

Modeling future tree species distributions under climate change to guide restoration planning: Application to the Brazilian Amazon

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Abstract

Addressing climate change and biodiversity loss requires innovative approaches to ecosystem restoration. This study aims to (1) develop a statistical tool to predict species distribution shifts under future climate scenarios and (2) apply it to 30 key tree species in the Brazilian Amazon, a biodiversity hotspot increasingly threatened by deforestation and climate change.

Using MaxEnt, we modeled species distributions under three climate scenarios (optimistic, medium, and pessimistic) for 2040, 2070, and 2100, integrating bioclimatic and soil variables. The tool generates interpretable maps highlighting areas of stability, expansion, and contraction for each species.

Results reveal a dual effect of climate change: while some species may initially expand their ranges, long-term survival is uncertain, particularly for those with low ecological plasticity. Functional trait analysis identified three species clusters, emphasizing the role of wood density, phenology, and

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plasticity in species selection for restoration.

Our findings highlight the need to integrate predictive modeling with ecological knowledge to guide species selection and enhance restoration success. By prioritizing climate-resilient species, this approach supports ecosystem stability and long-term conservation goals. Strengthening collaboration between scientists and practitioners is essential to refining and scaling these decision-support tools for effective restoration efforts.

Keywords: Ecological restoration, Prediction tool, Species distribution model, Climatic Scenarios, Tropical rainforest.

1. Introduction

The crucial link between climate change and biodiversity loss has been increasingly recognized. Addressing both challenges in restoration projects is essential to ensure ecosystems' resilience for future centuries.

Ensuring the long-term persistence of restored ecosystems requires restoration programs to be informed by a deep understanding of the ecology and evolutionary history of the species involved. This knowledge increases the likelihood of creating habitats suitable for local species while enhancing the ecosystems resilience to climate change.

In response to the growing ecological concerns of citizens, the number of ecosystem restoration projects has increased. For example, activities with significant environmental footprints are strongly encouraged to mitigate their impact by actively contributing to initiatives that promote biodiversity restoration or improve the carbon balance through sustainable practices (IPBES, 2019). Some actual restoration programs prioritize rapid actions

16 and immediate results, even if it involves agricultural or alien species (Mon-
17 temagni Almeida et al., ults; Suzuki et al., 2021). They provide an instant
18 public image improvement by quickly vegetating degraded areas. However,
19 such actions can harm local ecosystems through invasive competition and
20 resource degradation and fail to restore the degraded ecosystem all the more
21 so that, even in optimistic scenarios, ecosystems will face climatic changes.
22 The most effective restoration strategy implies careful species selection and
23 maximizes intra and inter-specific diversity (Butterfield et al., 2017).

24 Biodiversity loss has reached a critical point, necessitating actions focused
25 on areas with the greatest potential for success, protection of rare species, and
26 historically rich ecosystems, where diverse survival opportunities for planted
27 species and specimens can be maximized (van Tiel et al., 2024). The Ama-
28 zon is the largest existing rainforest, supporting the greatest biodiversity on
29 Earth and a major resource for the local population, but it is increasingly im-
30 pacted and threatened by unsustainable activities (Guayasamin et al., 2024).
31 For instance, in 2022, 15.5% of its surface was dedicated to monocultures and
32 pastures (Project, 2023), with projections suggesting that 40% of Amazon
33 forests could be eliminated by 2050 due to non-sustainable commercial agri-
34 cultural expansion (Soares-Filho et al., 2006). Its importance encompasses
35 numerous valuable ecosystem services, with regional climate regulation and
36 carbon stock being particularly noteworthy (Guayasamin et al., 2024). De-
37 forestation leads to significant regional climate changes, primarily reducing
38 rainfall, which, in turn, affects rural activities and the maintenance of mil-
39 lions of inhabitants who depend on the natural resources of forests, either for
40 income generation or for the production of their own medicines (Zemp et al.,

41 2017).

42 Yet, global warming presents a critical challenge to restoration projects
43 by amplifying extreme climatic events (Aleixo et al., 2019). To address these
44 challenges, large-scale forest restoration should prioritize the selection of key
45 native species that deliver multiple ecosystem services and can adapt to cli-
46 mate change within specific regions (Flores et al., 2024).

47 Species Distribution Modeling (SDM) is a well-established method in
48 biogeography and biodiversity research, particularly in data-scarce areas like
49 tropical forests (Elith and Leathwick, 2009; Rushton et al., 2004), where
50 many species remain understudied (Wilson et al., 2016). Despite its poten-
51 tial, SDM often stays within academia, with limited practical application.
52 To bridge this gap, we developed a tool linking scientific insights to real-
53 world restoration projects. Using SDM, we combined species presence or
54 abundance data with environmental variables to generate ecological insights,
55 predict distributions across landscapes, and provide outputs directly useful
56 for practitioners.

57 In this study, we aim to assess how native tree species in the Brazilian
58 Amazon forest could face climate changes in the next century and how to
59 improve the species selection for large-scale restoration projects in tropical
60 forests.

61 **2. Material and methods**

62 All the processing was made in R-4.3.3 (R Core Team, 2024), with pack-
63 age dismo (Hijmans et al., 2017) being used for SDM.

64 2.1. Study area

65 The Brazilian Amazon represents 60% of the total Amazon forest sur-
66 face area (Fig. 1)(Flores et al., 2024). According to Köppen classification,
67 the area has Tropical climate, mainly monsoon (49.8%) and without a dry
68 season (43.7%), with a small portion with dry-winter, part of the south-
69 ern border with the Cerrado (5.9%). The predominant soils are Argisols
70 (42.1%) and Latosols (32.9%). The relief is characterized mainly by vast
71 depressions (57.4%), with plateaus (16.5%) (Gerhard et al., 2020). There are
72 various vegetation types, mainly Dense Ombrophilous Forest (46.2%), Open
73 Ombrophilous Forest (22.3%), and contact zones/ecotones (12.5%)(IBGE,
74 2019).

75 2.2. Tree species selection and data

76 In total, 30 species were selected based on the following criteria: 1) use in
77 restoration programs; 2) seeds with orthodox storage behavior; 3) indigenous
78 to Brazil; 4) broad potential distribution; and 5) representation of different
79 ecological succession groups (Fig. 2, Tab. A1). *Psidium guajava* was in-
80 cluded because it is considered naturalized in Brazil, though of unknown
81 origin (Arévalo-Marín et al., 2021). *Eschweilera coriacea*, from a genus with
82 recalcitrant seeds (Calvi and Ferraz, 2014), was also included due to its im-
83 portance for the biome (Ter Steege et al., 2013). The number of presence
84 points ranged from 47 for *Samanea tubulosa* to 307 for *Trema micranthum*,
85 with a mean of 130 observations across the 30 species (Tab. A2).



Figure 1: Study area location. Red = Brazilian Amazon biome (IBGE, 2019), blue = Amazonia boundary (Eva and Huber, 2005).

2.3. Environmental data

Aiming at an improved prediction of plant distribution and migration, two types of environmental variables were considered: pedological and bioclimatic (Fig. 2) (Zuquim et al., 2020).

Pedological variable was analyzed at six soil depth levels: 05, 515, 1530, 3060, 60100, and 100200 cm. Bulk density at 05 cm was further divided into "upper" and "lower" layers. Soil variables were assumed to remain con-

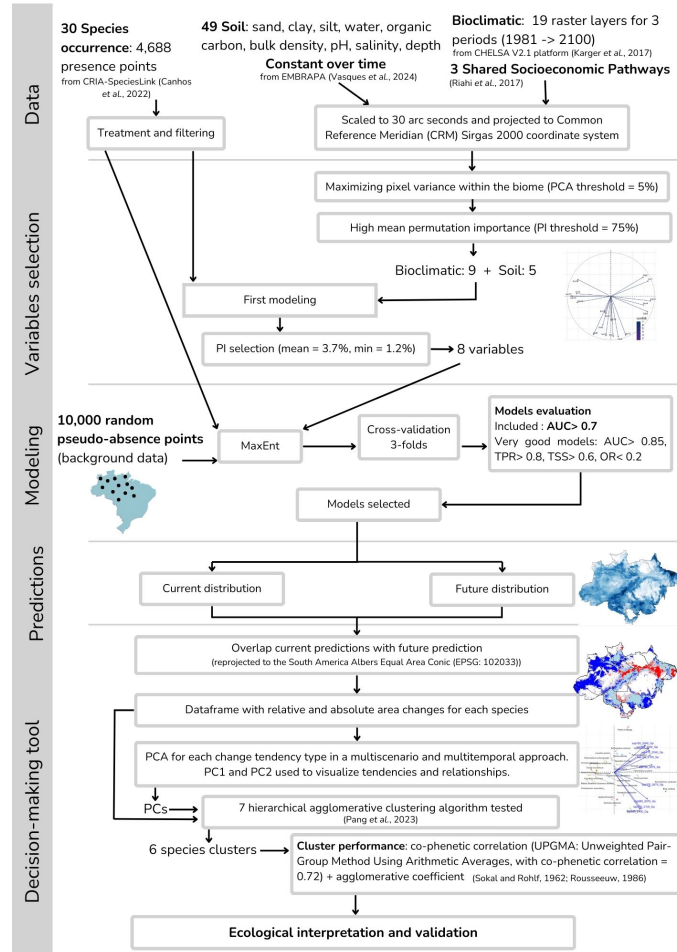


Figure 2: Overview of the framework used for model development. AUC : area under the ROC curve, TPR : True Positive Rate, TSS: True Skill Statistics, OR: Omission Rates, TNR: True Negative Rate (TNR).

stant over 100 years to serve as limiting factors in future species distribution estimations.

Bioclimatic data were high-resolution climatologies for Earth’s terrestrial surfaces, with a 30 arc seconds resolution. Nineteen raster layers were acquired for the periods 1981-2010 (influencing current species distribution), 2011-2040, 2041-2070, and 2071-2100. These future periods were analyzed under three different Shared Socioeconomic Pathways (Riahi et al., 2017) (SSP1-2.6, SSP3-7.0, SSP5-8.5 Fig. A1 here considered as "optimistic", "medium" and "pessimistic" scenarios, respectively). Future estimates are based on the GFDL-ESM 4 model Geophysical Fluid Dynamics Laboratory Earth System Model version 4, NOAA National Oceanic and Atmospheric Administration (Dunne et al., 2020).

To minimize spatial distortions, all layers were clipped to the respective biome extent, rescaled to 30 arc seconds when necessary, and reprojected to the CRM (Common Reference Meridian) Sirgas 2000 coordinate system.

2.3.1. Variables selection

The selection of variables for the model followed two steps in order to select those surpassing a 5% contribution threshold (PCA) and to minimize collinearity biases (PI, for more details see Fig. 2) (Smith and Santos, 2020). The 9 bioclimatic and 5 soil Principal Components (PCs) were selected and included in the first model run based on PCA and PI analysis (Fig. A2, A3 and Tab. A3). For the final models, eight variables were chosen based on their PI values (Tab. A4) (Altmann et al., 2010).

116 2.4. *MaxEnt model*

117 MaxEnt (Maximum Entropy) is a machine learning method that predicts
118 species' potential distributions using presence data, background data, and
119 environmental variables and is adaptable to small sample size. It creates
120 species probability distribution as uniform as possible within environmental
121 constraints by overlapping observed presence data with environmental pre-
122 dictors Phillips et al. (2006); Pearson et al. (2007); Elith et al. (2011). Ten
123 thousands random background data points, pseudo-absence points, were gen-
124 erated randomly for areas lacking presence data (Renner et al., 2015; Elith
125 and Leathwick, 2009).

126 We used 3-fold cross-validation, suitable for small samples, because it
127 performs better than the usually used 5-fold (James et al., 2013; van Tiel
128 et al., 2024; Guisan et al., 2017) (Fig. A4).

129 The models were evaluated using multiple metrics (Fig. 2). Models evalu-
130 ation is detailed in Appendix B. Models with an AUC >0.7 were accepted for
131 the binary predictions of species' potential distributions, using the threshold
132 that maximizes the sum of TPR and TNR. Models with TPR <0.6 , TSS
133 <0.4 , or OR >0.6 , but maintaining AUC >0.7 , were considered to have fair
134 performance and were used in the analysis.

135 2.5. *Decision-making tools*

136 To serve as practical tools, our models generated binary predicted dis-
137 tribution maps using estimated climatic conditions for present and future
138 periods, highlighting areas of increase, decrease, and stability relative to the
139 current distribution.

140 2.5.1. *Overlap maps principal component analysis*

141 As knowledge on tropical species grows (Reategui-Betancourt et al., 2025),
142 multivariate analyses are increasingly valuable for identifying patterns and
143 synthesizing information (Perelman and Puhl, 2023). Overlap map results
144 were used to calculate relative and absolute area changes per species for
145 each period and scenario. Values were categorized as "Loss" (L), "Gain" (G),
146 "Stability" (S), and "Net Change" (NC increase minus decrease), both as per-
147 centages (e.g., Gp = Gain percentage area) and absolutes (e.g., NCa = Net
148 change absolute area). PCA was performed on each subset, with biplots of
149 the first two PCs visualizing species impacts under climate change, showing
150 tendencies and relationships. This method offers restoration practitioners
151 an unified, multi-scenario approach for quickly comparing species tendencies
152 before consulting detailed maps.

153 2.5.2. *Overlap maps cluster analysis*

154 To simplify species selection, groups based on climate change effects on
155 species distribution were identified through Cluster Analysis using PCs from
156 the previous PCA (Fig. 2). Among the tested methods, the UPGMA (Un-
157 weighted Pair-Group Method Using Arithmetic Averages) algorithm was se-
158 lected, as it achieved the highest co-phenetic correlation (0.72). The cluster
159 analysis offers a quick overview of species tendencies by integrating uncer-
160 tainties for an initial global overview.

161 3. Results

162 3.1. Models evaluation

163 The 30 developed models achieve high performance, as all evaluation
164 metrics are far better than the thresholds (section 2.4, Appendix B). The
165 mean AUC, TPR, TSS, and OR were 0.83 ($\pm$ 0.05), 0.78 ($\pm$ 0.12), 0.55 ($\pm$
166 0.10), and 0.22 ($\pm$ 0.12), respectively. The species exhibiting the highest
167 model performance was *Chloroleucon acacioides* (AUC = 0.94, TSS = 0.75,
168 OR = 0), while the lowest performance model was for *Trema micranthum*
169 (AUC = 0.75, TSS = 0.68, OR = 0.32).

170 3.2. Environmental variables

171 The selected variables (Fig. 3) represent clear limiting factors in species
172 distribution. The variable with the greater average permutation importance
173 (PI) was Bio8 Mean air temperatures of the wettest quarter (31.8%) with
174 the period from 1981 to 2010 presenting a mean max. of 27.5 °C in the
175 Brazilian Amazon.

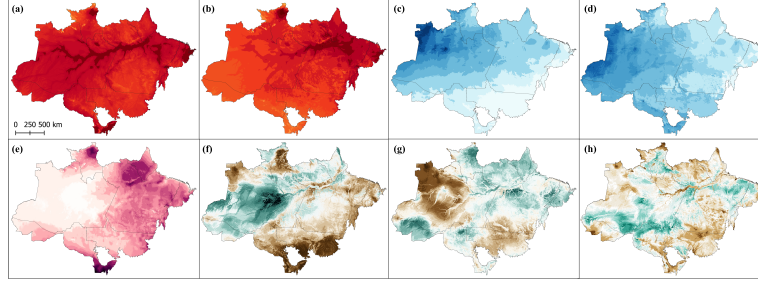


Figure 3: Environmental variables used in the models. (a) Bio8: mean daily air temperatures of the wettest quarter over one year, ranging from 11°C (yellow) to 30°C (dark red); (b) Bio9: mean daily air temperatures of the driest quarter over one year, from 11°C (yellow) to 30°C (dark red); (c) Bio17: mean precipitation of the driest quarter over one year, from 8 (light) to >800 mm/month (dark); (d) Bio18: mean precipitation of the warmest quarter over one year, from 8 (light) to >800 mm/month (dark); (e) Bio4: standard deviation of the monthly mean temperatures -seasonality-, from 0.2°C (light pink) to 1.7°C (dark purple). Panels (f), (g), and (h) represent PCA-derived variables summarizing soil property variations: (f) PC1: higher sand content and bulk density (brown) vs. higher water capacity and silt content (blue); (g) PC3: higher clay content (brown) vs. higher organic carbon (blue); (h) PC4: pH lower and less organic carbon (brown) vs higher pH and organic carbon (blue).

176 3.3. Principal component and cluster analysis

177 Analyzing the biplots (Fig. 4) provides an overview of species' response
 178 tendencies to climatic and soil conditions and highlights the scenarios where
 179 these responses are most pronounced. Although these results do not account
 180 for geographical coordinates, ecological interactions, or genetics of popula-
 181 tion, they offer a general perspective on the impacts of climate change on
 182 species.

183 PC1 and PC2 in each PCA accounted for over 95% of the variance among
 184 species for each tendency type. Strong correlations were observed between

185 later periods (2070, 2100) under medium and pessimistic scenarios (SSP370,
 186 SSP585), as well as between optimistic scenario (SSP126) and 2040 (Fig. A5
 187 for PCA correlation graphs). Thereby, the impact of climate change seems to
 188 increase over time, highlighting the need to include scenarios where actions
 189 to reduce climate change are unsuccessful.

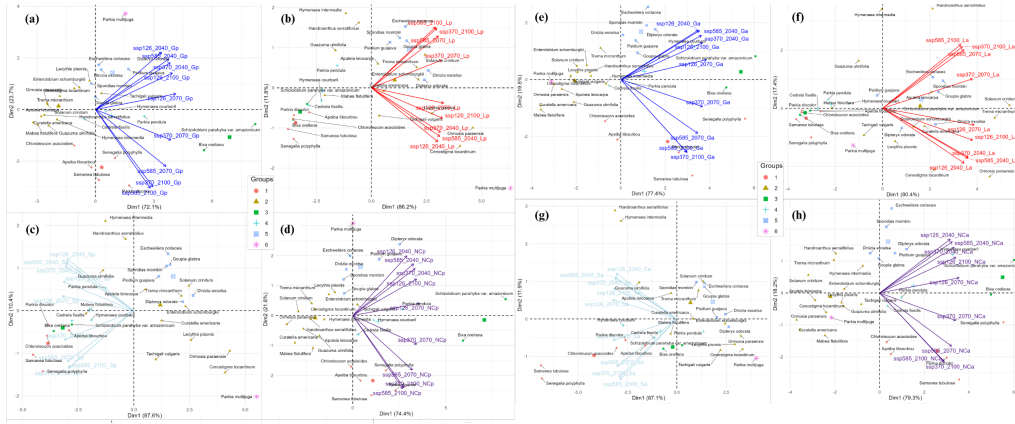


Figure 4: (a)(d): absolute area change biplots, (e)(h) relative change biplots. PC1 is positively correlated with tendency type, except for Stability (S) (c, g). For Gain (G) (a, e), Net Change (NC) (d, h), and S, PC2 is negatively correlated with later periods and high-emission scenarios, but positively correlated for Loss (L) (b, f). In NC (d, h), positive PC1 indicates net gain, while negative PC1 indicates net loss.

190 First, we'll present species clustering based on the model results. Using
 191 PCs 1 and 2 of Gp, Ga, Lp, La, NCp, and NCa as variables, this method
 192 integrates a multi-scenario perspective, facilitated by PCAs dimensionality
 193 reduction. While requiring careful interpretation, it reduces the risk of relying
 194 on a misleading single scenario crucial given the complexity of climate change
 195 and its multifaceted influence on species distribution.

196 In our case study, six species clusters were identified, with three par-

197 ticularly relevant for restoration in the Brazilian Amazon due to their high
198 success probability across all scenarios (Tab. 1). Cluster 1 and 3 showed
199 the greatest potential for range expansion, comprising seven pioneer species
200 likely to thrive across the Amazon, despite the limited current distribution of
201 two species in cluster 3. Cluster 4 grouped three species with minimal gains
202 or losses, maintaining stable areas and resulting in near-zero net change.

203 Clusters 2 and 5, which included 14 species, exhibited a general decline in
204 distribution. Higher emission scenarios exacerbated range loss, with cluster
205 5 showing a risk of extinction for some species by 2100 under the pessimistic
206 scenario. Although *Mabea fistulifera* was classified in cluster 2, 63% of its
207 current distribution is projected to remain stable by 2100. Finally, cluster 6,
208 composed of only *Parkia multijuga*, had a smaller current distribution and
209 tends to lose area or even face extinction.

210 3.4. Overlap maps

211 For a more refined species selection tailored to specific regions, overlap
212 maps offered a clear visualization of species distribution dynamics for each
213 scenario and period (Fig. A6). Figure 5 shows the evolution of spacial
214 distribution over time in the two opposite scenarios for two species with
215 opposite conduct: *Samanea tubulosa*, which tended to highly increase its
216 distribution, and *Solanum crinitum*, a species that may be extinct from the
217 Amazon in a pessimistic scenario (SSP585).

218 The results for 2040 suggest that short-term restoration efforts could ben-
219 efit from an increase in suitable areas for most species, a trend observed con-
220 sistently across all periods under a positive climate change scenario. This
221 observation is further supported by the variable correlations identified in the

Table 1: Species clusters description

Clusters	Cluster description	Species
1	Large stable area and great increase in distribution	<i>Apeiba tibourbou</i>
		<i>Chloroleucon aracioides</i>
		<i>Parkia discolor</i>
		<i>Senegalia polyphylla</i>
2	Great decrease in area	<i>Samanea tubulosa</i>
		<i>Apuleia leiocarpa</i>
		<i>Curatella americana</i>
		<i>Guazuma ulmifolia</i>
		<i>Mabea fistulifera</i>
		<i>Enterolobium schomburgkii</i>
		<i>Lecythis pisonis</i>
		<i>Cenostigma tocanthum</i>
		<i>Solanum crinitum</i>
		<i>Ormosia paraensis</i>
3	Extreme increase and small current distribution	<i>Tachigali vulgaris</i>
		<i>Trema micranthum</i>
		<i>Handroanthus serratifolius</i>
		<i>Hymenaea intermedia</i>
		<i>Bixa orellana</i>
		<i>Schizolobium parahyba</i> var. <i>am.</i>

Clusters	Cluster description	Species
4	Gains and losses, with considerable stable area	<i>Cedrela fissilis</i>
		<i>Hymenaea courbaril</i>
		<i>Parkia pendula</i>
5	Possible extinction in Amazon in 2100 under pessimistic scenario (SSP5-85)	<i>Eschweilera coriacea</i>
		<i>Dinizia excelsa</i>
		<i>Dipteryx odorata</i>
		<i>Goupia glabra</i>
		<i>Psidium guajava</i>
6	Small current distribution, possible extinction in Amazon under mitigate and pessmistic scenario	<i>Spondias mombin</i>
		<i>Parkia multijuga</i>

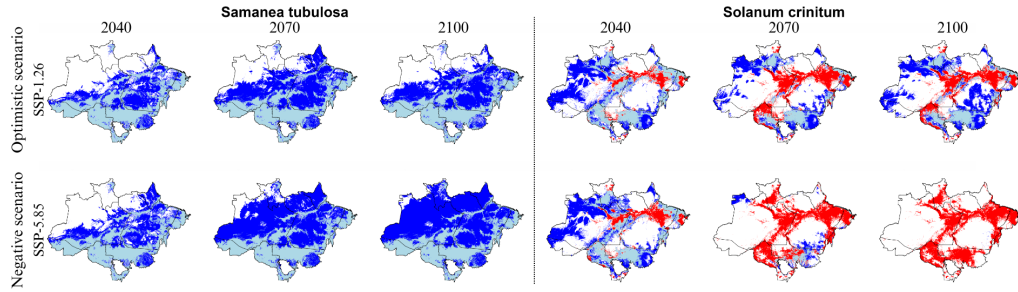


Figure 5: Overlap maps of *S. tubulosa* and *S. crinitum* in 2 climate change scenarios tested (with optimistic prediction above and with pessimist prediction at the bottom) for each prediction time. Light blue: stable distribution area, blue: expansion of distribution area, red: decrease in distribution area. Estimated current distribution is visualized by combining light blue and red areas.

222 PCA.

223 For the 2070 medium scenario (SSP370), the early-successional (ES)
224 species predicted to experience the greatest percentage loss of its current
225 distribution is *P. multijuga* (94%). In terms of absolute area, *S. crinitum*
226 faces the largest loss (890,480 kmš). Conversely, *S. parahyba* var. *ama-*
227 *zonicum* may experience the greatest relative expansion, increasing its area
228 by 394.2%, while *S. polyphylla* shows the largest absolute increase, totaling
229 2,361,756 kmš. Under the negative scenario for 2070, *P. multijuga* continues
230 to show the highest loss percentage (95%), and *S. parahyba* var. *amazon-*
231 *icum* maintains the greatest gain percentage (305%). In absolute terms, *H.*
232 *serratifolius* faces the greatest losses (1,085,974 kmš), whereas *S. tubulosa*
233 exhibits the highest gains (1,368,556 kmš).

234 For 2100, the late-successional (LS) species predicted to have the highest
235 percentage losses under the medium scenario is *E. coriacea* (98.5%), and un-
236 der the pessimistic scenario is *D. odorata* (99.5%). In terms of absolute area,
237 *H. intermedia* may face the greatest losses under both medium (204,753 kmš)
238 and pessimistic scenario (1,104,860 kmš). On the other hand, *P. pendula* may
239 have the greatest relative gain (125%), and *H. courbaril* the largest absolute
240 area increase (723,417 kmš) in the medium scenario. Under pessimistic, *H.*
241 *courbaril* presents the greatest relative (69%) and absolute gains (786,303
242 kmš).

243 Although individual maps are used for species selection, analyzing the
244 combined distribution maps of all species reveals significant trends, contribut-
245 ing to macroecological studies. The current and future predictions under a
246 negative scenario highlight areas where the probability of persistence of the

247 selected species is high and where only few or none of them may survive
 248 (Fig. 6). In our application, persistence probability is highest in the eastern
 249 Brazilian Amazon, around the Amazon River delta, and lowest in warmer,
 250 highly seasonal regions.

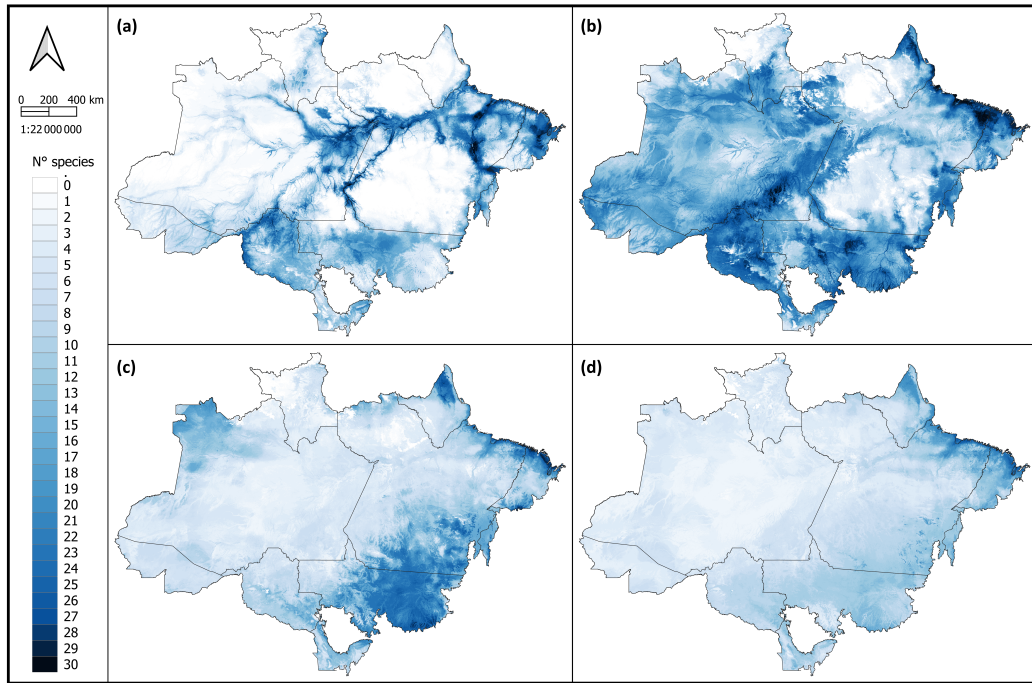


Figure 6: Compilation of 30 selected species distribution in the pessimist scenario (SSP5-8.5) of climate change varying in time. Darker color means more different species are predicted to be present, and white means no species are expected to be present. (a) The present distribution of species, (b) prediction for 2040, (c) prediction for 2070, and (d) prediction for 2100.

251 Analyzing combined distribution maps highlights critical regions for con-
 252 servation, like warmer and highly seasonal regions of the Amazon, where
 253 targeted efforts could maximize species persistence under varying climate
 254 scenarios, especially in areas predicted to face severe biodiversity loss.

255 4. Discussion

256 Climate change impacts species unevenly, with some unable to adapt
257 and facing potential extinction. Restoration strategies that disregard future
258 climate scenarios risk failure by contributing to biodiversity loss, facilitat-
259 ing the spread of invasive species, and intensifying climate change impacts,
260 ultimately perpetuating a harmful feedback loop.

261 4.1. *Distribution dynamic*

262 Model projections across three climate scenarios reveal varying species
263 distribution patterns. Initially, even under pessimistic scenarios, all species
264 exhibit greater area expansions than losses; however, most experience signif-
265 icant declines in later years. This suggests an initial resilience that gives way
266 to vulnerability as climate change intensifies. Zuidema et al. (2020) note that
267 tropical species may initially increase their drought resistance with elevated
268 atmospheric CO₂ until a temperature threshold. Then, CO₂ may increase
269 drought sensitivity (Chen et al., 2024). By 2070, species distributions show
270 a clear shift away from drought-prone regions of the Amazon.

271 In montane forests, such as the Andes and Central America, most species
272 are shifting upslope toward cooler environments (Fadrique et al., 2018; Fee-
273 ley et al., 2013). While lowland communities tend to remain relatively stable
274 under warming conditions (Freeman et al., 2018), some lowland-submontane
275 species are migrating upslope (Feeley, 2012). In the subtropical Atlantic
276 Forest, unique patterns emerge, including downward migrations driven by
277 biotic interactions (Bergamin et al., 2024). In the Amazon lowlands, drought-
278 tolerant genera are increasing as wet-affiliated taxa decline, although vege-

279 tation responses are lagging behind the pace of climate change (Esquivel-
280 Muelbert et al., 2019).

281 Past climate changes caused species to shift altitudes in tropical forests,
282 allowing time for migration (Bush et al., 2004). However, the long genera-
283 tion times of tropical trees delay their responses to current rapid warming, in-
284 creasing the risk of mass extinctions (Fadrique et al., 2018; Esquivel-Muelbert
285 et al., 2019). This observation underscores the need for assisted migration ex-
286 periments in restoration and enrichment projects to support further research
287 (Garcias-Morales et al., 2023).

288 Maps indicate that many studied species, currently found in Dense Om-
289 brophilous Forest, may shift to Evergreen Seasonal Forest regions by 20412070
290 under warmer scenarios. Despite a seasonal climate, these regions retain high
291 soil moisture, enabling deep-rooted trees to access water during dry periods,
292 avoid water stress, and retain leaves year-round (Ivanauskas et al., 2008).

293 By 2100, many species may shift to the eastern Amazon, offering higher
294 hydraulic safety margins (Tavares et al., 2023), or to coastal zones under
295 high-emission scenarios, where the GFDL-ESM 4 model projects lower tem-
296 perature seasonality. Historical migrations during the Last Glacial Maximum
297 similarly favored coastal areas with reduced continentality, suggesting these
298 regions may remain suitable for rainforest species under extreme climate
299 shifts (Pinaya et al., 2024).

300 Finally, the contraction and expansion of rainforests, dry seasonal forests,
301 and savannas, along with their floristic changes, are key aspects of Neotrop-
302 ical natural history (Pennington et al., 2006). Paleoecology studies reveal
303 potential ecosystem shifts, such as the dominance of drier-affiliated taxa

304 during Holocene dry conditions over current interfluvial wetlands (Spater
305 et al., 2024). These floristic changes may drive interspecific competition in
306 more suitable environments, creating biotic barriers to projected distribu-
307 tions (Webb et al., 2008).

308 The complexity of species suitability extends beyond current biome bound-
309 aries and the abiotic factors considered in this study. Transition zones,
310 such as those between the Amazon and Cerrado biomes, are highly dynamic
311 ecosystems shaped by factors like fire and phosphorus limitation (Dionizio
312 et al., 2018). Climate change and large-scale deforestation are projected to
313 amplify fire disturbances and drought events in the Amazon (Drücke et al.,
314 2023; Bottino et al., 2024). For instance, extreme droughts, once rare, could
315 occur every 1015 years with a 2°C increase in global temperatures (Clarke
316 et al., 2024). Therefore, drought and fires are critical factors to consider
317 in restoration projects. Otherwise, these projects may exacerbate regional
318 water cycle disruptions.

319 To build climate-resilient restoration strategies, it is essential to con-
320 sider the intricate impacts of climate change on species distributions, in-
321 crease species diversity in restoration planning, and prioritize species-specific
322 suitability assessments under changing conditions, supported by field exper-
323 iments to refine projections.

324 4.2. *Species functional ecology*

325 Reviewing species' biological characteristics in relation to our results is
326 essential for choosing the appropriate species mix for successful restoration
327 efforts.

328 Comparing models results with ecological traits (Tabs. A1, A5) allowed

329 hypotheses on cluster traits explaining species distribution changes. How-
330 ever, some species (*C. americana*, *E. schomburgkii*, *H. courbaril*, *T. micran-*
331 *thum*) showed variability in reported leaf deciduousness classes, underscoring
332 the need for further studies to characterize ecological traits across popula-
333 tions under diverse environmental conditions. Moreover, we identified eco-
334 logical evidence within each species cluster that explains distribution shifts
335 and informs the selection of optimal species for long-term restoration in the
336 Amazon.

337 Species in cluster 1 demonstrated significant expansion of suitable cli-
338 matic areas while maintaining large stable regions. All are known as pio-
339 neers, following a deciduous leaf phenology strategy except *P. discolor* (Tab.
340 A5). Deciduousness is linked to dry tolerance (de Oliveira et al., 2024), hy-
341 draulic safety (Oliveira et al., 2021), and CO₂ storage capacity (Rodrigues
342 et al., 2023), while pioneer species exhibit high plasticity in functional traits
343 under environmental changes (Wittemann et al., 2024; Manrique-Ascencio
344 et al., 2022) and strong dispersal and establishment rates that support mi-
345 gration (Laurance et al., 1998). *P. discolor* and *S. tubulosa* stand out in
346 literature for their high wood density (Tab. A5), which correlates negatively
347 with xylem cavitation, enhancing drought resistance (Serra-Maluquer et al.,
348 2022; Marchand, 2022). Their predicted success likely stems from two key
349 factors: pioneer traits enabling the colonization of suitable environments and
350 high wood density and/or a deciduous leaf strategy that improves drought
351 tolerance an important advantage under increasing Amazon drought condi-
352 tions.

353 Cluster 3 includes two pioneer species with low wood density, *B. orellana*

354 and *S. parahyba* var. *amazonicum*, the latter showing significant vertical
355 wood density variations (Romero et al., 2024). Both species, known for their
356 rapid growth (Rosa, 2006; Lorenzi, 2009), currently have limited distributions
357 but are projected to experience substantial expansion in the future. The
358 Amazon-endemic *S. parahyba* var. *amazonicum* may increase below-ground
359 biomass under water deficit conditions, supporting its future distribution
360 (Tourne et al., 2016). *B. orellana*, with a broad Neotropical range, shows a
361 net gain in suitable restoration areas but may face limitations due to high
362 Amazonian temperatures (Lorençone et al., 2024).

363 Cluster 4 comprises secondary successional species that, despite regional
364 losses across all scenarios, retained substantial stable areas and expanded
365 into colder regions. These species tolerate various soil conditions, includ-
366 ing poor soils, and employ drought survival strategies (Rodríguez-Ramírez
367 et al., 2022; Grogan and Schulze, 2012). For instance, *C. fissilis* mitigates
368 drought by shedding leaves early in the dry season, though drought reduces
369 its growth and wood density (Rodriguez et al., 2023; Mendivelso et al., 2016).
370 Understanding its interpopulation variability is vital, as old-growth *C. fis-*
371 *silis* forests thrive in drought-prone areas (Pereira et al., 2018). Similarly, *H.*
372 *courbaril* develops superficial roots and tolerates drought through reduced
373 photosynthesis, leaf loss, and high wood density (Da Silva-Pinheiro et al.,
374 2016; Luz et al., 2023).

375 In conclusion, functional ecology plays a crucial role in identifying species
376 with diverse potential for tropical forest restoration. Among the selected
377 species, we identified three climate-relevant patterns: (1) species with traits
378 that enhance water security, (2) fast-growing species with substantial fu-

ture area expansion, vital for rapid land cover recovery, and (3) secondary species adapted to poor soils, maintaining stable areas while ecologically complementing the other groups. These findings highlight the importance of selecting species with traits that foster plasticity, resilience, resistance, and adaptation to extreme climate events, ensuring the long-term success of restoration efforts.

4.3. Model and prediction improvements

This study demonstrates the value of statistical modeling as a decision-support tool for climate-resilient restoration, providing the first distribution estimates for 30 species in the Brazilian Amazon under various climate scenarios. While our approach advances evidence-based species selection, opportunities remain to refine accuracy and applicability by addressing challenges such as sampling biases, predictor selection, model validation, and generalizability (Vaughan and Ormerod, 2005; Gelfand, 2020).

Focusing on the Amazon biome, our models minimize biases by limiting analyses to regional populations, although broader ranges for non-endemic species and migration dynamics could enhance future applications. Addressing geographical biases in sampling, such as overrepresentation of accessible areas, remains critical. Although target-group background data is a promising solution (Phillips et al., 2017), we used a random background approach to ensure scalability across species.

Improving generalizability requires more robust validation. While k-fold cross-validation reduces overfitting, limited presence data (47 to 307 records per species) constrained the use of independent test sets, which are essential for validating performance under varied conditions. Tailoring predictors to

individual species and incorporating non-linear features like quadratic terms and hinge functions could further enhance accuracy (Phillips et al., 2017).

Climatic models also influence predictions. Future studies could improve robustness by comparing multiple models for each variable rather than relying on a single dataset (Rahman and Pekkat, 2024). Additionally, incorporating biotic interactions through Joint Species Distribution Models (JSDM) would enable better species combinations for restoration (Pollock et al., 2014).

Despite these challenges, the models achieved strong evaluation metrics, highlighting key trends in species behavior under climate change. These insights emphasize the need for continued collaboration between researchers and practitioners to refine tools and techniques, advancing tropical forest restoration in increasingly dynamic and degraded landscapes.

5. Conclusion

This study underscores the complexity of climate change impacts on species distributions and highlights the critical need for adaptive and evidence-based ecological restoration strategies. By combining modeling efforts with functional ecological analyses, we identified three distinct species clusters with unique restoration advantages: drought-resilient pioneers, fast-growing species for rapid land cover recovery, and secondary species adapted to poor soils and adverse conditions. These findings demonstrate the importance of incorporating ecological traits into species selection to enhance restoration outcomes and build climate-resilient forests. By fostering diversity across ecological groups, practitioners can bolster forest resilience to future climate extremes, offering a strategic framework for sustainable restoration. We em-

phasize the importance of collaboration between scientists and practitioners to refine decision-support tools that address the complex interplay of ecological and climatic factors, ultimately working to preserve and restore these increasingly vulnerable tropical ecosystems.

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8. Authors contribution

- Conceived the ideas and concept: EC, TOGT, RMA
- Data curation and formal analysis: TOGT
- Writing - original draft: TOGT, MV
- Writing - review & editing: MV, TOGT, RMA, LM, EC
- Supervision: EC

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