

1 **Climate change should drive mammal defaunation in tropical dry forests**

2

3 Mario R. Moura^{1,2*}, Gibran A. Oliveira³; Adriano P. Paglia⁴, Mathias M. Pires¹,

4 Bráulio A. Santos^{2,5}

5

6 ¹ Departamento de Biologia Animal, Instituto de Biologia, Universidade Estadual de

7 Campinas, Campinas, SP 13082-862, Brazil

8 ² Departamento de Ciências Biológicas, Universidade Federal da Paraíba, Areia, PB 58397-

9 000, Brazil

10 ³ Programa de Pós-Graduação em Ciências Biológicas, Universidade Federal da Paraíba, João

11 Pessoa, PB 58051-900, Brazil

12 ⁴ Departamento de Biologia Geral, Universidade Federal de Minas Gerais, Belo Horizonte,

13 MG 31270-910, Brazil

14 ⁵ Departamento de Sistemática e Ecologia, Universidade Federal da Paraíba, João Pessoa, PB

15 58051-900, Brazil

16 * Corresponding author: Mario R. Moura, mariormoura@gmail.com

17

18 **ABSTRACT**

19 Human-induced climate change has intensified negative impacts on socioeconomic factors,

20 the environment, and biodiversity, including changes in rainfall patterns and an increase in

21 global average temperatures. Drylands are particularly at risk, with projections suggesting

22 they will become hotter, drier, and less suitable for a significant portion of their species,

23 potentially leading to mammal defaunation. We use ecological niche modelling and

24 community ecology biodiversity metrics to examine potential geographical range shifts of

25 non-volant mammal species in the largest Neotropical dryland, the Caatinga, and evaluate

26 impacts of climate change on mammal assemblages. According to projections, 85% of the
27 mammal species will lose suitable habitats, with one quarter of species projected to
28 completely lose suitable habitats by 2060. This will result in a decrease in species richness for
29 more than 90% of assemblages and an increase in compositional similarity to nearby
30 assemblages (i.e., reduction in spatial beta diversity) for 70% of the assemblages. Small-sized
31 mammals will be the most impacted and lose most of their suitable habitats, especially in
32 highlands. The scenario is even worse in the eastern half of Caatinga where habitat
33 destruction already prevails, compounding the threats faced by species there. While species-
34 specific responses can vary with respect to dispersal, behaviour, and energy requirements, our
35 findings indicate that climate change can drive mammal assemblages to biotic
36 homogenisation and species loss, with drastic changes in assemblage trophic structure. For
37 successful long-term socioenvironmental policy and conservation planning, it is critical that
38 findings from biodiversity forecasts are considered.

39

40 **Keywords:** Beta-diversity, Biotic homogenisation, Body size, Drylands, Ecological Niche
41 Models; Mammals

42 **INTRODUCTION**

43 Defaunation typically refers to the depletion of fauna caused by overexploitation, habitat
44 destruction, and invasive species (Dirzo et al., 2014; Redford, 1992). At large spatial scales,
45 defaunation may generate complex spatial patterns rather than a simple reduction in species
46 richness, which depend on species-specific responses to defaunation drivers and landscape
47 configuration (Bogoni et al., 2020) Climate change adds another layer of complexity to the
48 spatial consequences of defaunation, since, besides posing an additional threat to wildlife, it is
49 expected to reshape species distribution patterns. In response to a changing the climate,
50 species can be displaced to regions with more favourable conditions, experiencing either
51 geographic range contraction or expansion (Lenoir & Svenning, 2015). Species with higher
52 tolerance to environmental change (e.g., disturbance-adapted, habitat generalists, wide-
53 ranging, and synanthropic species) are less likely to be affected and may even expand their
54 occurrence to novel habitats. In contrast, more sensitive species (e.g., habitat specialists,
55 narrow-ranging species) may lose suitable areas and eventually becoming locally extinct
56 (Filgueiras et al., 2021). These differences in species responses have the potential to change
57 richness and composition of local assemblages, ultimately affecting biodiversity patterns.

58 The widespread loss of specialist species reduces local species richness (alpha
59 diversity) and may increase the similarity in species composition across space, decreasing
60 beta diversity, a phenomenon termed biotic homogenisation (Mckinney & Lockwood, 1999).
61 Most often, biotic homogenization also result from increases in local richness due to the
62 colonization of species assemblages by generalists (Filgueiras et al., 2021; Socolar et al.,
63 2016). However, species redistribution may also increase the spatial heterogeneity in
64 assemblage composition, either due to the gain of disturbance-adapted species or to the loss of
65 widespread species (Socolar et al., 2016). Although studies on the effects of climate change
66 over biodiversity patterns often emphasize the biotic homogenization due to species loss

67 (Clavel et al., 2011; Hidasi-Neto et al., 2019; Moura et al., 2023), the prevalence each of
68 those process is likely context dependent, and spatial patterns will vary according to species
69 composition, the level of spatial heterogeneity in environmental conditions and the severity of
70 climate changes.

71 The potential effects of biotic homogenization have been studied mostly in tropical
72 rainforests (Sales et al., 2020), leaving other types of systems highly subject to climate change
73 understudied. Because future climate projections also include changes in the volume,
74 frequency, and geography of rainfalls (IPCC, 2021), climate change is particularly worrying
75 for regions already facing scarcity of water. For instance, drylands are expected to become
76 hotter, drier, and less suitable for a significant portion of their species (Aguirre-Gutiérrez et
77 al., 2020). If these projections are confirmed, it is likely that drylands will gradually become
78 impoverished, homogenised, and driven towards desertification (Moura et al., 2023; Torres et
79 al., 2017). One of Earth's most vulnerable drylands, the Caatinga, is also the largest tropical
80 dry forest in South America (Banda-R et al., 2016; Hoekstra et al., 2004; Silva et al., 2017). In
81 addition to being affected by chronic disturbances (Antongiovanni et al., 2020), this semiarid
82 region underwent a high degree of defaunation associated with habitat loss and poaching in
83 the past five centuries (Alves et al., 2012; Barboza et al., 2016; Bogoni et al., 2020), showing
84 a high proportion of locally threatened species, including endemic ones (Leal et al., 2005).
85 Besides being an ideal study system to the consequences of climate change on biodiversity
86 distribution patterns, investigating the response of tropical dry forest mammals to climate
87 change can help elucidate impacts of environmental change on dryland biodiversity.

88 In the Caatinga drylands, about half of the mammal species are non-volant
89 (Carmignotto & Astúa, 2018). Although many of these species are shared with neighbouring
90 biomes (Carmignotto et al., 2012), the composition of Caatinga mammals reflects a complex
91 biogeographic history that has involved periodical expansions and retractions of tropical dry

92 forests across different mountain ranges along the Pleistocene (Silva et al., 2017). On the one
93 hand, Caatinga species have historically experienced high climatic variation (Costa et al.,
94 2018), which may have selected organisms able to keep pace with climate change (Riddell et
95 al., 2021; Schloss et al., 2012). If so, future climate change would have limited influence on
96 species richness and composition of mammal assemblages. However, if Caatinga species are
97 already near their physiological limits (Araújo et al., 2013) or have relied on highland humid
98 enclaves as refuges over evolutionary time (Werneck et al., 2011), further increases in arid
99 conditions could trigger a range shift in these species with consequences for assemblage
100 structure.

101 Herein, we used ecological niche modelling and community ecology biodiversity
102 metrics to examine potential geographical range shifts of non-volant mammal species in the
103 Caatinga and evaluate impacts of climate change on mammal assemblages. We combined data
104 on species distribution and body mass to investigate projected changes in geographical
105 patterns of mammal richness and spatial dissimilarity across different future climate
106 scenarios. Specifically, we sought to determine whether the balance between potential range
107 contraction or expansion may increase or decrease species richness (alpha diversity) and how
108 those changes in distribution may impact homogenisation or heterogenisation of faunal
109 composition (beta diversity) across space. Because ecological losses are often non-random,
110 with large-sized and longer-lived non-volant mammals disappearing first (Carmona et al.,
111 2021; Cooke et al., 2019), we also examined how changes in average body mass per
112 assemblage (if any) was linked to species loss and biotic homogenisation. Because the
113 elevational gradient around highlands appears to sustain more favourable conditions for non-
114 volant mammals (Becker et al., 2007), we expected relatively lower changes in species
115 richness and composition of mammal assemblages at higher elevations, with overall decline
116 in richness and biotic homogenization associated with a reduction in average body mass.

117

118 **METHODS**

119 **Species Data**

120 We compiled occurrence data of Caatinga non-volant mammals searching for different term
121 combinations: “mamíferos”, “caatinga”, “nordeste”, “dataset”, “northeast”, “dryland”, and
122 “mammals” in Google Scholar, identifying 185 mammal species known to occur in the
123 Caatinga. We then used 19 published studies to extracted occurrence records collected
124 between 1957 and 2021 (Asfora et al., 2011; Brennand et al., 2013; Culot et al., 2019; Feijó &
125 Langguth, 2013; Freitas, 1957; Gardner, 2008; Geise et al., 2010; Gurgel-Filho et al., 2015;
126 Lima et al., 2017; Malcher et al., 2017; Mares et al., 1981; Mendonça et al., 2018; Nagy □ Reis
127 et al., 2020; Nascimento & Feijó, 2017; Oliveira et al., 2003; Patton et al., 2015; Pires &
128 Wied, 1965; Santos et al., 2019; Souza et al., 2019). We also incorporated data from the
129 mastozoological collection of Universidade Federal da Paraíba (the largest mammal collection
130 of Northeastern Brazil) and other collections included in the Global Biodiversity Information
131 Facility (GBIF, 2023). We included species occurrence records if information was available
132 on coordinates, collection year, and species taxonomy in agreement with specialized literature
133 (Carmignotto & Astúa, 2018; Feijó et al., 2016; Feijó & Langguth, 2013; Gardner, 2008;
134 Gurgel-Filho et al., 2015; Nascimento & Feijó, 2017; Oliveira & Langguth, 2004; Patton et
135 al., 2015; Quintela et al., 2020). After excluding the bat species, our database summed 39,459
136 occurrence records for 93 species of non-volant mammals.

137 We used the *CoordinateCleaner* R package (Zizka et al., 2019) to remove duplicates
138 and geoprocessing errors (records distant less than 1 km from municipality, state, or country
139 centroids, or located over water), leading to 18,758 records. To reduce the potential effect of
140 sampling bias and spatial autocorrelation in the occurrence dataset, we randomly filtered one
141 occurrence record for each species within a radius of ~10 km (Kramer-Schadt et al., 2013). At

142 this point, all species in the database had at least 5 occurrence records. Our final dataset
143 included 11,900 unique occurrence records of 93 species distributed across the Neotropical
144 realm (Fig. S1). Information on mammal body mass was extracted from the *EltonTraits*
145 (Wilman et al., 2014), *Phylacine* (Faurby et al., 2018) and *Combine* databases (Soria et al.,
146 2021) and complemented through specialised literature (see Data Availability for complete
147 sources on body mass data).

148

149 **Current and future projections**

150 We used 19 bioclimatic variables from the *WorldClim* v2.1 (Fick & Hijmans, 2017) in the
151 spatial resolution of 5 arc-min (~100 km² pixel) to represent the current climate. The global
152 bioclimatic layers were cropped to the extent of Neotropical realm (i.e., our model's
153 background). To avoid problems with multicollinearity and reduce the dimensionality of
154 predictor layers, we conducted a principal component analysis on the bioclimatic layers and
155 retained the predictor axes that cumulatively explained 95% of data variation (De Marco &
156 Nóbrega, 2018). We projected the linear relationships between raw predictors and principal
157 components onto new layers representing future climate scenarios using the PCA loading
158 coefficients derived from climatic data.

159 The future climate projections can vary according to different Shared Socioeconomic
160 Pathways (SSPs) that consider distinct paths to greenhouse gas emissions and the human
161 demographic growth (IPCC, 2021). We employed climate projections for the optimistic (SSP
162 245) and pessimistic (SSP 585) scenarios for the period of 2041-2060 (hereafter 2060) and for
163 the period 2081-2100 (hereafter 2100), both derived from the 6th IPCC Assessment Report
164 (IPCC, 2021). The SSPs were created in agreement with different Generalised Circulation
165 Models (GCMs) that simulate climatic alterations considering various atmospheric processes
166 (IPCC, 2021). To minimise uncertainties about the choice of a particular GCM (Diniz-Filho et

167 al., 2009; Thuiller et al., 2019), we selected the five distinct GCMs, namely: BCC-CSM2-MR,
168 CNRM-CM6-1, IPSL-CM6A-LR, MIROC6, and MRI-ESM2-0.

169

170 **Ecological niche models**

171 Recent investigations have showed that 17 occurrence records would be necessary to build
172 traditional ecological niche models (ENMs) for species in the Caatinga (Sampaio &
173 Cavalcante, 2023; van Proosdij et al., 2016). Because almost 20% of mammal species herein
174 considered did not reach this occurrence threshold, we separated our dataset into species with
175 either <20 presences (considered as ‘rare’) or ≥ 20 presences (considered as ‘common’). We
176 then applied the traditional ENM approach to model habitat suitability of common species
177 and used the Ensemble of Small Models (ESM) approach (Breiner et al., 2015) to model the
178 rare species. Before modelling, we established the calibration (accessible) area of each species
179 as a buffer around its occurrence records, with a width size equal to the maximum nearest
180 neighbour distance among pairs of occurrences (Barve et al., 2012). Within each species
181 calibration area, we computed pseudo-absences using the ratio of 0.5 presence-absence for
182 common species and 0.1 for rare species to avoid very unbalanced models while maximising
183 sampling units (Barbet-Massin et al., 2012; Liu et al., 2019). To increment discriminatory and
184 explanatory capacities of models, we allocated pseudoabsences following the environmentally
185 constrained method, based on the lowest suitable region predicted by a climate envelope
186 (Engler et al., 2004; Lobo & Tognelli, 2011).

187 Considering that the algorithm choice can affect the habitat suitability estimation
188 (Diniz-Filho et al., 2009; Rangel & Loyola, 2012), we computed an ensemble of projections
189 using four algorithms. For the species modelled using the traditional ENM approach, we used
190 the following algorithms: Generalised Linear Models (using linear and quadratic terms),
191 Generalised Additive Models (using smooth terms with three dimensions), Maximum Entropy

192 (using 10,000 background points and default features based on *MaxNet* package; Phillips et
193 al., 2017), and Random Forests (with the *mtry* parameter automatically tuned by growing
194 1000 trees through *tuneRF* function in *randomForest* package; Breiman, 2001; Liaw &
195 Wiener, 2002). For the species modelled using the ESM approach, we used the Generalised
196 Linear Models, Generalised Additive Models (using smooth terms with two dimensions), and
197 Gradient Boosting Models (using learning rate of 0.1 and 100 trees), and Neural Networks
198 (with 2 hidden layers, and decay parameters of 0; Breiner et al., 2018). For each method and
199 rare species, we obtained the ESM by averaging the habitat suitability of bivariate models
200 weighted by their respective model Somers' D [$D = 2 \times (AUC - 0.5)$] (Breiner et al., 2015).
201 The ESMs computed for the four abovementioned methods were then used to build an
202 ensemble of projections for each rare species.

203 When projecting ENMs to new regions or time periods, it is possible to project habitat
204 suitability for conditions outside the range represented by the training data (Elith et al., 2010).
205 To account for the impact of model extrapolation on each species projection, we computed
206 the Mobility-Oriented Parity (MOP) metric (Owens et al., 2013) within the calibration area of
207 each species. We calculated the MOP metric by measuring the Euclidean distance between
208 environmental conditions of the projected pixel and the nearest 10% training data
209 observations (Montti et al., 2021). The MOP metric was further normalized to 1 and
210 subtracted from 1 to reflect environmental similarity (Owens et al., 2013). We filtered habitat
211 suitability estimates for projected pixels showing very high (MOP values ≥ 0.9), high (MOP \geq
212 0.8), and moderate (MOP ≥ 0.7) environmental similarity with the training data. To minimise
213 issues with unlimited dispersal, we restricted all projections to the respective calibration area
214 defined for each species.

215 We calibrated the models using 5-folds cross-validation, with 80% of randomly
216 selected observations (presences and pseudo-absences) used for training, and the remaining

217 20% used for testing at each iteration (Roberts et al., 2017). Model performance was
218 evaluated through computation of Sorensen similarity index (ranging from 0 to 1) between
219 observations and binary predictions (Leroy et al., 2018)□. The habitat suitability threshold
220 selected to make predictions binary was chosen to maximise the Sorensen index. We also
221 computed complementary metrics of model performance, True Skill Statistic (TSS, ranging
222 from -1 to 1) and Area Under Curve (AUC, ranging from 0 to 1) (Liu et al., 2011), to
223 facilitate comparisons across literature. For the current climate, and for each combination of
224 GCM, SSP, and year, we computed the ensemble model as the average weighted habitat
225 suitability across algorithms, with the Sorensen index used as weight (Andrade et al., 2020).
226 The ensemble model was then made binary using average weighted binarization threshold,
227 with weights given by the Sorensen's index of the respective algorithm (Andrade et al., 2020;
228 Thuiller et al., 2019). We used the standard deviation of habitat suitability across the GCMs as
229 a measure of future model uncertainty.

230 Lastly, we applied spatial constraints *a posteriori* to minimise overprediction issues
231 associated with species binary maps derived from ENMs. We used the occurrence-based
232 threshold method (OBR) to exclude unreachable patches of current suitable habitats for each
233 species (Mendes et al., 2020). This approach assumes that suitable patches are reachable if
234 they either overlap with species presence records (occupied patch) or are within an edge-edge
235 distance threshold of an occupied suitable patch (Mendes et al., 2020). We defined the
236 distance threshold as the maximum nearest neighbour distance among pairs of occurrences of
237 each species. All computations were performed in R 4.2.0 (R Core Team, 2022) using the
238 *ENMTML* package (Andrade et al., 2020) to build the traditional ENMs and the *flexsdm*
239 package (Velazco et al., 2022) to compute the ESMs.

240

241 **Assemblage-level biodiversity metrics**

242 We divided the Caatinga using an equal-area projection grid cell of 10×10 km. We overlaid
243 our grid cells (i.e., species assemblages) with binary maps to build presence-absence matrices
244 for the current time and each future scenario (2060 SSP245, 2100 SSP245, 2060 SSP585, and
245 2100 SSP585). To represent the aggregate model uncertainty in future scenarios, we used the
246 average standard deviation of habitat suitability for species in each grid cell (species
247 assemblage). More specifically, we initially averaged the variances (i.e., the squared
248 deviations) for species habitat suitability in each cell, and then square rooted the outcome to
249 get the average standard deviation (AvgSD) for each future year-SSP scenario combination
250 (2060 SSP245, 2060 SSP585, 2100 SSP245, and 2100 SSP585).

251 Species richness corresponded to the number of species (S) present in each grid cell.
252 The spatial beta-diversity was represented by the multisite Simpson dissimilarity index – β_{SIM}
253 (Baselga, 2010), which is recommended for macroecological investigations given its
254 independence of richness differences (Kreft & Jetz, 2010). We computed β_{SIM} between each
255 focal cell and its immediate neighbouring cells. However, the number neighbouring cells is a
256 proxy to area and can therefore affect the β_{SIM} via species-area relationship (Baselga, 2013).
257 To circumvent this issue, we randomly selected four neighbouring cells around each focal cell
258 to compute β_{SIM} . We repeated this procedure 100 times and extracted the average β_{SIM} across
259 iterations to obtain the per cell β_{SIM} . Computations were performed in R using the *betapart*
260 package (Baselga & Orme, 2012).

261 For each grid cell, we also computed the geometric mean of \log_{10} body mass across its
262 member species (Avg_{mass}) as a proxy for the structure of mammal assemblages (Bogoni et al.,
263 2020). We calculated the richness difference between future and current period ($\Delta S = S_{\text{future}} -$
264 S_{current}) and change in spatial beta-diversity ($\Delta \beta_{\text{SIM}} = \beta_{\text{SIM.future}} - \beta_{\text{SIM.current}}$) to identify species
265 assemblages subject to biotic homogenization ($\Delta \beta_{\text{SIM}} < 0$) or heterogenization ($\Delta \beta_{\text{SIM}} > 0$).
266 Similarly, we computed the ratio of average body mass of future to current projections

267 (MassRatio = Avg_{mass.future} / Avg_{mass.current}) to quantify relative changes in mammal
268 assemblages. MassRatio < 1 indicated future assemblage with lower average body mass than
269 today, while MassRatio > 1 indicated the opposite.

270 To assess the influence of potential topographical refuges in shaping assemblage-level
271 biodiversity metrics in Caatinga, we also categorised grid cells between lowlands (i.e., areas
272 <500 m elevation) and highlands (i.e., areas >500 m elevation). The threshold of 500 meters
273 allowed the detection of the five major Caatinga mountain ranges (e.g., Chapada Diamantina,
274 Planalto da Borborema, Chapada do Araripe, Serra da Ibiapaba, and the highest parts of the
275 Serra da Capivara and Serra das Confusões, see Fig. S2). We used Kruskal-Wallis tests to
276 assess whether the medians of (i) Current species richness, (ii) ΔS , (iii) Avg_{mass.current}, and (iv)
277 MassRatio differed between assemblages subject to biotic homogenisation ($\Delta\beta_{SIM} < 0$) or
278 heterogenisation ($\Delta\beta_{SIM} > 0$) or located in lowlands versus highlands. Linear relationships
279 between projected changes in species richness (ΔS), changes in spatial beta-diversity ($\Delta\beta_{SIM}$),
280 relative changes in average body mass (MassRatio), and aggregated model uncertainty
281 (AvgSD) were verified through a modified t-test (Dutilleul, 1993) to spatially correct the
282 degrees of freedom of correlation coefficients. Computations were performed in R using the
283 package *SpatialPack* (Osorio et al., 2014).

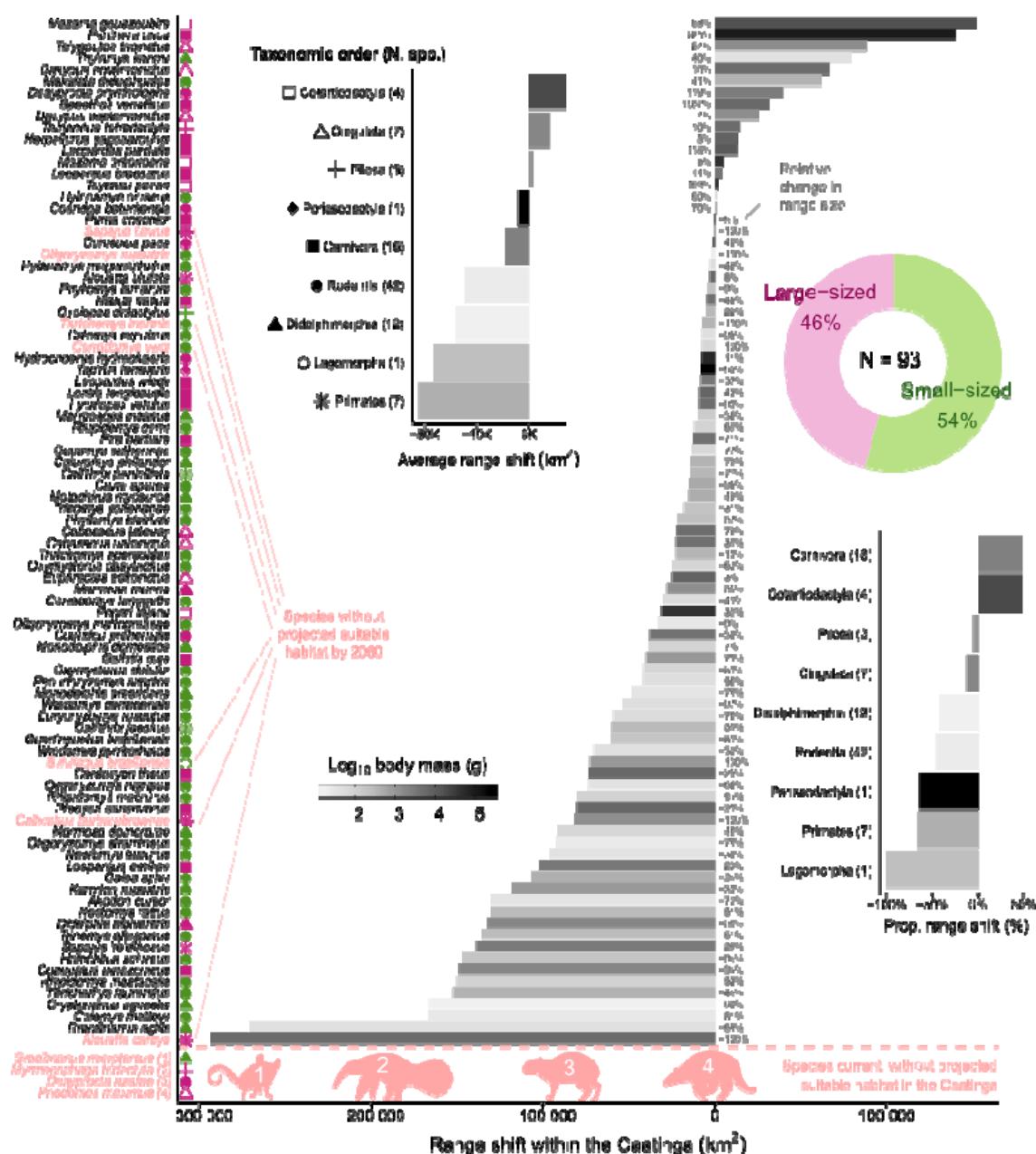
284

285 **RESULTS**

286 Across all non-volant mammal species in the Caatinga, the ensemble models showed
287 moderate to high predictive performance using either the traditional Ecological Niche
288 Modelling approach (median Sørensen similarity index = 0.68, range = 0.52–0.98; median
289 TSS = 0.52, range = 0.12–0.97; median AUC 0.78, range=0.52–0.99) or the Ensemble of
290 Small Models approach (median Sørensen similarity index = 0.60, range = 0.24–0.89; median
291 TSS = 0.6, range = 0.19–0.98; median AUC 0.85, range=0.43–0.99; Fig. S3). Although

292 quantitative differences emerged between the SSP scenarios (SSP245 and SSP585) and year
293 (2060 and 2100), results were qualitatively similar. Therefore, we focused here on projections
294 for 2060 and SSP245, and based on highly similar environmental conditions (MOP values \geq
295 0.9), but see the Supporting Information for results on complementary projections.

296 About 87% of non-volant mammal species were projected to lose suitable areas by
297 2060, with substantial reductions of suitable areas (i.e., $>50\%$ of geographic range loss)
298 occurring mainly inside the Caatinga (Fig. S4). For at least 12 modelled species (12.8%),
299 suitable habitats within the Caatinga were projected to be completely absent by 2060 under
300 the SSP245 scenario (Fig. 1), with this number reaching 28 species (30%) under the
301 pessimistic scenario (SSP585) by 2100 (Figs S5-S6). Our ensemble models projected that
302 four species would currently show suitable habitats only outside the Caatinga, suggesting
303 potential source-sink dynamics for these species (Fig. 1). However, it is worth noting that four
304 out of the five species without projected suitable habitats (*Dasyprocta azarae*, *Gracilinanus*
305 *microtarsus*, *Mirmecophaga tridactyla*, and *Priodontes maximus*,) lacked occurrence records
306 in the Caatinga, despite being listed in regional checklists (Carmignotto & Astúa, 2018).

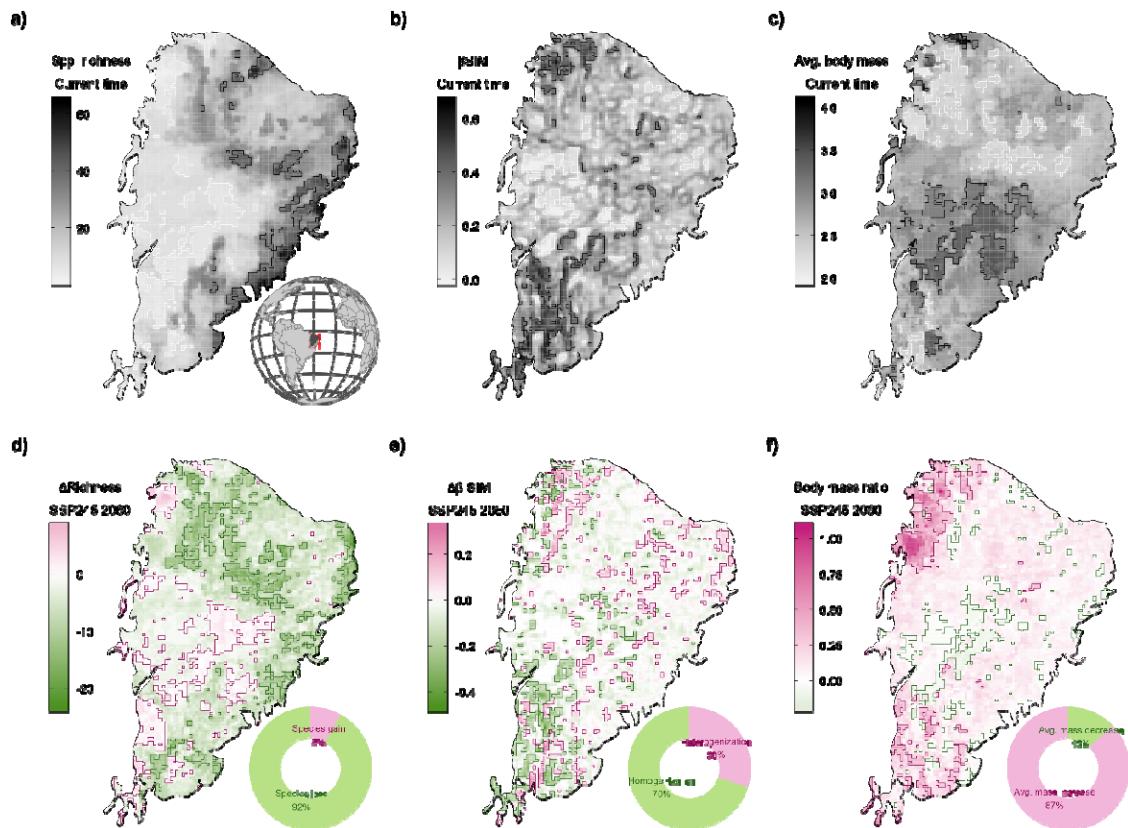


308 **Figure 1. Projected range shift for non-volant mammals in the Caatinga.** The four species below the red
309 dashed line showed no current suitable habitats within the Caatinga, although they are projected to occur
310 elsewhere in the Neotropical realm. Species labelled in red elsewhere indicate taxa without projected suitable
311 habitats for 2060 according to the scenario SSP245. Symbol colour on the left panel indicate if species body
312 mass is ≤ 1 kg (green, small-sized) or not (pink, large-sized). Symbol shape follow the taxonomic order indicated
313 in the top-left inset plot. See Figs S4-S6 for results on complementary projections.

314

315 Species loss was projected for 91.6% of species assemblages, with an average richness
316 difference of -4.7 species (range $\Delta S = -23\text{--}8$) across all assemblages, whereas 69.9% of
317 assemblages showed projected biotic homogenisation (Fig. 2). Median current species
318 richness is higher in regions projected to become more heterogeneous ($\chi^2 = 1167.7$, d. f. = 7, p
319 < 0.001 , Fig. 3a). Similarly, future assemblages projected to be more heterogeneous in the
320 future showed the most pronounced species loss (Fig. S11, Table S1), particularly those in
321 northern Caatinga (Fig. 2), with model uncertainty increasing with richness difference (Fig.
322 S20). Notably, model projections showed low uncertainty across regions subject either to
323 biotic homogenisation or heterogenization (Fig. S21). Assemblages located in lowlands or
324 highlands showed similar changes in species richness and spatial-beta diversity (Figs S12 and
325 S17-18).

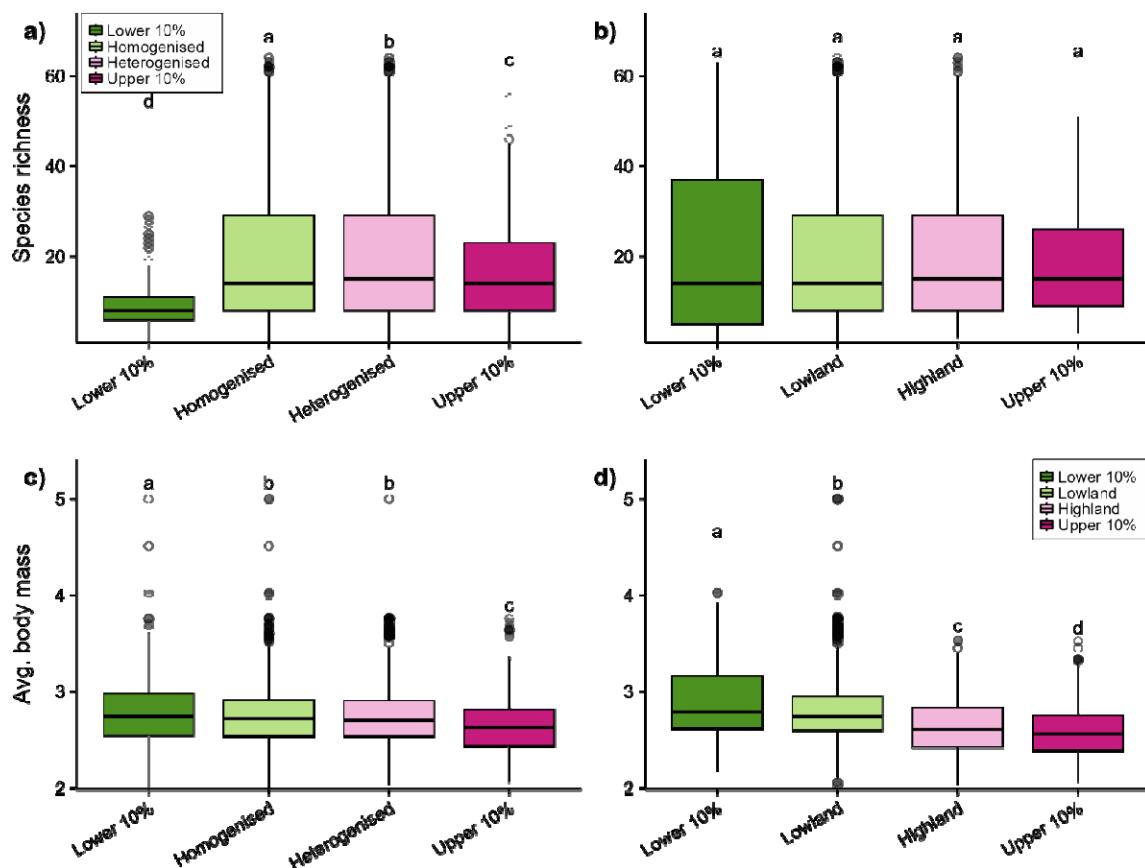
326 Average body mass in current assemblages was generally higher in lowlands than in
327 highlands ($\chi^2 = 435.6$, d. f. = 7, $p < 0.001$, Fig. 3c). Surprisingly, 87.7% of assemblages were
328 projected to experience an increase in average body mass of their member species,
329 particularly in the southern and northwestern portions of Caatinga (Fig. 2). The relative
330 change in average body mass was not associated with changes in either species richness (Figs
331 4c and S14d) or biotic change (Figs 4e and S15d), but tended to slightly increase with
332 elevation (Fig. S12i-l). Across most the SSP scenarios, time periods, and levels of
333 extrapolation constraints, our findings indicated no relationship between changes in average
334 body mass and aggregated model uncertainty (Fig. S22).



335

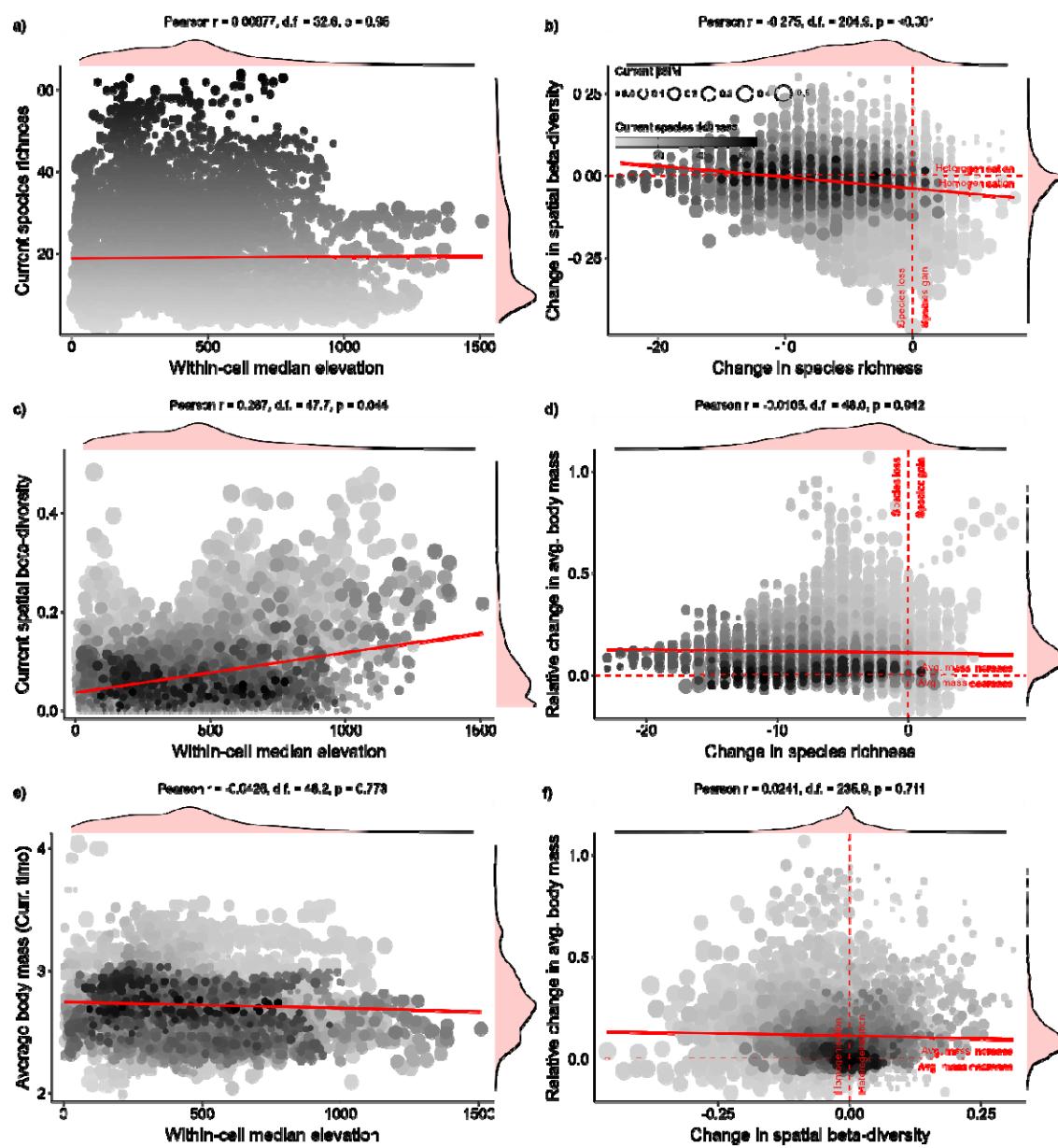
336 **Figure 2. Geographical patterns of species richness, spatial beta-diversity, and average body mass for**
337 **mammals in the Caatinga.** (a) Current species richness, (b) Spatial beta-diversity (β_{SIM}), (c) Average \log_{10} body
338 mass (g), (d) Projected richness difference (ΔS), (e) Projected change in spatial beta-diversity ($\Delta \beta_{\text{SIM}}$), (f)
339 Projected relative change in average body mass. All geographical patterns were derived from species projections
340 holding at least 90% of environmental similarity with training data. The contour lines denote the assemblages
341 (cells) in the upper and lower 10% of the mapped pattern. Plots are shown for the scenario SSP2/4.5 at the year
342 2060. See Figs S7-S10 for results on complementary projections and mapped uncertainty.

343



344

345 **Figure 3. Species richness and average body mass across mammal assemblages at different elevations and**
346 **levels of biotic change.** (a-b) Species richness and (c-d) average body mass. Each box denotes the median
347 (horizontal line), the 25th and 75th percentiles, the 95% confidence intervals (vertical line), and outliers (black
348 dots). Boxplots in darker greenish or pinkish colours denote were computed using the upper and lower 10%
349 assemblages (cells) in terms of biotic change (a, c) and elevation (b, d). Small capital letters denote the results of
350 the Kruskal-Wallis tests for the difference in medians across assemblages subject to different levels of biotic
351 homogenisation or located in lowlands or highlands (boxplots holding the same letter show statistically similar
352 median values under $p = 0.05$, using Bonferroni correction). Plots are shown for the scenario SSP245 at the year
353 2060. See Figs S11-S12 and Tables S1-S2 for complementary projections.



354

355 **Figure 4. Change in species richness, spatial beta-diversity, average body mass of mammal assemblages in**
356 **Caatinga.** Plots (a, c, e) illustrate the relationship between assemblage-level biodiversity metrics at the current
357 time and elevation, whereas plots (b, d, f) indicate how changes in biodiversity metrics are inter-related. All
358 geographical patterns were derived from species projections holding at least 90% of environmental similarity
359 with training data. Pearson correlations at the top of each panel were based on spatially corrected degrees of
360 freedom. Plots are shown for the scenario SSP245 at the year 2060. See Figs S13-S22 for results on
361 complementary projections.

362 **DISCUSSION**

363 Drylands in northern South America are expected to face temperature rise of up to 2.7°C by
364 2060, with changes in the number of consecutive dry days increasing by as much as 21 days
365 (IPCC, 2021). Our study reveals the potential for such changes to drastically erode the
366 diversity of non-volant mammals in the Caatinga. Our projections indicate that most species
367 will lose suitable environmental conditions within the Caatinga, while a few will expand their
368 distribution, which will result in lower species richness and increased compositional similarity
369 to nearby assemblages. Our results show that the biotic homogenisation and species loss are
370 projected in opposite directions, with species gain occurring mostly in regions that are
371 currently species-poor. Although the current beta-diversity is higher in highlands than
372 lowlands, projected changes in biotic composition are only weakly or not at all associated
373 with elevation. Most assemblages are expected to lose small-sized mammals, while large-
374 sized species are projected to colonise neighbouring assemblages. Overall, we reveal how
375 climate change strengthen the defaunation of non-volant mammals and produce complex
376 spatial patterns in the largest tropical dry forest of South America.

377 Despite mammal adaptations to survive in drylands (e.g., insectivorous diet, night
378 activity, and subterranean shelters), climate change can restrict their physiology and fitness by
379 increasing dehydration, overheating, starvation, and reducing reproduction (Fuller et al.,
380 2021). The projected loss of suitable habitat for almost 90% of all non-volant mammals of
381 Caatinga suggests that these species will have to cope with extreme climate conditions for
382 their dispersion across the biome. Among the main climatic “losers” – species with greatest
383 suitable habitat loss – are primates and the Brazilian cottontail rabbit, but several species from
384 the orders Didelphimorphia and Rodentia also emerge, such as the agile gracile opossum
385 (*Gracilinanus agilis*), the long-tailed climbing mouse (*Rhipidomys mastacalis*), and the white-
386 spined Atlantic spiny-rat (*Trinomys albispinus*). These animals are typically small-sized and

387 occupy lower trophic levels, usually producing a greater number of offspring when compared
388 with large-sized mammals (Carmignotto & Astúa, 2018; Feijó & Langguth, 2013; Santini et
389 al., 2013). The few “winner” species include the brown brocket (*Mazama gouazoubira*), the
390 black-rumped agouti (*Dasyprocta prymnolopha*), which have a wide-ranging distribution and
391 a large body size (Carmignotto & Astúa, 2018; Hetem et al., 2014; Santini et al., 2013), and
392 different species of armadillos, which generally have wide tolerance to warm-dry climates
393 (Soibelzon, 2019). These examples illustrate how animals with low vagility can be
394 disproportionately impacted by climate change, which is supported by our findings on the
395 decrease in the relative contribution of small-sized species across mammal assemblages.

396 The drastic species loss projected for the assemblages of non-volant mammals can be
397 attributed to changes in dispersal, behaviour, and resource availability due to increasing
398 aridity (Marengo et al., 2017; Torres et al., 2017). Firstly, increased aridity can shorten the
399 optimal period for foraging and breeding (Hetem et al., 2014), and ultimately impact the
400 ecological fitness and maintenance of mammal populations (Fuller et al., 2021). Secondly,
401 geographical barriers may further restrict dispersal and hinder access to suitable habitats
402 (Fuller et al., 2021). Thirdly, hotter and dryer conditions can reduce aboveground biomass
403 (Rito et al., 2017; Souza et al., 2019) and alter floristic composition (Rito et al., 2017; Vieira
404 et al., 2022), thereby impacting competition for food resources not only to herbivores, but also
405 to omnivores and carnivores (Marinho et al., 2020; Oliveira & Diniz-Filho, 2010)□□. Since
406 mammals can exhibit size-dependent variation in vagility, behaviour, and energy needs
407 (Ramesh et al., 2015; Santini et al., 2013; Shipley et al., 1994), prolonged periods of heat and
408 droughts can trigger heterogeneous species responses and enhance negative biotic
409 interactions, ultimately leading to the depletion of faunal assemblages.

410 The predominance of highly-vagile large-sized species across lowland assemblages
411 and the faster turnover of small-sized species in highlands help to explain the increase in

412 mammal beta-diversity along elevational gradients in the Caatinga[□] (Lopez et al., 2016; Melo
413 et al., 2009). While small-sized mammals certainly occur across Caatinga lowlands, the future
414 homogenisation is expected to be primarily driven by the loss of suitable habitats for typically
415 small-sized mammals – adults weighting ≤ 1 kg, *sensu* Chiarello (2000) – which constitute
416 54% of species in the region (Fig. 1). The current predominance of small-sized mammals
417 across highlands can be related to species persistence through elevational range shift across
418 time (Chen et al., 2011)[□], which is especially important in the Caatinga due to its climate
419 instability when compared with other regions in South America (Costa et al., 2018)[□].
420 Therefore, the impoverished and compositionally similar mammal assemblages in the
421 lowlands may have resulted from the historic accumulation of local extinctions in the
422 Caatinga, particularly of small-sized species with low vagility (Schloss et al., 2012).

423 Ecological niches of large-sized species may have been underestimated due to past
424 hunting and overexploitation (Sales et al., 2022), which could further increase in the relative
425 contribution of large-sized species in shaping mammal assemblage. However, our data entries
426 may have missed species entirely if past defaunation resulted in the extinction of large-sized
427 species in the Caatinga. Ungulates like the tapir, peccaries, and different deer species that had
428 wider ranges before European colonization are considered locally extinct across most regions
429 within the biome limits (Barboza et al., 2016). The largest extant mammal in most sites, and
430 the ones projected to increase in range are armadillos, which can be very resilient and often
431 thrive in human-modified landscapes (Bovo et al., 2018; Magalhães et al., 2023), with most
432 small mammals including rodents and marsupials projected to undergo range contractions
433 while the potential range of some of the larger-bodied extant species are projected to increase,
434 the average body mass increases as well. In that sense the pattern we found of increasing
435 mean average body mass is the consequence of the expansion of opportunistic species as well
436 as a legacy of past defaunation. It is worth noting that while the geographical pattern of

437 average body mass indicates a general increase in the relative contribution of large-sized
438 species, intraspecific responses may cause mammal body size to decrease in response to a
439 warming climate (Gardner et al., 2011; Villar & Naya, 2018).

440 While methodical choices and theoretical limitations like climate uncertainty, dispersal
441 limitations, niche conservatism and model transferability (Barve et al., 2012; Diniz-Filho et
442 al., 2009; Guisan & Thuiller, 2005; Owens et al., 2013; Thuiller et al., 2019) may have
443 affected our projections, we minimized these issues by offering an ensemble of projections
444 across various modelling algorithms (Araújo & New, 2007). We also implemented an
445 ensemble of future projections across different generalized circulation models and future
446 scenarios of climate change (Diniz-Filho et al., 2009; Thuiller et al., 2019). We also applied
447 species-specific spatial restrictions to remove unreachable patches of projected suitable
448 habitats and minimise overprediction issues related to unlimited dispersal by constraining
449 projections to species-specific calibration areas (Mendes et al., 2020). In addition,
450 assumptions of niche conservatism are likely applicable to mammals in the Caatinga, as the
451 upper limits of mammal thermal tolerance are highly conserved in tropical species (Araújo et
452 al., 2013; Khalil et al., 2015). To minimise model transferability issues, we constrained
453 habitat suitability estimates to environmental conditions similar to those in the training data
454 (Owens et al., 2013). Although the models used in this study varied quantitatively, the
455 projected changes consistently pointed in the same direction, conveying a unified message.

456 Our findings indicate a higher species loss for mammal assemblages in the eastern half
457 of Caatinga, which is also affected by chronic disturbances (Antongiovanni et al., 2020). The
458 highly fragmented and diminished vegetation cover of eastern Caatinga (Castanho et al.,
459 2020) impose additional challenges for non-volant mammals to track suitable habitats (Alves
460 et al., 2020), further contributing to depauperate the trophic structure of species assemblages
461 (Mendoza & Araújo, 2019). Although mammal assemblages subject to high species loss

462 exhibit more future uncertainty, a more optimistic outlook is unlikely as these regions also
463 overlap with heavily settled human-modified landscapes in the Caatinga (Antongiovanni et
464 al., 2018, 2020) and regions projected to vegetation complexity and diversity (Moura et al.,
465 2023). Therefore, the severe defaunation of Caatinga mammal assemblages is a probable
466 outcome, with small-sized species loss driven by climate change – at least partially – and the
467 depauperating of large-sized mammal further exacerbated by overexploitation and habitat
468 destruction (Alves et al., 2023; Bogoni et al., 2020). In the long-term, this drastic
469 simplification of mammal assemblages can disrupt biotic interactions and impact ecosystem
470 services in tropical dry forests, by reducing the potential for vegetation regeneration and
471 carbon storage (Bello et al., 2015; Fricke et al., 2022; Gardner et al., 2019). The success of
472 long-term socioenvironmental policy and biodiversity conservation planning necessitates that
473 findings derived from biodiversity forecasts are considered.

474

475 REFERENCES

476 Aguirre-Gutiérrez, J., Malhi, Y., Lewis, S. L., Fauset, S., Adu-Bredu, S., Affum-Baffoe, K.,
477 Baker, T. R., Gvozdevaite, A., Hubau, W., Moore, S., Peprah, T., Ziemińska, K.,
478 Phillips, O. L., & Oliveras, I. (2020). Long-term droughts may drive drier tropical forests
479 towards increased functional, taxonomic and phylogenetic homogeneity. *Nature
480 Communications*, 11(1), 1–10. <https://doi.org/10.1038/s41467-020-16973-4>

481 Alves, R. R. N., Gonçalves, M. Br., & Vieira, W. L. S. (2012). Caça, uso e conservação de
482 vertebrados no semiárido Brasileiro. *Tropical Conservation Science*, 5(3), 394–416.
483 <https://doi.org/10.1177/194008291200500312>

484 Alves, T. S., Alvarado, F., Arroyo-Rodríguez, V., & Santos, B. A. (2020). Landscape-scale
485 patterns and drivers of novel mammal communities in a human-modified protected area.
486 *Landscape Ecology*, 35(7), 1619–1633. <https://doi.org/10.1007/s10980-020-01040-6>

487 Alves, T. S., Alvarado, F., Arroyo-Rodríguez, V., & Santos, B. A. (2023). Foxes and goats:
488 the outcome of free-ranging livestock farming in Brazilian dry forests. *Biodiversity and*
489 *Conservation*, 32(2), 715–734. <https://doi.org/10.1007/s10531-022-02520-8>

490 Andrade, A. F. A., Velazco, S. J. E., & De-Marco, P. (2020). ENMTML: An R package for a
491 straightforward construction of complex ecological niche models. *Environmental*
492 *Modelling & Software*, 125(October 2019), 104615.
493 <https://doi.org/10.1016/j.envsoft.2019.104615>

494 Antongiovanni, M., Venticinque, E. M., & Fonseca, C. R. (2018). Fragmentation patterns of
495 the Caatinga drylands. *Landscape Ecology*, 33(8), 1353–1367.
496 <https://doi.org/10.1007/s10980-018-0672-6>

497 Antongiovanni, M., Venticinque, E. M., Matsumoto, M., & Fonseca, C. R. (2020). Chronic
498 anthropogenic disturbance on Caatinga dry forest fragments. *Journal of Applied Ecology*,
499 57(10), 2064–2074. <https://doi.org/10.1111/1365-2664.13686>

500 Araújo, M. B., Ferri-Yáñez, F., Bozinovic, F., Marquet, P. A., Valladares, F., & Chown, S. L.
501 (2013). Heat freezes niche evolution. *Ecology Letters*, 16(9), 1206–1219.
502 <https://doi.org/10.1111/ele.12155>

503 Araújo, M. B., & New, M. (2007). Ensemble forecasting of species distributions. *Trends in*
504 *Ecology & Evolution*, 22(1), 42–47. <https://doi.org/10.1016/j.tree.2006.09.010>

505 Asfora, P. H., Palma, A. R. T., Astúa, D., & Geise, L. (2011). Distribution of *Oecomys*
506 *catherinae* Thomas, 1909 (Rodentia: Cricetidae) in northeastern Brazil with karyotypical
507 and morphometrical notes. *Biota Neotropica*, 11(2), 415–424.
508 <https://doi.org/10.1590/S1676-06032011000200039>

509 Banda-R, K., Delgado-Salinas, A., Dexter, K. G., Linares-Palomino, R., Oliveira-Filho, A.,
510 Prado, D., Pullan, M., Quintana, C., Riina, R., Rodriguez M, G. M., Weintritt, J.,
511 Acevedo-Rodriguez, P., Adarve, J., Alvarez, E., Aranguren B, A., Arteaga, J. C.,

512 Aymard, G., Castano, A., Ceballos-Mago, N., ... Pennington, R. T. (2016). Plant
513 diversity patterns in neotropical dry forests and their conservation implications. *Science*,
514 353(6306), 1383–1387. <https://doi.org/10.1126/science.aaf5080>

515 Barbet-Massin, M., Jiguet, F., Albert, C. H., & Thuiller, W. (2012). Selecting pseudo-
516 absences for species distribution models: How, where and how many? *Methods in*
517 *Ecology and Evolution*, 3(2), 327–338. <https://doi.org/10.1111/j.2041->
518 210X.2011.00172.x

519 Barboza, R. R. D., Lopes, S. F., Souto, W. M. S., Fernandes-Ferreira, H., & Alves, R. R. N.
520 (2016). The role of game mammals as bushmeat in the Caatinga, northeast Brazil.
521 *Ecology and Society*, 21(2), art2. <https://doi.org/10.5751/ES-08358-210202>

522 Barve, N., Barve, V., Jiménez-valverde, A., Lira-noriega, A., Maher, S. P., Peterson, A. T.,
523 Soberón, J., & Villalobos, F. (2012). The crucial role of the accessible area in ecological
524 niche modeling and species distribution modeling. *Ecological Modelling*, 222(11), 1810–
525 1819. <https://doi.org/10.1016/j.ecolmodel.2011.02.011>

526 Baselga, A. (2010). Partitioning the turnover and nestedness components of beta diversity.
527 *Global Ecology and Biogeography*, 19(1), 134–143.

528 Baselga, A. (2013). Multiple site dissimilarity quantifies compositional heterogeneity among
529 several sites, while average pairwise dissimilarity may be misleading. *Ecography*, 36(2),
530 124–128. <https://doi.org/10.1111/j.1600-0587.2012.00124.x>

531 Baselga, A., & Orme, C. D. L. (2012). betapart: an R package for the study of beta diversity.
532 *Methods in Ecology and Evolution*, 3(5), 808–812.

533 Becker, A., Körner, C., Brun, J.-J., Guisan, A., & Tappeiner, U. (2007). Ecological and Land
534 Use Studies along Elevational Gradients. *Mountain Research and Development*, 27(1),
535 58–65. <http://www.jstor.org/stable/4540681>

536 Bello, C., Galetti, M., Pizo, M. A., Magnago, L. F. S., Rocha, M. F., Lima, R. A. F., Peres, C.

537 A., Ovaskainen, O., & Jordano, P. (2015). Defaunation affects carbon storage in tropical
538 forests. *Science Advances*, 1(11). <https://doi.org/10.1126/sciadv.1501105>

539 Bogoni, J. A., Peres, C. A., & Ferraz, K. M. P. M. B. (2020). Extent, intensity and drivers of
540 mammal defaunation: a continental-scale analysis across the Neotropics. *Scientific
541 Reports*, 10(1), 14750. <https://doi.org/10.1038/s41598-020-72010-w>

542 Bovo, A. A. de A., Magioli, M., Percequillo, A. R., Kruszynski, C., Alberici, V., Mello, M. A.
543 R., Correa, L. S., Gebin, J. C. Z., Ribeiro, Y. G. G., Costa, F. B., Ramos, V. N., Benatti,
544 H. R., Lopes, B., Martins, M. Z. A., Diniz-Reis, T. R., Camargo, P. B. de, Labruna, M.
545 B., & Ferraz, K. M. P. M. de B. (2018). Human-modified landscape acts as refuge for
546 mammals in Atlantic Forest. *Biota Neotropica*, 18(2). <https://doi.org/10.1590/1676-0611-bn-2017-0395>

548 Breiman, L. (2001). Random Forests. *Machine Learning*, 45(1), 5–32.
549 <https://doi.org/10.1023/A:1010933404324>

550 Breiner, F. T., Guisan, A., Bergamini, A., & Nobis, M. P. (2015). Overcoming limitations of
551 modelling rare species by using ensembles of small models. *Methods in Ecology and
552 Evolution*, 6(10), 1210–1218. <https://doi.org/10.1111/2041-210X.12403>

553 Breiner, F. T., Nobis, M. P., Bergamini, A., & Guisan, A. (2018). Optimizing ensembles of
554 small models for predicting the distribution of species with few occurrences. *Methods in
555 Ecology and Evolution*, 9(4), 802–808. <https://doi.org/10.1111/2041-210X.12957>

556 Brennand, P. G. G., Langguth, A., & Percequillo, A. R. (2013). The genus *Hylaeamys*
557 Weksler, Percequillo, and Voss 2006 (Rodentia: Cricetidae: Sigmodontinae) in the
558 Brazilian Atlantic Forest: geographic variation and species definition. *Journal of
559 Mammalogy*, 94(6), 1346–1363. <https://doi.org/10.1644/12-MAMM-A-312.1>

560 Carmignotto, A. P., & Astúa, D. (2018). Mammals of the Caatinga: Diversity, ecology,
561 biogeography, and conservation. In *Caatinga: The Largest Tropical Dry Forest Region*

562 *in South America*. https://doi.org/10.1007/978-3-319-68339-3_8

563 Carmignotto, A. P., Vivo, M. de, & Langguth, A. (2012). Mammals of the Cerrado and
564 Caatinga. In *Bones, Clones, and Biomes* (pp. 307–350). University of Chicago Press.
565 <https://doi.org/10.7208/chicago/9780226649214.003.0014>

566 Carmona, C. P., Tamme, R., Pärtel, M., de Bello, F., Brosse, S., Capdevila, P., González-M.,
567 R., González-Suárez, M., Salguero-Gómez, R., Vásquez-Valderrama, M., & Toussaint,
568 A. (2021). Erosion of global functional diversity across the tree of life. *Science*
569 *Advances*, 7(13). <https://doi.org/10.1126/sciadv.abf2675>

570 Castanho, A. D. A., Coe, M., Andrade, E. M., Walker, W., Baccini, A., Campos, D. A., &
571 Farina, M. (2020). A close look at above ground biomass of a large and heterogeneous
572 seasonally dry tropical forest-caatinga in north east of Brazil. *Anais Da Academia*
573 *Brasileira de Ciencias*, 92(1), 1–18. <https://doi.org/10.1590/0001-3765202020190282>

574 Chen, I.-C., Hill, J. K., Ohlemüller, R., Roy, D. B., & Thomas, C. D. (2011). Rapid Range
575 Shifts of Species Associated with High Levels of Climate Warming. *Science*, 333(6045),
576 1024–1026. <https://doi.org/10.1126/science.1206432>

577 Chiarello, A. G. (2000). Density and Population Size of Mammals in Remnants of Brazilian
578 Atlantic Forest. *Conservation Biology*, 14(6), 1649–1657.

579 Clavel, J., Julliard, R., & Devictor, V. (2011). Worldwide decline of specialist species:
580 Toward a global functional homogenization? *Frontiers in Ecology and the Environment*,
581 9(4), 222–228. <https://doi.org/10.1890/080216>

582 Cooke, R. S. C., Eigenbrod, F., & Bates, A. E. (2019). Projected losses of global mammal and
583 bird ecological strategies. *Nature Communications*, 10(1), 2279.
584 <https://doi.org/10.1038/s41467-019-10284-z>

585 Costa, G. C., Hampe, A., Ledru, M. P., Martinez, P. A., Mazzochini, G. G., Shepard, D. B.,
586 Werneck, F. P., Moritz, C., & Carnaval, A. C. (2018). Biome stability in South America

587 over the last 30 kyr: Inferences from long-term vegetation dynamics and habitat
588 modelling. *Global Ecology and Biogeography*, 27(3), 285–297.
589 <https://doi.org/10.1111/geb.12694>

590 Culot, L., Pereira, L. A., Agostini, I., Almeida, M. A. B., Alves, R. S. C., Aximoff, I., Bager,
591 A., Baldovino, M. C., Bella, T. R., Bicca□Marques, J. C., Braga, C., Brocardo, C. R.,
592 Campelo, A. K. N., Canale, G. R., Cardoso, J. C., Carrano, E., Casanova, D. C., Cassano,
593 C. R., Castro, E., ... Galetti, M. (2019). Atlantic Primates: a dataset of communities and
594 occurrences of primates in the Atlantic Forests of South America. *Ecology*, 100(1).
595 <https://doi.org/10.1002/ecy.2525>

596 De Marco, P., & Nóbrega, C. C. (2018). Evaluating collinearity effects on species distribution
597 models: An approach based on virtual species simulation. *PLOS ONE*, 13(9), e0202403.
598 <https://doi.org/10.1371/journal.pone.0202403>

599 Diniz-Filho, J. A. F., Bini, L. M., Rangel, T. F., Loyola, R. D., Hof, C., Nogués-Bravo, D., &
600 Araújo, M. B. (2009). Partitioning and mapping uncertainties in ensembles of forecasts
601 of species turnover under climate change. *Ecography*, 32(6), 897–906.
602 <https://doi.org/10.1111/j.1600-0587.2009.06196.x>

603 Dirzo, R., Young, H. S., Galetti, M., Ceballos, G., Isaac, N. J. B., & Collen, B. (2014).
604 Defaunation in the Anthropocene. *Science*, 345(6195), 401–406.
605 <https://doi.org/10.1126/science.1251817>

606 Dutilleul, P. (1993). Modifying the t Test for Assessing the Correlation Between Two Spatial
607 Processes. *Biometrics*, 49(1), 305–314.

608 Elith, J., Kearney, M., & Phillips, S. (2010). The art of modelling range-shifting species.
609 *Methods in Ecology and Evolution*, 1(4), 330–342. <https://doi.org/10.1111/j.2041-210X.2010.00036.x>

611 Engler, R., Guisan, A., & Rechsteiner, L. (2004). An improved approach for predicting the

612 distribution of rare and endangered species from occurrence and pseudo-absence data.

613 *Journal of Applied Ecology*, 41(2), 263–274. <https://doi.org/10.1111/j.0021-8901.2004.00881.x>

615 Faurby, S., Davis, M., Pedersen, R. Ø., Schowanek, S. D., Antonelli1, A., & Svenning, J.

616 (2018). PHYLACINE 1.2: The Phylogenetic Atlas of Mammal Macroecology. *Ecology*,

617 99(11), 2626–2626. <https://doi.org/10.1002/ecy.2443>

618 Feijó, A., & Langguth, A. (2013). Mamíferos de médio e grande porte do Nordeste do Brasil:

619 distribuição e taxonomia, com descrição de novas espécies. *Revista Nordestina de*

620 *Biologia*, 3–225.

621 Feijó, A., Nunes, H., & Langguth, A. (2016). Mamíferos da Reserva Biológica Guaribas,

622 Paraíba, Brasil. *Revista Nordestina de Biologia*, 24(1), 57–74.

623 Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: new 1° km spatial resolution climate

624 surfaces for global land areas. *International Journal of Climatology*, 37(12), 4302–4315.

625 <https://doi.org/10.1002/joc.5086>

626 Filgueiras, B. K. C., Peres, C. A., Melo, F. P. L., Leal, I. R., & Tabarelli, M. (2021). Winner–

627 Loser Species Replacements in Human-Modified Landscapes. *Trends in Ecology &*

628 *Evolution*, 36(6), 545–555. <https://doi.org/10.1016/j.tree.2021.02.006>

629 Freitas, C. A. de. (1957). Notícia sobre a peste no Nordeste. *Revista Brasileira de*

630 *Malaria e Doenças Tropicais*, 9(1), 123–133.

631 Fricke, E. C., Ordóñez, A., Rogers, H. S., & Svenning, J.-C. (2022). The effects of

632 defaunation on plants' capacity to track climate change. *Science*, 375(6577), 210–214.

633 <https://doi.org/10.1126/science.abk3510>

634 Fuller, A., Mitchell, D., Maloney, S. K., Hetem, R. S., Fonsêca, V. F. C., Meyer, L. C. R., van

635 de Ven, T. M. F. N., & Snelling, E. P. (2021). How dryland mammals will respond to

636 climate change: the effects of body size, heat load and a lack of food and water. *Journal*

637 *of Experimental Biology*, 224(Suppl_1). <https://doi.org/10.1242/jeb.238113>

638 Gardner, A. L. (2008). *Mammals of South America, volume 1: Marsupials, xenarthrans,*
639 *shrews, and bats* (Vol. 1). University of Chicago Press.

640 Gardner, C. J., Bicknell, J. E., Baldwin-Cantello, W., Struebig, M. J., & Davies, Z. G. (2019).
641 Quantifying the impacts of defaunation on natural forest regeneration in a global meta-
642 analysis. *Nature Communications*, 10(1), 4590. [https://doi.org/10.1038/s41467-019-12539-1](https://doi.org/10.1038/s41467-019-
643 12539-1)

644 Gardner, J. L., Peters, A., Kearney, M. R., Joseph, L., & Heinsohn, R. (2011). Declining body
645 size: a third universal response to warming? *Trends in Ecology & Evolution*, 26(6), 285–
646 291. <https://doi.org/10.1016/j.tree.2011.03.005>

647 GBIF. (2023). *Global Biodiversity Information Facility – Free and Open Access to*
648 *Biodiversity Data* (p. Selected mammal species occurrences).
649 <https://doi.org/10.15468/dl.zncm2h>

650 Geise, L., Paresque, R., Sebastião, H., Shirai, L. T., Astúa, D., & Marroig, G. (2010). Non-
651 volant mammals, Parque Nacional do Catimbau, Vale do Catimbau, Buíque, state of
652 Pernambuco, Brazil, with karyologic data. *Check List*, 6(1), 180.
653 <https://doi.org/10.15560/6.1.180>

654 Guisan, A., & Thuiller, W. (2005). Predicting species distribution: Offering more than simple
655 habitat models. *Ecology Letters*, 8(9), 993–1009. [https://doi.org/10.1111/j.1461-0248.2005.00792.x](https://doi.org/10.1111/j.1461-
656 0248.2005.00792.x)

657 Gurgel-Filho, N. M., Feijó, A., & Langguth, A. (2015). Pequenos mamíferos do Ceará
658 (marsupiais, morcegos e roedores sigmodontíneos) com discussão taxonômica de
659 algumas espécies. *Revista Nordestina de Biologia*, 23(2), 3–150.

660 Hetem, R. S., Fuller, A., Maloney, S. K., & Mitchell, D. (2014). Responses of large mammals
661 to climate change. *Temperature*, 1(2), 115–127. <https://doi.org/10.4161/temp.29651>

662 Hidasi-Neto, J., Joner, D. C., Resende, F., Monteiro, L. de M., Faleiro, F. V., Loyola, R. D.,
663 & Cianciaruso, M. V. (2019). Climate change will drive mammal species loss and biotic
664 homogenization in the Cerrado Biodiversity Hotspot. *Perspectives in Ecology and*
665 *Conservation*, 17(2), 57–63. <https://doi.org/10.1016/j.pecon.2019.02.001>

666 Hoekstra, J. M., Boucher, T. M., Ricketts, T. H., & Roberts, C. (2004). Confronting a biome
667 crisis: global disparities of habitat loss and protection. *Ecology Letters*, 8(1), 23–29.
668 <https://doi.org/10.1111/j.1461-0248.2004.00686.x>

669 IPCC. (2021). *Climate Change 2021: The Physical Science Basis. Contribution of Working*
670 *Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate*
671 *Change* (V. Masson-Delmotte, P. Zhai, A. Pirani, S. L. Connors, C. Péan, S. Berger, N.
672 Caud, Y. Chen, L. Goldfarb, M. I. Gomis, M. Huang, K. Leitzell, E. Lonnoy, J. B. R.
673 Matthews, T. K. Maycock, T. Waterfield, O. Yelekçi, R. Yu, & B. Zho (eds.)).
674 Cambridge University Press.

675 Khaliq, I., Fritz, S. A., Prinzinger, R., Pfenninger, M., Böhning-Gaese, K., & Hof, C. (2015).
676 Global variation in thermal physiology of birds and mammals: evidence for phylogenetic
677 niche conservatism only in the tropics. *Journal of Biogeography*, 42(11), 2187–2196.
678 <https://doi.org/10.1111/jbi.12573>

679 Kramer-Schadt, S., Niedballa, J., Pilgrim, J. D., Schröder, B., Lindenborn, J., Reinfelder, V.,
680 Stillfried, M., Heckmann, I., Scharf, A. K., Augeri, D. M., Cheyne, S. M., Hearn, A. J.,
681 Ross, J., Macdonald, D. W., Mathai, J., Eaton, J., Marshall, A. J., Semiadi, G., Rustam,
682 R., ... Wilting, A. (2013). The importance of correcting for sampling bias in MaxEnt
683 species distribution models. *Diversity and Distributions*, 19(11), 1366–1379.
684 <https://doi.org/10.1111/ddi.12096>

685 Kreft, H., & Jetz, W. (2010). A framework for delineating biogeographical regions based on
686 species distributions. *Journal of Biogeography*, 37(11), 2029–2053.

687 <https://doi.org/10.1111/j.1365-2699.2010.02375.x>

688 Leal, I. R., Da-Silva, J. M. C., Tabarelli, M., & Lacher, T. E. (2005). Changing the Course of
689 Biodiversity Conservation in the Caatinga of Northeastern Brazil. *Conservation Biology*,
690 19(3), 701–706. <https://doi.org/10.1111/j.1523-1739.2005.00703.x>

691 Lenoir, J., & Svenning, J. C. (2015). Climate-related range shifts - a global multidimensional
692 synthesis and new research directions. *Ecography*, 38(1), 15–28.

693 <https://doi.org/10.1111/ecog.00967>

694 Leroy, B., Delsol, R., Hugueny, B., Meynard, C. N., Barhoumi, C., Barbet-Massin, M., &
695 Bellard, C. (2018). Without quality presence-absence data, discrimination metrics such
696 as TSS can be misleading measures of model performance. *Journal of Biogeography*,
697 45(9), 1994–2002. <https://doi.org/10.1111/jbi.13402>

698 Liaw, A., & Wiener, M. (2002). Classification and Regression by randomForest. *R News*,
699 2(3), 18–22. <https://cran.r-project.org/doc/Rnews/>

700 Lima, F., Beca, G., Muylaert, R. L., Jenkins, C. N., Perilli, M. L. L., Paschoal, A. M. O.,
701 Massara, R. L., Paglia, A. P., Chiarello, A. G., Graipel, M. E., Cherem, J. J., Regolin, A.
702 L., Oliveira Santos, L. G. R., Brocardo, C. R., Paviolo, A., Di Bitetti, M. S., Scoss, L.
703 M., Rocha, F. L., Fusco-Costa, R., ... Galetti, M. (2017). ATLANTIC-CAMTRAPS: a
704 dataset of medium and large terrestrial mammal communities in the Atlantic Forest of
705 South America. *Ecology*, 98(11), 2979–2979. <https://doi.org/10.1002/ecy.1998>

706 Liu, C., Newell, G., & White, M. (2019). The effect of sample size on the accuracy of species
707 distribution models: considering both presences and pseudo-absences or background
708 sites. *Ecography*, 42(3), 535–548. <https://doi.org/10.1111/ecog.03188>

709 Liu, C., White, M., & Newell, G. (2011). Measuring and comparing the accuracy of species
710 distribution models with presence-absence data. *Ecography*, 34(2), 232–243.

711 <https://doi.org/10.1111/j.1600-0587.2010.06354.x>

712 Lobo, J. M., & Tognelli, M. F. (2011). Exploring the effects of quantity and location of
713 pseudo-absences and sampling biases on the performance of distribution models with
714 limited point occurrence data. *Journal for Nature Conservation*, 19(1), 1–7.
715 <https://doi.org/10.1016/j.jnc.2010.03.002>

716 Lopez, L. C. S., Figueiredo, M. S. L., Fracasso, M. P. A., Mesquita, D. O., Anjos, U. U., &
717 Grelle, C. E. V. (2016). The role of local versus biogeographical processes in influencing
718 diversity and body size variation in mammal assemblages. *Ecology and Evolution*, 6(5),
719 1447–1456. <https://doi.org/10.1002/ece3.1978>

720 Magalhães, R. A., Massara, R. L., de Oliveira, F. S., & Rodrigues, F. H. G. (2023). The
721 Brazilian three-banded armadillo is widely distributed in a human-modified landscape in
722 northeastern Brazil. *Mammal Research*, 68(1), 53–62. <https://doi.org/10.1007/s13364-022-00651-5>

724 Malcher, S. M., Pieczarka, J. C., Geise, L., Rossi, R. V., Pereira, A. L., O'Brien, P. C. M.,
725 Asfora, P. H., Fonsêca da Silva, V., Sampaio, M. I., Ferguson-Smith, M. A., &
726 Nagamachi, C. Y. (2017). *Oecomys catherinae* (Sigmodontinae, Cricetidae): Evidence
727 for chromosomal speciation? *PLOS ONE*, 12(7), e0181434.
728 <https://doi.org/10.1371/journal.pone.0181434>

729 Marengo, J. A., Torres, R. R., & Alves, L. M. (2017). Drought in Northeast Brazil—past,
730 present, and future. *Theoretical and Applied Climatology*, 129(3–4), 1189–1200.
731 <https://doi.org/10.1007/s00704-016-1840-8>

732 Mares, M. A., Willig, M. R., Streilein, K. E., & Lacher, T. E. (1981). *The mammals of
733 northeastern Brazil: a preliminary assessment*. Carnegie Museum of Natural History.

734 Marinho, P. H., Fonseca, C. R., Sarmento, P., Fonseca, C., & Venticinque, E. M. (2020).
735 Temporal niche overlap among mesocarnivores in a Caatinga dry forest. *European
736 Journal of Wildlife Research*, 66(2), 34. <https://doi.org/10.1007/s10344-020-1371-6>

737 Mckinney, M. L., & Lockwood, J. L. (1999). Biotic homogenization: a few winners
738 replacing many losers in the next mass extinction. *Trends in Ecology & Evolution*,
739 5347(11), 450–453.

740 Melo, A. S., Rangel, T. F. L. V. B., & Diniz-Filho, J. A. F. (2009). Environmental drivers of
741 beta-diversity patterns in New-World birds and mammals. *Ecography*, 32(2), 226–236.

742 Mendes, P., Velazco, S. J. E., de Andrade, A. F. A., & De Marco, P. (2020). Dealing with
743 overprediction in species distribution models: How adding distance constraints can
744 improve model accuracy. *Ecological Modelling*, 431(August 2019), 109180.
745 <https://doi.org/10.1016/j.ecolmodel.2020.109180>

746 Mendonça, A., Percequillo, A. R., Camargo, N. F., Ribeiro, J. F., Palma, A. R. T., Oliveira, L.
747 C., Câmara, E. M. V. C., & Vieira, E. M. (2018). Cerrado Small Mammals: abundance
748 and distribution of marsupials, lagomorphs, and rodents in a Neotropical savanna.
749 *Ecology*, 99(8), 1900–1900. <https://doi.org/10.1002/ecy.2367>

750 Mendoza, M., & Araújo, M. B. (2019). Climate shapes mammal community trophic structures
751 and humans simplify them. *Nature Communications*, 10(1), 5197.
752 <https://doi.org/10.1038/s41467-019-12995-9>

753 Montti, L., Velazco, S. J. E., Travis, J. M. J., & Grau, H. R. (2021). Predicting current and
754 future global distribution of invasive *Ligustrum lucidum* W.T. Aiton: Assessing
755 emerging risks to biodiversity hotspots. *Diversity and Distributions*, 27(8), 1568–1583.
756 <https://doi.org/10.1111/ddi.13303>

757 Moura, M. R., do Nascimento, F. A. O., Paolucci, L. N., Silva, D. P., & Santos, B. A. (2023).
758 Pervasive impacts of climate change on the woodiness and ecological generalism of dry
759 forest plant assemblages. *Journal of Ecology*, 111(8), 1762–1776.
760 <https://doi.org/10.1111/1365-2745.14139>

761 Nagy Reis, M., Oshima, J. E. de F., Kanda, C. Z., Palmeira, F. B. L., Melo, F. R., Morato, R.

762 G., Bonjorne, L., Magioli, M., Leuchtenberger, C., Rohe, F., Lemos, F. G., Martello, F.,
763 Alves-Eigenheer, M., Silva, R. A., Silveira dos Santos, J., Priante, C. F., Bernardo, R.,
764 Rogeri, P., Assis, J. C., ... Ribeiro, M. C. (2020). Neotropical Carnivores: a data set on
765 carnivore distribution in the Neotropics. *Ecology*, 101(11).
766 <https://doi.org/10.1002/ecy.3128>

767 Nascimento, F. O., & Feijó, A. (2017). Taxonomic revision of the tigrina *Leopardus tigrinus*
768 (Schreber, 1775) species group (Carnivora, Felidae). *Papéis Avulsos de Zoologia (São
769 Paulo)*, 57(19), 231. <https://doi.org/10.11606/0031-1049.2017.57.19>

770 Oliveira, F. F. de, & Langguth, A. (2004). Pequenos mamíferos (Didelphimorphia e Rodentia)
771 de Paraíba e Pernambuco, Brasil. *Revista Nordestina de Biologia*, 19–86.

772 Oliveira, G., & Diniz-Filho, J. A. F. (2010). Spatial patterns of terrestrial vertebrates richness
773 in Brazilian semiarid, Northeastern Brazil: Selecting hypotheses and revealing
774 constraints. *Journal of Arid Environments*, 74(11), 1418–1426.

775 Oliveira, J. A., Gonçalves, P. R., & Bonvicino, C. R. (2003). Mamíferos da Caatinga. In I. R.
776 Leal, M. Tabarelli, & J. M. C. Da-Silva (Eds.), *Ecologia e Conservação da Caatinga*
777 (pp. 275–335). Universidade Federal de Pernambuco.

778 Osorio, F., Vallejos, R., Cuevas, F., & Mancilla, D. (2014). *SpatialPack: Package for
779 analysis of spatial data* (p. <http://spatialpack.mat.utfsm.cl>).

780 <http://spatialpack.mat.utfsm.cl>

781 Owens, H. L., Campbell, L. P., Dornak, L. L., Saupe, E. E., Barve, N., Soberón, J., Ingenloff,
782 K., Lira-Noriega, A., Hensz, C. M., Myers, C. E., & Peterson, A. T. (2013). Constraints
783 on interpretation of ecological niche models by limited environmental ranges on
784 calibration areas. *Ecological Modelling*, 263, 10–18.

785 <https://doi.org/10.1016/j.ecolmodel.2013.04.011>

786 Patton, J. L., Pardiñas, U. F. J., & D'Elía, G. (2015). *Mammals of South America, volume 2*:

787 *Rodents*. University of Chicago Press.

788 Phillips, S. J., Anderson, R. P., Dudík, M., Schapire, R. E., & Blair, M. E. (2017). Opening
789 the black box: an open-source release of Maxent. *Ecography*, 40(7), 887–893.
790 <https://doi.org/10.1111/ecog.03049>

791 Pires, F. D. A., & Wied, M. (1965). *The type specimens of Brazilian mammals collected by*
792 *Prince Maximilian zu Wied. American Museum Novitates*. 2209, 1–21.

793 Quintela, F. M., Da Rosa, C. A., & Feijó, A. (2020). Updated and annotated checklist of
794 recent mammals from Brazil. *Anais Da Academia Brasileira de Ciências*, 92(suppl 2).
795 <https://doi.org/10.1590/0001-3765202020191004>

796 R Core Team. (2022). *R: A Language and Environment for Statistical Computing* (p. v.
797 4.2.0). The R Foundation for Statistical Computing Platform.

798 Ramesh, T., Kalle, R., Sankar, K., & Qureshi, Q. (2015). Role of body size in activity budgets
799 of mammals in the Western Ghats of India. *Journal of Tropical Ecology*, 31(4), 315–
800 323. <https://doi.org/10.1017/S0266467415000188>

801 Rangel, T. F., & Loyola, R. D. (2012). Labeling Ecological Niche Models. *Natureza &*
802 *Conservação*, 10(2), 119–126. <https://doi.org/10.4322/natcon.2012.030>

803 Redford, K. H. (1992). The Empty Forest. *BioScience*, 42(6), 412–422.
804 <https://doi.org/10.2307/1311860>

805 Riddell, E. A., Iknayan, K. J., Hargrove, L., Tremor, S., Patton, J. L., Ramirez, R., Wolf, B.
806 O., & Beissinger, S. R. (2021). Exposure to climate change drives stability or collapse of
807 desert mammal and bird communities. *Science*, 371(6529), 633–636.
808 <https://doi.org/10.1126/science.abd4605>

809 Rito, K. F., Tabarelli, M., & Leal, I. R. (2017). Euphorbiaceae responses to chronic
810 anthropogenic disturbances in Caatinga vegetation: from species proliferation to biotic
811 homogenization. *Plant Ecology*, 218(6), 749–759. [36](https://doi.org/10.1007/s11258-017-</p></div><div data-bbox=)

812 0726-x

813 Roberts, D. R., Bahn, V., Ciuti, S., Boyce, M. S., Elith, J., Guillera-Arroita, G., Hauenstein,
814 S., Lahoz-Monfort, J. J., Schröder, B., Thuiller, W., Warton, D. I., Wintle, B. A., Hartig,
815 F., & Dormann, C. F. (2017). Cross-validation strategies for data with temporal, spatial,
816 hierarchical, or phylogenetic structure. *Ecography*, 40(8), 913–929.
817 <https://doi.org/10.1111/ecog.02881>

818 Sales, L. P., Galetti, M., Carnaval, A., Monsarrat, S., Svenning, J., & Pires, M. M. (2022).
819 The effect of past defaunation on ranges, niches, and future biodiversity forecasts.
820 *Global Change Biology*, 28(11), 3683–3693. <https://doi.org/10.1111/gcb.16145>

821 Sales, L. P., Galetti, M., & Pires, M. M. (2020). Climate and land-use change will lead to a
822 faunal “savannization” on tropical rainforests. *Global Change Biology*, 26(12), 7036–
823 7044. <https://doi.org/10.1111/gcb.15374>

824 Sampaio, A. C. P., & Cavalcante, A. M. B. (2023). Accurate species distribution models:
825 minimum required number of specimen records in the Caatinga biome. *Anais Da
826 Academia Brasileira de Ciências*, 95(2), e20201421. [https://doi.org/10.1590/0001-3765202320201421](https://doi.org/10.1590/0001-
827 3765202320201421)

828 Santini, L., Marco, M. Di, Visconti, P., Baisero, D., Boitani, L., & Rondinini, C. (2013).
829 Ecological correlates of dispersal distance in terrestrial mammals. *Hystrix*, 24(2), 181–
830 186. <https://doi.org/10.4404/hystrix-24.2-8746>

831 Santos, P. M., Bocchiglieri, A., Chiarello, A. G., Paglia, A. P., Moreira, A., Souza, A. C.,
832 Abba, A. M., Paviolo, A., Gatica, A., Medeiro, A. Z., Costa, A. N., Gallina, A. G.,
833 Yanosky, A. A., Jesus, A., Bertassoni, A., Rocha, A., Bovo, A. A. A., Bager, A., Mol, A.
834 C., ... Galetti, M. (2019). Neotropical Xenarthrans: a data set of occurrence of
835 xenarthran species in the Neotropics. *Ecology*, 100(7). <https://doi.org/10.1002/ecy.2663>

836 Schloss, C. A., Nuñez, T. A., & Lawler, J. J. (2012). Dispersal will limit ability of mammals

837 to track climate change in the Western Hemisphere. *Proceedings of the National*
838 *Academy of Sciences of the United States of America*, 109(22), 8606–8611.
839 <https://doi.org/10.1073/pnas.1116791109>

840 Shipley, L. A., Gross, J. E., Spalinger, D. E., Hobbs, N. T., & Wunder, B. A. (1994). The
841 scaling of intake rate in mammalian herbivores. *The American Naturalist*, 143(6), 1055–
842 1082.

843 Silva, J M C, Barbosa, L. C. F., Leal, I. R., & Tabarelli, M. (2017). The Caatinga:
844 Understanding the challenges. In J M Cardoso da Silva, I. R. Leal, & M. Tabarelli (Eds.),
845 *Caatinga: The Largest Tropical Dry Forest Region in South America* (pp. 3–19).
846 Springer.

847 Silva, José M C, Leal, I. R., & Tabarelli, M. (2017). Caatinga. In José Maria Cardoso da
848 Silva, I. R. Leal, & M. Tabarelli (Eds.), *Caatinga: The Largest Tropical Dry Forest*
849 *Region in South America*. Springer International Publishing. <https://doi.org/10.1007/978-3-319-68339-3>

850 Socolar, J. B., Gilroy, J. J., Kunin, W. E., & Edwards, D. P. (2016). How Should Beta-
851 Diversity Inform Biodiversity Conservation? *Trends in Ecology & Evolution*, 31(1), 67–
852 80. <https://doi.org/10.1016/j.tree.2015.11.005>

853 Soibelzon, E. (2019). Using Paleoclimate and the Fossil Record to Explain Past and Present
854 Distributions of Armadillos (Xenarthra, Dasypodidae). *Journal of Mammalian*
855 *Evolution*, 26(1), 61–70. <https://doi.org/10.1007/s10914-017-9395-8>

856 Soria, C. D., Pacifici, M., Di Marco, M., Stephen, S. M., & Rondinini, C. (2021). COMBINE:
857 a coalesced mammal database of intrinsic and extrinsic traits. *Ecology*, 102(6), e03344.
858 <https://doi.org/10.1002/ECY.3344/SUPPINFO>

859 Souza, D. G., Sfair, J. C., de Paula, A. S., Barros, M. F., Rito, K. F., & Tabarelli, M. (2019).
860 Multiple drivers of aboveground biomass in a human-modified landscape of the Caatinga
861

862 dry forest. *Forest Ecology and Management*, 435, 57–65.

863 <https://doi.org/10.1016/j.foreco.2018.12.042>

864 Souza, Y., Gonçalves, F., Lautenschlager, L., Akkawi, P., Mendes, C., Carvalho, M. M.,

865 Bovendorp, R. S., Fernandes Ferreira, H., Rosa, C., Graipel, M. E., Peroni, N., Cherem,

866 J. J., Bogoni, J. A., Brocardo, C. R., Miranda, J., Zago da Silva, L., Melo, G., Cáceres,

867 N., Sponchiado, J., ... Galetti, M. (2019). Atlantic Mammals: a data set of assemblages

868 of medium and large sized mammals of the Atlantic Forest of South America.

869 *Ecology*, 100(10). <https://doi.org/10.1002/ecy.2785>

870 Thuiller, W., Guéguen, M., Renaud, J., Karger, D. N., & Zimmermann, N. E. (2019).

871 Uncertainty in ensembles of global biodiversity scenarios. *Nature Communications*,

872 10(1), 1–9. <https://doi.org/10.1038/s41467-019-09519-w>

873 Torres, R. R., Lapola, D. M., & Gamarra, N. L. R. (2017). Future Climate Change in the

874 Caatinga. In *Caatinga* (pp. 383–410). Springer International Publishing.

875 https://doi.org/10.1007/978-3-319-68339-3_15

876 van Proosdij, A. S. J., Sosef, M. S. M., Wieringa, J. J., & Raes, N. (2016). Minimum required

877 number of specimen records to develop accurate species distribution models. *Ecography*,

878 39(6), 542–552. <https://doi.org/10.1111/ecog.01509>

879 Velazco, S. J. E., Rose, M. B., Andrade, A. F. A., Minoli, I., & Franklin, J. (2022). flexsdm:

880 An R package for supporting a comprehensive and flexible species distribution

881 modelling workflow. *Methods in Ecology and Evolution*, 13(8), 1661–1669.

882 <https://doi.org/10.1111/2041-210X.13874>

883 Vieira, L. A. F., Tabarelli, M., Souza, G., Queiroz, R. T., & Santos, B. A. (2022). Divergent

884 herb communities in drier and chronically disturbed areas of the Brazilian Caatinga.

885 *Perspectives in Ecology and Conservation*, Early view.

886 <https://doi.org/10.1016/j.pecon.2021.12.002>

887 Villar, C. H., & Naya, D. E. (2018). Climate change and temporal trends in body size: the
888 case of rodents. *Oikos*, 127(8), 1186–1194. <https://doi.org/10.1111/oik.04884>

889 Werneck, F. P., Costa, G. C., Colli, G. R., Prado, D. E., & Sites Jr, J. W. (2011). Revisiting
890 the historical distribution of Seasonally Dry Tropical Forests: new insights based on
891 palaeodistribution modelling and palynological evidence. *Global Ecology and*
892 *Biogeography*, 20(2), 272–288. <https://doi.org/10.1111/j.1466-8238.2010.00596.x>

893 Wilman, H., Belmaker, J., Simpson, J., de la Rosa, C., Rivadeneira, M. M., & Jetz, W. (2014).
894 EltonTraits 1.0: Species-level foraging attributes of the world's birds and mammals.
895 *Ecology*, 95(7), 2027–2027. <https://doi.org/10.1890/13-1917.1>

896 Zizka, A., Silvestro, D., Andermann, T., Azevedo, J., Duarte Ritter, C., Edler, D., Farooq, H.,
897 Herdean, A., Ariza, M., Scharn, R., Svantesson, S., Wengström, N., Zizka, V., &
898 Antonelli, A. (2019). CoordinateCleaner: Standardized cleaning of occurrence records
899 from biological collection databases. *Methods in Ecology and Evolution*, 10(5), 744–751.
900 <https://doi.org/10.1111/2041-210X.13152>

901

902 **ACKNOWLEDGEMENTS**

903 We are grateful to Pedro C. Estrela, Anderson Feijó, Thais Kubik, Daniel P. Silva and Cibele
904 R. Bonvicino for comments on previous versions of this manuscript. To the Mammal
905 Collection from Universidade Federal da Paraíba for providing occurrences data. To
906 Fundação de Amparo à Pesquisa do Estado de São Paulo for grants to MRM (FAPESP
907 #2021/11840-6 and #2022/12231-6) and MMP (FAPESP #2019/25478-7). To Conselho
908 Nacional de Desenvolvimento Científico e Tecnológico for grants (CNPq #312178/2019-0
909 and #307260/2022-4) and to Universidade Federal da Paraíba (PVA-13357-2020) for grants
910 to BAS. To Re:wild and Dimensions Sciences Bridges for grants to GAO. To Fundação de
911 Amparo à Pesquisa do Estado de Minas Gerais for grants to APP. To Coordenação de

912 Aperfeiçoamento de Pessoal de Nível Superior for a scholarship to GAO and fellowship to
913 APP.

914

915 **COMPETING INTERESTS**

916 The authors have no relevant financial or non-financial interests to disclose.

917

918 **AUTHOR CONTRIBUTIONS**

919 MRM, GAO, and BAS conceived the study; GAO and APP compiled the data; MRM
920 analysed the data. MRM developed the figures and led the writing. All authors contributed
921 critically to the drafts and gave final approval for publication.

922

923 **SUPPLEMENTARY MATERIAL**

924 Supplementary Material is available for this manuscript, including Supplementary Tables
925 (S1–S2) and Supplementary Figures (S1–S22).

