

1 **Climate-sensitivity of secondary forests**

2

3 **Assessing the growth and climate sensitivity of secondary forests in highly deforested**

4 **Amazonian landscapes**

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27

## 28 **Abstract**

29 Tropical forests hold 30% of Earth's terrestrial carbon and at least 60% of its terrestrial  
30 biodiversity, but forest loss and degradation are jeopardizing these ecosystems. Although the  
31 regrowth of secondary forests has the potential to offset some of the losses of carbon and  
32 biodiversity, it remains unclear if secondary regeneration will be affected by climate changes such  
33 as higher temperatures and more frequent extreme droughts. We used a dataset of 10 repeated  
34 forest inventories spanning two decades (1999-2017) to investigate carbon and tree species  
35 recovery and how climate and landscape context influence carbon dynamics in an older secondary  
36 forest located in one of the oldest post-Columbian agricultural frontiers in the Brazilian Amazon.  
37 Carbon accumulation averaged  $1.08 \text{ Mg ha}^{-1} \text{ yr}^{-1}$ , while species richness was effectively constant  
38 over the studied period. Moreover, we provide evidence that secondary forests are vulnerable to  
39 drought stress: carbon balance and growth rates were lower in drier periods. This contrasts with  
40 drought responses in primary forests, where changes in carbon dynamics are driven by increased  
41 stem mortality. These results highlight an important climate change-vegetation feedback, whereby  
42 the increasing dry-season lengths being observed across parts of Amazonia may reduce the  
43 effectiveness of secondary forests in sequestering carbon and mitigating climate change. In  
44 addition, the current rate of forest regrowth in this region was low compared with previous pan-  
45 tropical and Amazonian assessments – our secondary forests reached just 41.1% of the average  
46 carbon and 56% of the tree diversity in the nearest primary forests — suggesting that these areas

47 are unlikely to return to their original levels on politically meaningful timescales.

## 48 **Keywords**

49 Amazon, Bragantina region, biodiversity, carbon, climate change, secondary forests

50

## 51 **Introduction**

52 Secondary forests regenerating after land clearance represent > 50% of all tropical forests  
53 (Chazdon et al. 2009), and there is hope that they can cost-effectively mitigate climate change and  
54 biodiversity loss (Chazdon 2014, Lewis et al. 2019) – two of the defining crises of the  
55 Anthropocene (Malhi et al. 2014). For example, secondary forest carbon uptake is estimated to be  
56 11 times higher than that of Neotropical primary forests (Poorter et al. 2016), providing an  
57 estimated global carbon sink of 130 Pg between 2016 and 2100 (Houghton and Nassikas 2018).  
58 Secondary forests can also provide important biodiversity co-benefits in landscapes otherwise  
59 devoid of primary forests or with high levels of deforestation (Vieira and Gardner 2012, Lennox  
60 et al. 2018, Matos et al. 2019). However, to realize their potential to mitigate climate change and  
61 biodiversity loss, tropical secondary forests must be able to recover under novel climatic  
62 conditions.

63 Global climate change is affecting the humid tropics through higher temperatures and  
64 levels of atmospheric CO<sub>2</sub> (Malhi et al. 2014), increases in dry-season length (Fu et al. 2013) and  
65 the frequency and intensity of climate extremes (Brando et al. 2019). These climate changes may  
66 be exacerbated by declines in precipitation and increases in temperature linked to regional  
67 deforestation (Spracklen et al. 2018, Baker and Spracklen 2019). Three types of evidence suggest  
68 tropical secondary forests will be sensitive to these changes. First, primary forest estimates show  
69 a decrease in the carbon sink during extreme droughts (Brienen et al. 2015). Second, large-scale

70 studies of secondary forests indicate a strong effect of climate on the recovery rates of carbon and  
71 biodiversity (Anderson-Teixeira et al. 2013, Poorter et al. 2016, Rozendaal et al. 2019). Third,  
72 longitudinal studies have revealed how droughts modulate recovery speed, increase mortality and  
73 reduce recruitment and growth (Chazdon et al. 2005, Maza-Villalobos et al. 2013, Martínez-  
74 Ramos et al. 2018), due to the negative effects on the water balance and photosynthetic rates of  
75 trees, especially in the earlier stages of succession (Bretfeld et al. 2018).

76         While these studies provide a useful knowledge base, there are some important limitations.  
77 First, secondary forests are likely to be even more sensitive than primary forests to changes in  
78 precipitation (Uriarte et al. 2016) because pioneer species are more vulnerable to embolism  
79 (Markestijn et al. 2011). Second, the large-scale studies that have inferred temporal trends from  
80 spatial data (i.e. the chronosequence approach) are complicated by factors such as species turnover  
81 and natural variation between samples (Johnson and Miyanishi 2008, Norden et al. 2015, França  
82 et al. 2016) and idiosyncratic determinants of recovery (Chazdon et al. 2007, Arroyo-Rodríguez et  
83 al. 2017). Third, most longitudinal studies focus on short-term assessments restricted to a single  
84 drought event (Chazdon et al. 2005, Maza-Villalobos et al. 2013, Bretfeld et al. 2018, Martínez-  
85 Ramos et al. 2018), which cannot detect responses to longer-term increases in temperature or post-  
86 drought growth compensation (Berenguer et al. 2018). Furthermore, the few longer-term studies  
87 relating secondary forest carbon dynamics to climate focus on tropical dry forests (e.g., Álvarez-  
88 Yépiz et al. 2018, Martínez-Ramos et al. 2018), meaning there is a lack of research in humid  
89 tropical regions where species may be even more sensitive to drought (Esquivel-Muelbert et al.  
90 2019).

91         Initiatives such as the Bonn Challenge highlight two additional knowledge gaps linked to  
92 management. It seems likely that the increase in landscape-scale restoration will also increase

93 secondary forest permanence, moving beyond the current situation where secondary forests are  
94 often cleared again within 5-20 years (Aguiar et al. 2016, Reid et al. 2018). Although our current  
95 understanding of younger forests is good (Poorter et al. 2015, 2016, 2019, Martínez-Ramos et al.  
96 2018, Villa et al. 2018, Rozendaal et al. 2019), and the non-linear response of forest recovery over  
97 time is well established (Poorter et al. 2016, Ferreira et al. 2018, Lennox et al. 2018, Requena  
98 Suarez et al. 2019, Rozendaal et al. 2019), there is far too much variation in the relationship to use  
99 young forests to accurately predict recovery rates in older forests. Moreover, the relative recovery  
100 rates of carbon and biodiversity are unclear. While some regional assessments report a tight  
101 coupling at all stages of succession (Lennox et al. 2018), continent-scale assessments suggest a  
102 much faster recovery of biodiversity: plots recovered 80% of tree species richness 20 years after  
103 abandonment (Rozendaal et al. 2019) and only 27% of the carbon stock (Poorter et al. 2016). As  
104 recovery of both carbon and biodiversity are mediated by factors such as stand age and landscape  
105 and local conditions (Jakovac et al. 2015, Magnago et al. 2017, Villa et al. 2018, Ferreira et al.  
106 2018, Lennox et al. 2018, Matos et al. 2019), it is not clear how these rates compare in heavily  
107 deforested landscapes.

108         Here, we address these knowledge gaps by investigating secondary forest recovery in the  
109 Bragantina region, the oldest deforestation frontier in the Brazilian Amazon (Almeida et al. 2010).  
110 We undertook 10 repeated censuses of 3 ha of older secondary forests (~60 years) over 18 years  
111 and addressed four questions: 1) What are the recovery rates of carbon stocks and tree species  
112 richness, and what is the relationship between these measures? 2) Does variation in seasonal  
113 temperature, water stress and landscape context influence carbon dynamics? 3) How does carbon  
114 recovery in the Bragantina region compare to estimates from other tropical regions? 4) What is the  
115 timeframe for carbon to return to typical primary forest levels?

116

## 117 **Methods**

### 118 *Study area and landscape context*

119 Our study focused on the eastern-Amazonian municipality of Bragança (Appendix S1: Fig.  
120 S1). This municipality has lost 90.2% of its native forests and mangrove areas. Secondary forest  
121 covers 28.8% of the landscape, accounting for 67.5% of the total forest cover (including mangrove  
122 areas) (Appendix S1: Fig. S1). Primary and secondary forests (established post-1985) are situated  
123 in small, isolated, and selectively logged fragments (~30 to 60 hectares; MapBiomias 2019).

124 We established three study-plot classes. In 1999, we began inventories in 12 secondary  
125 forest plots (50 x 50 m = 0.25 ha; Appendix S1: Fig. S1, Table S1; hereafter, “*long-term plots*”).  
126 These plots were separated by a mean distance of 265 m (range 70-590 m). In 2017, we established  
127 an additional four secondary forest plots (250 x 10 m = 0.25 ha; hereafter, “*extra plots*”) in different  
128 fragments of the Bragança municipality. In 2017, we also established three plots in primary forests  
129 (250 x 10 m 0.25 ha; Appendix S1: Fig. S1; hereafter “*primary forest plots*”).

130 Both long-term and extra secondary forest plots were abandoned after successive cycles of  
131 slash-and-burn agriculture (for manioc, maize, and rice cultivation). There was no record of  
132 wildfires after agricultural abandonment at our plots. Given that undisturbed primary forests are  
133 extremely rare in the region, to select primary forest plots we conducted interviews with local  
134 people to identify sites that retain the structural characteristics of Amazonian old-growth forests;  
135 nonetheless, it is likely that selective logging and edge effects have already altered our primary  
136 forest plots. All plots were located in *terra-firme* areas. The predominant soils across all plots are  
137 oxisols with low fertility and 15-35% clay in the superficial layers (Da Silva Castro et al. 2013).  
138 Plots were flat, and average elevation was 35 m (range: 30-66 m).

139

140 *Age of secondary forests*

141           We used two approaches to evaluate secondary forest age. The long-term plots are older  
142 than the existing satellite record and were provisionally aged by interviews conducted by the  
143 researchers who established them in 1999. The estimated age in 2017 was c. 48-58 years old.  
144 Unfortunately, Landsat 1 images from the region (1974) were also too cloudy to support these  
145 interviews. We therefore estimated ages by back casting the non-linear growth trajectories  
146 (Question 4). For the extra plots recovering post 1985, we used the MapBiomass 3.1 dataset to  
147 estimate their ages (details in Appendix S1; MapBiomass 2019).

148

149 *Tree censuses*

150           The long-term secondary forest plots were established with a full tree census in 1999, with  
151 repeated surveys taking place annually between 2000-2004 then subsequently in 2006, 2011, 2014  
152 and 2017, while a full tree census was undertaken in the extra and primary forest plots when they  
153 were established in 2017. In all plots, we measured all trees  $\geq 10$  cm diameter at breast height  
154 (DBH). In the last census, we also estimated tree height by visual assessment. Plant identification  
155 was conducted in the field and when necessary botanical samples were collected for comparisons  
156 from the Herbário IAN (Embrapa Amazônia Oriental) collection. Tree census data are available at  
157 ForestPlots.net (Lopez-Gonzalez et al. 2011).

158

159 *Estimation of carbon stocks and tree species richness*

160           We used three approaches to estimate the above-ground biomass (AGB) of individual  
161 stems. First, we calculated AGB using the allometric equation:  $AGB = 0.637 \times (\rho D^2 H)^{0.976}$

162 where  $\rho$  represents tree wood density ( $\text{g cm}^{-3}$ ),  $D$  represents stem DBH (cm) and  $H$  represents stem  
163 height (Chave et al. 2014). Stem wood densities were taken from the Global Wood Density  
164 Database (Chave et al. 2009). We subset the data to entries for South America and used the mean  
165 wood density across entries at the lowest available taxonomic level (e.g. where no data was  
166 available for a species, we used the genus average).

167 To estimate the height of stems for censuses prior to 2017, we used non-linear least-squares  
168 to determine height-DBH relationships at each study plot. Using the 2017 height and DBH values  
169 as training data, we assumed a functional relationship described by the Michaelis-Menten model:  
170  $H = \frac{a \times D}{b \times D}$ , where  $a$  and  $b$  are estimated from the training data. Second, due to potential errors in  
171 the tree height sample caused by our visual assessment approach, we applied correction functions  
172 to the 2017 stem heights then determined pre-2017 tree heights as described above. The height-  
173 correction functions were derived from large primary and second secondary forest tree samples (c.  
174 500 individuals in both forest types) from the eastern Brazilian Amazon for which visual and laser-  
175 based heights were estimated. These data suggest that visual assessments tend to underestimate  
176 stem height, especially stems  $< 15$  m tall in secondary forests (Appendix S1: Fig. S2). Finally, we  
177 also estimated stem biomass using the following allometric equation that does not include a height  
178 parameter:  $AGB = \exp [-1.803 - 0.976E + 0.976 \ln (\rho) + 2.673 \ln (D) - 0.299 \ln (D)^2]$ ,  
179 where  $E$  is a measure of environmental stress, defined by cumulative water deficit and temperature  
180 and precipitation seasonality (Chave et al. 2014).

181 Results across these approaches suggest that use of the uncorrected values of stem height  
182 values underestimates plot-level carbon by around 10-20%, so we do not report results from this  
183 approach. In the main text, we focus on results from the height-corrected estimation technique  
184 because including height is known to improve AGB estimates (Sullivan et al. 2018). However, the



185 height-corrected approach returned highly similar carbon estimates to those obtained using the  
186 allometric equation that does not include height (mean root square difference  $< 1.5 \text{ Mg C ha}^{-1}$ ).  
187 The results for this latter approach can be found in Appendix S1: Fig. S6. We assumed that the  
188 carbon content of the individuals represents 50% of the AGB. Tree species richness (of individuals  
189  $> 10 \text{ cm DBH}$ ) in each plot was assessed by rarefying richness to 100 individuals, the minimum  
190 abundance in the sampled plots.

191

### 192 *Climatological and landscape predictors of carbon dynamics*

193 Monthly precipitation and temperature for each census year were determined using data  
194 collected at a local meteorological station (INMET 2018; Appendix S1: Fig. S1). These data show  
195 that the study region has annual precipitation of 1,850 mm, with a rainy season from December to  
196 July ( $222 \text{ mm month}^{-1}$ ) and a dry season from August to November ( $19.5 \text{ mm month}^{-1}$ ).

197 We calculated three climatological predictors of carbon dynamics: the Standardized  
198 Precipitation Evapotranspiration Index (SPEI; Vicente-Serrano et al. 2010), the Maximum  
199 Climatological Water Deficit (MCWD; Malhi et al. 2009), and the maximum dry season  
200 temperature (MDST). SPEI is a measure of water stress based on the difference between monthly  
201 precipitation and potential evapotranspiration expressed as a standardized index, with negative  
202 values representing drier periods over the timescale considered relative to median values for a  
203 long-term reference time-series. To account for medium-term water deficit, we estimated monthly  
204 SPEI values for a 12-month moving window from May to April. MCWD is the most negative  
205 accumulated value of the climatological water deficit (CWD) over each one-year period (between  
206 May and April; 1973-2017). CWD is defined as monthly precipitation, minus evapotranspiration,  
207 minus the CWD of the previous month (Malhi et al. 2009). MDST was measured as the highest

208 monthly temperature value during the dry season (i.e., between August and November). Finally,  
209 we used edge distance as our predictor of landscape context effects on carbon dynamics. For each  
210 secondary forest plot, edge distance was calculated as the distance from the plot centroid to the  
211 nearest forest edge using images from Google Earth 7.1.7.2600 (earth.google.com).

212

### 213 *Carbon anomalies*

214 We calculated the amount of carbon incorporated by growth (G) and recruitment (R), as  
215 well as that lost by mortality (M) for each census interval, thus obtaining periodic carbon balance  
216 ( $B = G + R - M$ ). We used anomalies to subtract the expected natural carbon accumulation that  
217 occurs through time. Censuses occurred at varying intervals (1, 2, 3 and 5 years). Let  $i \in 1, 2, \dots,$   
218 9 be one of the intervals, let  $T_{-i}$  be the total length of the time series minus the length of interval  
219  $i$ , let  $C_{-i}$  be the change in carbon balance or one of its components over all intervals not including  
220  $i$ , let  $n_i$  be the number of years in interval  $i$ , and let  $a_i$  be the observed change  $C$  in interval  $i$ .  
221 Therefore, the expected change in  $C$  in interval  $i$  is  $E(C_i) = \frac{n_i \times C_{-i}}{T_{-i}}$ , and the anomaly is  $a_i - E(C_i)$ .

222

### 223 *Statistical analysis*

224 We used Bayesian piecewise linear splines to estimate i) carbon recovery with time; ii) tree  
225 species richness recovery with time; and iii) the relationship between carbon and tree species  
226 richness recovery (Question 1). Bayesian model comparison with reversible jump Markov Chain  
227 Monte Carlo simulations (Lunn et al. 2009) was used to average multiple piecewise-linear models  
228 to produce smoothed curvilinear relationships (Thomson et al. 2010). The number and location of  
229 change-points were assigned hierarchical prior distributions that included zero changepoints as a  
230 possibility. In each simulation, the spline function was comprised of up to  $k = 6$  linear

231 coefficients (i.e., between zero and six) and  $k - 1$  corresponding changepoints. The resulting  
232 posterior distributions yielded model-averaged parameter estimates and 95% credible intervals that  
233 account for uncertainties about model structure. The model for long-term secondary forest  
234 recovery included plot-level random effects to account for expected similarities between plots.

235 To explore whether variation in maximum dry season temperature, water stress (SPEI and  
236 MCWD) and landscape context (edge distance) influence tree growth, recruitment, mortality and  
237 carbon dynamics (Question 2), we used Bayesian variable selection with nonlinear covariate  
238 effects (Thomson et al. 2010). We used the lowest recorded value of MCWD in a given period as  
239 our measure of one-off drought severity (see also Esquivel-Muelbert et al. 2019). We used SPEI  
240 values (Vicente-Serrano et al. 2010) as a measure of the longer-term (here 12-month) water  
241 balance, which is known to be significant for tree growth (Greenwood et al. 2017). The relative  
242 importance of an explanatory variable was assessed by the posterior probability of a non-zero  
243 effect. We considered posterior probabilities  $> 0.75$  to be indicative of a statistical association.

244 We compared the average carbon accumulation rates of our secondary forest plots (both  
245 long-term and extra plots) to estimates of carbon accumulation from leading tropical and global  
246 assessments (Bonner et al. 2013, Poorter et al. 2016, Lennox et al. 2018, Requena Suarez et al.  
247 2019) and pan-Amazonian estimates in old-growth and logged primary forests (Brienen et al. 2015,  
248 Rutishauser et al. 2015) (Question 3). To investigate secondary forest recovery timeframes  
249 (Question 4), we fit monotonically increasing and marginally decreasing rational functions, based  
250 on third-order polynomials as the numerator and second-order polynomials as the denominator, to  
251 the median and lower and upper bounds of the 95% credible intervals for carbon levels in the long-  
252 term plots (Fig. 1A).

253

## 254 **Results**

### 255 *Climate variation over the time-series (1972-2017)*

256           The maximum dry season temperature increased by 0.1 °C per decade across our time series  
257 (Appendix S1: Fig. S5). Water stress (MCWD and SPEI values) was highly variable, declined  
258 weakly, and was highest (lowest values of MCWD and SPEI) in strong El-Niño years. MCWD  
259 and SPEI were only weakly related ( $r = 0.44$  across the 1973-2017 time series;  $r = 0.19$  during  
260 census years – Appendix S1: Fig. S3).

261

### 262 *Carbon and tree species richness recovery*

263           The average carbon stock in 2017 was 141.7 ( $\pm 16.3$  SE), 58.3 ( $\pm 2.7$ ) and 4.27 ( $\pm 1.19$ ) Mg  
264 ha<sup>-1</sup> in, respectively, the primary forest, long-term, and extra plots, whereas rarefied richness was  
265 60.05 ( $\pm 4.07$ ), 41.2 ( $\pm 1.4$ ) and 33.9 ( $\pm 3.5$ ) (Appendix S1: Table S1). In the long-term secondary  
266 forest plots, the recovery of carbon and rarefied richness showed different trajectories among  
267 census (Fig. 1A-B). The mean accumulation of carbon in our long-term plots was 1.08 Mg ha<sup>-1</sup> yr<sup>-1</sup>  
268 between 1999 and 2017. Carbon and time were associated at the 0.07 level (i.e., 93% of the  $R^2$   
269 posterior mass was greater than zero). Rarefied richness displayed a much weaker relationship  
270 with time, being associated only at the 0.33 level and with a mean trend of 0.21 species yr<sup>-1</sup>. Carbon  
271 stock in the long-term secondary forest plots reached only 41.1% of the average primary forest  
272 level in 2017, while rarefied richness recovered to 56%. Above-ground carbon stocks and plant  
273 diversity were not related to each other over time (Fig. 1).

274

### 275 *Influence of climate and edge distance on carbon anomalies*

276           Carbon balance was positively related to SPEI in the long-term plots. These changes were

277 driven by variation in stem growth, with lower than average carbon accumulation in drier periods  
278 (Fig. 2). Although the maximum dry season temperature did not affect the overall carbon balance,  
279 it had countervailing effects on carbon growth and recruitment: growth was highest and  
280 recruitment lowest in the warmest years and vice versa. Carbon loss from mortality was not  
281 associated with any of the predictors (Fig 2), and edge distance and MCWD were not associated  
282 with any of the carbon anomalies (Appendix S1: Fig. S7).

283

#### 284 *Comparison between carbon recovery rates*

285 The carbon recovery rate in the long-term plots was lower than most estimates of secondary  
286 forest recovery from the Amazon or across the tropics, and our younger extra plots had even lower  
287 recovery rates than the older long-term plots (Fig. 3). Recovery rates at our study plots were also  
288 below Amazon-wide estimates of primary forest recovery after selective logging and were only  
289 slightly higher than the average carbon uptake rate of tropical primary forests (Fig. 3).

290

#### 291 *Extrapolating carbon recovery timeframes*

292 Our backwards extrapolation (to zero) gives approximate ages for the long-term secondary  
293 forests of 39 and 48 years in 2017 (Fig. 4), which is marginally lower but generally consistent with  
294 the ages reported during interviews (c. 48-58 years old in 2017). As a consequence of the low  
295 carbon recovery rates of the long-term plots, our extrapolation of future carbon levels — aimed at  
296 providing a rough estimate of a plausible recovery window under present-day conditions —  
297 suggests that it will take at least another century (c. 150 years since abandonment) until the site  
298 regains carbon levels similar to local primary forests (Fig. 4).

299

## 300 **Discussion**

### 301 *Influence of climate on carbon recovery in secondary forests*

302 Our results show for the first time that secondary forest carbon accumulation in the Amazon  
303 can be influenced by periods of water deficit. This suggests that the role of water availability in  
304 regulating carbon uptake observed in humid primary forests (e.g., Phillips et al. 2009, Anderson  
305 et al. 2018), dry primary (Mendivelso et al. 2014, Álvarez-Yépiz et al. 2018) and dry secondary  
306 forests (Maza-Villalobos et al. 2013, Martínez-Ramos et al. 2018) also extends to humid secondary  
307 forests. The generality of this finding is consistent with the strong link between the  
308 evapotranspiration index SPEI and spatial variation in carbon recovery in tropical forests  
309 (Schwalm et al. 2017). Indeed, secondary forests in the humid tropics may be even more sensitive  
310 than those in tropical dry regions given that the former show longer recovery times in the face of  
311 seasonal water availability (Poorter et al. 2019). Despite the similarity of the findings across forest  
312 types, our results also suggest that different mechanisms may underpin the sensitivity of the carbon  
313 balance to water deficit. Drought-mediated changes in primary forest carbon balance are driven by  
314 increased mortality (Phillips et al. 2009, Anderson et al. 2018), while the changes in the carbon  
315 balance observed in this study were primarily driven by reduced growth (Fig. 2).

316 Although the maximum dry season temperature (MDST) had no influence on the carbon  
317 balance of the studied secondary forests, increasing MDST increased the growth of established  
318 stems while reducing recruitment. The mechanistic explanation for such contrasting results  
319 requires further investigation. However, it might indicate a differential temperature effect between  
320 stems size classes. For example, higher temperatures exacerbate the physiological consequences  
321 of acute water stress (Lloyd and Farquhar 2008, Markesteijn et al. 2011), and shallow-rooted  
322 smaller stems (<10cm DBH) may be more sensitive to drought effects than the medium-sized

323 stems (10-30 cm DBH) (Elias et al. 2018). The increase in growth also suggests that established  
324 stems that can cope with higher temperatures may also benefit from factors associated with hotter  
325 years, such as better light conditions (Bentos et al. 2017) or faster litter decomposition rates and  
326 nutrient cycling (Eichenberg et al. 2013).

327         The positive relationship between temperature and growth in the assessed secondary forest  
328 contrasts with findings in tropical primary forests, where negative relationships (e.g. Feeley et al  
329 2007) and a lack of any relationship (e.g. Rowland et al. 2014) have been detected. This difference  
330 may be explained by the dominance in secondary forests of fast growing, heliophilic species  
331 (Vieira et al. 1994, Chazdon 2014), which tend to show relatively high optimum temperature points  
332 (Slot et al. 2014). A more complete understanding of secondary forest temperature responses is  
333 crucial given their importance as a climate change mitigation technology.

334

### 335 *Carbon recovery*

336         Carbon accumulation rates in our long-term study plots (48-58 years old) were low  
337 compared to most other studies (Fig. 3), and only around twice that recorded in Amazonia's  
338 primary forests. Although this rate of carbon accumulation is comparable to recent continental-  
339 scale estimates of biomass recovery in older (20-80 years old) tropical secondary rainforests in the  
340 Americas (Requena Suarez et al. 2019; Fig. 3), this similarity masks one important difference: our  
341 long-term plots had a much lower lifetime recovery rate than the same continent-scale estimates  
342 (Fig. 4B). Combining the mean < 20- and 20-80-year-old accumulation rates of Requena Suarez  
343 et al. (2019) suggests that a typical American tropical secondary rainforest will accumulate the  
344 median carbon seen at our study site (Fig. 1) in just 20-21 years, less than half the site's estimated  
345 age (Fig 4B). Moreover, even the lower bound of the Requena Suarez et al. (2019) 95%

346 accumulation rate confidence intervals suggests that American tropical secondary rainforests  
347 should attain our site's median carbon in 28 years.

348         The low lifetime recovery rate and equivalent rates of recovery over the last two decades  
349 can only be reconciled if forests in the Bragantina region have a very slow rate of early forest  
350 succession (Fig 4B). This is supported by the four younger extra secondary forest plots, which  
351 displayed even lower recovery rates than the long-term plots and are far below the predictions of  
352 Requena Suarez et al. (2019) for age-equivalent plots (Fig. 3). Furthermore, our backward  
353 extrapolation of growth tended to underestimate the secondary forest age when compared to  
354 interview data – if we assume the interview-based dates are correct, this would be consistent with  
355 slower than predicted growth rates when the forests were younger.

356         Such slow early-successional recovery rates could reduce the effectiveness of climate  
357 mitigation strategies in regions that have a long history of human occupation, have lost most of  
358 the original forest cover, and have suffered the widespread defaunation of large-bodied vertebrates  
359 through hunting (Almeida et al. 2010, Moura et al. 2014). These factors reduce the dispersal and  
360 colonization of forest tree species (Hooper et al. 2005), reduce carbon stocks (Bello et al. 2015)  
361 and increase recovery times (Jakovac et al. 2015, Chazdon 2014, Villa et al. 2018). Moreover, it  
362 is important to note that these measures of carbon recovery were observed under the climatic and  
363 landscape conditions over the lifetimes of the secondary forest plots. Future recovery could be  
364 slower if the last forest remnants are lost, further decreasing forest connectivity (Aguiar et al. 2016,  
365 Reid et al. 2018, Matos et al. 2019), if the frequency of farm-fallow cycles increases (Jakovac et  
366 al. 2015, Villa et al. 2018), or if deforestation and climate change further increase water deficits  
367 (Fu et al. 2013, Spracklen et al. 2018).

368         Interesting insights can be drawn from the two predictors – the Maximum Climatological



369 Water Deficit (MCWD) and edge distance – that had no discernible impact on carbon balance.  
370 First, MCWD is one of the most frequently used measures of water deficit in studies of tropical  
371 forests (e.g., Malhi et al. 2009, Anderson et al. 2018, Berenguer et al. 2018, Esquivel-Muelbert et  
372 al. 2017, 2019), but it appears that longer-term measures such as the 12-month SPEI index can  
373 reveal ecological processes that are not influenced by inter-period water deficit maximums.  
374 Second, edge effects have been detected in a wide range of contexts, including in secondary forests  
375 (e.g. Magnago et al. 2017); the lack of any effect in our study could be due to the limited range of  
376 distance-to-edge (62-266 m) or the possibility that all long-term study plots were under some form  
377 of edge influence in this highly deforested landscape.

378

### 379 *The recovery of biodiversity*

380         Although rarefied richness exhibited greater convergence to primary forest levels (56%)  
381 than carbon (41.1%), there was a near-zero increase in secondary forest rarefied richness between  
382 1999 and 2017. Richness therefore responds differently to carbon recovery, as tree diversity  
383 appears to have increased quickly in the initial stages of succession (see also Lennox et al. 2018)  
384 before reaching a state of impeded or arrested succession (Arroyo-Rodríguez et al. 2017). This  
385 slowdown could be due to the absence of diverse seed inputs and the slow generation time of trees  
386 limiting the recruitment of older-growth species. It also suggests that the strong carbon-  
387 biodiversity relationships observed in recovering forests elsewhere (Gilroy et al. 2014, Ferreira et  
388 al. 2018, Lennox et al. 2018) may not occur in older secondary forests or in highly deforested  
389 landscapes. Finally, it is also likely that we are overestimating the relative recovery of biodiversity:  
390 although we rarefied richness by 100 stems, which is two to five times higher than previous studies  
391 assessing biodiversity recovery (Rozendaal et al. 2019), the absolute difference between primary

392 and secondary forest would likely be much greater if we considered larger plots that capture more  
393 of the high beta diversity of primary forest (e.g., Solar et al. 2015).

394

### 395 **Conclusion**

396 The capacity of regenerating tropical secondary forests to sequester carbon and provide  
397 habitat for tropical species has profound implications for global climate change and biodiversity  
398 conservation. Our study is among the first to utilize data collected over two decades through  
399 periodic resampling and finds that the ability of secondary forests to mitigate climate change and  
400 limit biodiversity loss are likely to be negatively affected by increases in the rate of tropical  
401 deforestation and ongoing climate change. Understanding the generality and future climate  
402 sensitivity of these responses will require further investment in long term studies in human  
403 modified tropical forests.

404

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412

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571

## 572 **Figure Legends**

573 Figure 1: The recovery of secondary forests in Bragança. Carbon (A) and rarefied species richness  
574 (B) and the relationship between carbon and rarefied richness (C) between 1999 and 2017 in the  
575 twelve long-term study plots. Points show results at each census. Points and lines are color-coded

576 by plot. The black line shows the median trend. The grey band shows the 95% credible interval.

577 Figure 2: Climate and secondary forest carbon dynamics. The marginal effect of the standardized  
578 precipitation-evapotranspiration index (SPEI; A, C, E, G) and the maximum dry season  
579 temperature (Max temperature; B, D, F, H) on carbon balance (A-B), growth (C-D), mortality (E-  
580 F) and recruitment (G-H) in the twelve long-term secondary forest study plots. Lines show the  
581 median relationship. Bands show the 95% credible interval. A statistical association was assumed  
582 for posterior probabilities of a non-zero effect ( $Pr(>0) > 0.75$ ).

583 Figure 3: Estimates of carbon accumulation rates from previous studies compared to those from  
584 the twelve long-term and four extra secondary forest study plots. Bars show median values (or the  
585 mean where the median was unavailable). Error bars show 95% confidence/credible intervals. The  
586 Poorter et al. (2016) tropical secondary forest estimate uses only Neotropical plots. For the  
587 Requena Suarez et al. (2016) study, we used their estimates from tropical rainforests in the  
588 Americas. The Rutishauser et al. (2015) and Brienen et al. (2015) studies are from the Amazon.

589 Figure 4. (A) Extrapolation of past and future carbon levels for the 12 long-term study plots. The  
590 white line shows median carbon; the grey band shows a possible range. These estimates were  
591 derived by fitting rational functions to the median and 95% credible lower and upper bounds of  
592 carbon recovery shown in Fig. 1A. The inset shows the data. Points shows carbon levels at each  
593 census. Points and lines are color coded by plot. The black dashed line shows mean primary forest  
594 carbon. (B) Comparison of carbon recovery trajectories from the present study and Requena  
595 Suarez et al. (2019). For this comparison, we used the Requena Suarez et al. (2019) 95%  
596 confidence interval carbon accumulation rates for <20- and >20-year-old tropical American  
597 secondary rainforests. For the present study, we assumed the 12 long-term study plots were 50

598 years old, meaning that the first census occurred (in 1999) at age 32 (shown by the vertical dashed  
599 line). Carbon recovery rates post this age were taken from the 95% credible lower and upper  
600 bounds (Fig. 1A). Rates prior to this age were extrapolated linearly from the 32-year-old 95%  
601 credible lower and upper bound values.