made by including NDVI,

1692 GI, and other spectral bands alongside NBR in models to predict liana load. However, remote sensing
1693 imagery greater than 10 m resolution, such drone imagery (van der Heijden et al., 2022; Waite et al.,
1694 2019), may be required to draw detailed conclusions about forest dynamics and help to ascertain the
1695 nuanced impacts of the restoration technique. For example, individual tree crown liana abundance
1696 could be monitored by combining airborne or satellite data with machine learning and some field data
1697 on liana infestation (Chandler et al., 2021b) and hyper-spectral data could quantify canopy plant
1698 diversity (Clark et al., 2005; Zhao et al., 2018).

1699 In this thesis I also demonstrate that the impacts of lianas and their removal varies across
1700 different spatial scales, from small scale (4 ha) treatment blocks (Chapter 3) to field sites in different
1701 countries (Chapter 2). Much of the variation in all three chapters could be due to differences in liana
1702 abundance resulting from the patchy intensity in timber harvesting that is characteristic of selective
1703 logging (Putz et al., 2019). However, less than half of the studies in the meta-analysis reported liana
1704 abundance, and this data was not available for the commercial logging compartments in Chapter 4,
1705 preventing me from investigating the impact of liana abundance fully in this thesis.

1706 Variation in the impact of liana removal is also likely influenced by the intensity (or
1707 “completeness”) of removal, but, to my knowledge, there are only two studies that report this data
1708 (Mills et al., 2019; Pinard and Putz, 1996). The provision of liana abundance and removal
1709 completeness data would make it possible to determine whether there is a critical level of liana
1710 abundance or removal intensity under which trees are not released from lianas sufficiently to enhance
1711 timber and carbon stocks – information that is critical for the effective restoration of logged forests
1712 using liana removal. In cases where collecting liana abundance data in the field is not feasible (Londe
1713 et al., 2022), remote sensing methods that detect liana abundance could be employed, as discussed
1714 above (Chandler et al., 2021b).

1715 This thesis has provided some new insights into liana ecology in terms of carbon and canopy
1716 dynamics, but there is still a lot that we do not yet know about this understudied plant group (van der
1717 Heijden et al., 2023). While many studies have investigate the impact of removal on aboveground

1718 carbon, for example, there is a dearth of studies considering the impact on belowground carbon pools
1719 (Meunier et al., 2021a). Moreover, while lianas are represented as a group of plants that share traits –
1720 fast-growing, flexible stems and competing extensively with trees – there is substantial variation
1721 between liana species (Coppieters et al., 2022), suggesting that the response of a forest to liana
1722 removal may depend heavily on liana species composition. Liana abundance may also determine the
1723 outcome of liana removal, but only a few drivers of liana abundance across the tropics, such as
1724 precipitation patterns and disturbance, are well-studied (DeWalt et al., 2015; Schnitzer et al., 2014).
1725 Finally, lianas provide myriad functions for faunal taxa, but very few studies consider this interaction
1726 (Arroyo-Rodriguez et al., 2015), and even fewer the impact of liana removal on faunal species
1727 (Schnitzer et al., 2020). Overall, this highlights the need for caution when promoting liana removal to
1728 restore the growth of timber trees and carbon stocks in degraded forests – we could be removing
1729 lianas from an area of forest that they have not yet been studied and without knowing the full range of
1730 impacts that their removal could have. This issue is discussed further in *The unknown impact of forest*
1731 *restoration on biodiversity* section, later in this chapter.

1732 **Regional bias in tropical research**

1733 Variation in the efficacy of liana removal in my meta-analysis (Chapter 2) is likely to be partly
1734 explained by regional or climatic differences. While a meta-analysis by Estrada-Villegas *et al* (2022),
1735 which is analogous to mine, concluded no effect of rainfall on liana removal efficacy, the
1736 concentration of liana removal studies in the Neotropics, particularly in Panama, could prevent the
1737 impact of climate (and region) from being fully assessed in both studies.

1738 The bias of scientific studies towards the Neotropics has been noted in tropical ecology over
1739 the past 40 years (Clark, 1985; Deikumah et al., 2014), preventing the generalisability of findings, and
1740 causing a concerning lack of understanding of tropical ecology in poorly studied regions. This paucity
1741 of research is particularly troubling regarding forest management research, considering that Southeast
1742 Asia has some of the highest rates of forest disturbance whilst hosting several biodiversity hotspots
1743 (Fisher et al., 2011a), and deforestation has the slowest deceleration rates in the African tropics

1744 (Deikumah et al., 2014). Results in my thesis emphasise the need for greater study of tropical
1745 phenomena and forest systems in the Asian and African tropics.

1746 In Chapters 3 and 4 I develop a remote sensing method to detect liana removal based on
1747 Sabah, Malaysian Borneo. Since lianas have similar ecology across tropical forests (Schnitzer and
1748 Bongers, 2002), I anticipate that liana removal in other regions will also generate a satellite signal
1749 based on changes in canopy greenness. However, the magnitude and temporal trend in canopy
1750 greenness post-removal may vary due to liana abundance (DeWalt et al., 2015), tree and liana species
1751 composition (Schnitzer, 2018; Venegas-Gonzalez et al., 2020), and timber extraction methods in
1752 different regions (see Box S1 from (Marshall et al., 2020)). Establishing a network of standardised
1753 experiments and commercial liana removal sites across different tropical countries, such as the system
1754 of Center for Tropical Forest Science (CTFS) – Forest Global Earth Observatory (ForestGEO) plots
1755 that monitor the response of tropical forests to global change (Anderson-teixeira et al., 2014), would
1756 be the gold standard to robustly quantify the efficacy and remote-sensing signal of this promising
1757 restoration technique. Such a research network would facilitate fast and effective introduction of liana
1758 removal across the tropics. I recommend testing the remote sensing signal of liana removal with the
1759 numerous existing removal experiments and areas where liana removal has already been applied.

1760

1761 **The unknown impact of forest restoration on biodiversity**

1762 A critical element of tropical forests that is often overlooked when implementing logged forest
1763 restoration is the impact on biodiversity (Cerullo and Edwards, 2019). Pettorelli *et al* (2021) discuss
1764 how nature-based solutions – methods that work with nature to solve environmental issues (Seddon et
1765 al., 2021) – risk having overall negative impacts on the environment when their focus is too narrow,
1766 such as only considering the impact of restoration on carbon. While there are synergies between
1767 carbon stocks and biodiversity in many cases, enhancing forest carbon does not universally enhance
1768 biodiversity (Strassburg et al., 2010). In the case of liana removal, there are only five studies that have

1769 investigated the response of biodiversity compared to more than 60 that focus on the tree response
1770 (Estrada-Villegas and Schnitzer, 2018), and the results show that the impact varies depending on taxa,
1771 functional group, and tropical region (Benjamin J Adams et al., 2019; Cerullo et al., 2019; Cosset and
1772 Edwards, 2017; Edwards et al., 2009; Schnitzer et al., 2020). Therefore, to ensure that restoration
1773 actions result in fully functioning, biodiverse tropical ecosystems, and to prevent our attempts to
1774 mitigate the climate crisis from accelerating biodiversity loss, it is imperative to assess the influence
1775 of restoration methods on biodiversity. This should be a priority for further research into liana
1776 removal.

1777 While the results in this thesis show that partial removal has less of an impact on the canopy
1778 than complete removal, remote sensing data alone could not determine whether this translates into a
1779 smaller impact on biodiversity. A crucial extension to the liana removal experiment in Chapter 3 is
1780 measuring changes to faunal communities post-removal and between removal intensities. Baseline
1781 data of dung beetle communities and soundscapes has already been collected from this experiment for
1782 this purpose. Post-treatment data on faunal communities would explicitly show the impact of liana
1783 removal on faunal diversity and whether partial removal reduces biodiversity impacts. Moreover,
1784 concurrently measuring tree growth in the experiment, for which baseline data has also been
1785 collected, could determine whether there is a trade-off between biodiversity and timber and carbon
1786 enhancement. Such trade-offs are inevitable in restoration (Edwards et al., 2021), necessitating data
1787 on both the desired and unintended consequences of restoration actions.

1788 In addition to extending my experimental work, research assessing the impact of liana
1789 removal on biodiversity should consider other configurations of partial removal. This could include
1790 cutting lianas only on trees of commercial interest, such as in Mills *et al* (2019) or Putz *et al* (2023),
1791 to enhance growth in valuable timber trees while allowing lianas to persist in the remainder of the
1792 forest. Alternatively, liana removal could avoid liana species that are most ecologically important in
1793 terms of the volume of food or nesting resources they provide (Addo-Fordjour et al., 2016), for
1794 example, or only cut the more common liana species in an attempt to preserve liana diversity. Such

1795 nuanced liana removal could also reduce the cost of removal by limiting unnecessary cutting. These
1796 methods, however, require substantial knowledge about lianas, a plant group that is chronically
1797 understudied (di Porcia e Brugnara et al., 2019). Further research into liana function and diversity
1798 would assist with developing methods of liana removal that minimise the impact on biodiversity,
1799

1800 **Monitoring large-scale restoration**

1801 I have shown that developing methods to monitor restoration can be achieved with freely available
1802 and easily accessible remote sensing data products. I focussed on the European Space Agency's
1803 Sentinel-2 data, but similar products, such as Planet's Dove satellites, also provide freely available
1804 data at similar temporal and spatial resolutions (Roy et al., 2021). While there are more advanced
1805 remote sensing methods for landscape monitoring (Reiche et al., 2016), the simplicity of my approach
1806 could make it easier to adopt. This is important for countries that may not have the skills or budget for
1807 sophisticated solutions, but in which the restoration of logged forests is crucial (Misiukas et al., 2021).
1808 Accessible monitoring methods are important to facilitate financial support for restoration projects
1809 through schemes such as REDD+ (GOFC-GOLD, 2016), especially if interventions are to be rolled
1810 out across the nearly 300 million ha proposed for liana removal in Chapter 2, and if progress towards
1811 restoration targets, such as those proposed by the Bonn Challenge, need to be measured (Strassburg et
1812 al., 2020).

1813 I recommend further collaboration between researchers in the fields of remote sensing and
1814 conservation to generate new solutions to the biodiversity and climate crises, and to explore other
1815 ways in which remote sensing could benefit the application of liana removal (Pettorelli et al., 2014).
1816 For example, NASA's recently launched Global Ecosystem Dynamics Investigation (GEDI) product
1817 provides biomass estimates across the globe at 1 km resolution (Dubayah et al., 2022). Such data will
1818 greatly enhance the monitoring of restoration activities aimed at sequestering carbon, but advances are
1819 required, potentially using field data, to quantify biomass at greater spatial resolution. GEDI data

1820 could also be used to study the impacts of liana removal on forest structure. These data are generated
1821 using satellite-borne lidar sensors, providing information about canopy height and indices related to
1822 leaf cover (plant area index: PAI) and plant density that have been used to study lianas (Rodríguez-
1823 Ronderos et al., 2016; Tymen et al., 2016). For example, we would expect lower PAI in the months
1824 following liana removal and increased canopy height as tree growth is enhanced. Combining
1825 alternative sources of spectral imagery from drones and Unmanned Aerial Vehicles (UAVs) with
1826 liana removal studies could also provide higher resolution imagery that can quantify liana abundance
1827 (van der Heijden et al., 2022; Waite et al., 2019), creating more nuanced remote sensing tools for
1828 monitoring liana removal and revealing more insights about liana ecology.

1829

1830 **Conclusions**

1831 Liana removal is an affordable method of forest restoration that has yet untapped potential for
1832 enhancing the sustainability of logging and as a nature-based solution to the climate crisis. I find that
1833 the positive impact of liana removal is well supported in the Neotropics, making this good candidate
1834 for rolling out implementation. However, while the carbon and timber benefits of liana removal are
1835 well documented, much is yet unknown about liana ecology and the impacts of liana removal on
1836 overall biodiversity and forest function. Hence, research should urgently focus on these two fields to
1837 prevent adverse impacts on the already imperilled tropical biodiversity and we implore liana removal
1838 initiatives to leave a substantial proportion of the land untreated. Further work is required to minimise
1839 the potentially harmful impacts of liana removal, to build certainty in the efficacy of the technique in
1840 the African and Asian tropics, and to test my remote sensing monitoring and detection method in
1841 wider contexts. There is a wide and exciting scope of further research into liana ecology and removal
1842 that will make liana removal a key player during the UN's Decade on Ecosystem Restoration.

1843 SUPPLEMENTARY INFORMATION: Chapter 2

1844 **Appendix A: Literature search and screening**

1845 **Table S4: Literature search strings for Web of Science, SCOPUS and Google Scholar.** Two
 1846 different search strings per database.

Pre disturbance/ any	Database	Search string	Further refinement ^a
Any	Web of Science (All databases)	TOPIC: ((liana* OR vine* OR climb*) AND (remov* OR cut* OR clear* OR thin* OR liberat* OR experiment*) AND (forest*), NOT vineyard, NOT medical	<ul style="list-style-type: none"> - Refined by Science and Technology - Excluding patent and clinical trials and engineering research domain
Any	SCOPUS	(TITLE-ABS-KEY (liana* OR vine* OR climb*) AND TITLE-ABS-KEY (remov* OR cut* OR clear* OR thin* OR liberat* OR experiment*) AND TITLE-ABS-KEY (forest*) AND NOT TITLE-ABS-KEY (vineyard) AND NOT TITLE-ABS-KEY (medical)) AND (EXCLUDE (SUBJAREA , "ENGI"))	<ul style="list-style-type: none"> - Exclude Social Sciences and Engineering
Any	Google Scholar	(liana OR vine OR climb) AND (remove OR cut OR clear OR thin OR liberat OR experiment) AND (forest)	-
Pre	Web of Science (All databases)	TOPIC: ((“pre-disturb*” OR “pre-log*” OR “pre-fell*” OR “pre-harvest*” OR “pre-exploit*” OR prefell* OR “prior to log*” OR “prior to disturb*” OR “prior to fell*” OR “prior to harvest*” OR “prior to exploit*”) AND ((liana* OR vine* OR climb*) AND (remov* OR cut*	<ul style="list-style-type: none"> - Refine by (forest* OR concession* OR “logging operation”) and Science/Technology - Exclude Patents/News

		<p>OR clear* OR thin* OR liberat* OR experiment*) OR "thinning operation*")</p> <p>OR TOPIC: (RIL OR "reduced-impact log*" OR "silvicultur* field experiment" OR "planned fell*" OR "planned log*" OR "planned harvest*" OR "FSC cert*")</p> <p>OR TOPIC: ("silvicultur* treatment*" AND (liana* or vine* OR climb* OR RIL OR "reduced-impact log*"))</p>	
Pre	SCOPUS	<p>(TITLE-ABS-KEY ((("pre-disturb*" OR "pre-log*" OR "pre-fell*" OR "pre-harvest*" OR "pre-exploit*" OR prefell* OR "prior to log*" OR "prior to disturb*" OR "prior to fell*" OR "prior to harvest*" OR "prior to exploit*") AND ((liana* OR vine* OR climb*) AND (remov* OR cut* OR clear* OR thin* OR liberat* OR experiment*)) OR "thinning operation*") OR (ril OR "reduced-impact log*" OR "silvicultur* field experiment" OR "planned fell*" OR "planned log*" OR "planned harvest*" OR "FSC cert*") OR ("silvicultur* treatment*" AND (liana* OR vine* OR climb* OR ril OR "reduced-impact log*")))) AND (forest* OR concession* OR "logging operation")</p>	- Exclude Social Sciences
Pre	Google Scholar	<p>(("pre-logging" OR "pre-harvest" OR "prior to logging") AND (liana OR vine) AND (removal</p>	-

		OR cut OR cutting OR liberation) OR "thinning operation") OR RIL OR "reduced impact logging" OR "planned logging" OR "FSC certified" OR "silviculture treatment"	
<p>^a Any further filtering applied to the search results after using the indicated search string.</p>			

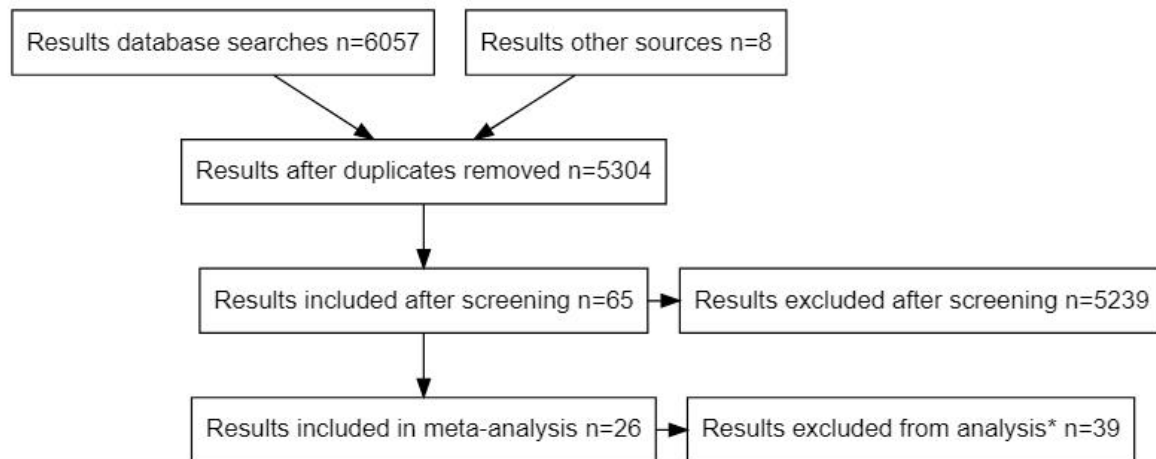
1847

1848 **Table S5: Inclusion criteria.**

PICO ^a	Inclusion criteria
Population	<p>Tropical (latitudes between 26°C North and South, inclusive)</p> <p>Selectively logged (i.e., never fully clear-cut), secondary (clear-cut and regrowth) and undisturbed forest</p> <p>Natural forest system, i.e., not the following:</p> <ul style="list-style-type: none"> ○ Tree plantation ○ Vineyard <p>Not mangrove forest</p> <p>Experimental removal of climbers; not modelling paper</p>
Intervention	<p>Climber removal (by any method such as cutting with machete or poisoning) explicitly applied</p>
Comparator	<p>Control sites in tropical forest with the same level of disturbance in which no climber removal was applied</p>
Outcome	<p>Tree growth (diameter, basal area, biomass, height, etc.)</p>

^a PICO elements are used to structure a search strategy and eligibility criteria aimed at answering a specific question (Livreil et al., 2017).

1849



1850

1851 **Figure S12:** Flow chart illustrating literature search and screening process

1852 *These 39 results were excluded for the following reasons: additional vegetation management,
 1853 duplicated data, not useful tree growth metric, mean growth data unavailable for climber removal and/or
 1854 control treatments.

1855 **Table S6: Studies not included in meta-analysis after data extraction and full text assessment.**

Author and year	Excluded reason category	Reason, full
<i>Cardoso et al 2014</i>	Additional vegetation removal	Additional silvicultural treatment other than just climber or understory removal (e.g., thinning of competing trees or planting of seedlings)
<i>Heuberger et al 2002</i>		
<i>Pena-Claros et al 2002</i>		
<i>Putz et al 1984</i>		
<i>Schiotz et al 2006</i>		
<i>Schwartz et al 2013</i>		
<i>Villegas et al 2009</i>		
<i>Guaragiata 1999</i>		
<i>Butarbutar et al 2019</i>		
<i>Coimbra Cordeiro et al 2019</i>		
<i>Oliveria et al (unpublished thesis chapter)</i>		
<i>Minh Quang et al 2020</i>		
<i>Truong et al 2021</i>		
<i>Schnitzer et al 2014</i>	Duplicate data	Only data available (biomass growth) represents the same tree growth (using the same plots and treatments) as <i>Schnitzer et al, 2010</i>
<i>Schnitzer et al 2004</i>		Duplicate data using same plots and treatments as <i>Parren, 2003</i>
<i>Taffarel and de Carvalho et al 2014</i>		Only has growth data for individual species that contribute to overall growth in <i>de Souza et al, 2015</i>

<i>Vatraz et al 2012</i>		Only has growth data for individual species that contribute to overall growth in <i>de Souza et al, 2015</i>
<i>Venturoli and Carvalho et al 2015</i>		Duplicate data from same experimental sites in <i>Freitas Xavier et al, 2017</i>
<i>Venturoli and Franco et al 2015</i>		Duplicate data from same experimental sites in <i>Freitas Xavier et al, 2017</i>
<i>Estrada-Villegas 2019</i>		Duplicate data in <i>Estrada-Villegas et al, 2020</i>
<i>Douglas 1996</i>	Not useful growth metric	Only has data for post-treatment size of tallest tree
<i>Campanello et al 2012</i>	Not useful growth metric: Net growth	Tree growth in basal area of entire plot, could include recruitment
<i>Forshed 2006</i>		Net growth including recruitment and mortality of trees
<i>Forshed et al 2008</i>		Net growth including recruitment and mortality of trees
<i>Mendez-Toribio et al 2019</i>		Net growth including recruitment and mortality of trees
<i>Philipson et al 2020</i>		Net growth including recruitment of trees
<i>Lussetti 2017</i>	Missing mean growth data	-
<i>Okali 1987</i>		
<i>Strugnell 1939</i>		
<i>Vidal et al 2016</i>		
<i>West et al 2014</i>		
<i>Do et al 2019</i>	No control data	Not appropriate controls and sampling to assess impact of liana removal on tree growth
<i>Inada and Widiyatno et al 2017</i>		-
<i>Pena-Claros and Fredericksen et al 2008</i>		

<i>Pena-Claros and Peters et al 2008</i>		
<i>Schulze, 2003</i>		
<i>Vidal et al 2002</i>		
<i>de Avila, 2016</i>		
<i>Roopsind et al 2008</i>		

1856

1857 **Table S7: List of studies included in meta-analysis and summary of study details.**

Study ID	Author & Year	Country	Latitude	Longitude	Elevation (m.a.s.l)	Total rainfall (mm year ⁻¹)	Mean temp (°C)	Dry season length (months)	Disturbance type ^a	Removal before disturbance (months)	Disturbance before removal (months)	Removal number (max) ^b	Removal method ^c
2	Alvarez-Cansino et al 2015	Panama	9.11	-79.85	82	2866	26.3	4	S	NA	660	4	all
33	Campanello et al 2007	Argentina	-25.97	-54.22	255	1883	21.6	0	SL	NA	2	1	all
43	Cesar et al 2016	Brazil	-22.71	-47.63	555	1583	22.4	6	SL	NA	420	3	all
69	Freitas Xavier et al 2017	Brazil	-15.85	-48.96	776	1732	23.7	5	SL	NA	132	0	all
74	Gerwing 2001	Brazil	-3	-50	65	2325	27.8	5	SL	NA	96	1	all
79	Grauel et al 2004	Panama	8.12	-77.87	13	1495	26.8	5	SL	NA	120	0	all
82	Grogan et al 2009	Brazil	-7.83	-50.27	246	1878	26.5	4	SL	NA	48	1	tree centred
86	van der Heijden et al 2015	Panama	9.11	-79.85	82	2896	26.5	4	S	NA	720	13	all
87	van der Heijden et al 2019	Panama	9.11	-79.85	82	2870	26.6	4	S	NA	720	21	all
123	Lussetti et al 2016	Malaysia	4.55	117.03	533	2743	24.7	0	SL	12	NA	0	all
125	Marshall et al 2017	Tanzania	-7.82	36.98	290	1144	21.5	7	SL+S	NA	384	10	tree centred
126	Martinez-Izquierdo et al 2016	Panama	9.11	-79.85	82	2848	26.4	4	S	NA	720	12	all
133	Mills et al 2019	Belize	17.25	-89	80	2048	25.7	3	NA	1	NA	0	tree centred
139	O'Brien et al 2019	Malaysia	5.09	117.64	144	2964	25.7	0	SL	NA	240	1	all
146	Parren 2003	Cameroon	3	10	475	2393	25.4	4	SL+S	9	NA	0	all
177	Schnitzer et al 2010	Panama	9.17	-79.85	86	2943	26.3	4	S	NA	600	27	all

1859 *Table S7 continued:*

Study ID	Author & Year	Country	Latitude	Longitude	Elevation (m.a.s.l)	Total rainfall (mm year ⁻¹)	Mean temp (°C)	Dry season length (months)	Disturbance type(s) ^a	Removal before disturbance (months)	Disturbance before removal (months)	Removal repeats (max) ^b	Removal method ^c
198	de Souza et al 2014	Brazil	-3.62	-48.62	141	2490	28	4	SL	NA	1	0	tree centred
205	Taffarel et al 2014	Brazil	-3.62	-48.62	141	2490	28	4	SL	NA	1	0	tree centred
219	Verwer et al 2008	Bolivia	-15.78	-62.92	233	1133	24.7	6	SL	NA	1	0	tree centred
224	Wright et al 2015	Panama	9.17	-79.85	86	2920	26.3	4	S	NA	720	8	all
226	Perez-Salicrup 2001	Bolivia	-14.75	-62	194	1237	25.7	6	NA	NA	NA	0	all
227	Perez-Salicrup et al 2000	Bolivia	-14.75	-62	194	1347	25.6	6	NA	NA	NA	0	tree centred
246	Estrada-Villegas et al 2020	Panama	9.2	-79.75	198	2871	26.7	4	S	NA	270	4	all
271	Venegas-Gonzalez et al 2020	Brazil	-22.71	-47.63	555	1501	22.3	4	SL	NA	384	0	all
323	Estrada-Villegas et al 2021	Panama	7.43	80.18	73	2296	27.5	2	SL+S	NA	420	4	all

1860 ^a Type of forest disturbance: SL = selectively logged, S = secondary forest (forest regrowth after clear cutting), NA = undisturbed forest1861 ^b Number of times climber removal was repeated1862 ^c Removal of all climbers from the plot/stand (“all”), or removal of climbers from focal trees only (“tree centred”)

1863 **Appendix B: Data extraction and explanatory variables**1864 *Tree growth response data*

1865 We used relative growth rate (RGR) where possible to standardise tree growth by tree size,
 1866 accounting for differences in growth rate across life stages and sizes. Tree growth was typically
 1867 reported as change in diameter (d) at breast height (dbh) (20 studies), but also as change in biomass,
 1868 basal area, or height (six studies). Some studies calculated RGR using equation (1) or (2) below, and
 1869 we calculated RGR using the same equations where possible if RGR was not given. When initial size
 1870 was not available, but the study used a narrow tree size class (e.g., 5-10 cm dbh), RGR was estimated
 1871 using the mid-point of the size class. RGR was not available nor could be estimated for seven studies.
 1872 Whether a study response variable is based on RGR is included in the study quality index (see Table
 1873 2).

$$1874 \quad RGR = \frac{\ln(d_1) - \ln(d_0)}{t_1 - t_0} \quad (1)$$

$$1875 \quad RGR = \left(\frac{1}{d_0}\right) \left(\frac{d_1 - d_0}{t_1 - t_0}\right) \quad (2)$$

1876 d_0 initial diameter/basal area/biomass/height; d_1 final diameter/basal area/biomass/height;

1877 t_0 initial time; t_1 final time.

1878 If a study reported multiple growth rates for individual species or subsets of species, we
 1879 aggregated them to obtain a single mean growth rate per study. Some studies measured the growth of
 1880 the whole tree community in the experimental site, while others only measured a subset of species.
 1881 We included the number of species measured in each study as a covariate. If a study did not state the
 1882 number of species measured, we took the average number of species in the ‘whole community’ or
 1883 ‘subset community’ from the other studies in the meta-analysis (160 and 10 species, respectively).

1884

1885 *Biomass response data*

1886 We quantified the effect of climber removal on biomass from a subset of data that met two criteria: 1)
 1887 the outcome of climber removal on biomass was available or could be calculated, and 2) data was
 1888 from trees 5 cm dbh or greater as they have the greatest contribution to aboveground biomass. This
 1889 resulted in 12 studies. Biomass was already reported in four of these studies, but we calculated
 1890 biomass in the remaining studies from the tree growth data. In studies for which we had individual
 1891 tree diameter measurements (N=5), we estimated the biomass using a pan-tropical allometry for moist
 1892 tropical forests using the equation:

$$1893 \quad AGB = \exp(-2.024 - 0.896E + \log(W) + 2.795 \log(D) - 0.0461[\log(D)]^2) \quad (3)$$

1894 (Chave et al., 2014)

1895 E is a variable that represents climatic factors for each region that constrain the height-diameter
 1896 relationship when height measurements are not available; W is wood density (g cm^3); D is the
 1897 diameter (cm). W was acquired from the global wood density database (Zanne et al., 2009). We used
 1898 wood density specific to species and region where possible, followed by median wood density for
 1899 genus and region, or median wood density for the dataset when species name was missing or did not
 1900 match the wood density database. When individual tree level measurements were unavailable but
 1901 narrow diameter classes were reported (N=3 studies), we estimated change in biomass using the mid-
 1902 point of the reported diameter class.

1903

1904 *Missing data*

1905 We contacted authors when there were missing values for growth rate, variance, sample size, or other
 1906 study design data. If data were still not available but presented in a figure, we extracted values using
 1907 DigitizeIT software (Bormann, 2020). Studies were excluded from analysis if mean tree growth or
 1908 biomass increase was still unavailable. However, we used multiple imputation to estimate missing
 1909 variances following (Kambach et al., 2020)) and using the *mice* R package (van Buuren and
 1910 Groothuis-Oudshoorn, 2011). We imputed missing variance using the linear relationship between

1911 variance, mean growth and sample size because mean and sample size explained a high percentage of
1912 the variance. We ran 10 imputation iterations, generating 10 tree growth and biomass datasets.

1913

1914 *Variables relating to the efficacy of climber removal*

1915 Climate measures were obtained for each study using high-resolution (0.5 x 0.5 degree) data from the
1916 Climate Research Unit (CRU) (Harris et al., 2020). The variables calculated were mean annual
1917 temperature, total annual precipitation, presence of dry season, dry season length (dry season defined
1918 as any month <100mm total rainfall), total dry season precipitation, and mean dry season temperature.
1919 We used the International Centre for Tropical Agriculture (CIAT) dataset to obtain elevation for each
1920 study site, using the site coordinates with a 1 km buffer (Jarvis et al., 2008). All other potential
1921 explanatory variables were extracted directly from the paper.

1922 **Table S8: Criteria for ordinal study quality score.** Study quality is included in models as to
 1923 account for variation due to study design.

Total score and quality category	Score*	Criteria
Low <6	1 1 (0.33 per part)	Sample size <4 Sample area <1000 / #trees <50 Design <ul style="list-style-type: none"> - just post-treatment + not RGR; - >10km between treatment and control plots; - different forest disturbance history in treatment and control plots
Med 6-7	2 2 (0.66 per part)	Sample size 4-10 Sample area 1000-10,000 / #trees 50-100 Design <ul style="list-style-type: none"> - before/after data without RGR (or vice-versa); - 1-10 km between treatment and control plots; - Different disturbance type/ logging type/ secondary forest age between treatment and control plots
High ≥8	3 3 (1 per part)	Sample size >10 Sample area >10,000 / #trees >100 Design <ul style="list-style-type: none"> - before/after design + RGR; - <1km between treatment and control; - no differences in disturbance history between treatment and control

1924 * score of .99 is rounded up. E.g., 7.99 rounds up to 8

1925

1926 **Table S9: Explanatory parameters that could not be included in the tree growth models for**
 1927 **Objective 2 (main nor supplementary models).**

Driver of variation	Parameter	Reason not assessed in Objective 2
Region and climate	Region	Too few studies in each category level / correlated with other variable
	Continent	Too few studies in each category level / correlated with other variable
	KPG Climate Classification	Too few studies in each category level / correlated with other variable
	Seasonality	Too few studies in each category level / correlated with other variable
Forest type and disturbance	Forest disturbance context	Too few studies in each category level / correlated with other variable
	Secondary forest age	Too few studies in secondary forest
	Liana abundance	Too few studies reporting data
	Tree species or functional group	Too few studies reporting data
Liana removal method	LR pre or post disturbance	Too few studies in each category level / correlated with other variable
	Time LR pre disturbance	Too few studies

1928

1929 **Appendix C: Model specifications**

1930 **Table S10: Model specification for quantifying the magnitude of climber removal efficacy**
 1931 **(objective 1) and for assessing drivers of variation in efficacy (objective 2).** All models used SMD
 1932 (standardised mean difference) effect size as response variable, were weighted by 1/SMD variance, and
 1933 included study as random effect. ‘Nuisance’ variables of study quality, number of species used to
 1934 calculate mean growth, and time elapsed between removal and measurement were also included as fixed
 1935 effects in all models.

<i>Objective number</i>	<i>Objective</i>	<i>Response variable</i>	<i>Explanatory variable</i>
Objective 1.1	Quantify magnitude of, and variance in, efficacy of CR to promote tree growth	<ul style="list-style-type: none"> • Tree growth 	<ul style="list-style-type: none"> • <i>None</i>
Objective 1.2	Quantify magnitude of, and variance in, efficacy of CR to promote aboveground biomass accumulation	<ul style="list-style-type: none"> • AGB change 	<ul style="list-style-type: none"> • <i>None</i>
Objective 2.1	Assess the drivers of variation in	<ul style="list-style-type: none"> • Tree growth 	<ul style="list-style-type: none"> • Logged forest (Y/N), • Repeat removal (Y/N), • Elevation,

	efficacy of CR to promote tree growth		<ul style="list-style-type: none"> • Dry season length, • Annual precipitation, • Average temperature • Removal method (remove climbers on focal tree / climbers from entire area)
Objective 2.2a	Assess the drivers of variation in efficacy of CR to promote aboveground biomass accumulation	<ul style="list-style-type: none"> • AGB change 	<ul style="list-style-type: none"> • Repeat removal (number of times repeated)
Objective 2.2b			<ul style="list-style-type: none"> • Repeat removal (Y/N)
Objective 2.2c			<ul style="list-style-type: none"> • Repeat removal (number of times repeated) • Time since disturbance (time between disturbance and treatment)

1936

1937 **Table S11: Supplementary models assessing additional drivers of variation in climber removal**1938 **efficacy for tree growth (objective 2.1) which could not be included in the main model.** Each

1939 model includes an additional explanatory variable that could not be assessed in the objective 2 model

1940 in the main text, highlighted in bold. All models used SMD (standardised mean difference) as

1941 response variable, were weighted by 1/SMD variance and included study as random effect. ‘Nuisance’

1942 variables study quality, number of species used to calculate mean growth and time elapsed between

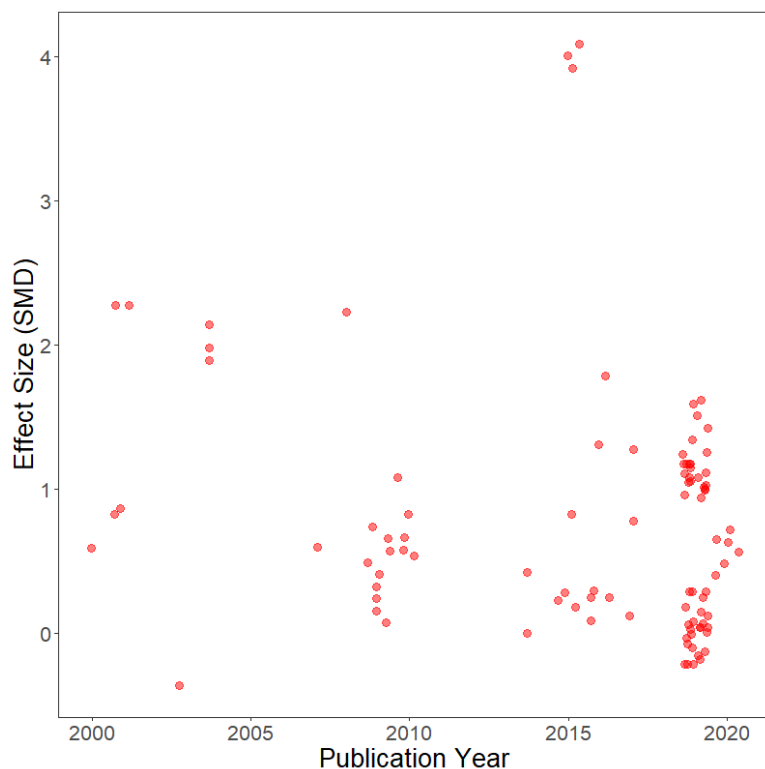
1943 removal and measurement were also included as fixed effects in all models.

<i>Additional variable assessed</i>	<i>Explanatory variable</i>
Latitude	<ul style="list-style-type: none"> • Logged forest (Y/N), • Repeat removal (Y/N),

	<ul style="list-style-type: none"> • Elevation, • Dry season length, • Annual precipitation, • Average temperature • Latitude
Number of times removal repeated	<ul style="list-style-type: none"> • Logged forest (Y/N), • Elevation, • Dry season length, • Annual precipitation, • Average temperature, • Repeat removal (number of times repeated)
Time since disturbance (post-treatment studies only)	<ul style="list-style-type: none"> • Logged forest (Y/N), • Repeat removal (Y/N), • Elevation, • Average temperature, • Time since disturbance (time between disturbance and treatment)
Dry season climate (dry season studies only)	<ul style="list-style-type: none"> • Logged forest (Y/N), • Repeat removal (Y/N), • Elevation, • Dry season length, • Dry season precipitation, • Dry season temperature

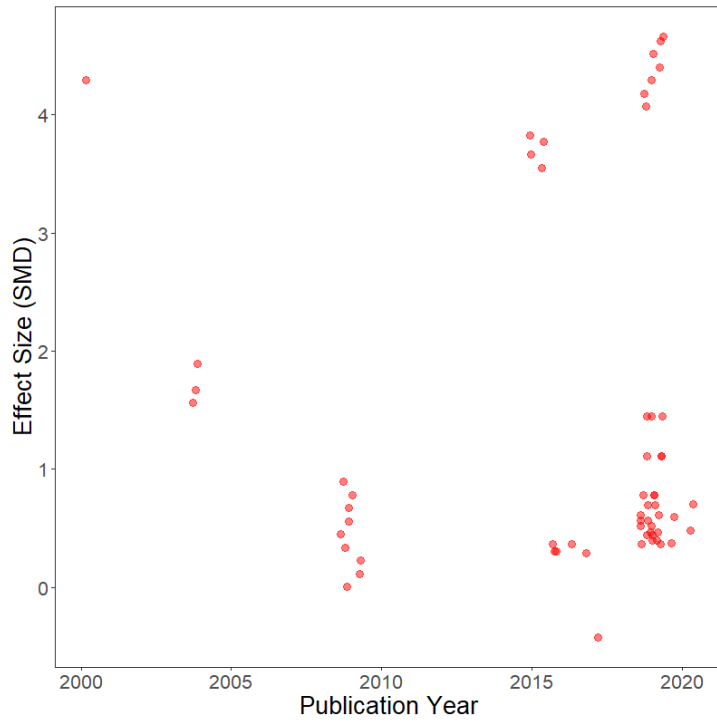
1945 **Appendix D: Additional analyses**1946 *Sensitivity analysis and publication bias*

1947 We found some evidence for publication bias in our meta-analysis. While there was no relationship
 1948 between publication year and effect size for tree growth and biomass analyses (Appendix D, Figure 1,
 1949 2), the funnel plots of effect size against variance were asymmetric (Appendix D, Figure 3, 4), and the
 1950 Eggers test indicates a significant relationship between effect size and variance ($p < 0.01$ and $p <$
 1951 0.0001 for tree growth and biomass, respectively). However, fail-safe numbers indicate that the meta-
 1952 analysis results are robust. According to the Rosenberg and Rosenthal methods, there would need to
 1953 be between 310-560 additional studies with null results to reduce the significance level of the tree
 1954 growth summary effect size to above $\alpha = 0.05$, and 118-294 for the biomass effect size.
 1955 Alternatively, according to the Orwin method, there would need to be 26 and 12 further studies with
 1956 null results to reduce the tree growth and biomass summary effect sizes by half, respectively.



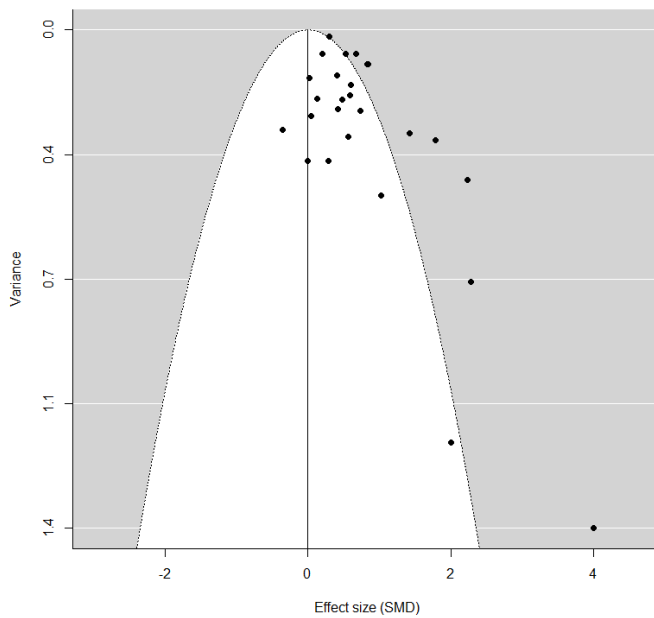
1957

1958 **Figure S13: Relationship between publication year and tree growth effect size.** Publication year is
 1959 plotted against average study tree growth effect size (average of individual effect sizes in each study),
 1960 predicted from growth summary ES model (objective 1.1), to assess publication bias.



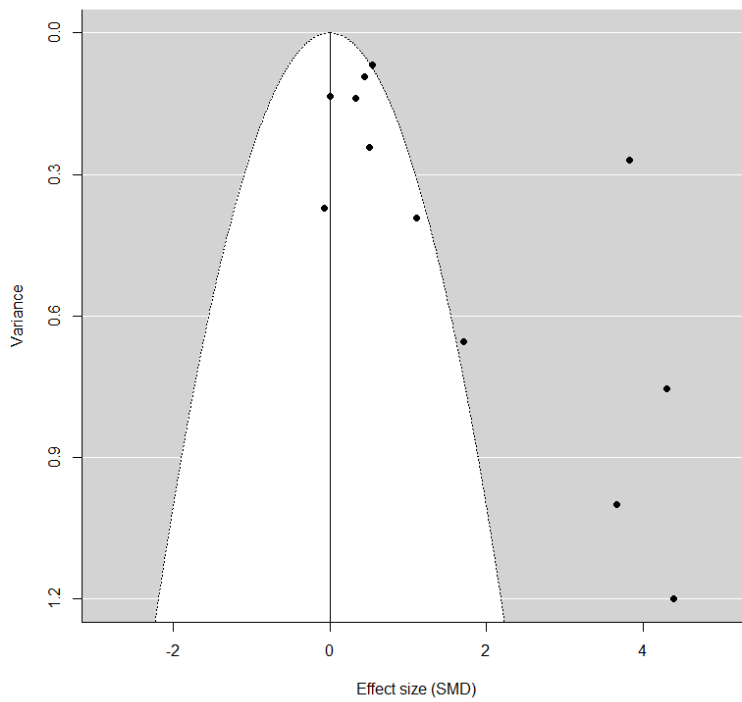
1961

1962 **Figure S14: Relationship between publication year and AGB effect size.** Publication year is
 1963 plotted against average study AGB effect size (average of individual effect sizes in each study),
 1964 predicted from growth summary ES model (objective 1.2), to assess publication bias.



1965

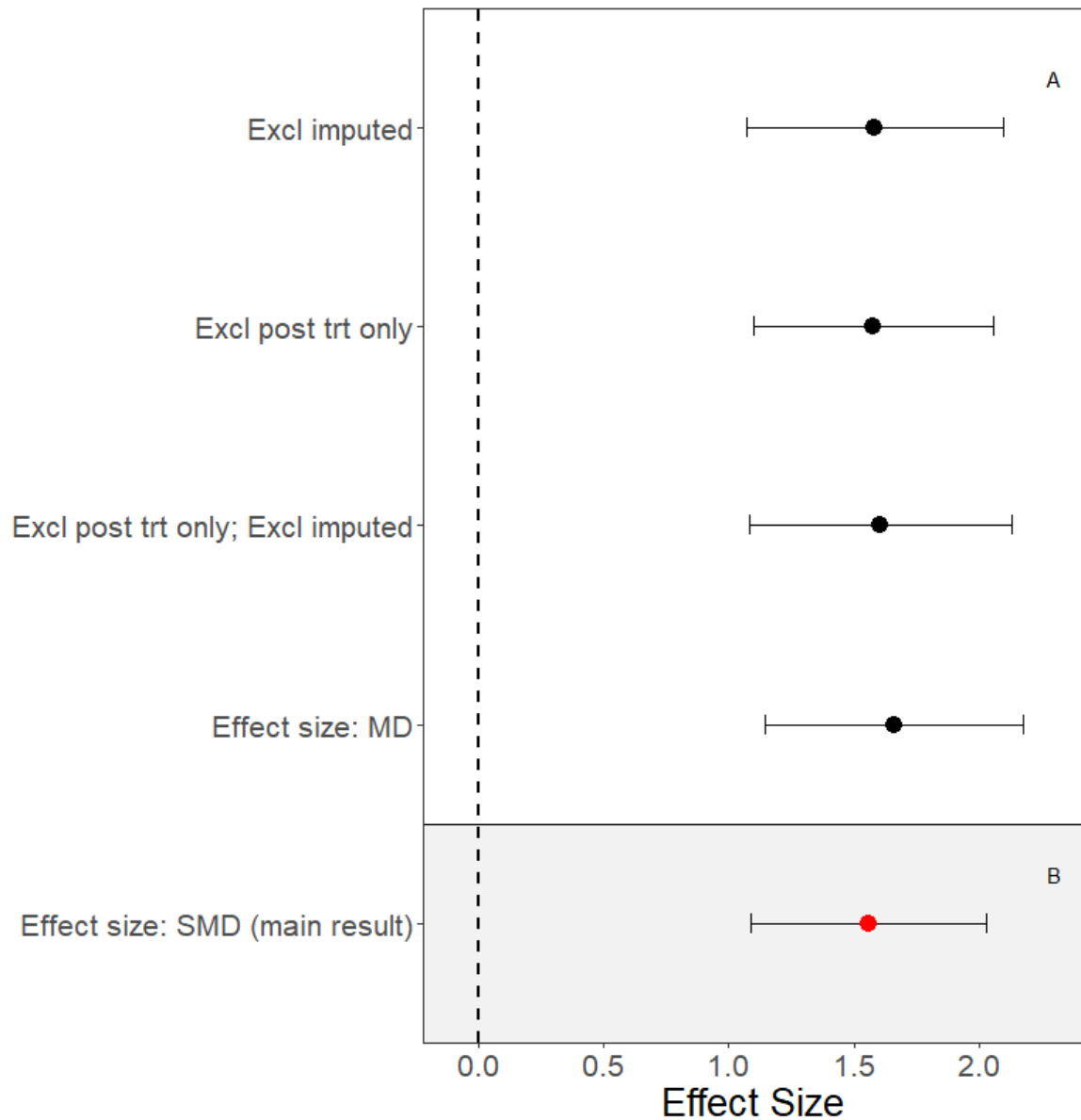
1966 **Figure S15: Funnel plot of study tree growth effect size (SMD) (average of individual effect sizes in**
 1967 **each study predicted from objective 1.1 model) against effect size variance.**



1968

1969 **Figure S16:** Funnel plot of biomass study effect size (SMD) (average of individual effect sizes in

1970 each study predicted from objective 1.2 model) against effect size variance.



1971

1972 **Figure S17:** Efficacy of climber removal for enhancing tree growth depending on data type and effect

1973 size, calculated using model for objective 1.1 (response variable tree growth) with different

1974 combinations of data: a) excluding imputed data, excluding studies with just post-treatment data,

1975 excluding both data, using MD as effect size rather than SMD, b) final tree growth summary effect

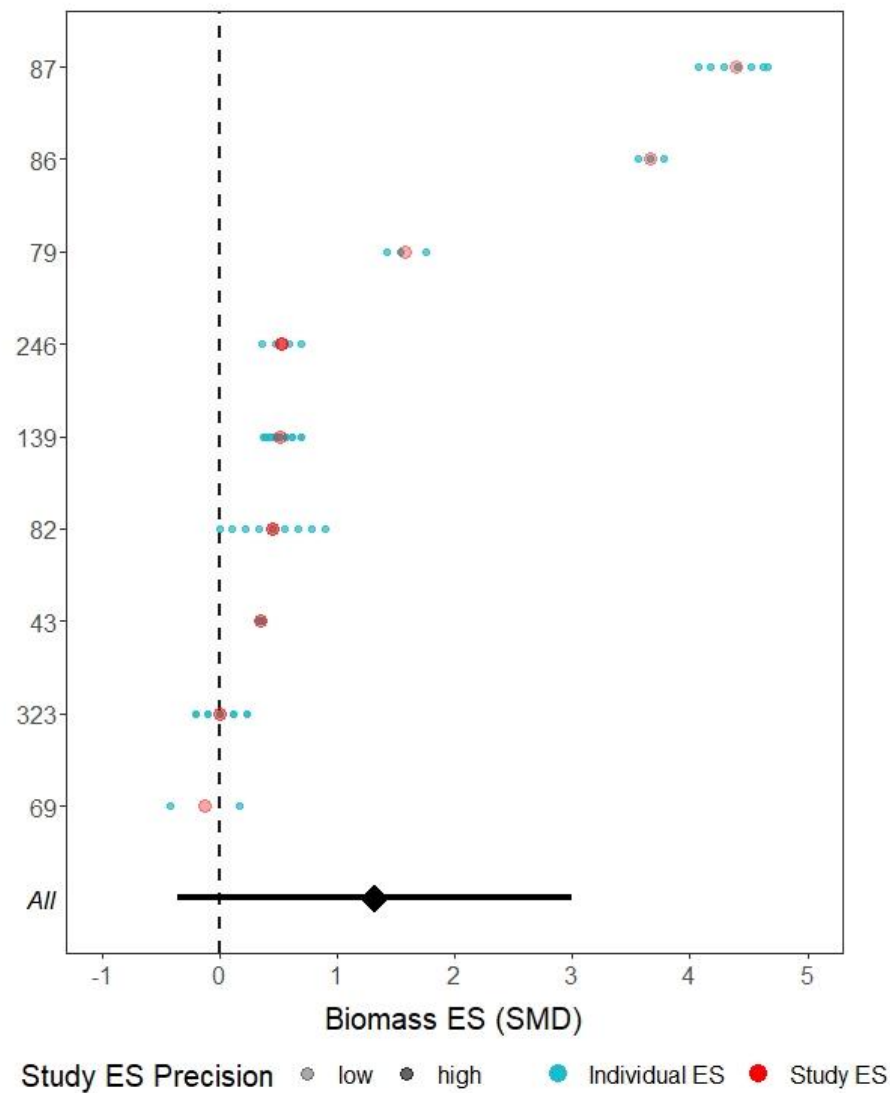
1976 size used in the manuscript: including imputed data calculated using linear regression, studies with

1977 just post-treatment data and using SMD.

1978 **Table S12: Magnitude and direction of climber removal efficacy on tree growth without van der Heijden et al (2015) outlier.** Results of models for
 1979 Objective 1.1 (tree growth) without outlier. ‘Tree growth Effect Size (ES)’ are the intercept of the model and show the number of times greater tree growth
 1980 with climber removal versus untreated control plots. Results are the average of 10 Linear Mixed Models using 10 datasets imputed using linear regression,
 1981 including the study with just post-treatment data (N=25 studies). See Supplementary Information, Appendix C for full description of models. Bolded effect
 1982 sizes indicate level of significance at either 0.05,0.01, or 0.001.

<i>Objective</i>	<i>Fixed effect</i>	<i>Estimate (SE)</i>	<i>Confidence Intervals</i>	<i>Degrees of Freedom</i>
<i>Objective 1.1:</i>	<u>Tree growth ES</u>	1.38 (0.19)***	0.98 – 1.78	27
<i>Tree growth</i>	Study quality High:Low	-1.12 (0.34)**	-1.81 – -0.43	64
	Study quality High:Med	-1.11 (0.14)***	-1.39 – -0.83	86
	<i>Number of species</i>	0.00 (0.00)	0.00 – 0.00	89
	Time elapsed since removal	0.01 (0.00)***	0.00 – 0.01	89

1983 * $p < 0.05$, ** $p < 0.01$. *** $p < 0.001$



1984

1985 **Figure S18:** Overall, individual, and study average effect sizes (ES) of climber removal for promoting
 1986 AGB accumulation, without including imputed data. Blue dots are individual effect sizes within a
 1987 study, predicted from the models for Objective 1.2 and averaged for all imputed datasets. Red circles
 1988 are the study ES (the average of the individual ES); the size of the circle represents precision of the
 1989 study ES and is proportional to the inverse of the variance of the individual effect sizes, averaged by
 1990 study. The black diamond at the bottom of each figure is the overall summary effect size of climber
 1991 removal for promoting tree growth and biomass, taken from the intercept of the models for Objective
 1992 1.2 when continuous covariates are at their mean value and study quality is set to high; error bar
 1993 shows 95% credible intervals.

1994 **Table S13: Additional drivers of variation in the efficacy of climber removal for tree growth.**

1995 Table shows results of supplementary models for objective 2.1, averaged from 10 Linear Mixed

1996 Models using 10 imputed datasets (imputed using linear regression) and including one study with just

1997 post-treatment data (N=26 studies). Response variable is tree growth, see full model details in

1998 Supplementary Information, Appendix C.

<i>Model</i>	<i>Explanatory parameter</i>	<i>Estimate (SE)</i>	<i>Degrees of Freedom</i>
a	<i>Time elapsed since removal</i>	0.28 (0.07)***	85
	<i>Repeat removal (Y/N)</i>	-0.34 (0.20)	91
	<i>Logged forest</i>	-0.30 (0.61)	16
	<i>Dry season length</i>	0.56 (0.38)	16
	<i>Annual precip</i>	0.26 (0.40)	17
	<i>Annual temp</i>	-0.7 (0.27)	18
	<i>Elevation</i>	-0.26 (0.29)	22
	<i>Latitude</i>	-0.03 (0.34)	19
b	<i>Time elapsed since removal</i>	0.21 (0.07)**	84
	<i>Repeat removal (number)</i>	0.12 (0.13)	87
	<i>Logged forest</i>	-0.32 (0.60)	17
	<i>Dry season length</i>	0.39 (0.40)	20
	<i>Annual temp</i>	0.15 (0.27)	21
	<i>Annual precip</i>	0.02 (0.37)	20
	<i>Elevation</i>	-0.04 (0.28)	22
c	<i>Time elapsed since removal</i>	0.31 (0.09)**	60
	<i>Repeat removal (Y/N)</i>	-0.37 (0.23)	68
	<i>Time since disturbance</i>	-0.01 (0.22)	15
	<i>Dry season length</i>	0.53 (0.36)	13
	<i>Elevation</i>	-0.29 (0.32)	14

	<i>Annual temp</i>	-0.01 (0.24)	15
d	<i>Time elapsed since removal</i>	0.17 (0.07)*	43
	<i>Repeat removal (Y/N)</i>	0.04 (0.22)	53
	<i>Logged forest</i>	0.03 (0.54)	14
	<i>Dry season length</i>	0.95 (0.58)	14
	<i>Elevation</i>	-0.29 (0.31)	15
	<i>Dry season annual temp</i>	0.02 (0.34)	15
	<i>Dry season annual precip</i>	-0.15 (0.29)	14

1999 * $p < 0.05$, ** $p < 0.01$. *** $p < 0.001$

2000 SUPPLEMENTARY INFORMATION Chapter 3

2001 **Table S14: List of dates of Sentinel-2 images used within the study.** Representing the first image
 2002 acquisition in study region through until one year after the final block was treated with liana removal

Month Yr	S2 image dates	No. images
Dec 2018	17/12/2018; 22/12/2018	2
Jan 2019	06/01/2019; 11/01/2019; 21/01/2019	3
Feb 2019	10/02/2019; 15/02/2019; 20/02/2019; 25/02/2019	4
Mar 2019	02/03/2019; 07/03/2019; 12/03/2019; 17/03/2019; 22/03/2019; 27/03/2019	6
Apr 2019	06/04/2019; 16/04/2019; 21/04/2019	3
May 2019	06/05/2019; 11/05/2019; 16/05/2019; 26/05/2019; 31/05/2019	5
June 2019	25/06/2019	1
July 2019	20/07/2019; 30/07/2019	2
Aug 2019	14/08/2019; 19/08/2019	2
Sep 2019	08/09/2019; 23/09/2019; 28/09/2019	3
Oct 2019	03/10/2019; 08/10/2019; 13/10/2019; 18/10/2019; 28/10/2019	5
Nov 2019	07/11/2019; 12/11/2019; 17/11/2019; 22/11/2019; 27/11/2019	5
Dec 2019	07/12/2019; 17/12/2019; 22/12/2019; 27/12/2019	4
Jan 2020	06/01/2020	1
Feb 2020	20/02/2020; 25/02/2020	2
Mar 2020	16/03/2020; 21/03/2020; 26/03/2020; 31/03/2020	4
Apr 2020	05/04/2020; 10/04/2020; 15/04/2020; 20/04/2020; 30/04/2020	5
May 2020	05/05/2020; 10/05/2020; 15/05/2020; 30/05/2020	4
June 2020	04/06/2020; 24/06/2020	2
Jul 2020	14/07/2020; 19/07/2020; 29/07/2020	3
Aug 2020	03/08/2020; 08/08/2020; 23/08/2020; 28/08/2020	4
Sept 2020	02/09/2020; 07/09/2020; 12/09/2020; 27/09/2020	4
Oct 2020	02/10/2020; 07/10/2020	2
Nov 2020	06/11/2020; 16/11/2020	2

2003

2004

2005 **Other satellite imagery and metrics**

2006 We calculated three additional vegetation indices to verify results in the main text that are based on
 2007 NBR. The greenness index (GI) was used as it focuses solely on leaf pigments and correlates with
 2008 liana infestation (Chandler et al., 2021b), normalized difference vegetation index (NDVI) includes
 2009 spectral bands that are influenced by leaf pigment, indicating the “greenness” of the canopy (Huete et
 2010 al., 1997), and enhanced vegetation index (EVI) is similar to NDVI but optimises the vegetation
 2011 signal in high plant biomass regions (Huete et al., 1997). Lower values of GI, NDVI, and EVI within
 2012 forests indicate lower concentrations of leaf pigments and signal fewer photosynthetically active
 2013 leaves in the canopy, canopy gaps, or leaves with lower pigment content. We calculated GI, NDVI,
 2014 and EVI using equations S1-S3, below. As remnant clouds and cloud shadows impacted the
 2015 calculation of EVI, NDVI, and GI, we excluded pixels with EVI, NDVI, and GI values less than the
 2016 lower 99% confidence interval pre-treatment (Table S2). We calculated the median and proportion of
 2017 canopy with decrease in these three additional indices.

2018

$$2019 \quad GI = G/(R+B+G) \quad (S1)$$

$$2020 \quad NDVI = (N-R)/(N+R) \quad (S2)$$

$$2021 \quad EVI = 2.5 (N-R)/((N+6R-7.5B)+1) \quad (S3)$$

2022 *Letters indicate spectral reflectance bands: G = green (560 nm); R = red (664.5 nm); B = blue (496.6*
 2023 *nm); N = near-infrared (835.1 nm).*

2024

2025 We also explored different summary metrics for each vegetation index, including minimum
 2026 NBR to verify the effect of liana removal on median NBR. We expected minimum NBR to have a
 2027 larger response to liana removal than median NBR, but we focus the results of the manuscript on
 2028 median NBR due to the lower variation in this summary statistic. This metric was calculated by
 2029 creating a mosaic of the minimum NBR value per pixel across all S2 images in each month post-
 2030 treatment. This was summarised per treatment block, resulting in the median minimum NBR pixel
 2031 value per treatment block per month post-treatment. We also found that there was a clearer signal of
 2032 liana removal when comparing the proportion of pixels with >5% change in NBR than the proportion
 2033 of pixels with more than z-score change between treatment and control blocks.

2034 There was no visual signal of liana removal in radar (Sentinel-1), so we did not pursue this
 2035 remote sensing data. Liana removal was more visible with Sentinel-2 than with Landsat 8, and we

2036 thought that the higher resolution S2 data would be more suited to detecting liana removal, so we
 2037 focussed on S2 images.

2038

2039 **Table S15: Mean and confidence intervals of three vegetation indices before treatment to**
 2040 **calculate cloud filters for Google Earth Engine.** Data are shown for Surface Reflectance Sentinel-2
 2041 data (SR) [used in the study] and Top of Atmosphere Sentinel-2 data (TOA), using a 150 m buffer
 2042 around cloud pixels, no buffer [used in the study], or the in-built cloud buffer for TOA.

Index S2	Mean	SE	Lower 99% CI	Upper 99% CI
EVI SR; 150m buffer	0.328695	0.003679	0.319195	0.338195
EVI SR; No buffer	0.31591	0.00259	0.309231	0.322589
EVI TOA; in-built cloud mask	0.332972	0.00168	0.328643	0.337301
NDVI SR; 150m buffer	0.787811	0.001918	0.782858	0.792764
NDVI SR; No buffer	0.715604	0.002671	0.708716	0.722492
NDVI TOA; in-built cloud mask	0.489484	0.002663	0.482621	0.496347
GI SR; 150m buffer	0.40213	0.001084	0.399331	0.40493
GI SR; No buffer	0.383332	0.000694	0.381541	0.385122
GI TOA; in-built cloud mask	0.331781	0.00016	0.33137	0.332192

2043

2044

2045 **Table S16: Effect of different intensities of removal (60, 80, 100%) on the canopy across 1- and**
 2046 **12- months post treatment in terms of median NBR, proportion of the canopy with decreased**
 2047 **NBR (“Prop decr NBR”), intact patch size (“Area intact patch”), and aggregation (“Agg intact**
 2048 **patch”).** Table gives the coefficient for the difference between each intensity of liana removal and
 2049 control, the difference between removal treatments, and, where significant, the influence of rain. 1-
 2050 month coefficients are from linear mixed effects models, and 12-month coefficients are from
 2051 generalized additive models. Response variables are normalized prior to running models. Row and
 2052 column fixed effects are not presented but did absorb some variation.

Months post treatment	Metric	Contract / fixed effect	Estimate	SE	P-value
1	Median NBR	60 - 0	-0.58	0.164	0.003
	Median NBR	80 - 0	-0.59	0.164	0.002
	Median NBR	80 - 60	-0.01	0.155	> 0.999
	Median NBR	100 - 0	-1.03	0.163	< 0.001
	Median NBR	100 - 60	-0.45	0.155	0.022
	Median NBR	100 - 80	-0.43	0.154	0.028
	Prop decr NBR	100 - 0	1.81	0.142	< 0.001
	Prop decr NBR	60 - 0	1.13	0.142	< 0.001
	Prop decr NBR	60 - 100	-0.68	0.132	< 0.001
	Prop decr NBR	80 - 0	1.32	0.139	< 0.001
	Prop decr NBR	80 - 100	-0.48	0.131	0.002
	Prop decr NBR	80 - 60	0.20775	0.131	0.433
	Prop decr NBR	Rain	0.03	0.008	< 0.001
	Area intact patch	100 - 0	-1.07	0.185	< 0.001
	Area intact patch	60 - 0	-0.70	0.185	0.001
	Area intact patch	60 - 100	0.37	0.173	0.150
	Area intact patch	80 - 0	-0.82	0.182	< 0.001
	Area intact patch	80 - 100	0.25	0.172	0.474
	Area intact patch	80 - 60	-0.12	0.172	0.902
	Area intact patch	Rain	-0.03	0.010	0.006
Agg intact patch	100 - 0	-0.85	0.188	< 0.001	
Agg intact patch	60 - 0	-0.61	0.189	0.009	
Agg intact patch	60 - 100	0.24	0.177	0.537	
Agg intact patch	80 - 0	-0.62	0.187	0.006	

	Agg intact patch	80 - 100	0.23	0.176	0.569
	Agg intact patch	80 - 60	-0.01	0.176	> 0.999
12	Median NBR	100 - 0	-0.48	0.037	< 0.001
	Median NBR	60 - 0	-0.30	0.037	< 0.001
	Median NBR	60 - 100	0.18	0.038	< 0.001
	Median NBR	80 - 0	-0.32	0.037	< 0.001
	Median NBR	80 - 100	0.15	0.038	< 0.001
	Median NBR	80 - 60	-0.02	0.038	0.929
	Prop decr NBR	100 - 0	0.64	0.039	< 0.001
	Prop decr NBR	60 - 0	0.41	0.039	< 0.001
	Prop decr NBR	60 - 100	-0.23	0.037	< 0.001
	Prop decr NBR	80 - 0	0.51	0.039	< 0.001
	Prop decr NBR	80 - 100	-0.13	0.037	0.003
	Prop decr NBR	80 - 60	0.10	0.037	0.030
	Area intact patch	100 - 0	-0.18	0.043	< 0.001
	Area intact patch	60 - 0	-0.08	0.043	0.294
	Area intact patch	60 - 100	0.11	0.042	0.054
	Area intact patch	80 - 0	-0.05	0.043	0.619
	Area intact patch	80 - 100	0.13	0.042	0.010
	Area intact patch	80 - 60	0.02	0.041	0.940
	Agg intact patch	100 - 0	-0.19945	0.042806	< 0.001
	Agg intact patch	60 - 0	-0.0711	0.043257	0.354
Agg intact patch	60 - 100	0.128347	0.040947	0.009	
Agg intact patch	80 - 0	0.041312	0.042686	0.768	
Agg intact patch	80 - 100	0.240762	0.040876	< 0.001	
Agg intact patch	80 - 60	0.112415	0.040896	0.031	

2053

2054 **Table S17: Effect of different intensities of liana removal (60, 80, 100%) on the canopy across 1-**
2055 **and 12-months post treatment in terms of proportion of the canopy with decreased NBR (“Prop**
2056 **decr NBR”), intact patch size (“Area intact patch”) and aggregation (“Agg intact patch”), using**
2057 **the 10% threshold for change in NBR.** Table gives the coefficient for the difference between each
2058 intensity of liana removal and control, the difference between removal treatments, and, where
2059 significant, the influence of rain and liana load. 1-month coefficients are from linear mixed effects
2060 models, and 12-month coefficients are from generalized additive models. Response variables are

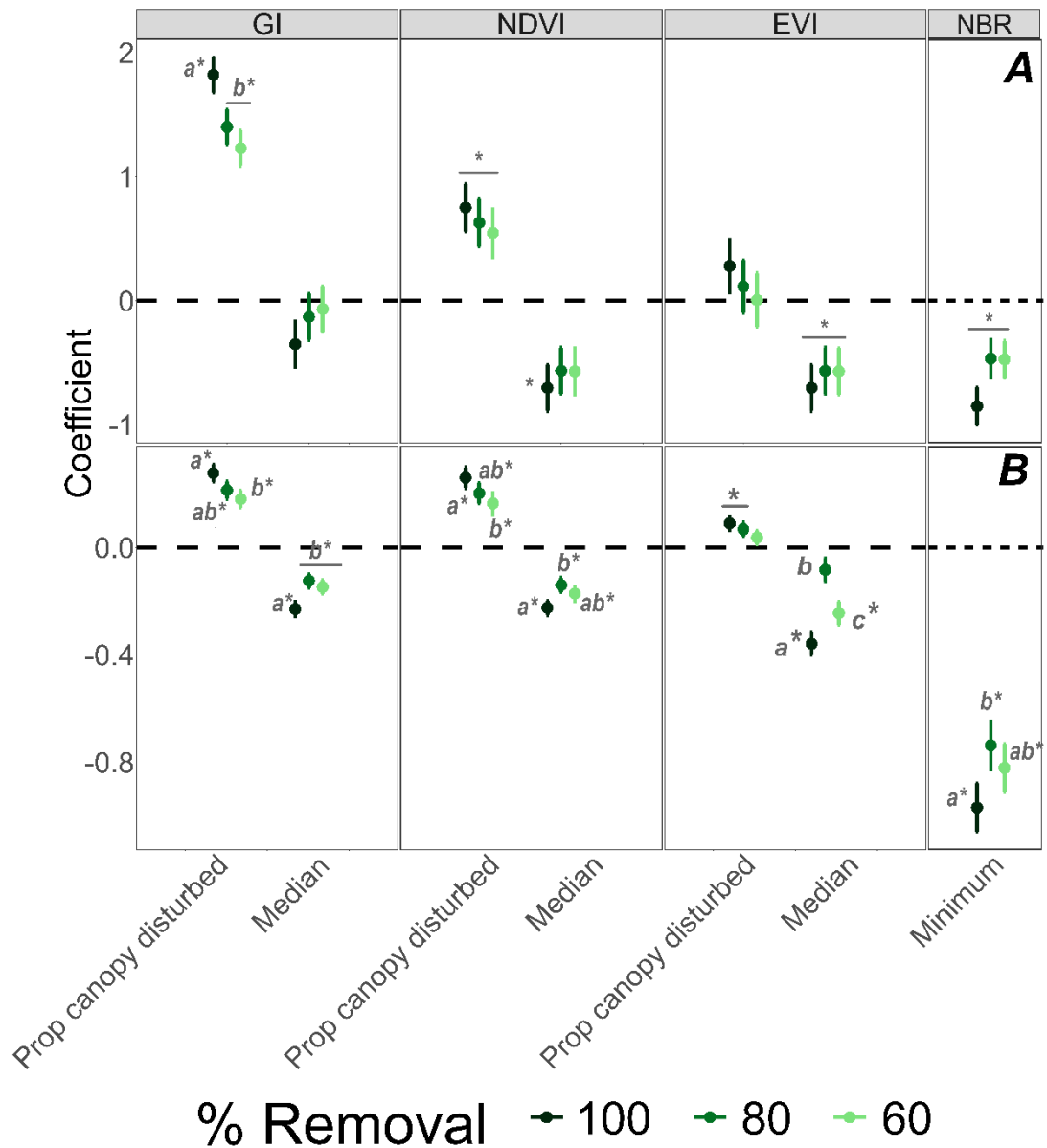
2061 normalized prior to running models. Row and column fixed effects are not presented but absorbed
 2062 some variation.

2063

Months post treatment	Metric	Contrast / Fixed effect	Estimate	SE	P-value
1	Prop decr NBR	100 - 0	1.87	0.152	< 0.001
	Prop decr NBR	60 - 0	1.27	0.152	< 0.001
	Prop decr NBR	60 - 100	-0.60	0.136	< 0.001
	Prop decr NBR	80 - 0	1.46	0.149	< 0.001
	Prop decr NBR	80 - 100	-0.41	0.135	0.014
	Prop decr NBR	80 - 60	0.19	0.135	0.509
	Prop decr NBR	Rain	0.03	0.008	< 0.001
	Area intact patch	100 - 0	-1.15	0.187	< 0.001
	Area intact patch	60 - 0	-1.03	0.186	< 0.001
	Area intact patch	60 - 100	0.13	0.174	0.882
	Area intact patch	80 - 0	-1.08	0.184	< 0.001
	Area intact patch	80 - 100	0.08	0.174	0.971
	Area intact patch	80 - 60	-0.05	0.173	0.991
	Area intact patch	Rain	-0.03	0.010	0.003
	Agg intact patch	100 - 0	-1.22	0.184	< 0.001
	Agg intact patch	60 - 0	-0.92	0.184	< 0.001
	Agg intact patch	60 - 100	0.30	0.171	0.299
	Agg intact patch	80 - 0	-0.96	0.181	< 0.001
	Agg intact patch	80 - 100	0.23	0.171	0.444
	Agg intact patch	80 - 60	-0.05	0.170	0.993
Agg intact patch	Rain	-0.02	0.010	0.015	
12	Prop decr NBR	100 - 0	0.59	0.045	< 0.001
	Prop decr NBR	60 - 0	0.36	0.045	< 0.001
	Prop decr NBR	60 - 100	-0.23	0.042	< 0.001
	Prop decr NBR	80 - 0	0.41	0.045	< 0.001
	Prop decr NBR	80 - 100	-0.19	0.041	< 0.001
	Prop decr NBR	80 - 60	0.04	0.042	0.740
	Area intact patch	100 - 0	-0.22	0.042	< 0.001
	Area intact patch	60 - 0	-0.16	0.042	0.001
	Area intact patch	60 - 100	0.066	0.040	0.359

Area intact patch	80 - 0	-0.12	0.042	0.024
Area intact patch	80 - 100	0.10	0.040	0.050
Area intact patch	80 - 60	0.04	0.040	0.788
Area intact patch	Liana load	-0.45	0.211	0.033
Agg intact patch	100 - 0	-0.26	0.041	< 0.001
Agg intact patch	60 - 0	-0.15	0.042	0.002
Agg intact patch	60 - 100	0.11	0.039	0.019
Agg intact patch	80 - 0	-0.09	0.041	0.154
Agg intact patch	80 - 100	0.18	0.039	< 0.001
Agg intact patch	80 - 60	0.06	0.039	0.393
Agg intact patch	Liana load	-0.46	0.207	0.026

2064



2065

2066 **Figure S19:** Effects of different intensities of liana removal (60, 80, and 100% removal) on median
 2067 GI, NDVI, and EVI, the proportion of the canopy with decrease in GI, NDVI, and EVI, and minimum
 2068 NBR. These metrics are detected from S2 images acquired during 1-month (A) and 12-months (B)
 2069 post-treatment. Points show coefficients of treatment intensities from linear models in A, and from
 2070 GAMs in (B); response variables are normalized prior to running models. The dotted line shows
 2071 control, 0% removal; coefficients below the line indicate a decrease compared to control, and above
 2072 the line indicate an increase compared to control. Different grey letters indicate a significant
 2073 difference between percentage removal treatments, and “*” indicates removal treatments that are
 2074 significantly different from control (zero). Error bars show standard error.

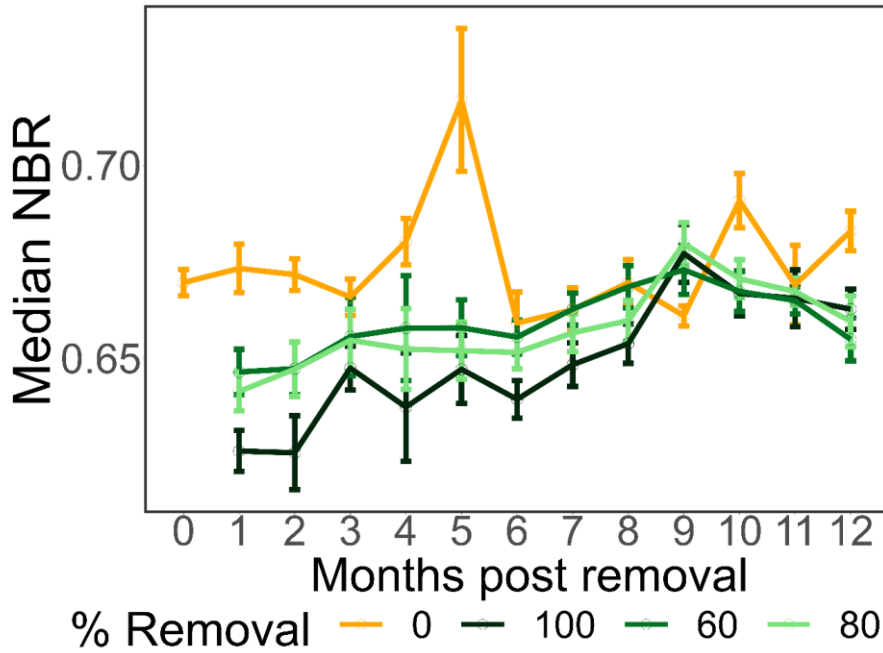
2075

2076 **Table S18: Model summaries for the effect of different intensities of removal (60, 80, 100%) on**
 2077 **the canopy across 1- and 12-months post treatment in terms of minimum NBR, median GI,**
 2078 **NDVI, and EVI, and the proportion of the canopy with decreased GI, NDVI, and EVI (“Prop**
 2079 **decr”).** 1-month coefficients are from linear mixed effects models, and 12-month coefficients are
 2080 from generalized additive models. Table gives the difference between each intensity of liana removal
 2081 and control, the difference between removal treatments, and the influence of rainfall, when
 2082 significant. Response variables are normalized prior to running models. Row and column fixed effects
 2083 are not presented.

Months post treatment	Metric	Contrast / Fixed effect	Estimate	SE	P-value
1	Minimum NBR	100 - 0	-0.85	0.150	< 0.001
	Minimum NBR	60 - 0	-0.47	0.150	0.009
	Minimum NBR	60 - 100	0.38	0.206	0.259
	Minimum NBR	80 - 0	-0.47	0.151	0.012
	Minimum NBR	80 - 100	0.38	0.207	0.249
	Minimum NBR	80 - 60	0.01	0.207	> 0.999
	Minimum NBR	Rain	0.06	0.006	< 0.001
	Median GI	60 - 0	-0.07	0.185	0.984
	Median GI	80 - 0	-0.13	0.186	0.898
	Median GI	80 - 60	-0.06	0.176	0.984
	Median GI	100 - 0	-0.35	0.184	0.231
	Median GI	100 - 60	-0.28	0.176	0.372
	Median GI	100 - 80	-0.22	0.175	0.588
	Median NDVI	60 - 0	-0.14	0.179	0.861
	Median NDVI	80 - 0	-0.18	0.179	0.747
	Median NDVI	80 - 60	-0.04	0.170	0.995
	Median NDVI	100 - 0	-0.48	0.178	0.039
	Median NDVI	100 - 60	-0.34	0.169	0.193
	Median NDVI	100 - 80	-0.30	0.169	0.291
	Median EVI	60 - 0	-0.57	0.186	0.014
	Median EVI	80 - 0	-0.56	0.187	0.015
	Median EVI	80 - 60	< 0.01	0.177	0.100
	Median EVI	100 - 0	-0.70	0.185	0.001
	Median EVI	100 - 60	-0.13	0.177	0.873
Median EVI	100 - 80	-0.14	0.176	0.861	

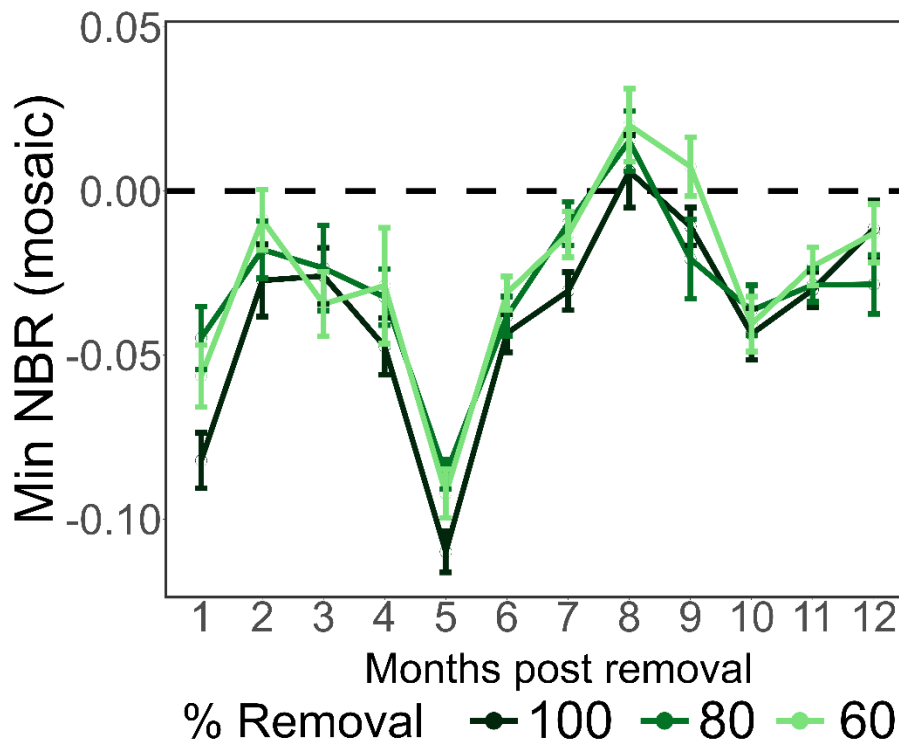
	Prop decr GI	100 - 0	1.82	0.141	<0.001
	Prop decr GI	60 - 0	1.23	0.141	<0.001
	Prop decr GI	60 - 100	-0.59	0.131	<0.001
	Prop decr GI	80 - 0	1.40	0.139	<0.001
	Prop decr GI	80 - 100	-0.42	0.130	0.008
	Prop decr GI	80 - 60	0.17	0.130	0.554
	Prop decr GI	Rain	0.03	0.008	<0.001
	Prop decr NDVI	100 - 0	0.75	0.193	0.001
	Prop decr NDVI	60 - 0	0.55	0.194	0.027
	Prop decr NDVI	60 - 100	-0.20	0.173	0.640
	Prop decr NDVI	80 - 0	0.63	0.191	0.007
	Prop decr NDVI	80 - 100	-0.12	0.172	0.895
	Prop decr NDVI	80 - 60	0.08	0.172	0.963
	Prop decr EVI	100 - 0	0.28	0.211	0.543
	Prop decr EVI	60 - 0	0.01	0.216	0.100
	Prop decr EVI	60 - 100	-0.27	0.201	0.522
	Prop decr EVI	80 - 0	0.11	0.212	0.959
	Prop decr EVI	80 - 100	-0.17	0.196	0.830
	Prop decr EVI	80 - 60	0.11	0.202	0.950
	Prop decr EVI	Rain	-0.04	0.012	0.003
12	Minimum NBR	100 - 0	-0.97	0.090	< 0.001
	Minimum NBR	60 - 0	-0.82	0.091	< 0.001
	Minimum NBR	60 - 100	0.15	0.063	0.0932
	Minimum NBR	80 - 0	-0.74	0.089	< 0.001
	Minimum NBR	80 - 100	0.23	0.064	0.0019
	Minimum NBR	80 - 60	0.08	0.062	0.5223
	Median GI	100 - 0	-0.23	0.026	<0.001
	Median GI	60 - 0	-0.15	0.026	<0.001
	Median GI	60 - 100	0.08	0.026	0.011
	Median GI	80 - 0	-0.12	0.026	<0.001
	Median GI	80 - 100	0.11	0.026	<0.001
	Median GI	80 - 60	0.02	0.026	0.809
	Median GI	Rain	0.38	0.170	0.0248
	Median NDVI	100 - 0	-0.22	0.027	<0.001
	Median NDVI	60 - 0	-0.17	0.027	<0.001

Median NDVI	60 - 100	0.05	0.028	0.224
Median NDVI	80 - 0	-0.14	0.027	<0.001
Median NDVI	80 - 100	0.08	0.028	0.012
Median NDVI	80 - 60	0.03	0.028	0.656
Median NDVI	Rain	0.44	0.178	0.014
Median EVI	100 - 0	-0.36	0.043	<0.001
Median EVI	60 - 0	-0.24	0.043	<0.001
Median EVI	60 - 100	0.11	0.044	0.045
Median EVI	80 - 0	-0.08	0.043	0.209
Median EVI	80 - 100	0.27	0.044	<0.001
Median EVI	80 - 60	0.16	0.043	0.001
Median EVI	Rain	0.90	0.280	0.001
Prop decr GI	100 - 0	0.28	0.032	<0.001
Prop decr GI	60 - 0	0.18	0.033	<0.001
Prop decr GI	60 - 100	-0.10	0.031	0.010
Prop decr GI	80 - 0	0.21	0.032	<0.001
Prop decr GI	80 - 100	-0.06	0.031	0.171
Prop decr GI	80 - 60	0.03	0.031	0.700
Prop decr NDVI	100 - 0	0.26	0.038	<0.001
Prop decr NDVI	60 - 0	0.16	0.039	<0.001
Prop decr NDVI	60 - 100	-0.10	0.036	0.039
Prop decr NDVI	80 - 0	0.20	0.038	<0.001
Prop decr NDVI	80 - 100	-0.06	0.036	0.363
Prop decr NDVI	80 - 60	0.04	0.036	0.723
Prop decr EVI	100 - 0	0.09	0.025	0.002
Prop decr EVI	60 - 0	0.04	0.025	0.439
Prop decr EVI	60 - 100	-0.05	0.024	0.135
Prop decr EVI	80 - 0	0.07	0.025	0.034
Prop decr EVI	80 - 100	-0.02	0.024	0.801
Prop decr EVI	80 - 60	0.03	0.024	0.595



2085

2086 **Figure S20:** Median NBR across 12-months post treatment for all removal intensities and control (0%
 2087 removal). Error bars indicate standard error.

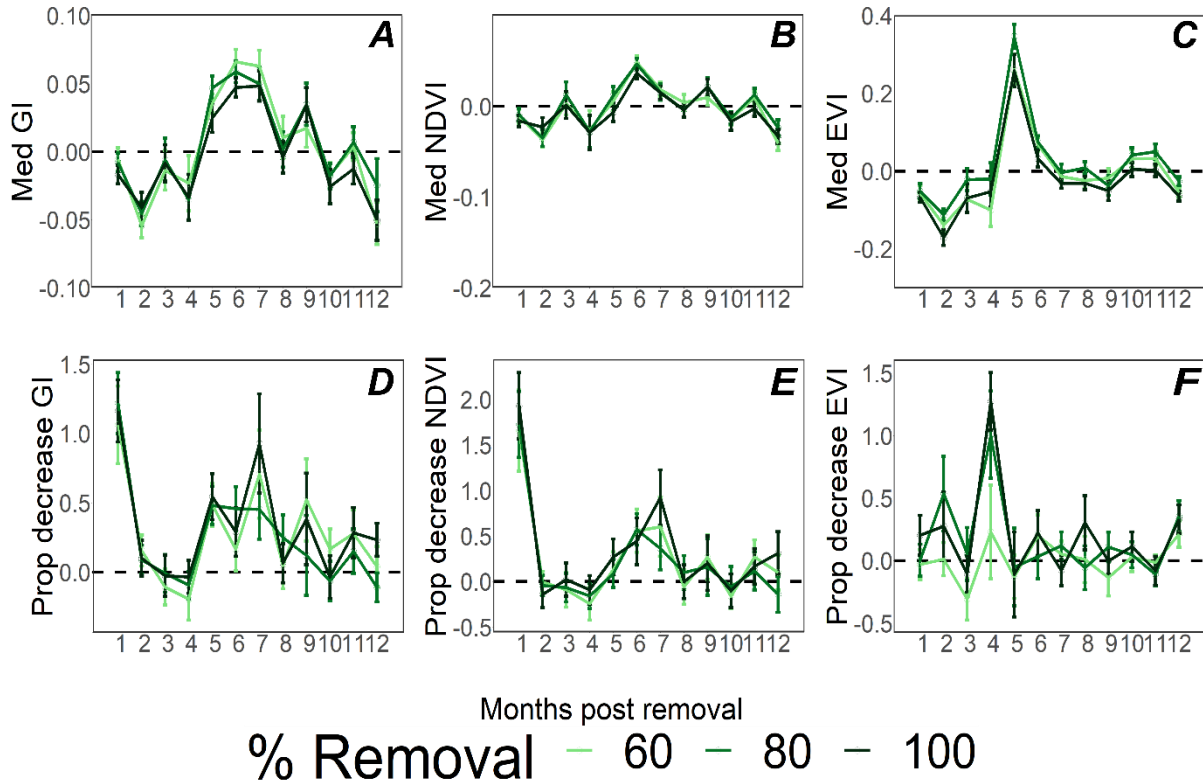


2088

2089 **Figure S21:** Effect of liana removal on minimum NBR over 12-months post-treatment. Green lines
 2090 represent the average minimum NBR for each treatment and month post-treatment, and relative to the
 2091 mean control value at each month (dotted black line at zero). The dotted lines indicate mean values

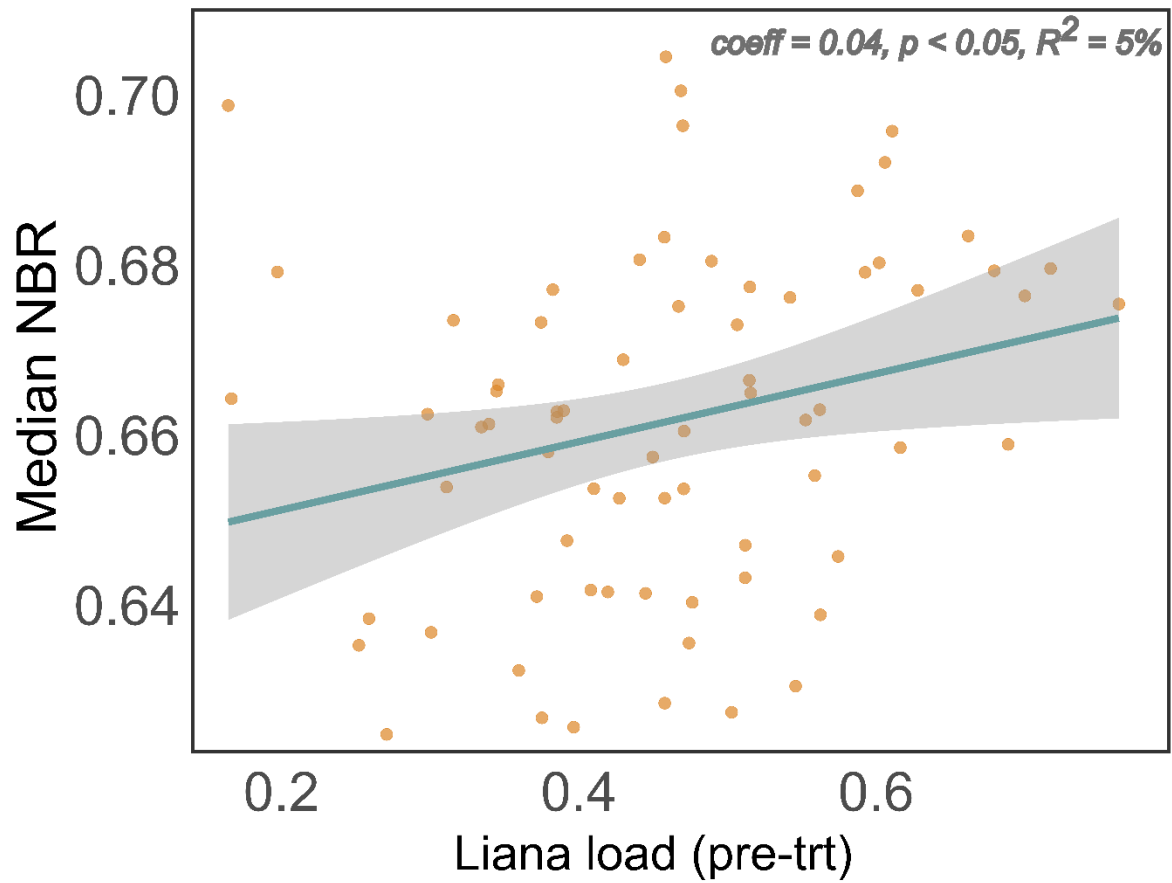
2092 for control blocks, normalised to zero. Values above the line indicate increases relative to control, and
 2093 values below the line indicate decreases relative to control. Error bars show standard error.

2094



2095

2096 **Figure S22:** Impact of climber removal on median GI (A), NDVI (B), and EVI (C) values and on the
 2097 proportion of the canopy with decreased GI (D), NDVI (E), and EVI (F) over 12 months post-
 2098 treatment. Green lines represent the average of each metric for each treatment and month post-
 2099 treatment, and relative to the mean control value at each month (dotted black line at zero). The dotted
 2100 lines indicate mean values for control blocks, normalised to zero. Values above the line indicate
 2101 increases relative to control, and values below the line indicate decreases relative to control. Error
 2102 bars show standard error.



2103

2104 **Figure S23:** Correlation between pre-treatment liana load and median NBR. Coefficient, p-value and
2105 r^2 are calculated using linear regression.

2106 SUPPLEMENTARY INFORMATION Chapter 4

2107 **Table S19: Effect of covariates on minimum NBR and the proportion of the canopy with decreased NBR in generalized additive models, including**
 2108 **supplementary models based on subsets of compartments or data.** Effect given in terms of coefficient estimates for fixed effects, or EDF for smooth
 2109 terms. “Months treated” indicates if model includes subset of treatment compartments that were treated within the smallest time-period. “Images during
 2110 treatment” indicate if model includes Sentinel-2 images that were collecting during the months in which compartments were treated.

<i>NBR metric</i>	<i>Covariate</i>	<i>Months treated¹</i>	<i>Images during treatment²</i>	<i>Estimate</i>	<i>SE</i>	<i>EDF</i>	<i>F</i>	<i>P-value</i>
Minimum NBR	Intercept	all	Y	0.179	0.016			p<0.001
	Trt (Ref:Trt)	all	Y	0.075	0.030			p < 0.05
	Daily precip	all	Y	0.054	0.004			p<0.001
	Compart area	all	Y	-0.198	0.015			p<0.001
	2017 : 2019	all	Y	-0.083	0.011			p<0.001
	2017 : 2020	all	Y	-0.322	0.011			p<0.001
	2017 : 2021	all	Y	-0.315	0.012			p<0.001
	2020 - 2019	all	Y	-0.239	0.009			p<0.001
	2021 - 2019	all	Y	-0.231	0.009			p<0.001
	2021 - 2020	all	Y	0.007	0.010			p = 0.9
	Month	all	Y			10.947	112.594	p<0.001
	Compartment ID	all	Y			199.768	14.468	p<0.001
	Forest reserve	all	Y			<0.001	<0.001	p = 0.6
	Intercept	fewest	Y	0.153	0.018			p<0.001

Trt (Ref:Trt)	fewest	Y	0.103	0.035			p<0.01
Daily precip	fewest	Y	0.049	0.004			p<0.001
Compart area	fewest	Y	-0.196	0.016			p<0.001
2017 : 2019	fewest	Y	-0.030	0.013			p<0.05
2017 : 2020	fewest	Y	-0.282	0.013			p<0.001
2017 : 2021	fewest	Y	-0.273	0.013			p<0.001
2020 - 2019	fewest	Y	-0.253	0.009			p<0.001
2021 - 2019	fewest	Y	-0.243	0.010			p<0.001
2021 - 2020	fewest	Y	0.009	0.010			p = 0.8
Month	fewest	Y			10.938	100.006	p<0.001
Compartment ID	fewest	Y			193.072	13.744	p<0.001
Forest reserve	fewest	Y			<0.001	<0.001	p = 0.6
Intercept	all	N	0.208	0.076			p<0.01
Trt (Ref:Trt)	all	N	0.058	0.113			p = 0.6
Daily precip	all	N	0.054	0.004			p<0.001
Compart area	all	N	-0.197	0.017			p<0.001
2017 : 2019	all	N	-0.083	0.011			p<0.001
2017 : 2020	all	N	-0.322	0.011			p<0.001
2017 : 2021	all	N	-0.314	0.012			p<0.001
2020 - 2019	all	N	-0.239	0.009			p<0.001
2021 - 2019	all	N	-0.231	0.009			p<0.001
2021 - 2020	all	N	0.008	0.010			p = 0.9
Month	all	N			10.987	112.177	p<0.001
Compartment ID	all	N			197.894	15.486	p<0.001
Forest reserve*Trt(R)	all	N			1.845	485.242	p=0.1
Forest reserve*Trt(T)	all	N			1.676	12.640	p=0.1

Proportion of canopy with decrease in NBR	Intercept	all	Y	-0.102	0.045			p<0.05
	Trt (Ref:Trt)	all	Y	-0.148	0.341			p = 0.7
	Daily precip	all	Y	0.010	0.002			p<0.001
	Compart area	all	Y	<0.001	<0.001			p = 0.1
	2017 : 2019	all	Y	0.425	0.036			p<0.001
	2017 : 2020	all	Y	-0.050	0.036			p = 0.1
	2017 : 2021	all	Y	-0.262	0.037			p<0.001
	2020 : 2019	all	Y	-0.474	0.031			p<0.001
	2021 : 2019	all	Y	-0.687	0.037			p<0.001
	2021 : 2020	all	Y	-0.213	0.036			p<0.001
	Trt*Daily precip	all	Y	-0.037	0.011			p<0.001
	Month	all	Y			10.564	72.431	p<0.001
	Compartment ID	all	Y			123.343	1.611	p<0.001
	Forest reserve*Trt(R)	all	Y			<0.001	<0.001	p = 0.5
	Forest reserve*Trt(T)	all	Y			1.878	25.569	p<0.001
	Intercept	fewest	Y	0.049	0.056			p = 0.4
	Trt (Ref:Trt)	fewest	Y	-0.280	0.456			p = 0.5
	Daily precip	fewest	Y	0.011	0.003			p<0.001
	Compart area	fewest	Y	<0.001	<0.001			p = 0.2
	2017 : 2019	fewest	Y	0.310	0.047			p<0.001
	2017 : 2020	fewest	Y	-0.173	0.045			p<0.001
	2017 : 2021	fewest	Y	-0.436	0.047			p<0.001
	Trt*Daily precip	fewest	Y	-0.030	0.013			p<0.05
	2020 : 2019	fewest	Y	-0.483	0.034			p<0.001
	2021 : 2019	fewest	Y	-0.746	0.039			p<0.001
	2021 : 2020	fewest	Y	-0.263	0.037			p<0.001
Month	fewest	Y			10.308	58.818	p<0.001	
Compartment ID	fewest	Y			112.240	1.385	p<0.001	

Forest reserve*Trt(R)	fewest	Y			0.339	0.720	p = 0.2
Forest reserve*Trt(T)	fewest	Y			1.885	10.701	p<0.01
Intercept	all	N	-0.093	0.045			p<0.05
Trt (Ref:Trt)	all	N	-0.170	0.340			p = 0.6
Daily precip	all	N	0.010	0.002			p<0.001
Compart area	all	N	<0.001	<0.001			p = 0.1
2017 : 2019	all	N	0.416	0.036			p<0.001
2017 : 2020	all	N	-0.055	0.036			p = 0.1
2017 : 2021	all	N	-0.272	0.037			p<0.001
2020 : 2019	all	N	-0.471	0.032			p<0.001
2021 : 2019	all	N	-0.688	0.037			p<0.001
2021 : 2020	all	N	-0.217	0.036			p<0.001
Trt*Daily precip	all	N	-0.051	0.013			p<0.001
Month	all	N			10.445	72.090	p<0.001
Compartment ID	all	N			120.516	1.590	p<0.001
Forest reserve*Trt(R)	all	N			<0.001	<0.001	p = 0.5
Forest reserve*Trt(T)	all	N			1.848	20.870	p<0.001

2112

2113 ¹ Indicates whether model includes all compartments in which > 90% of the area was treated within 12 months (“all”), or whether model only included

2114 compartments that were treated within the fewest month in each treatment year (“fewest”: compartments treated within 3 months for those treated in 2017,

2115 2019, and 2020, compartments treated within 6 months for those treated in 2021).

2116 ² Indicates whether model includes all Sentinel-2 images acquired after the first day of the annual quarter in which each compartment was first treated (“Y”),

2117 or only includes Sentinel-2 images acquired after the end of the last annual quarter in which treatment was completed in each compartment (“N”).

2118

2119 **Table S20: Effect of covariates on minimum NBR and the proportion of canopy with decreased NBR in sub-compartment linear mixed effect**

2120 **models.** There are four models per treatment year: (a) does not include sub-compartment as a random effect, (b) includes sub-compartment as random effect,

2121 (c) includes sub-compartment random effect and slope and distance from main roads as fixed effects, and (d) includes sub-compartment random effect and

2122 slope and distance from active roads as fixed effects. Main effect coefficients are shown first, and coefficients for interaction with treatment “Trt (R:T) *” are

2123 shown second. The model covariates *not* underlined and in **bold** are influenced by pseudo-replication and should be interpreted with caution.

<i>NBR metric</i>	<i>Model</i>	<i>Covariate</i>	<i>Estimate</i>	<i>SE</i>	<i>P-value</i>
Minimum NBR	a	Intercept	0.638	0.047	p<0.001
	a	Trt (Ref:Trt)	0.035	0.006	p<0.001
	a	Daily precip	0.005	0.001	p<0.001
	a	Forest reserve (BukP:MFR)	-0.197	0.040	p<0.001
	a	Forest reserve (BukP:USFR)	-0.095	0.043	p<0.05
	a	Trt (R:T) * Daily precip	0.022	0.002	p<0.001
	a	Trt (R:T) * Trt year (2017:2019)	-0.057	0.002	p<0.001
	a	Trt (R:T) * Trt year (2017:2020)	-0.990	0.002	p<0.001
	a	Trt (R:T) * Trt year (2017:2021)	-0.930	0.002	p<0.001
	a	Trt (R:T) * Trt year (2020:2019)	-0.933	0.002	p<0.001
	a	Trt (R:T) * Trt year (2021:2019)	-0.873	0.002	p<0.001
	a	Trt (R:T) * Trt year (2021:2020)	0.060	0.002	p<0.001
	a	Trt (R:T) * Forest res (BukP:MFR)	0.035	0.009	p<0.001
	a	Trt (R:T) * Forest res (BukP:USFR)	-0.054	0.010	p<0.001
	b	Intercept	0.651	0.047	p<0.001
	b	Trt (Ref:Trt)	0.037	0.005	p<0.001
	b	Daily precip	0.006	0.001	p<0.001

b	Forest reserve (BukP:MFR)	-0.194	0.041	p<0.001
b	Forest reserve (BukP:USFR)	-0.090	0.044	p<0.05
b	Trt (R:T) * Daily precip	0.022	0.002	p<0.001
b	Trt (R:T) * Trt year (2017:2019)	-0.058	0.002	p<0.001
b	Trt (R:T) * Trt year (2017:2020)	-0.998	0.002	p<0.001
b	Trt (R:T) * Trt year (2017:2021)	-0.938	0.002	p<0.001
b	Trt (R:T) * Trt year (2020:2019)	-0.940	0.002	p<0.001
b	Trt (R:T) * Trt year (2021:2019)	-0.880	0.002	p<0.001
b	Trt (R:T) * Trt year (2021:2020)	0.060	0.002	p<0.001
b	Trt (R:T) * Forest res (BukP:MFR)	0.032	0.008	p<0.001
b	Trt (R:T) * Forest res (BukP:USFR)	-0.053	0.009	p<0.001
c	Intercept	0.635	0.047	p<0.001
c	Trt (Ref:Trt)	-0.079	0.011	p<0.001
c	Daily precip	0.006	0.001	p<0.001
c	Forest reserve (BukP:MFR)	-0.189	0.042	p<0.001
c	Forest reserve (BukP:USFR)	-0.067	0.045	p = 0.1
c	<u>Slope</u>	-0.028	0.005	p<0.001
c	<u>Dist main rd</u>	-0.006	0.010	p = 0.6
c	Trt (R:T) * Daily precip	0.022	0.002	p<0.001
c	Trt (R:T) * Trt year (2017:2019)	-0.058	0.002	p<0.001
c	Trt (R:T) * Trt year (2017:2020)	-0.998	0.002	p<0.001
c	Trt (R:T) * Trt year (2017:2021)	-0.938	0.002	p<0.001
c	Trt (R:T) * Trt year (2020:2019)	-0.961	0.005	p<0.001
c	Trt (R:T) * Trt year (2021:2019)	-0.862	0.008	p<0.001
c	Trt (R:T) * Trt year (2021:2020)	0.099	0.009	p<0.001
c	<u>Trt (R:T) * Slope</u>	0.038	0.004	p<0.001
c	<u>Trt (R:T) * Dist main rd</u>	-0.036	0.005	p<0.001
d	Intercept	0.515	0.061	p<0.001

	d	Trt (Ref:Trt)	0.017	0.010	p = 0.1
	d	Daily precip	0.006	0.001	p<0.001
	d	Forest reserve (BukP:MFR)	0.052	0.088	p = 0.6
	d	Forest reserve (BukP:USFR)	-0.041	0.045	p = 0.4
	d	<u>Slope</u>	-0.027	0.005	p<0.001
	d	<u>Dist second rd</u>	-0.104	0.033	p<0.05
	d	Trt (R:T) * Daily precip	0.022	0.002	p<0.001
	d	Trt (R:T) * Trt year (2017:2019)	-0.057	0.002	p<0.001
	d	Trt (R:T) * Trt year (2017:2020)	-0.998	0.002	p<0.001
	d	Trt (R:T) * Trt year (2017:2021)	-0.938	0.002	p<0.001
	d	Trt (R:T) * Trt year (2020:2019)	-0.973	0.007	p<0.001
	d	Trt (R:T) * Trt year (2021:2019)	-0.894	0.010	p<0.001
	d	Trt (R:T) * Trt year (2021:2020)	0.080	0.008	p<0.001
	d	<u>Trt (R:T) * Slope</u>	0.037	0.004	p<0.001
	d	<u>Trt (R:T) * Dist second rd</u>	0.031	0.006	p<0.001
	Proportion of canopy with decreased NBR	a	Intercept	-0.191	0.074
a		Trt (Ref:Trt)	-0.320	0.072	p<0.001
a		Daily precip	0.010	0.001	p<0.001
a		Forest reserve (BukP:MFR)	0.148	0.055	p<0.01
a		Forest reserve (BukP:USFR)	0.062	0.059	p<0.05
a		Trt (R:T) * Daily precip	-0.100	0.004	p<0.001
a		Trt (R:T) * Trt year (2017:2019)	0.232	0.004	p<0.001
a		Trt (R:T) * Trt year (2017:2020)	0.066	0.004	p<0.001
a		Trt (R:T) * Trt year (2017:2021)	-0.039	0.004	p<0.001
a		Trt (R:T) * Trt year (2020:2019)	-0.166	0.003	p<0.001
a		Trt (R:T) * Trt year (2021:2019)	-0.270	0.003	p<0.001
a		Trt (R:T) * Trt year (2021:2020)	-0.104	0.003	p<0.001
a		Trt (R:T) * Forest res (Bukp:MFR)	0.227	0.083	p<0.01

a	Trt (R:T) * Forest res (Bukp:USFR)	0.656	0.087	p<0.001
b	Intercept	-0.176	0.074	p<0.05
b	Trt (Ref:Trt)	-0.343	0.071	p<0.001
b	Daily precip	0.009	0.001	p<0.001
b	Forest reserve (BukP:MFR)	0.136	0.054	p<0.05
b	Forest reserve (BukP:USFR)	0.056	0.058	p = 0.3
b	Trt (R:T) * Daily precip	-0.099	0.003	p<0.001
b	Trt (R:T) * Trt year (2017:2019)	0.232	0.004	p<0.001
b	Trt (R:T) * Trt year (2017:2020)	0.065	0.004	p<0.001
b	Trt (R:T) * Trt year (2017:2021)	-0.041	0.004	p<0.001
b	Trt (R:T) * Trt year (2020:2019)	-0.168	0.003	p<0.001
b	Trt (R:T) * Trt year (2021:2019)	-0.273	0.003	p<0.001
b	Trt (R:T) * Trt year (2021:2020)	-0.105	0.003	p<0.001
b	Trt (R:T) * Forest res (Bukp:MFR)	0.255	0.082	p<0.01
b	Trt (R:T) * Forest res (Bukp:USFR)	0.679	0.086	p<0.001
c	Intercept	-0.176	0.079	p<0.05
c	Trt (Ref:Trt)	-0.391	0.082	p<0.001
c	Daily precip	0.009	0.001	p<0.001
c	Forest reserve (BukP:MFR)	0.138	0.062	p < 0.05
c	Forest reserve (BukP:USFR)	0.060	0.067	p = 0.4
c	<u>Slope</u>	0.009	0.004	p<0.05
c	<u>Dist main rd</u>	-0.037	0.009	p<0.001
c	Trt (R:T) * Daily precip	-0.099	0.003	p<0.001
c	Trt (R:T) * Trt year (2017:2019)	0.232	0.004	p<0.001
c	Trt (R:T) * Trt year (2017:2020)	0.065	0.004	p<0.001
c	Trt (R:T) * Trt year (2017:2021)	-0.040	0.004	p<0.001
c	Trt (R:T) * Trt year (2020:2019)	-0.168	0.003	p<0.001
c	Trt (R:T) * Trt year (2021:2019)	-0.273	0.003	p<0.001

c	Trt (R:T) * Trt year (2021:2020)	-0.105	0.003	p<0.001
c	Trt (R:T) * Forest res (Bukp:MFR)	0.061	0.097	p = 0.5
c	Trt (R:T) * Forest res (Bukp:USFR)	0.430	0.103	p<0.001
c	<u>Trt (R:T) * Slope</u>	-0.024	0.007	p<0.001
c	<u>Trt (R:T) * Dist main rd</u>	-0.143	0.022	p<0.001
d	Intercept	-0.074	0.086	p = 0.4
d	Trt (Ref:Trt)	-0.599	0.119	p<0.001
d	Daily precip	0.009	0.001	p<0.001
d	Forest reserve (BukP:MFR)	-0.039	0.092	p = 0.7
d	Forest reserve (BukP:USFR)	0.008	0.062	p = 0.9
d	<u>Slope</u>	0.009	0.004	p<0.05
d	<u>Dist second rd</u>	0.075	0.032	p<0.05
d	Trt (R:T) * Daily precip	-0.099	0.003	p<0.001
d	Trt (R:T) * Trt year (2017:2019)	0.232	0.004	p<0.001
d	Trt (R:T) * Trt year (2017:2020)	0.065	0.004	p<0.001
d	Trt (R:T) * Trt year (2017:2021)	-0.041	0.004	p<0.001
d	Trt (R:T) * Trt year (2020:2019)	-0.168	0.003	p<0.001
d	Trt (R:T) * Trt year (2021:2019)	-0.273	0.003	p<0.001
d	Trt (R:T) * Trt year (2021:2020)	-0.105	0.003	p<0.001
d	Trt (R:T) * Forest res (Bukp:MFR)	0.668	0.181	p<0.001
d	Trt (R:T) * Forest res (Bukp:USFR)	0.730	0.090	p<0.001
d	<u>Trt (R:T) * Slope</u>	-0.030	0.007	p<0.001
d	<u>Trt (R:T) * Dist second rd</u>	-0.176	0.069	p = 0.1

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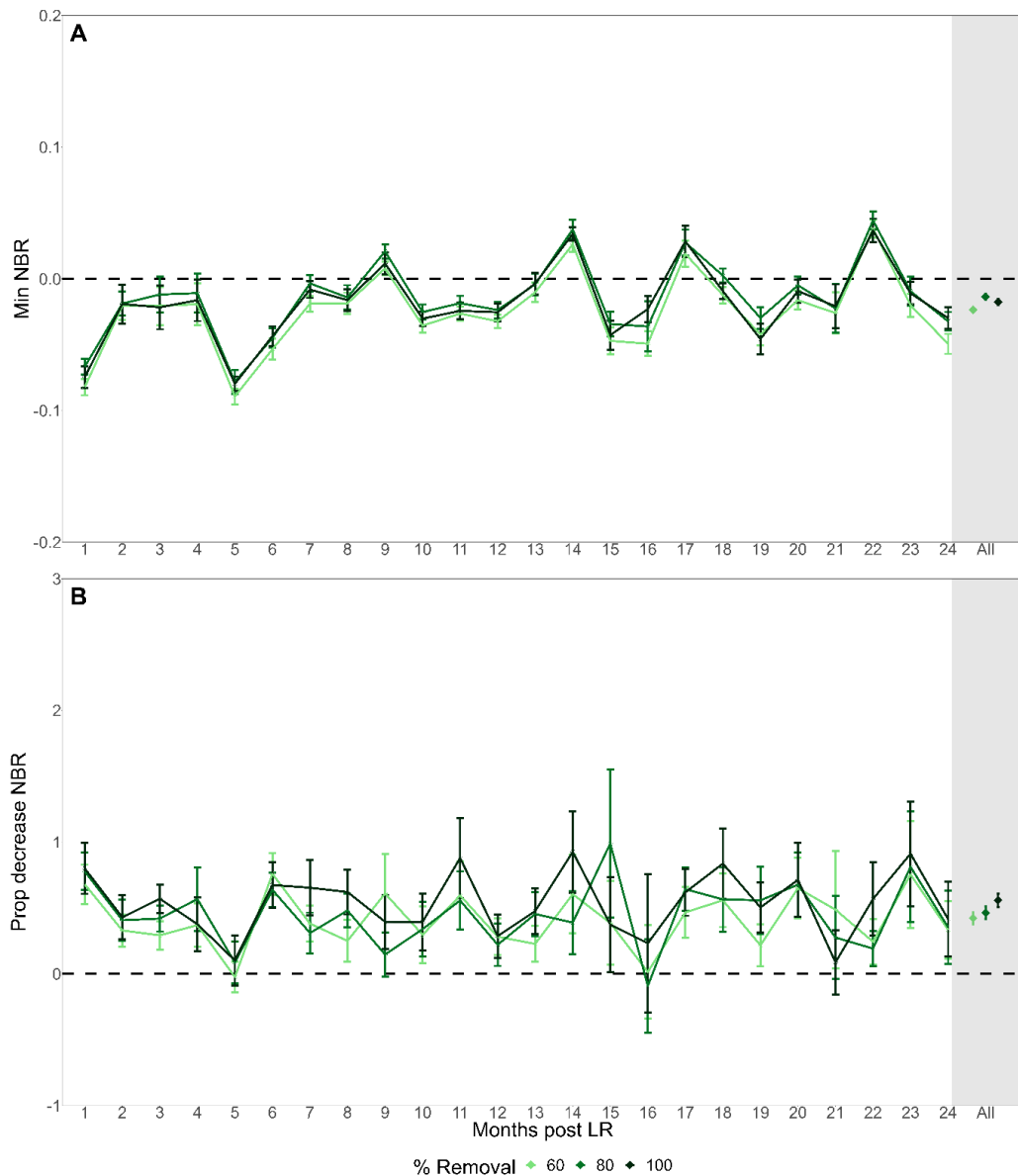


Figure S24: Effect of different intensities of experimental liana removal on minimum NBR (A) and the proportion of the canopy with decreased NBR (B) over 24-months post-treatment. This figure is based on additional Sentinel-2 data acquired for the liana removal experiment in Finlayson and Hethcoat et al (2022). Lines represent predicted values from GAMs, averaged for each removal intensity treatment and month post-treatment, and relative to the mean value for untreated blocks at each month. The dotted lines indicate mean values for untreated blocks, normalised to zero. Values above the line indicate increases in NBR metrics relative to control, and values below the line indicate decreases relative to control. The three points to the far right of each panel are the average over the whole 24 months. Error bars show standard error.

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