

1 Global patterns of vulnerability to wildlife exploitation 2 in tropical birds and mammals

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12

13 Abstract

14 Wildlife exploitation is one of the most pervasive anthropogenic pressures in tropical ecosystems
15 and a major driver of vertebrate population declines, yet global assessments of species
16 vulnerability to hunting remain spatially imprecise and methodologically inconsistent. We combine
17 exposure to hunting with species-specific sensitivity and adaptive capacity to deliver a spatially
18 explicit pantropical vulnerability assessment for 6,338 bird and 3,837 mammal species across
19 three exploitation purposes: direct consumption, product trade, and pet trade. We computed both
20 species-level vulnerability across each species' range and assemblage-level vulnerability across
21 the tropics. Phylogenetically, the most vulnerable groups include large herbivores, pangolins,
22 medium- and large-sized birds, ground-dwelling birds, and primates, with primates showing
23 discrepancy compared to the IUCN Red List assessments for the Indomalayan realm. At the
24 assemblage level, vulnerability hotspots emerge across Sundaland, southeastern China, western
25 and southern Africa, the Atlantic Forest, and the southern Gran Chaco. Spatial patterns are
26 broadly congruent across taxa and exploitation purposes, but regional divergences arise,
27 particularly for birds on islands and for mammals in New Guinea and the Neotropics. Our

28 framework provides a standardized, flexible, and updatable tool to complement existing
29 assessments and support conservation prioritization of areas and taxa under hunting pressure
30 across the tropics.

31

32 Main

33 For humans, hunting is among the oldest known practices which, combined with an exceptional
34 capacity for innovation, allowed our species to expand from the savannahs of Africa to the dense
35 tropical forests of Sri Lanka or the Amazon basin ¹⁻³. Yet, this age-old practice comes at a cost.
36 When unsustainable, hunting becomes one of the primary, yet most underestimated, drivers of
37 biodiversity loss ^{4,5}. In tropical forests, home to exceptional and irreplaceable biodiversity ⁶,
38 hunting is driving local population declines of birds and mammals (i.e., defaunation; ^{7,8}) and
39 contributing significantly to species extinctions ^{9,10}.

40 Accurately identifying where hunting occurs, and which species are affected is essential
41 for achieving the 2030 targets of the Kunming–Montreal Global Biodiversity Framework. Previous
42 efforts have been constrained either by limited data availability (e.g., ^{11,12}) or by a lack of reliable
43 and spatially explicit information on hunting pressure (e.g., ^{13,14}). Trait-based vulnerability
44 assessments provide a complementary line of evidence by addressing different limitations
45 through the systematic integration of species' biological, morphological, and ecological traits.
46 Originally developed to assess species vulnerability to climate change ¹⁵, the vulnerability
47 assessment framework was later refined to capture spatial variation ¹⁶ and expanded to evaluate
48 impacts from pollution ¹⁷ or multiple threats in insular ecosystems ¹⁸. It quantifies vulnerability
49 through three components: (i) exposure to single or multiple threats, (ii) sensitivity based on
50 species-specific intrinsic traits, and (iii) adaptive capacity, reflecting the ability of species to cope
51 with and respond to threats. Combining these three components into a single vulnerability metric
52 would help overcome the current limitation of vulnerability indicators for large-scale hunting, as
53 the most common indicators focus either on areas where hunting might occur ¹⁹, or on areas
54 where species threatened by hunting are found ¹³, but no existing metric combines these two
55 pieces of information: where hunters are likely to hunt and which species are likely to be targeted
56 more by hunters at pantropical scale.

57 Hunting is particularly well-suited to trait-based vulnerability assessments, as it is neither
58 spatially or biologically random: hunting pressure spatially concentrates in accessible areas ^{8,20-}
59 ²³ and particularly targets species with a certain set of traits ^{7,24} (but see ²⁵ for an example applied
60 to hunting). Hunted species are targeted for distinct purposes, including direct consumption (here
61 referring to subsistence hunting), the pet or product trade. In turn, the scale of wildlife use can be

62 local (subsistence or local trade), or can extend up to the national or international markets ^{7,10}.
63 Subsistence hunting generally focuses on large-bodied, locally abundant species that maximize
64 returns per unit effort ^{7,14,24} whereas species targeted for trade are often selected for rarity,
65 distinctive morphology, conspicuous coloration, or phylogenetic distinctiveness, traits associated
66 with higher market value ^{24,26,27}. Because these hunting motivations are linked to well-established
67 trait combinations (e.g. body mass or plumage), trait-based assessments, particularly for birds
68 and mammals, offer a promising framework for evaluating species' vulnerability to hunting.

69 Building on this premise, we present the first spatially explicit, trait-based assessment of
70 vulnerability to hunting for 6,338 tropical bird and 3,837 mammal species, the two most
71 overexploited taxa in the tropics ^{28,29}. We combined a recent pantropical map of exposure to
72 hunting pressure ²³ with species sensitivity and adaptive capacity derived from biological,
73 ecological, and morphological traits, phylogenetic information, and empirical data on hunting,
74 trapping and trade. Sensitivity was estimated using documented evidence of subsistence and
75 commercial hunting ³⁰ and trait-based predictions of the likelihood that species are hunted for
76 subsistence, the pet trade, or product trade (see Fig. 1 and methodological details in Fig. S1 &
77 S2). Separate sensitivity scores were calculated for each of these three hunting purposes.
78 Adaptive capacity was quantified using traits related to detectability, accessibility, and resilience,
79 including activity period, habitat use, mobility, dispersal ability, reproductive rate, and geographic
80 range size. For each species, vulnerability was computed as $Vulnerability = Exposure + Sensitivity$
81 $- Adaptive Capacity$, with each component rescaled to [0, 1], yielding a score ranging from -1
82 (least vulnerable) to 2 (most vulnerable). Exposure was based on a map of hunting pressure
83 rescaled to 20 x 20 km resolution²³, whereas sensitivity and adaptive capacity were calculated at
84 the species level. (Fig. 1). Exposure reflects local hunting pressure, Sensitivity the likelihood of
85 being targeted, and Adaptive Capacity the species' ability to withstand offtake. Two summary
86 metrics were derived: a species-level score (mean Vulnerability across all spatial units within the
87 species' Area of Habitat AoH ³¹, restricted to species with $\geq 90\%$ AoH overlap with the exposure
88 layer) and an assemblage-level score (mean Vulnerability across all species occurring in each 20
89 x 20 km spatial unit). Both metrics are interpreted in relative terms only, as raw scores are not
90 comparable across taxa or hunting purposes. Subsequently, we assessed whether vulnerability
91 scores concentrated for certain taxonomic families and orders, and ranked species and areas
92 according to vulnerability scores to derive species prioritization lists and pinpoint vulnerability
93 hotspots. Finally, species-level scores were validated against information from IUCN Red List

94 assessments by classifying species as not threatened by hunting, threatened by hunting but not
95 globally threatened with extinction, or threatened by both hunting and extinction.

96 **Results**

97 *Species-level Vulnerability*

98 For mammals, species-level Vulnerability scores ranged from (Mean \pm SD) 0.42 ± 0.24 (pet trade)
99 to 0.51 ± 0.29 (product trade), and 0.59 ± 0.39 (subsistence hunting), with strong phylogenetic
100 structuring across all purposes (Fig. 2). Pet trade maximum Vulnerability was concentrated in
101 primates, pangolins, and carnivores, while product trade and subsistence hunting showed broader
102 phylogenetic distributions in Vulnerability values spanning primates, bats, large herbivores,
103 elephants, and pangolins. Vulnerability showed significant phylogenetic signal across all
104 purposes (all $p < 0.01$), with high Pagel's λ (pet: 0.96; product: 0.96; subsistence: 0.98) indicating
105 deep node conservatism, and Blomberg's K below 1 (pet: 0.05; product: 0.10; subsistence: 0.19),
106 and Moran's I confirming a gradient of increasing conservatism from pet to subsistence hunting
107 (pet: 0.72; product: 0.80; subsistence: 0.83). Vulnerability ranking discriminated significantly
108 among IUCN threat categories (all pairwise $p < 0.001$), with ordinal regression explaining 21%,
109 39%, and 40% of variance for pet trade, product trade, and subsistence hunting respectively (Fig.
110 2B). Species traded as pet reached higher threat categories at lower vulnerability thresholds, with
111 the highest-ranked species, *Elephas maximus* (1.75 ± 0.11), *Pongo pygmaeus* (1.54 ± 0.16), and
112 *Macaca nigra* (1.49 ± 0.02), threatened by both hunting and extinction (Supp. Data 1).

113 For birds, species-level Vulnerability scores were 0.69 ± 0.23 (subsistence), 0.69 ± 0.18
114 (product trade), and 0.86 ± 0.25 (pet trade). Maximum values of Vulnerability for pet trade were
115 concentrated in parrots, hornbills, raptors, and certain passerines (mainly Cakatuidae,
116 Musophagidae, Picathartidae); for product trade, high Vulnerability species were more broadly
117 distributed across parrots, Bucerotiformes, Galliformes, Cracidae, and Odontophoridae; and for
118 subsistence hunting top-ranked species were primarily concentrated in Galliformes (Cracidae,
119 Odontophoridae, Phasianidae; Fig. 2D–F). Phylogenetic signal was significant across all
120 purposes (all $p < 0.01$), with the same gradient as mammals: Pagel's λ ranging from 0.80 to 0.86,
121 Blomberg's K from 0.07 to 0.50, and Moran's I from 0.68 to 0.82, all increasing from pet to
122 subsistence hunting. As for mammals, Vulnerability ranking discriminated significantly among
123 IUCN threat categories (all $p < 0.001$; $R^2 = 0.15, 0.29, 0.19$ for pet, product, and subsistence; Fig.
124 3C–D), though a higher proportion of highly vulnerable bird species were unrecognized by the

125 IUCN as threatened by hunting, particularly for subsistence hunting (6 of the 20 most vulnerable
126 species; Supp. Data 2). The most vulnerable species were *Triclaria malachitacea* (1.54 ± 0.09),
127 *Polyplectron malacense* (1.48 ± 0.08), and *Crax rubra* (1.69 ± 0.11) for pet, product, and
128 subsistence hunting respectively.

129 Sensitivity and Adaptive capacity at the species level were highly robust across different
130 weightings and trait compositions, regardless of taxon or hunting purpose (see Supplementary
131 Information, Fig. S17 & S18 for more details)

132 *Spatial patterns of Vulnerability*

133 Indomalayan realm consistently showed the highest assemblage-level Vulnerability
134 scores across all purposes and taxa (birds: 0.86 ± 0.14 ; mammals: 0.63 ± 0.15), significantly
135 exceeding the Afrotropics (marginal mean differences: $0.085\text{--}0.11$, $p < 0.001$) and Neotropics
136 ($0.14\text{--}0.30$, $p < 0.001$), with the strongest contrasts observed for mammal subsistence hunting.
137 The Afrotropics in turn ranked significantly higher than the Neotropics across all purposes (0.056--
138 0.29 , $p < 0.001$; Fig. 4). Spatial patterns of Vulnerability were consistent across purposes and
139 taxa, with pairwise Spearman correlations among the six maps ranging from 0.78 to 1.00 (all $p <$
140 0.001 ; Fig. 5), indicating that the same locations tend to emerge as highly vulnerable regardless
141 of taxon or hunting purpose. High-vulnerability regions consistently combined high Exposure with
142 high Intrinsic Vulnerability (IV = Sensitivity – Adaptive Capacity), while low-Vulnerability regions
143 were more heterogeneous. The Amazon Basin and Central Africa ranked among the least
144 vulnerable due to jointly low Exposure and low IV, whereas other low-ranking regions, like central
145 Borneo, northern Gran Chaco, or northern Myanmar, showed low Exposure despite intermediate
146 IV, suggesting these areas may act as refugia for intrinsically sensitive species that are currently
147 less exposed to hunting. Among intermediate-ranking regions, Caribbean islands and the
148 Philippines showed high Exposure paired with relatively low IV, while most Afrotropical and
149 Indomalayan intermediate-ranking areas showed the inverse pattern of low Exposure combined
150 with higher IV (Fig. 6).

151 Assemblage-level Vulnerability hotspots (top 20% of all spatial units) were predominantly
152 located in Indomalaya, including southeast China, western India, Sri Lanka, the Malay Peninsula,
153 Java, Sumatra, southern Sulawesi, and coastal Borneo. In the Afrotropics, hotspots concentrated
154 in West Africa, Southern Africa, and the Atsinanana rainforests of eastern Madagascar, while
155 Neotropical hotspots were found in the Caribbean islands, the Atlantic Forest, the southern Gran
156 Chaco, and coastal Gulf of Mexico regions (Fig. 5). Conversely, low-Vulnerability areas (bottom

157 20%) were largely absent from Indomalaya except in New Guinea, central Borneo, and northern
158 Myanmar, and were most extensive across the Amazon Basin, Central Africa, and the
159 Mesoamerican Biological Corridor. Among the notable regional differences observed across
160 taxonomic groups and hunting practices, we found that mammals hunted for subsistence were
161 ranked as relatively less vulnerable in the Neotropical regions, particularly in the Atlantic Forest
162 and the Mesoamerican Biological Corridor. Additionally, for birds, the vulnerability to exploitation
163 was ranked higher on islands compared to continents (the Caribbean, the Philippines, and
164 northern Sulawesi), with the opposite trend observed in northern Myanmar and the far west of
165 China (Fig. 5). This pattern was not observed in mammals.

166

167 **Discussion**

168 In this study, we present what is, to our knowledge, the first spatially explicit, species-level
169 assessment of vulnerability to hunting for tropical birds and mammals across the entire
170 pantropical area. Building on a three-dimensional vulnerability framework commonly used in
171 climate vulnerability assessments (e.g., ¹⁶), we combine, (i) fine-scale maps of hunting pressure
172 ²³ to define species' Exposure; (ii) species-specific Sensitivity, based on traits linked to the
173 likelihood and scale of being hunted and traded; and (ii) Adaptive capacity, derived from traits that
174 could mitigate the impact of hunting (e.g., reproductive rate, mobility, global population size, see
175 ^{16–18}). This approach offers three major advantages. First, it provides high-resolution vulnerability
176 maps for one of the most spatially heterogeneous, hard-to-monitor at large scale, and context-
177 dependent pressures in the tropics ³², facilitating the integration of hunting pressure into spatial
178 prioritization and conservation planning. Second, it is customizable and trait-based, allowing for
179 refinement across taxa and regions according to different hypotheses. Finally, our results remain
180 robust across a wide range of methodological changes, ensuring the reliability of our approach
181 for future applications (see Supplementary Information, Fig. S17 & S18).

182 For mammals, our results confirm prior findings that large-bodied herbivores are among
183 the most vulnerable to hunting ¹¹. This is consistent with patterns observed in seizure records of
184 illegal wildlife trade ³³ and broader megafauna declines ³⁴. Bird Vulnerability scores followed
185 similar patterns. Larger-bodied birds were more vulnerable across all hunting purposes. Parrots,
186 for example, were the most vulnerable group for pet trade. For product trade and subsistence,

187 ground-dwelling species were more affected. Across both birds and mammals, species-level
188 Vulnerability showed significant and consistent phylogenetic signal regardless of hunting purpose,
189 indicating that susceptibility to overexploitation is not randomly distributed on the tree of life but
190 reflects ancestral trait conservatism. The combination of high Pagel's λ and low Blomberg's K in
191 both taxa reveals that this signal is predominantly concentrated at deep nodes, most certainly at
192 the order and family level, rather than among closely related species, a pattern that is stronger in
193 mammals ($\lambda = 0.96\text{--}0.98$) than in birds ($\lambda = 0.80\text{--}0.86$). This is at least partly expected, since our
194 vulnerability score was computed using a sensitivity approach that explicitly incorporates family-
195 and order-level but also traits, such as body size or reproductive rate, which are among the most
196 phylogenetically conserved traits in vertebrates. Nonetheless, these findings are broadly
197 congruent with Scheffers et al. ⁹, who demonstrated that certain orders and families are
198 disproportionately represented in wildlife trade . A novel aspect in our analysis is that, beyond
199 wildlife trade, hunting for local food consumption consistently showed the strongest phylogenetic
200 signal across both taxa, while Vulnerability for pet trade was the most labile. This gradient likely
201 reflects that subsistence hunting targets body-size and life-history traits deeply conserved across
202 vertebrate phylogenies, whereas commercial hunting additionally incorporates geographic and
203 market-demand components, such as end-use diversity, and commodity-specific traits like
204 coloration or horn morphology ⁹, that track human preferences rather than evolutionary history,
205 diluting the phylogenetic signal. These results suggest that phylogenetic information is most
206 actionable for prioritizing- species threatened by subsistence hunting, while tackling deleterious
207 effects of commercial trade on species conservation may require demand-specific frameworks
208 operating below the family level. Importantly, we did not integrate data on whether a species is
209 protected (e.g., through national laws or religious beliefs), nor the effectiveness of such
210 protections. While the Conservation Actions Classification Scheme provides species-level
211 conservation measures, it lacks spatial detail and information on effectiveness ²⁶. This may partly
212 explain mismatches, e.g., giant panda (*Ailuropoda melanoleuca*) shares many traits with hunted
213 mammals but is no longer vulnerable to this threat due to effective protections. Standardized,
214 spatially explicit frameworks like the IUCN Green List ³⁵ or the Conservation Evidence database
215 ³⁶ offer promising tools to address these gaps and could be integrated into future assessments by
216 modulating the final vulnerability score for species with conservation actions in place.

217 The IUCN Red List, now integrated with CITES data on species trade and hunting status,
218 remains a cornerstone for global biodiversity threat assessments. It has been essential for

219 identifying which species are most affected by trade and where these species occur (e.g., ⁹), for
220 highlighting species most likely to be threatened by international trade (e.g., ¹⁰), and for building
221 scoring systems that link wildlife trade to community-level ecological shifts (e.g., ³⁷). While the
222 Red List and CITES databases are extremely valuable, their effectiveness can be limited by
223 known biases in threat documentation and species coverage (^{38,39}; and see Red List Guidelines
224 updates on Threats Classification Scheme (Version 3.3)). However, ongoing efforts to improve
225 data standardization and threat classification could address several of these limitations in the
226 future ^{40,41}. Considering both the strengths and limitations of the IUCN Red List, we developed
227 our Sensitivity and Adaptive capacity scores by combining its information with a trait-based
228 scoring system based on literature-based hypotheses about species' responses to hunting.
229 Despite using a limited set of traits, our models performed well, especially for birds, where
230 phylogeny explained less variance, likely reflecting less data gaps in trait databases that can be
231 linked to subsistence or commercial hunting compared to mammals (see Supplementary
232 Information). For mammals, traits such as trophy value or market rarity, often linked to price, are
233 difficult to quantify but strongly influence hunting pressure ⁴². These factors were partially captured
234 through the phylogenetic component of our models, but their importance also underscores the
235 current lack of comprehensive trait databases that include characteristics that render species
236 more appealing to hunters (see Supplementary Information, Fig. S6–S16). Our resulting
237 composite vulnerability scores aligned well with IUCN hunting threat categories, even after
238 minimizing the influence of IUCN-derived information (e.g. geographic range size, see
239 Supplementary Information, Fig S18). Overall, species classified as more threatened by hunting
240 (i.e., threatened by hunting and with extinction according to the IUCN) were generally more
241 sensitive and less resilient to hunting, and thus more vulnerable (see Supplementary Information,
242 Fig S9). Hence, our approach can reinforce IUCN Red List assessments and provide a first
243 indication of extinction risk category upgrading or assignment for species with outdated
244 assessments or that are data deficient, respectively ⁴¹. While Morton et al. ⁴³ already
245 demonstrated that population declines due to wildlife trade are stronger in species with a higher
246 extinction risk category, here we also provide evidence that species vulnerable to subsistence
247 hunting but that are not necessarily traded can also be threatened. Importantly, our framework
248 allows for the identification of species not currently known to be used for subsistence or traded,
249 but that share key traits with known target species. Some examples include the Kashmir Gray
250 Langur (*Semnopithecus ajax*) or Kinda Baboon (*Papio kindae*) for mammals, and Sri Lanka
251 Junglefowl (*Gallus lafayettii*) or Spot-winged Wood-quail (*Odontophorus capueira*) for birds.

252 These species are assigned high vulnerability scores, and should be tracked closely in order to
253 prevent future threats from hunting activities (see also ¹⁴).

254 At the regional level, the top 20% most vulnerable spatial units were concentrated in the
255 Indomalayan realm, notably southeast China, western India, Sri Lanka, the Malay Peninsula,
256 Java, Sumatra, southern Sulawesi, and coastal Borneo. In the Afrotropics, hotspots included West
257 Africa, Southern Africa, and eastern Madagascar. In the Neotropics, vulnerable zones included
258 the Caribbean, Atlantic Forest, and Gulf of Mexico coast. In contrast, low-vulnerability areas
259 (bottom 20%) were rare in Indomalaya (mainly New Guinea, central Borneo and Northern
260 Myanmar), more common in Central Africa (see ²⁵), and most extensive in the Amazon Basin,
261 Honduras, and northeastern Nicaragua. Our vulnerability maps differ notably from existing hunting
262 threat maps based on IUCN Red List (e.g., ^{13,14}), which often assume uniform threat levels across
263 species' entire ranges and consequently do not capture local variation on hunting risk. Our results
264 better reflect ecological realities and align with prior regional studies in West Africa ⁴⁴ and in
265 Southeast Asia ⁴⁵, and match patterns of illegal hunting in China ⁴⁶. While few spatial assessments
266 exist for South America, Bogoni et al. ¹⁹ used theoretical relationships to estimate hunting
267 pressure, an approach more comparable to our exposure layer than our full vulnerability model.
268 Their findings, which suggest high hunting pressure in the Amazon Basin and low pressure in the
269 Atlantic Forest, contrast with our results and previous studies ⁴⁷⁻⁵⁰, and could differ for various
270 reasons, such as not focusing only on forest ecosystems or not accounting for the specific types
271 of species present in each location, unlike our approach. Ultimately, our integrated vulnerability
272 framework, combining Exposure, Sensitivity, and Adaptive capacity, reveals consistent global
273 patterns of hunting threat. Vulnerability decreased from Indomalaya to the Neotropics, a gradient
274 that mirrors observed late-Quaternary declines in biomass and community downsizing ⁵¹,
275 reinforcing the ecological plausibility of our approach. Additionally, by decoupling Sensitivity -
276 Adaptive capacity (i.e., Intrinsic Vulnerability (IV)) and Exposure, our approach identified areas
277 where species known to be threatened by hunting are not currently vulnerable due to their remote
278 distribution. This is notably the case for regions such as central Borneo and New Guinea, which
279 emerge as potential refugia for threatened species. These findings also highlight limitations of the
280 IUCN Red List when used to spatialize threats, as it may overestimate risk in areas where
281 exposure is minimal. Conversely, regions characterized by high Exposure, but low assemblage-
282 level Vulnerability may warrant further investigation: they could represent barriers to range shifts

283 by hunted species under climate change, or alternatively, indicate areas where the most
284 intrinsically vulnerable species have already been locally extirpated.

285 As Tulloch et al.⁵² highlighted nearly a decade ago, mapping threats at regional and global
286 scales has become increasingly common, using a large set of methodologies. Some approaches
287 are based on species distributions and their reported threats, such as IUCN Red List-based maps
288 ^{13,53,54}. Others focus on directly mapping threats, often using remote sensing to assess habitat
289 loss or degradation ^{55,56}, natural hazard data ⁵⁷, or more integrated frameworks combining
290 exposure, sensitivity, and adaptive capacity, as we did in this study ^{16,17}. Although our goal was
291 not to explicitly produce spatial conservation prioritization maps aligned with the Kunming–
292 Montreal Global Biodiversity Framework, our vulnerability maps can support such planning. We
293 acknowledge ongoing debates around global priority mapping, which has been criticized as overly
294 technocratic and disconnected from local knowledge, practices, and cultural contexts ⁵⁸. These
295 concerns are especially relevant for hunting, a highly context-dependent activity shaped by local
296 beliefs, taboos, and socioeconomic conditions ^{32,59,60}. Our analysis does not account for fine-scale
297 socio-economic factors — such as local wealth, product prices, or hunter density — widely
298 recognized as important drivers of hunting pressure ⁶¹. Nevertheless, by applying a vulnerability
299 framework at fine spatial and species-specific resolution, we provide one of the most
300 comprehensive assessments of tropical hunting pressure to date, yielding outputs adaptable by
301 practitioners and policymakers to local needs. Refining individual components, by replacing binary
302 distributions with abundance data, incorporating more granular hunting intensity measures, or
303 integrating volume-based trade records, would further strengthen the framework at regional or
304 national scales.

305 This study presents the first pantropical, species-specific assessment of vulnerability to
306 hunting, integrating exposure, sensitivity, and adaptive capacity into a unified framework. While
307 local protection measures and cultural taboos remain to be incorporated, the vulnerability maps
308 and species rankings provide actionable tools for conservation prioritization, and future work
309 should integrate socio-cultural dynamics to further refine global assessments.

310

311 **Electronic Supplementary Information**

312 Supplementary data containing species-level metrics, assemblage-level vulnerability rasters, and
313 all code necessary to reproduce the analyses and figures are available at the following Zenodo
314 repository: <https://doi.org/10.5281/zenodo.19452348>. The supplementary materials are
315 organized into three folders. The species-level dataset folder contains Excel files with species-
316 level vulnerability metrics. The landscape-level folder contains rasters of either the spatial
317 distribution of vulnerability across each species' area of habitat or the assemblage-level
318 vulnerability, computed as the mean across all co-occurring species. The R-scripts folder contains
319 two R projects: S1 covers the computation of Sensitivity and Adaptive Capacity scores and the
320 robustness analyses, and S2 covers vulnerability computation, mapping, and phylogenetic
321 analyses.

322

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327

328 **Methods**

329 *1. Data collection*

330 We selected mammal and bird species whose distributions intersect the pantropical forest zone,
331 as defined by Potapov et al. ⁶² (i.e. areas with > 20% forest cover covering the (sub)tropics) Global
332 range maps were obtained from the IUCN Red List ³⁰ for mammals and from the BirdLife
333 International data portal ⁶³ for birds; for migratory bird species, only resident ranges were retained.
334 This filtering resulted in a final dataset of 4,450 mammal species and 8,106 bird species. For all
335 selected species, we retrieved the information required to compute the sensitivity and adaptive
336 capacity components in the vulnerability framework, which were based on information on hunting
337 status, species traits, and area of habitat.

338

339 *1.1. Hunting status*

340 Information on species hunting status was compiled by combining data from the IUCN Red List
341 ³⁰ and Hughes et al. ³⁷. For each species, we retrieved information on (i) hunting purpose (*end*
342 *uses*) and (ii) the geographic scale of hunting from the IUCN Red List. End uses were extracted

343 from the IUCN Red List using the General Use and Trade Classification Scheme (version 1.0)
344 and correspond to the number of unique IUCN use codes (1–18) associated with each species.
345 Based on the combination of *end use* information and geographic commercial scale, we classified
346 species into three independent binary hunting categories following commonly used classifications
347 in the literature (e.g., ⁹): “subsistence”, “product trade”, and “pet trade”. Species were classified
348 as hunted for “subsistence” if they were explicitly reported as hunted for meat consumption (IUCN
349 *code 1*) and for *subsistence*. Species were classified as hunted for the “pet trade” if they were
350 associated with the IUCN pet trade code (*code 13*) and reported at least in one geographic
351 commercial scale. Species were classified as hunted for “product trade” if they were associated
352 with IUCN use codes other than *code 13* and reported at least at one geographic commercial
353 scale. Species not meeting these criteria were classified as not hunted for the corresponding
354 category. Classifications for “pet trade” and “product trade” were cross validated and
355 complemented using the information provided by Hughes et al. ³⁷. Information on global extinction
356 risk (Least Concern, Vulnerable, Endangered, Critically Endangered) and hunting threat status
357 (i.e. whether a species is identified as threatened by hunting) was also extracted from the IUCN
358 Red List. This process resulted in six distinct datasets corresponding to the combination of two
359 taxa (birds and mammals) and three hunting purposes (“subsistence”, “pet trade”, and “product
360 trade”). Although each dataset includes the full species list for the focal taxon, they differ in the
361 type of hunting information they contain. Specifically, the “subsistence” datasets include binary
362 information (1: hunted vs 0: non-hunted) on whether species are hunted for “subsistence”,
363 whereas the “pet trade” and “product trade” datasets additionally include information on the
364 geographic commercial scale (*local, national, and/or international*). Because the IUCN Red List
365 does not distinguish between hunting for direct consumption or local trade, species reported as
366 hunted for subsistence were considered subject to both direct use and local commercialization.
367 For “product trade”, datasets further include the number of documented *end use* per species.
368 These purpose-specific datasets were used to parameterize the vulnerability analyses for each
369 hunting objective separately.

370

371 *1.2. Traits*

372 For birds, morphological and ecological traits were obtained primarily from the AVONET database
373 ⁶⁴, including body mass, hand-wing index, beak length, tail length, and primary lifestyle. Color
374 elaboration was sourced from Santangeli et al. ²⁷, and corresponds to the mean distance between

375 the colors expressed by a species and the global average color across all species (brown–grey).
376 Population density estimates were obtained from Santini et al. ⁶⁵, while clutch size and nocturnality
377 were extracted from Marino et al. ⁶⁶. Taxonomic information (order and family) and extent of
378 occurrence were obtained from BirdLife ⁶³.

379 For mammals, body mass, brain mass, foraging stratum, nocturnality, generation length,
380 age at first reproduction, litter size, and number of litters per year were compiled from the
381 COMBINE database ⁶⁷. Population density estimates were sourced from Santini et al. ⁶⁸, and
382 taxonomic information (order and family) and extent of occurrence were obtained from the IUCN
383 Red List ³⁰.

384 Detailed descriptions of all traits, along with their rationale for inclusion in the vulnerability
385 framework, are provided in Supplementary Information (Fig. S1 & S2).

386

387 *1.3. Area of habitat*

388 Species distributions were based on area of habitat maps from Lumbierres et al. ³¹, which provide
389 a refined and more realistic representation of species' distributions by accounting for actual
390 habitat use and reducing commission errors inherent to broad IUCN range maps. These areas of
391 habitat layers were further masked to retain only the pan-tropical portion of each species'
392 distribution and were provided at a spatial resolution of 1/1008° (approximately 100 m at the
393 equator) and aggregated at 20 × 20 km using the nearest-neighbor method.

394

395 *2. Vulnerability framework*

396 We derived vulnerability scores independently for each taxon and each hunting purpose based
397 on the corresponding datasets described above. Because the following frameworks differ in their
398 underlying information and structure, Vulnerability is not directly comparable across taxa or
399 hunting purposes; they are therefore interpreted only as relative rankings within each taxon ×
400 purpose combination. Below, we detail the vulnerability framework applied to each of these
401 combinations.

402

403 *2.1. Exposure*

404 Exposure to hunting was defined identically for both taxa and across the three hunting purposes.
405 We used the hunting pressure map developed by Philippe-Lesaffre et al. ²³, which estimates the
406 predicted probability that a 1 × 1 km spatial unit is subject to hunting across the pan-tropical region

407 for 2015. This map is based on a random forest binary classifier trained on a global dataset of
408 hunted versus non-hunted sites, integrating accessibility, socio-economic, and ecological
409 predictors. The training data encompass hunting events involving both birds and mammals,
410 across subsistence and trade purposes, and including both legal and illegal activities.

411 To align the exposure layer with species distributions, the hunting pressure map was used
412 as the spatial reference. For each species, Exposure (i.e., hunting pressure) was extracted for all
413 1 × 1 km spatial units overlapping its area of habitat. spatial units where the species was present
414 were assigned the corresponding Exposure, whereas cells outside the species' distribution were
415 assigned a value of zero. Species-level exposure was then aggregated to a 20 × 20 km resolution
416 by calculating the mean hunting pressure across all occupied spatial units.

417 Importantly, Exposure is independent of species identity and depends solely on spatial
418 location. Consequently, multiple species occurring within the same spatial unit share the same
419 exposure value for that cell.

420

421 *2.2. Sensitivity*

422 Sensitivity is a species-level metric, with a single value derived for each species separately for
423 each taxon and hunting purpose, reflecting the distinct mechanisms by which species are targeted
424 by hunters. This score is assumed to be constant across a species' area of habitat and is based
425 solely on intrinsic species characteristics. Sensitivity represents the likelihood that a species will
426 be targeted (and continue to be targeted) if hunting occurs in an area where the species is present,
427 with higher values indicating greater targeting pressure.

428

429 *2.2.1. Probability of a species being hunted*

430 Although information exists on which species are currently hunted and for which purposes, our
431 objective was to refine this binary information by estimating continuous sensitivity scores that
432 capture how likely a species is to be targeted based on its traits and evolutionary history, including
433 for species not currently documented as hunted. This approach allows the identification of species
434 potentially sensitive to hunting now or in the future, despite gaps in hunting or trade records.

435 Sensitivity was defined differently for each hunting purpose. For “subsistence” (direct
436 consumption), Sensitivity was based solely on the predicted probability that a species would be
437 hunted for “subsistence”. For the “pet trade”, Sensitivity combined the probability of being hunted
438 for commercial purposes with information on the geographic commercial scale. For the “product

439 trade”, Sensitivity incorporated the probability of being hunted for commercial purposes, the
440 number of documented *end uses*, and the geographic commercial scale. The probability of being
441 hunted constitutes the common component across all Sensitivity scores, but probabilities were
442 modelled separately for each purpose and taxon (Fig S4 & S5).

443 Trait selection reflected purpose-specific hypotheses. For “subsistence”, body mass and
444 population density were used for both birds and mammals, based on the assumption that species
445 hunted for direct consumption are those maximizing caloric returns⁶⁹. For “pet trade” and “product
446 trade”, we included traits associated with attractiveness or desirability: color elaboration, beak
447 length, and tail length for birds, and brain mass for mammals²⁷. Phylogenetic structure was
448 explicitly incorporated to account for shared, unmeasured characteristics among related species
449 that render them attractive but for which there is no systematic account (see Fig. S1 & S2 for
450 more details).

451 To estimate hunting probabilities, we used a bootstrap resampling approach to generate
452 100 training–testing dataset pairs, each consisting of 70% training and 30% testing data, stratified
453 by family to ensure taxonomic representation. For each bootstrap iteration, generalized linear
454 mixed-effects models (GLMMs) with a binomial error distribution were fitted using the *glmer()*
455 function in the lme4 R package⁷⁰. Models were trained using binary response variables indicating
456 presence (1) or absence (0) of hunting for each purpose and then used to predict hunting
457 probabilities for all species.

458 For each species, predicted probabilities were averaged across the 100 bootstrap
459 iterations to obtain mean sensitivity scores for subsistence hunting ($\hat{p}(\textit{subsistence})$), pet trade
460 ($\hat{p}(\textit{pet})$), and product trade ($\hat{p}(\textit{product})$). Separate model structures were fitted for birds and
461 mammals, as follows.

462 For birds:

$$463 \quad \textit{Subsistence}_i \sim \log_e(\textit{body mass}_i) + \textit{res}(\textit{density})_i + (1 \mid \textit{Order}_i/\textit{Family}_i) + \varepsilon_i$$

$$464 \quad \textit{Pet trade}_i \sim \log_e(\textit{body mass}_i) + \textit{res}(\textit{density})_i + \textit{elaboration}_i + \textit{res}(\textit{tail length})_i \\ 465 \quad \quad \quad + \textit{res}(\textit{beak length})_i + (1 \mid \textit{Order}_i/\textit{Family}_i) + \varepsilon_i$$

$$466 \quad \textit{Product trade}_i \sim \log_e(\textit{body mass}_i) + \textit{res}(\textit{density})_i + \textit{elaboration}_i + \textit{res}(\textit{tail length})_i \\ 467 \quad \quad \quad + \textit{res}(\textit{beak length})_i + (1 \mid \textit{Order}_i/\textit{Family}_i) + \varepsilon_i$$

468 For mammals:

$$469 \quad \textit{Subsistence}_i \sim \log_e(\textit{body mass}_i) + \textit{res}(\textit{density})_i + (1 \mid \textit{Order}_i/\textit{Family}_i) + \varepsilon_i$$

$$470 \quad \textit{Pet trade}_{i_i} \sim \log_e(\textit{body mass}_i) + \textit{res}(\textit{density})_i + \textit{res}(\textit{brain size})_i + (1 \mid \textit{Order}_i/\textit{Family}_i) \\ 471 \quad \quad \quad + \varepsilon_i$$

472
$$Product\ trade_i \sim \log_e(body\ mass_i) + res(density)_i + res(brain\ size)_i$$

473
$$+ (1 | Order_i/Family_i) + \varepsilon_i$$

474 To account for allometric relationships, we controlled for body mass when analyzing tail length,
475 beak length, population density, and brain size by fitting linear models between body mass and
476 each trait and using the residuals of these relationships in the models (e.g. positive residuals in
477 the brain-body mass relationship indicate larger brain than expected for a given body mass, and
478 hence higher cognitive capacity, ⁷¹). Model performance was assessed using marginal and
479 conditional R² values calculated with the *r2()* function from the performance R package ⁷². Detailed
480 results of this modelling approach are provided in the Supplementary Information.

481

482 2.2.2. Geographic trade scale and end uses

483 For species hunted either for “pet trade” or “product trade”, we used information on the geographic
484 commercial scale from the IUCN Red List. This information is provided as binary variables
485 indicating whether a species is known to be commercialized for *subsistence*, traded at the *national*
486 level, and/or traded at the *international* level (1 = yes, 0 = no). We incorporated these data under
487 the assumption that species traded across multiple and increasingly broader geographic scales
488 experience higher targeting pressure than species commercialized for *subsistence* or locally.
489 Accordingly, trade scale was categorized as *subsistence* commercialization (score = 1), *national*
490 trade (score = 2), and *international* trade (score = 3). These scores were summed to generate a
491 total trade-scale index ranging from 0 (no recorded trade) to 6 (trade documented at all three
492 geographic scales), which was incorporated into Sensitivity for “pet trade” and “product trade”.

493 Species traded for the “pet trade” are associated with a single *end use*, whereas species
494 hunted for “product trade” may be associated with multiple *end uses*. To account for this
495 difference, we constructed a cumulative trade-scale score for product-traded species by summing
496 trade-scale scores across all relevant product use codes (i.e. all IUCN use codes except code
497 13). Thus, for the “pet trade”, the trade-scale score reflects a single *end use* and its associated
498 geographic commercial scale, whereas for “product trade” it integrates across multiple *end uses*
499 and their associated geographic commercial scale. All trade-scale scores were subsequently
500 normalized using min–max scaling to match the magnitude of the corresponding hunting
501 probability estimates ($\hat{p}(pet)$ and $\hat{p}(product)$).

502

503 2.2.3. Sensitivity scoring

504 Species Sensitivity scores were calculated for each species i separately for “subsistence”, “pet
505 trade”, and “product trade” as follows:

$$506 \quad \text{Sensitivity}(\text{subsistence})_i = \hat{p}(\text{subsistence})$$

$$507 \quad \text{Sensitivity}(\text{pet trade})_i = \frac{\hat{p}(\text{pet trade})_i + \min - \max(\text{scale}(\text{pet trade})_i)}{2}$$

$$508 \quad \text{Sensitivity}(\text{product trade})_i = \frac{\hat{p}(\text{product trade})_i + \min - \max(\Sigma \text{scale}(\text{product trade})_i)}{2}$$

509 For “subsistence”, Sensitivity is defined solely by the probability that a species is hunted for
510 “subsistence”. For “pet trade” and “product trade”, Sensitivity combines two components: (i) the
511 probability that a species is targeted for that purpose and (ii) the geographic commercial scale.
512 Both components are scaling with min–max to range between 0 and 1, and equal weight is given
513 to targeting likelihood and trade scale. Alternative scoring approaches are provided in
514 Supplementary Information to assess robustness of our framework.

515

516 *2.3. Adaptive capacity*

517 Adaptive capacity was computed at the species level and was therefore assumed to be constant
518 across each species’ area of habitat and constant across hunting purposes. For both mammals
519 and birds, traits were selected based on their broad availability across species and their
520 hypothesized relevance to a species’ ability to recover from harvesting. Each trait was chosen to
521 represent one of several mechanisms expected to enhance adaptive capacity under hunting
522 pressure. Ordered from lowest to highest presumed importance, these mechanisms include: (1)
523 behaviors that reduce detectability or accessibility to hunters, (2) low fitness costs associated with
524 behavioral avoidance, (3) the ability to disperse away from heavily hunted areas, (4) fast life-
525 history strategies, and (5) the presence of large source populations capable of supporting
526 recolonization.

527

528 *2.3.1. Birds*

529 For birds, adaptive capacity was described using primary lifestyle, hand-wing index, clutch size,
530 and extent of occurrence. Primary lifestyle was treated as an ordinal variable reflecting
531 accessibility to hunters, with ground-dwelling species assigned the highest accessibility (1),
532 insessorial, generalist, or aquatic species intermediate accessibility (2), and aerial species the
533 lowest accessibility (3). The hand-wing index was used as a morphological proxy for dispersal

534 ability, with higher values indicating greater dispersal potential. Clutch size was included as a
535 proxy for life-history strategy, and extent of occurrence (EOO; km²) represented the availability of
536 large source populations capable of supporting recolonization.

537

538 *2.3.2. Mammals*

539 For mammals, adaptive capacity was described using foraging stratum, nocturnality, dispersal
540 ability, life-history strategy, and EOO. Foraging stratum was treated as an ordinal variable
541 reflecting accessibility to hunters, with ground-dwelling species assigned the highest accessibility
542 (1), followed by scansorial species (2), arboreal species (3), and aerial species with the lowest
543 accessibility (4). Nocturnality was coded as a binary variable (0 = diurnal, 1 = nocturnal), reflecting
544 the potential for temporal refuge from human activity. Dispersal ability was initially represented by
545 dispersal distance, defined as the distance between an individual's birthplace and its reproductive
546 site (km), capturing the capacity to move away from heavily hunted areas. Life-history strategy
547 was quantified using generation length, age at first reproduction, litter size, and number of litters
548 per year; these traits were combined using a principal component analysis performed with the R
549 function *prcomp()* in R stats. The first principal component, explaining 69.5% of the variance
550 (compared with 16.5% for the second and 12.3% for the third), was retained as a composite
551 measure of reproductive rate. EOO (km²) was included as a proxy for the presence of large source
552 populations and the potential for recolonization.

553 Adaptive capacity for mammals was calculated as a weighted mean of standardized trait
554 values, with negative weighting applied to foraging stratum to reflect increased accessibility to
555 hunters. Dispersal distance was ultimately excluded from the final formulation because data were
556 unavailable for many species and imputed based on body mass. See Supplementary Information,
557 Fig. S17 & S18, for more details.

558

559 *2.3.3. Adaptive capacity scoring*

560 Species Adaptive capacity scores were calculated, for each species *i*, in the same way for
561 "subsistence", "pet trade", and "product trade", with different formulas for birds and mammals.
562 Because species-level Adaptive capacity is intended to counterbalance Sensitivity to a given

563 threat—here, hunting—it was defined as a value, with a maximum of 1 and a minimum of 0. Higher
564 values therefore indicate a greater ability to cope with hunting pressure.

565

566 For birds:

567 *Adaptive capacity_i*

$$568 = \frac{A * \min - \max(\text{primary lifestyle}_i) + B * \min - \max(\text{hand wing index}_i) + C * \min - \max(\text{clutch size}_i) - D}{A + B + C + D}$$

569 For mammals:

570 *Adaptive capacity_i*

$$571 = \frac{A * \min - \max(\text{foraging stratum}_i) + B * \min - \max(\text{nocturnality}_i) + C * \min - \max(\text{reproductive rate}_i) - D}{A + B + C + D}$$

572 All trait values were scaled using min–max normalization to preserve their relative distribution
573 across species, such that values ranged between the minimum and maximum observed across
574 species, enabling direct comparison among traits. As not all traits were expected to contribute
575 equally to adaptive capacity, we applied a weighted scoring scheme reflecting their presumed
576 importance, with weights increasing from traits associated with local-scale behavioral responses
577 to those linked to long-term population persistence, i.e., A = 1, B = 2, C = 3 & D = 4. This weighting
578 was motivated by evidence from IUCN Red List assessments, which consistently identify
579 restricted geographic range and low reproductive rate as primary drivers of extinction risk, while
580 dispersal plays an intermediate role, and behavioral traits primarily influence local-scale
581 responses. Robustness analyses exploring alternative weighting schemes are provided in the
582 Supplementary Information.

583

584 *2.4. Vulnerability*

585 *2.4.1. Calculation of species-level Vulnerability per spatial unit*

586 Vulnerability was computed independently for each taxon and each hunting purpose. For each
587 species, computations were restricted to the 20 × 20 km spatial units within tropical forests that
588 intersected its area of habitat for which we extracted the Exposure. spatial units falling outside a
589 species' area of habitat were assigned a Vulnerability of zero and were not considered in next
590 steps. For each species *i* and spatial unit *j* where the species occurs, Vulnerability was calculated
591 as:

$$592 \text{Vulnerability}_{ij} = \text{Exposure}_j + \text{Sensitivity}_i - \text{Adaptive capacity}_i$$

593 In this formulation, $Exposure_j$ represents the hunting pressure at spatial unit j and ranges from 0
594 to 1. $Sensitivity_i$ and $Adaptive\ capacity_i$ are species-level attributes bounded between 0 and 1
595 respectively. $Vulnerability_{i,j}$ ranged between -1 and 2, from the least to the most vulnerable
596 species or assemblages. During $Vulnerability_{i,j}$ calculations, species were progressively
597 excluded due to data limitations. For mammals, $Sensitivity_i$ and $Adaptive\ capacity_i$ could be
598 computed for 3,956 of the 4,450 species, decreasing to 3,697 species after intersecting areas of
599 habitat with the $Exposure_j$. For birds, species numbers declined from 8,106 to 7,829 for "pet
600 trade" and "product trade" and to 7,868 for "subsistence" due to missing trait data; after
601 intersecting areas of habitat with the $Exposure_j$ 6,238 species were retained for "pet trade" and
602 "product trade" analyses and 6,251 for "subsistence". $Sensitivity_i - Adaptive\ capacity_i$ is
603 referred as *Intrinsic Vulnerability_i* (IV_i) hereafter.

604

605 *2.4.2. Species-level and assemblage-level Vulnerability*

606 Once Vulnerability scores were calculated for each species in each spatial unit, we derived two
607 summary metrics. Species-level Vulnerability was computed as the mean Vulnerability per
608 species across all 20 × 20 km spatial units within the tropical portion of each species' area of
609 habitat, capturing overall Vulnerability to hunting within tropical forests. For species-level
610 analyses, we retained only species for which at least 90% of their area of habitats spatial units
611 overlapped with the hunting exposure layer, ensuring consistency with IUCN comparisons and
612 avoiding inflation of Vulnerability scores for species minimally exposed to hunting. This filtering
613 retained 2,477 mammal species and 3,852 bird species for pet and product trade, and 3,862 bird
614 species for subsistence hunting. Vulnerability scores for all species with any portion of their area
615 of habitat overlapping the Exposure layer are provided in the Supplementary Data 1 & 2.
616 assemblage-level Vulnerability was calculated as the mean Vulnerability per spatial unit j across
617 all species occurring in that cell (i.e. species with $Exposure_j > 0$), to identify hotspots where high
618 hunting pressure coincides with assemblages of sensitive species with low adaptive capacity.
619 Because Vulnerability was computed independently for each taxon and hunting purpose, species
620 and assemblage-level Vulnerability were estimated separately for "subsistence", "pet trade", and
621 "product trade" for mammals and birds, resulting in six distinct analyses (two taxa × three hunting
622 purposes).

623

624 *3. Further analyses*

625 3.1. IUCN Red List cross-validation

626 To assess whether our species-level indices (IV and Vulnerability) were consistent with IUCN
627 assessments of hunting, we performed six ordinal regression analyses using the *vgam()* function
628 from the *vgam* R package ⁷³. One model was fitted for each combination of taxon (birds or
629 mammals) and hunting purpose (“pet trade”, “product trade”, or “subsistence”). The IUCN Red
630 List provides two complementary types of species-level information. First, global extinction risk
631 (hereafter IUCN threat status) is expressed as an ordinal category reflecting increasing extinction
632 risk: Least Concern (LC), Near Threatened (NT), Vulnerable (VU), Endangered (EN), and
633 Critically Endangered (CR). Second, the Red List documents specific threats affecting species
634 using the IUCN Threats Classification Scheme (version 3.3). Hunting is coded as threat 5.1.1
635 (“Hunting & collecting terrestrial animals” under “Intentional use, where the species being
636 assessed is the target”). Species were considered threatened by hunting when this code was
637 listed in their threat assessment. Using this information, we derived a three-level ordinal response
638 variable describing hunting-related extinction risk. Species without the hunting threat code were
639 classified as *Not threatened by hunting*, regardless of their IUCN threat status. Species listed as
640 threatened by hunting but classified as LC, NT, or Data Deficient (DD) were categorized as
641 *Threatened by hunting but not threatened with extinction*. Species listed as threatened by hunting
642 and classified as VU, EN, or CR were categorized as *Threatened by hunting and threatened with*
643 *extinction*. Because the extinction risk of DD species is uncertain, we additionally conducted a
644 sensitivity analysis in which DD species were grouped with the extinction-threatened category.
645 Each ordinal regression tested the relationship between one of our composite indices (either IV
646 or Vulnerability) and this three-level response variable, allowing us to evaluate whether higher
647 index values were associated with increasing IUCN-assessed hunting-related threat.

648 The models followed the formula:

$$649 \quad IUCN \text{ hunting threat category}_{i,k,l} \sim IV_{i,k,l}$$
$$650 \quad IUCN \text{ hunting threat category}_{i,k,l} \sim Vulnerability_{i,k,l}$$

651 Each score and category were computed for each species *i*, and models were independently
652 computed for each hunting purpose *k* and taxon *l*. Model assumptions were evaluated using
653 multiple diagnostic tests: the Lipsitz test, Hosmer–Lemeshow test, Likelihood Ratio test of the
654 proportional odds assumption, and Brant test, implemented with the *gofcat* R package ⁷⁴. Residual

655 diagnostics were performed with the DHARMA R package ⁷⁵. The significance of the relationship
656 between our scoring system and IUCN categories was assessed using the p-values of the model
657 slope estimates and Likelihood Ratio tests comparing the full model with a null model containing
658 only the intercept.

659

660 *3.2. Statistical analysis*

661 To test for differences in IV or Vulnerability scores across categorical groups (e.g., realm, taxon,
662 hunting purpose), we used linear models computed using the R function *lm()* function in R stats.
663 Post hoc pairwise comparisons were performed using pairwise comparisons of least-squares
664 means with Šidák correction, implemented via the *emmeans()* function from the *emmeans* R
665 package ⁷⁶ and the *clm()* function from the *multcomp* R package ⁷⁷. Significance was assessed at
666 $\alpha = 0.05$.

667 We assessed the phylogenetic signal of species-level vulnerability for each hunting
668 purpose (pet trade, product trade, subsistence) using three complementary metrics computed
669 using the R package *phytools* ⁷⁸: (i) Blomberg's K, which tests whether trait similarity among
670 relatives exceeds random expectation under Brownian motion ⁷⁹; (ii) Pagel's λ , estimated by
671 maximum likelihood, which rescales internal branch lengths to quantify how much of the trait
672 variance is explained by phylogenetic structure ⁸⁰(Pagel 1999); (iii) sparse Moran's I statistic
673 based on a k-nearest-neighbour phylogenetic weight matrix ($k = 50$), which measures local
674 autocorrelation between a species' vulnerability and that of its closest relatives on the tree.
675 Statistical significance for K and Moran's I was assessed by permutation and λ was tested via a
676 likelihood ratio test against a white-noise model ($\lambda = 0$). Phylogenies were extracted from Upham
677 et al. ⁸¹ and Jetz et al. ⁸² and a consensus tree, calculated from 100 random trees, was constructed
678 for each taxon.

679

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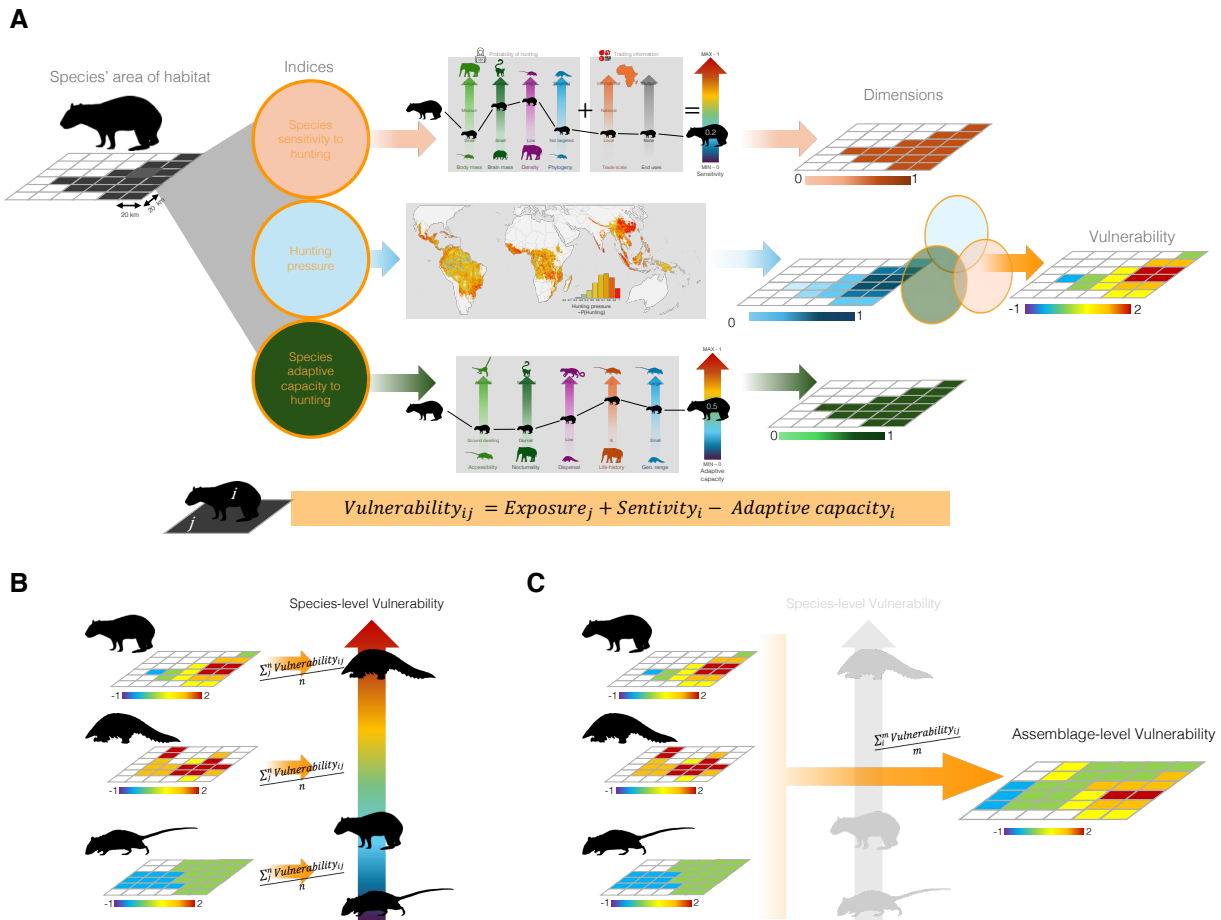
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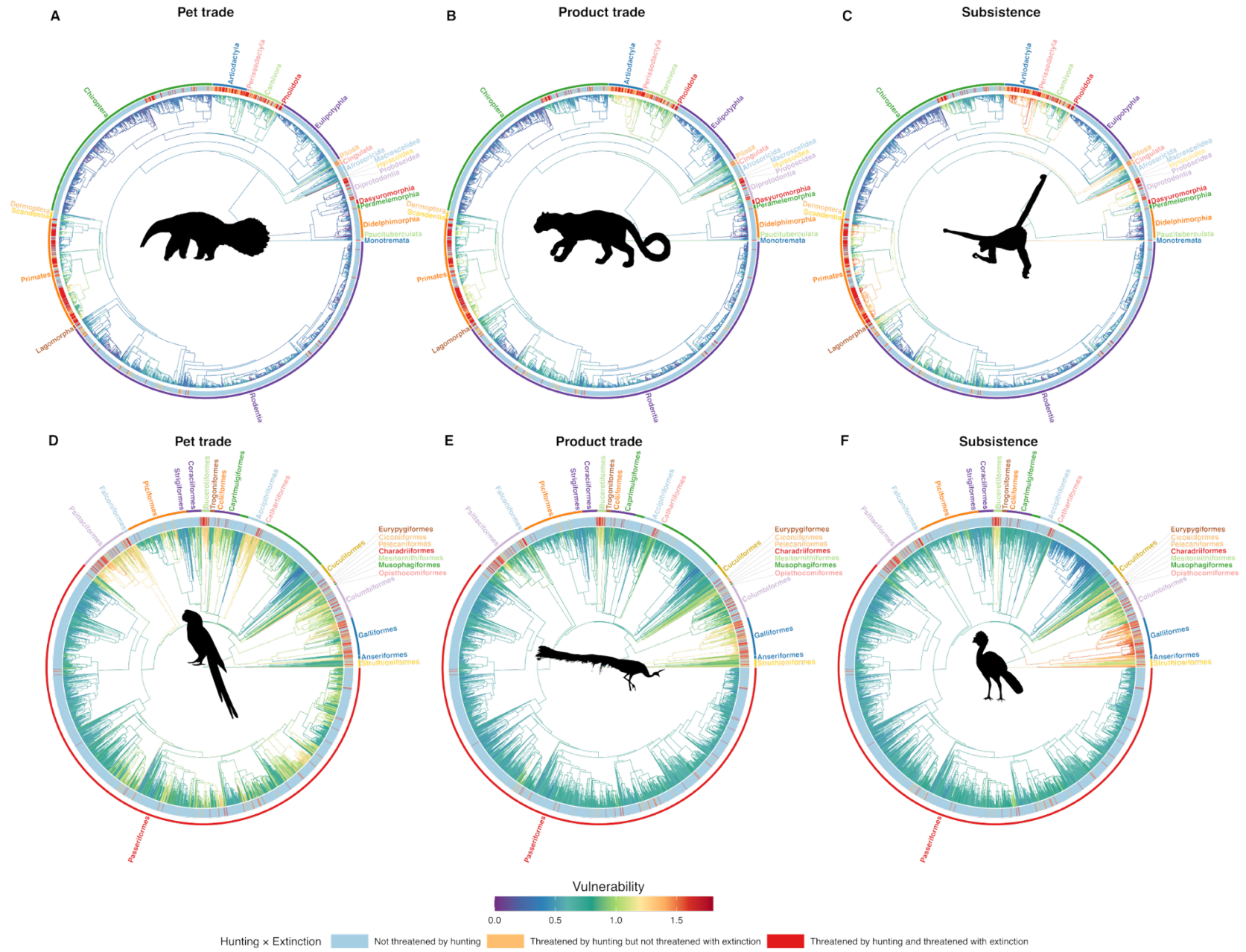


860

861 **Figure 1. Species-specific and spatially explicit scoring of hunting vulnerability for tropical**
 862 **birds and mammals.**

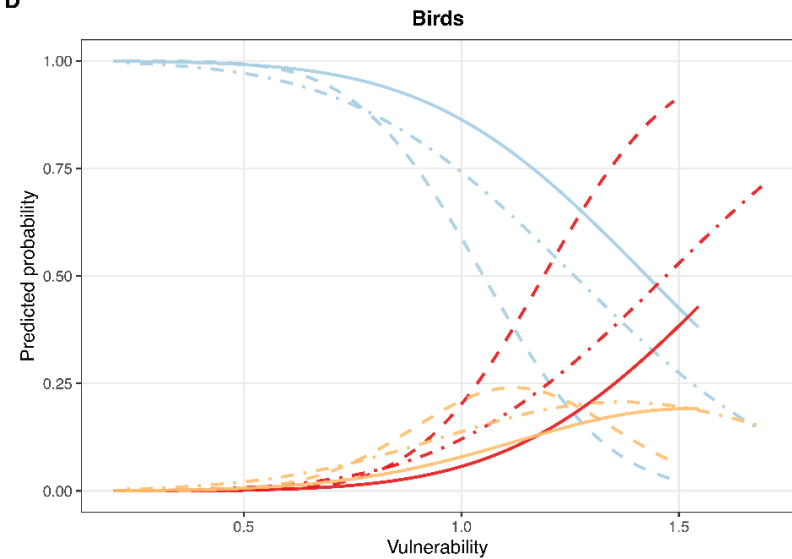
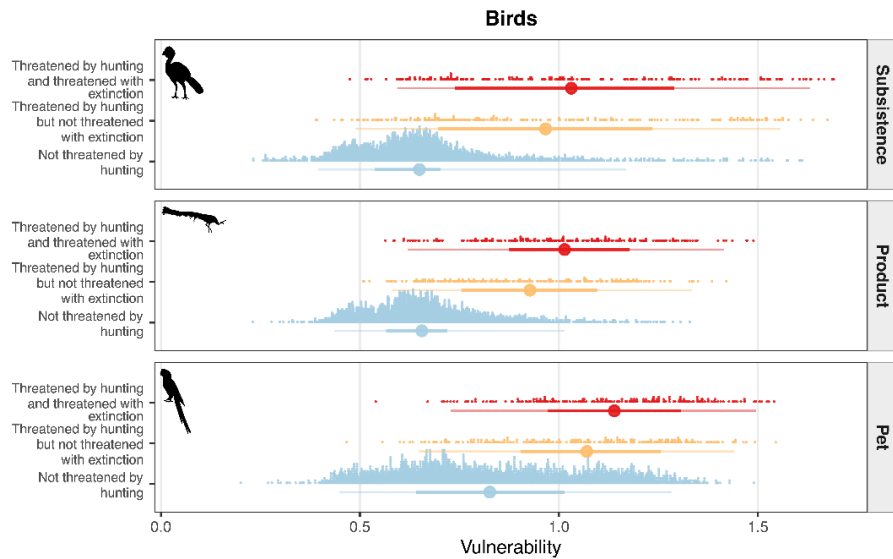
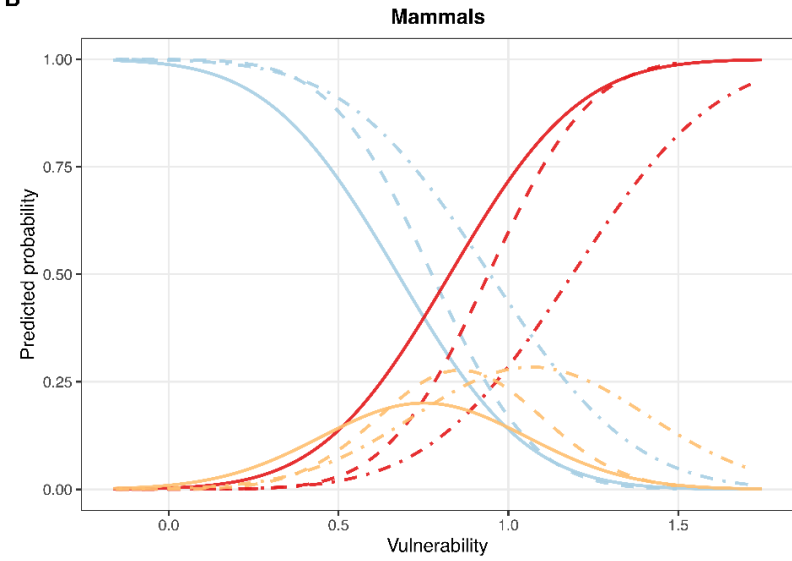
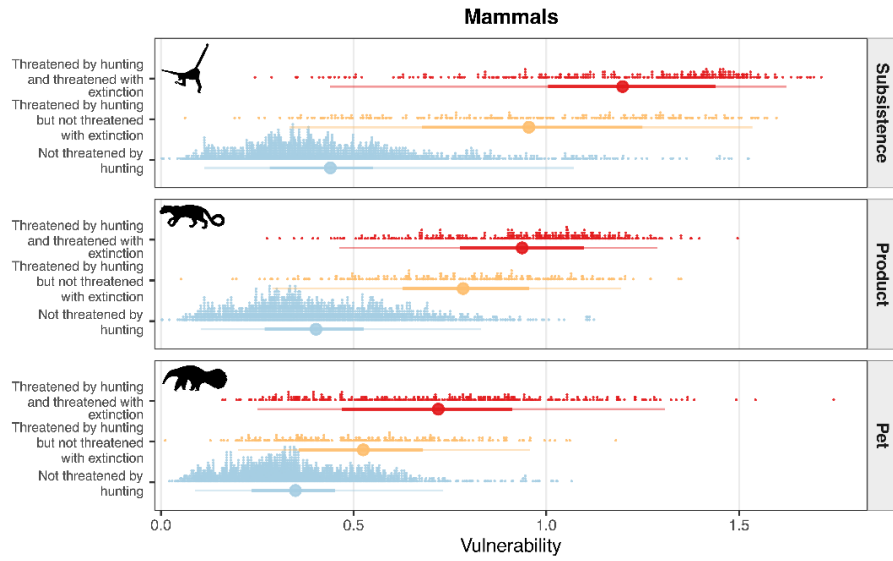
863 Panel A illustrates the general framework: for each species, a Vulnerability score is computed at
 864 each 20 × 20 km spatial unit within its area of habitat (AoH) by combining a spatially explicit
 865 measure of Exposure to hunting, corresponding to the predicted probability of hunting occurrence,
 866 with two species-specific components (constant across all spatial units within a species' AoH):
 867 Sensitivity, reflecting the likelihood of being targeted, and Adaptive Capacity, reflecting the ability
 868 to sustain hunting offtake. The resulting Vulnerability score, defined as Exposure + Sensitivity –
 869 Adaptive Capacity, is thus resolved at the 20 × 20 km spatial unit level. Panels B and C display
 870 two complementary summary metrics derived from this score: the species-level Vulnerability
 871 (Panel B), computed as the mean Vulnerability across all spatial units within a species' AoH, and

872 the assemblage-level Vulnerability (Panel C), computed for each 20 × 20 km spatial unit as the
873 mean score across all occurring species. Silhouettes were sourced from PhyloPic.org (T. Michael
874 Keesey, 2025).



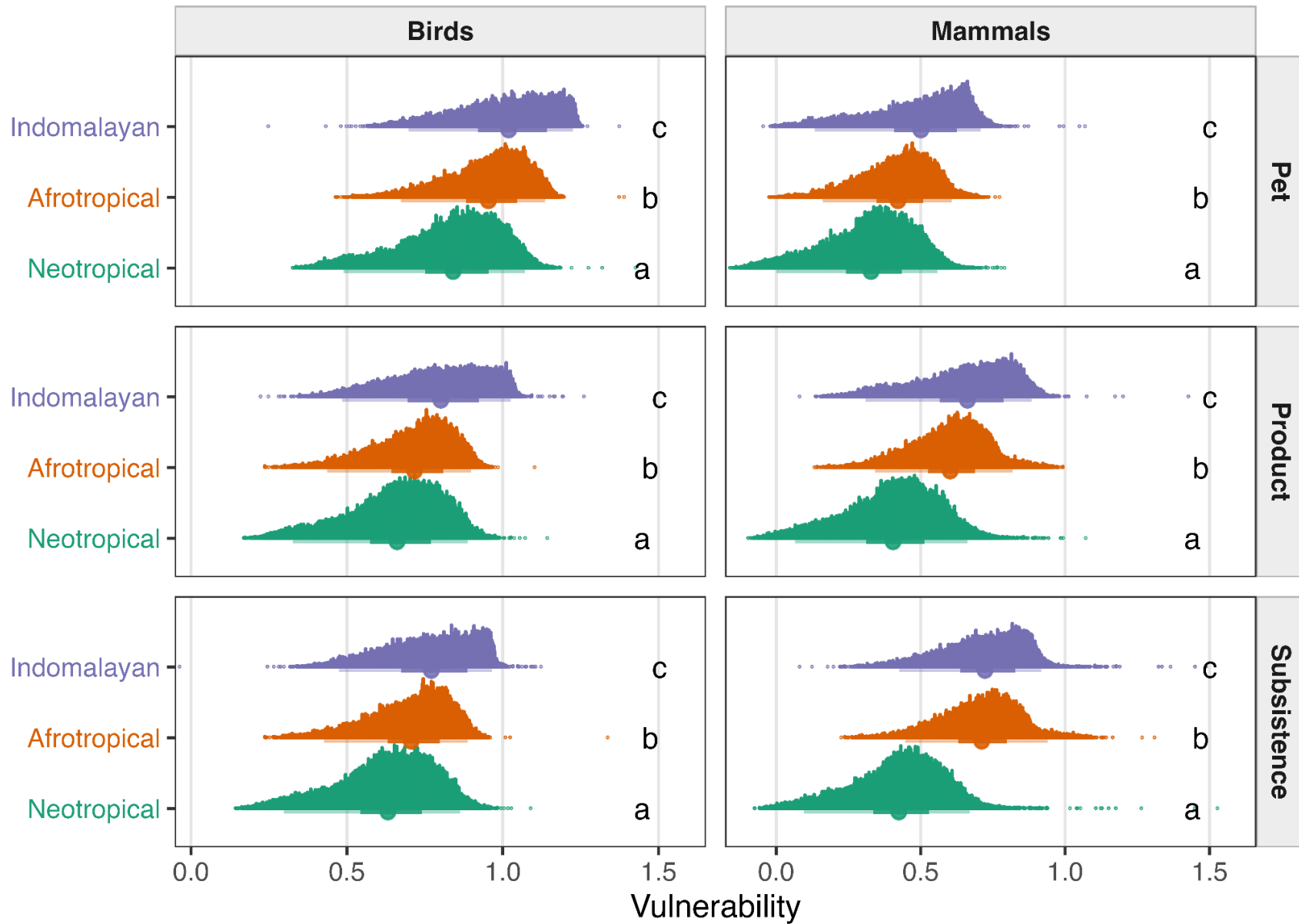
876 **Figure 2. Vulnerability to hunting across the avian and mammalian phylogenies.**

877 The mammalian phylogeny (A, B, C) and the avian phylogeny (D, E, F) are colored according to species-level Vulnerability scores.
878 Separate panels are shown for each hunting purpose. The outer ring encodes the IUCN Hunting × Extinction threat categories based
879 on IUCN Red List status and threat assessments: species listed as Vulnerable, Endangered, or Critically Endangered and also
880 assessed as threatened by hunting are shown in red (*Threatened by hunting and at risk of extinction*); species listed as Least Concern
881 or Near Threatened but still assessed as threatened by hunting are shown in yellow (*Threatened by hunting but not at risk of extinction*);
882 species assessed as not threatened by hunting are shown in blue (*Not threatened by hunting*). Taxonomic orders are labeled in bold
883 on the outer edge of the tree to highlight phylogenetic structure in vulnerability and threat status. Black and gray colors have been
884 alternated to improve the visibility of order changes. Phylogenies were extracted from Upham et al.⁸¹ and Jetz et al.⁸². Silhouettes
885 were sourced from PhyloPic.org (T. Michael Keeseey, 2025).



887 **Figure 3. Species-level Vulnerability in tropical birds and mammals.**

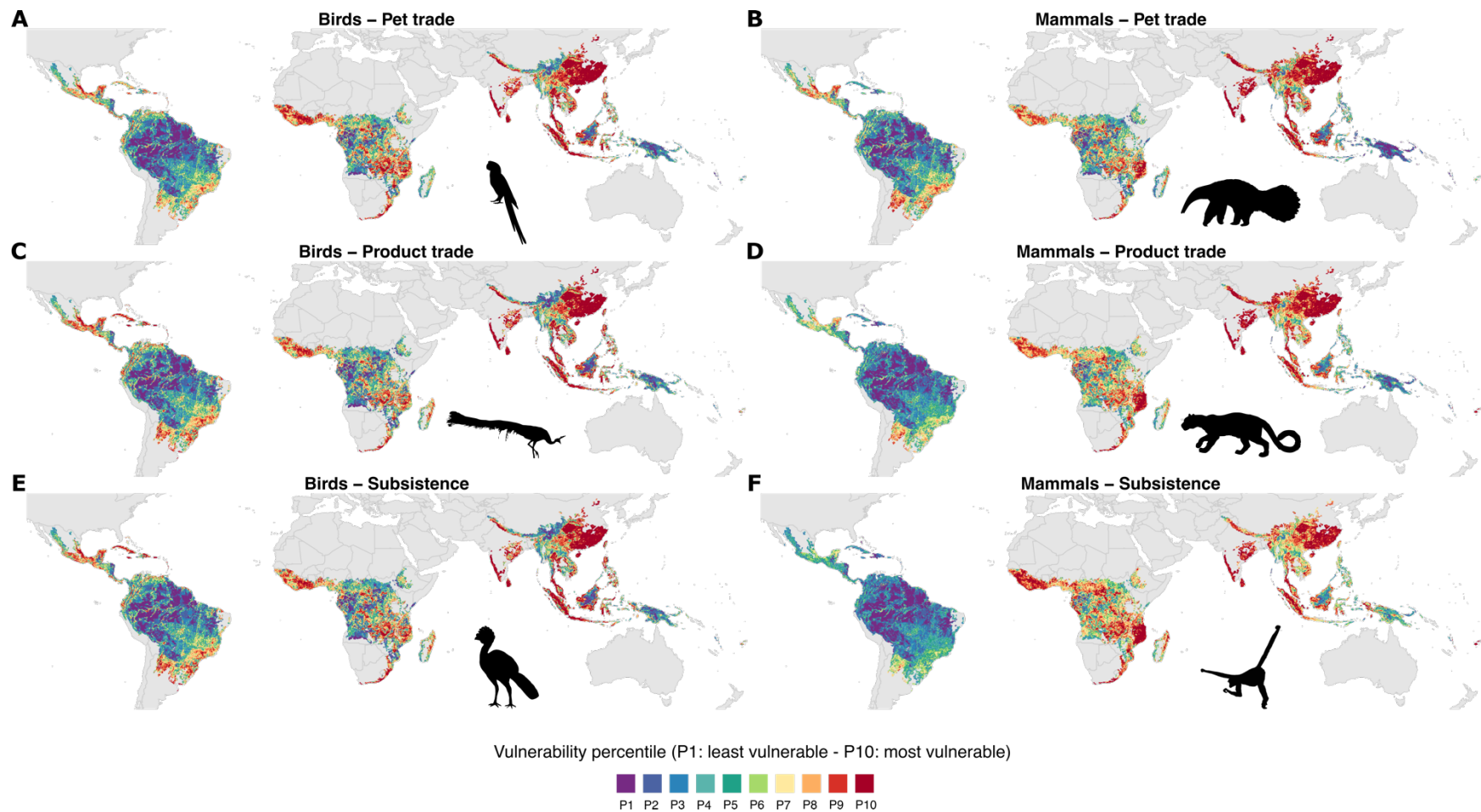
888 Species are color-coded by IUCN hunting and global extinction risk status: red indicates species assessed as threatened by hunting
889 and at risk of extinction (listed as Vulnerable, Endangered, or Critically Endangered); yellow indicates species threatened by hunting
890 but not at risk of extinction (Least Concern, Near Threatened or Data Deficient); and blue indicates species not threatened by hunting.
891 Panels A and C show the distribution of species-level Vulnerability for tropical mammals and birds, respectively. Species-level
892 Vulnerability is computed as the mean Vulnerability score across all 20 × 20 km spatial units within each species' range. Dot plots
893 depict the distribution of scores for each IUCN hunting threat category (defined by the combination of hunting threat and extinction
894 risk), ordered from least to most threatened. Thick colored bars show the 50% interval and thin bars the 95% interval around the mean,
895 computed per threat category within each hunting purpose (Pet, Product, Subsistence). Panels B and D illustrate the relationship
896 between species vulnerability scores and the probability of assignment to each IUCN hunting threat category (Hunting × Extinction).
897 Fitted lines are derived from ordinal regression models (IUCN hunting threat category ~ Vulnerability), run separately for each hunting
898 purpose. In all models, slope estimates were significant based on likelihood ratio tests, indicating that species with lower vulnerability
899 scores were more likely to be classified as not threatened by hunting, whereas higher scores increased the probability of being classified
900 as threatened by hunting and at risk of extinction. Silhouettes were sourced from PhyloPic.org (T. Michael Keeseey, 2025).



902

903 **Figure 4. Comparisons of assemblage-level Vulnerability across realms.**

904 Each distribution represents assemblage-level Vulnerability per spatial unit, calculated as the average Vulnerability of all species
905 occurring within each 20 × 20 km spatial unit. Thick colored bars show the 50% interval and thin bars the 95% interval around the
906 mean, computed per threat category within each hunting purpose (Pet, Product, Subsistence). Comparisons were conducted
907 separately for each taxon and hunting purpose using pairwise comparisons of least-squares means with Šidák correction. Letters show
908 statistically distinct groups, ordered from lowest (a) to highest mean vulnerability (c); realms sharing the same letter do not differ
909 significantly. White diamonds indicate mean values per realm, while boxplots show the median and interquartile range.

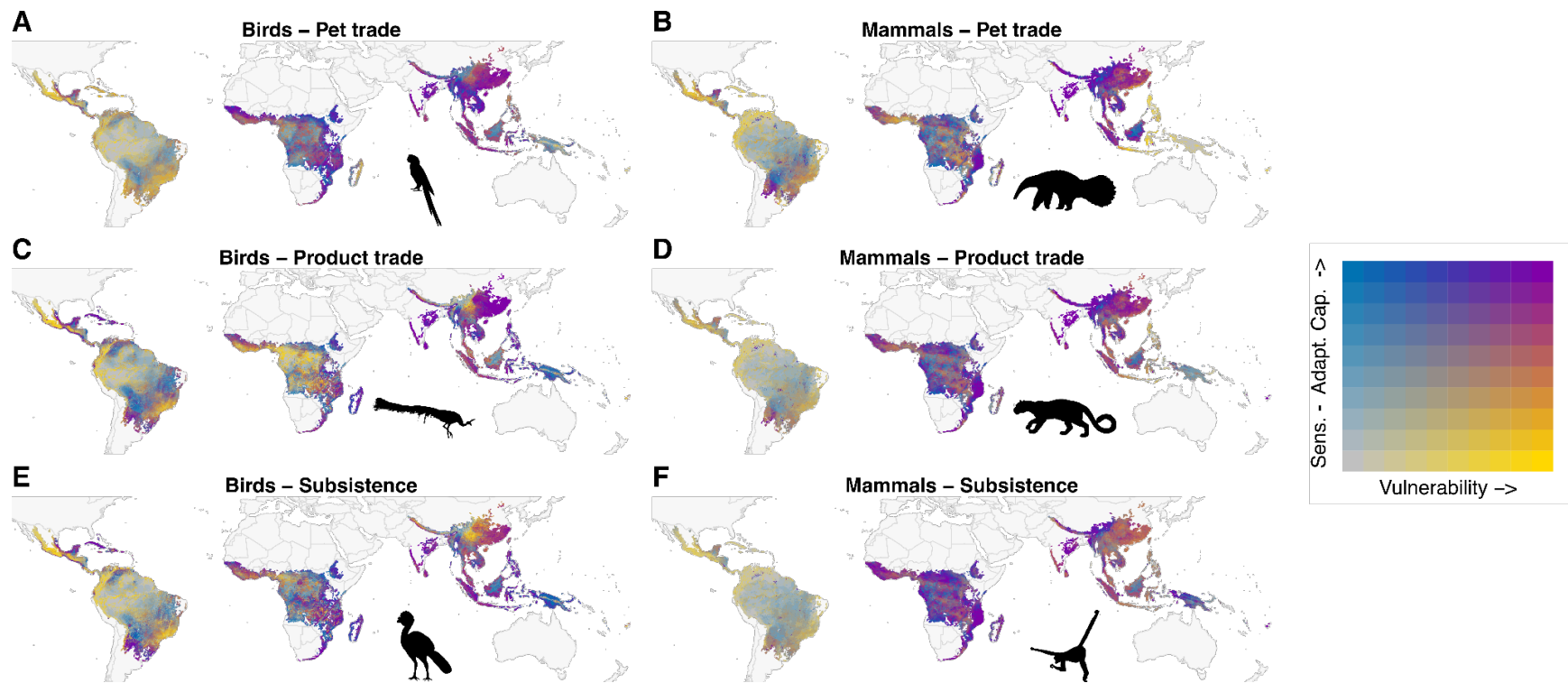


910

911 **Figure 5. Spatial distribution of assemblage-level Vulnerability in tropical birds and mammals.**

912 Panels A–C–E represent birds, and B–D–F represent mammals. Hunting purposes are divided as follows: A–B for pet trade, C–D for
 913 product trade, and E–F for subsistence hunting. Each map is divided into 10 equal-sized percentile classes (P1 to P10) since raw

914 vulnerability scores are not directly interpretable, where P1 indicates the 10% of 20 × 20 km spatial units with the lowest assemblage-
915 level Vulnerability and P10 the 10% with the highest assemblage-level Vulnerability. Assemblage-level Vulnerability represents the
916 mean Vulnerability score across all species occurring within a given 20 × 20 km spatial unit. Percentiles are calculated separately for
917 each taxon–purpose combination to ensure comparability within each category. Percentile of assemblage-level Vulnerability is shown
918 using a color gradient from purple (lowest vulnerability) to red (highest vulnerability), with green representing intermediate values.
919 Silhouettes were sourced from PhyloPic.org (T. Michael Keeseey, 2025).



920

921 **Figure 6. Bivariate maps of the spatial distribution of assemblage-level Sensitivity - Adaptive capacity and Vulnerability.**

922 Panels A, C, and E represent birds, while panels B, D, and F correspond to mammals. Hunting purposes are categorized as follows:
 923 A–B for pet trade, C–D for product trade, and E–F for subsistence hunting. Each map is divided into 10 equal-sized percentile classes
 924 (P1 to P10), where P1 indicates the 10% of 20 × 20 km spatial units with the lowest assemblage-level scores and P10 the 10% with
 925 the highest assemblage-level scores for both Sensitivity - Adaptive capacity, i.e Intrinsic Vulnerability (IV), and Vulnerability. Percentiles
 926 are computed independently for each taxon–purpose combination to ensure comparability. The color gradient represents the joint
 927 variability of both scores. Grey areas indicate locations with both low Vulnerability and low IV, while purple areas reflect locations where

928 both scores are high, indicating hotspots of concern. Yellow regions represent areas with high Vulnerability but low IV, suggesting high
929 exposure but relatively low intrinsic vulnerability. In contrast, blue areas denote low Vulnerability and high IV, potentially identifying
930 refugia where sensitive species are less exposed. Diagonal transitions from grey to purple reflect strong concordance between
931 exposure and intrinsic susceptibility, whereas yellow and blue areas represent spatial mismatches between the two dimensions.
932 Silhouettes were sourced from PhyloPic.org (T. Michael Keeseey, 2025).

Supplementary Information

Supplementary Methods

2.2. Sensitivity

2.2.1. Probability of hunting

To assess the reliability of our modelling approach, we conducted additional validation analyses. Because our framework relied on bootstrapping, we obtained 100 fitted generalized linear mixed-effects models (GLMMs) for each combination of taxon and hunting purpose. Each model predicted species hunting status (1 = hunted, 0 = non-hunted) as a function of species traits included as fixed effects, with phylogeny modelled as a nested random effect (order/family). This structure accounts for shared evolutionary history, under the assumption that closely related species may share latent characteristics not explicitly captured by the selected traits. From the 100 fitted models, we extracted estimates of both fixed and random effects across bootstrap iterations. To evaluate the overall contribution of each trait, we applied a meta-analytic approach using the *rma()* function from the `metafor` R package ¹. Because all traits were standardized prior to modelling, effect sizes are directly comparable and provide an estimate of the relative importance of each trait in predicting whether a species is classified as hunted or non-hunted. Similarly, we extracted family-level random effects to assess the influence of phylogenetic structure in the models, allowing us to evaluate whether residual variation in hunting status was associated with taxonomic relatedness beyond the included trait predictors.

3.3. Robustness analysis

To assess the influence of our weighting scheme on species-level Sensitivity and Adaptive capacity scores, we compared the reference model to a range of alternative weighting scenarios. For Sensitivity, we tested different combinations of weights applied to the components (e.g., probability of being hunted and trade scale) for both pet and product trade, keeping the sum of the weights constant at 2. Specifically, we varied the weight of each component (A and B) from 0 to 2 in steps of 0.3, with the constraint $B = 2 - A$. Subsistence hunting was excluded from this analysis, as it lacks a trade scale component. For Adaptive capacity, we explored weighting

schemes using trait data, maintaining total weights of 10 for birds (four traits) and 15 for mammals (five traits). We varied the individual weights (A–D or A–E) from 1 to 5 in steps of 1 and generated all possible combinations that respected the total sum constraint. For each weighting configuration, we recalculated the combined Sensitivity - Adaptive capacity score across species and compared it to the reference score using Spearman correlation coefficients. To quantify how variation in individual weightings affected similarity to the reference model, we ran linear models using $lm()$ with difference in weight values between reference and tested scenario as predictors of the correlation outcome. The resulting regression coefficients indicated which trait weights had the strongest impact on the final scores, and whether increasing a weight made the alternative scenario consistent with the reference.

Supplementary Results

3. Sensitivity and Adaptive capacity of tropical birds and mammals

Our mixed models on the likelihood of birds and mammals being hunted showed good predictive performance across all purposes, with conditional R^2 values (mean \pm SD) ranging from 0.50 ± 0.01 to 0.74 ± 0.01 (Fig. S6). We observed high variability in the predicted likelihood of species being hunted, depending on both taxonomic group and hunting type. Birds were most likely to be hunted for the pet trade (0.40 ± 0.29) than mammals (0.11 ± 0.21); whereas mammals were particularly harvested for the product trade (0.30 ± 0.37) and for subsistence (0.24 ± 0.32). The likelihood of birds being hunted for product trade (0.19 ± 0.25) or subsistence (0.12 ± 0.19) was considerably lower (Fig. S7). Phylogeny played a more important role in modeling the likelihood of being hunted for mammals than for birds, with the proportion of variance explained by phylogeny ranging from 0.46 ± 0.033 to 0.82 ± 0.013 in mammals, compared to 0.14 ± 0.021 to 0.28 ± 0.032 in birds (Fig S6).

When assessing the geographic scale of trade for each species, i.e., whether a species was traded for subsistence purposes and/or traded nationally and/or internationally, and for how many 'end uses' (only 1 for pets, and up to 16 for products for birds and mammals), we found that mammals are generally traded as products across for more end uses and broader spatial scales than birds (mean absolute trade score = 0.89 ± 2.39 for mammals vs. 0.46 ± 1.28 for birds).

When assessing the geographic scale and purpose of trade for each species—including whether species are used for subsistence and/or traded at national and/or international levels, and the number of end uses (only 1 for pets, and up to 16 for products for birds and mammals)—we found that mammals are generally traded for a wider range of products and across broader spatial scales than birds. On average, mammals showed higher trade scores than birds (mean \pm SD: 0.89 ± 2.39 vs. 0.46 ± 1.28 , respectively). In contrast, birds were traded more extensively as pets (1.15 ± 1.50 , i.e. nationally and internationally) than mammals (0.13 ± 0.65 , i.e. mostly locally). The maximum trade score for pet trade was 6 for both birds and mammals, indicating trade across all geographical scales. For product trade, the highest score reached was 26 for mammals (*Acinonyx jubatus*) and 12 for birds (*Pavo muticus*). After min-max standardization, bird pet trade showed the highest mean value (0.19 ± 0.25), followed by product trade for birds (0.04 ± 0.11) and mammals (0.03 ± 0.1), which were not statistically different. Mammal pet trade exhibited the lowest standardized value (0.02 ± 0.11) (Fig. S8).

Species Sensitivity (ranging from 0 to 1) and adaptive capacity were combined into a single composite metric of Intrinsic Vulnerability (IV) to hunting, calculated as $IV = S - AC$. Adaptive capacity was defined such that higher values (closer to 0) indicate lower capacity to cope with hunting, whereas more negative values indicate greater adaptive capacity. Adaptive capacity ranged from -0.69 (*Hirundo rustica*) to -0.015 (*Neomorphus geoffroyi*) for birds (mean \pm SD: -0.13 ± 0.06), and from -0.64 (*Mustela nivalis*) to 0.005 (*Elephas maximus*) for mammals (mean \pm SD: -0.30 ± 0.11). For both mammals and birds, species not threatened by hunting exhibited significantly lower IV scores than those identified as threatened by hunting or threatened by hunting and at risk of extinction (extinction risk: Vulnerable, Endangered or Critically Endangered according to the IUCN RedList, Fig. S9). We did not observe consistent significant differences in intrinsic vulnerability between species threatened by hunting and at risk of extinction and those threatened by hunting but not currently at risk, with two exceptions, mammals targeted by the pet trade and birds hunted for subsistence, for which non-globally threatened species exhibited higher IV (Fig. S9).

Body mass was positively correlated with hunting status across both taxa and all hunting purposes and consistently showed the strongest effect (Fig. S10). Population density was positively associated with hunting status in birds for pet trade and subsistence hunting, but negatively associated in mammals. For birds, this positive relationship may reflect the social

behavior of species targeted for the pet trade and subsistence, where locally abundant and easily captured species are preferentially hunted. The negative relationship observed in mammals was unexpected and may reflect unmeasured traits associated with hunting preference—such as meat quality, behavioral characteristics desirable for the pet trade, or aesthetic features—that could be negatively correlated with density. In birds, tail length and color elaboration were positively correlated with hunting status for both pet and product trade, consistent with the hypothesis that visually conspicuous traits increase desirability. Beak size was negatively associated with pet trade, possibly reflecting the targeting of smaller, vocal passerines, although the absence of a significant positive effect for product trade was contrary to expectations. In mammals, brain mass (controlled for body mass) was positively associated with hunting status for the pet trade, consistent with the idea that relative brain size may act as a proxy for perceived intelligence, a trait valued in traded species. The weaker effect observed for product trade may reflect selective targeting of specific taxa, such as large carnivores, for products.

Phylogenetic effects across taxa and hunting purposes reflected biologically coherent patterns. For mammals, lemurs were predicted to be particularly targeted for subsistence hunting, whereas felids showed lower predicted probabilities (Fig. S11). Similarly, in the pet trade models, primates were more likely to be classified as hunted, while rodents showed lower probabilities (Fig. S12). For product trade, lemurs, civets, and rhinoceroses exhibited higher predicted hunting probabilities than rodents (Fig. S13). For birds, galliform species were more likely to be targeted for subsistence hunting than passerines (Fig. S14). In the pet trade models, colorful passerines, raptors, and parrots showed higher predicted hunting probabilities than nocturnal or crepuscular species and dull-colored passerines (Fig. S15). For product trade, hummingbirds, galliformes, and hornbills were more frequently predicted as hunted compared with small, dull-colored passerines (Fig. S16).

4. Result robustness


Sensitivity and Adaptive capacity, both combined into the final Vulnerability score, were non-spatialized components computed at the species level using a custom scoring system based on a set of predefined assumptions. These scoring choices directly influenced the distribution of Vulnerability values and species rankings across taxa and hunting purposes. To assess the


robustness of our framework, we compared the reference scoring configuration to several alternatives. These included varying the weights assigned to (1) hunting probability, (2) trade scale, and (3) traits contributing to adaptive capacity. Overall, species rankings based on the composite score (Sensitivity - Adaptive capacity) remained relatively stable across alternative scenarios. Spearman correlation coefficients ranged from 0.85 ± 0.10 (pet trade), 0.85 ± 0.15 (product trade), and 0.86 ± 0.24 (subsistence) for mammals, and from 0.95 ± 0.053 (pet), 0.92 ± 0.078 (product), and 0.89 ± 0.18 (subsistence) for birds (Fig. S17). Among all tested modifications, changing the weight of hunting probability had the strongest effect (Fig. S18). For mammals, reducing its weight relative to trade scale decreased correlation with the reference score from 0.99 (SE = 0.0057) at maximum weight to 0.75 (SE = 0.0052) at minimum weight. For birds, the drop was similar: from 1.01 (SE = 0.0028) to 0.91 (SE = 0.0030) (Fig. S18). Trait weightings also influenced species rankings, though to a lesser extent. In birds, adjusting the weight of primary lifestyle traits reduced the Spearman correlation of vulnerability rankings from 0.98 to 0.91 (SE = 0.0027 in both cases). In mammals, trait weighting had minimal impact on species rankings, indicating greater stability in the vulnerability score. The weighting of trade scale, set in the reference model as international = 3, national = 2, and local = 1, was particularly important for ranking bird species in the pet trade. Apart from one alternative weighting (local = 2, national = 1, international = 3), which reached a Spearman correlation of 1.00 with the reference model, all other combinations resulted in lower correlations, ranging from 0.21 to 0.41. In contrast, changes in trade scale weights had minimal effect on Vulnerability rankings for mammals (in both pet and product trade) and for birds in the product trade category, with correlation coefficients consistently above 0.99.

Supplementary References

1. Viechtbauer, W. metafor: Meta-Analysis Package for R. (2025).

Supplementary Figures

		1. Sensitivity		
		Subsistence	Product trade	Pet trade
A. Probability of hunting (modelled likelihood)				
Status	1.1.1. IUCN General Use and Trade Classification Scheme (Version 1.0)			
Hunted	Code 1 ("Food – human") with scale marked as subsistence	Codes 1–12 and 14–17 (i.e., excluding pet trade).	Code 13 only	
Trait	Human attractiveness			
Body mass	Larger and more abundant species are easier to find, capture, and yield higher nutritional or financial returns.			
Population density				
Brain mass	Brain mass may reflect head morphology traits valued in trophy or ornamental hunting.		Intelligent species, such as primates, may be more desirable as pets	
Order & Family	Because key traits such as coloration, behavior, and morphological features (e.g., horns, skin texture) are often unavailable across species, we used taxonomic order and family as proxies for unmeasured but phylogenetically conserved characteristics . This approach allowed us to partially account for lineage-specific factors likely to influence human preferences across different hunting purpose , such as meat quality for subsistence, cultural or ornamental value for product trade, and attractiveness or tolerance to captivity for the pet trade			
Info	Modelling			
Formula	Hunted ~ standardized(log(body mass)) + residuals(population density) + (1 order / family)	Hunted ~ standardized(log(body mass)) + residuals(population density) + residuals(brain mass) + (1 order / family)		
Response	Binary variable: 1 if the species is hunted for the specific purpose, 0 if not.			
Fixed effects	Body mass: Log-transformed, then centered and scaled (mean = 0, SD = 1) to aid model convergence and interpretation.			
Random effects	Order and family: Hierarchical modelling were used to consider the phylogenetic relationships.			
Strategy	The model was trained on 70% of the dataset, with species evenly distributed across families to ensure taxonomic balance. The remaining 30% was used to predict the probability of a species being hunted based on the former model. This procedure was repeated 100 times so that each species was included in several test sets and received multiple predicted probabilities. The final probability per species was calculated as the mean across all these predictions.			
B. IUCN trading information (composite score)				
Scores	Hypothesis			
Trade scale	This score reflects the geographic scale of trade based on IUCN data: local (1), national (2), and international (3) . Scores are summed (range: 0–6), assuming broader trade increases pressure and species sensitivity .			
End uses	This score reflects the number of distinct use types per species (excluding pet trade, code 13) based on IUCN classifications. Species used for more purposes are assumed to face higher hunting pressure . Values range from 1 (single use) to 17 (multiple uses).			
Scores	Scoring			
Trade scale	Trade scale score = min-max(local + 2×national+ 3×international) If the species is known to be traded at a specific scale the value is 1 otherwise it is 0. Scores are scaled between 0 and 1 using a min-max normalization function to conserve the distribution of values.			
End uses	End uses score = min-max(Σ _{i=1 to 13} code _i) If the species is known to be traded for a specific use the value is 1 otherwise it is 0.			
Final score	Trading information score = (Trade scale score + End use score)/2		Trading information score = Trade scale score	
C. Sensitivity final score				
Formula	Sensitivity = Probability of hunting for subsistence		Sensitivity = (Probability of hunting for product trade + Trading information score)/2	

2. Adaptive capacity			
Subsistence	Product trade	Pet trade	
A. Trait-based approach			
Expected response			Trait
Species less accessible to hunters , such as arboreal species that occupy higher forest strata , are considered to have higher adaptive capacity . In contrast, ground-dwelling species are more accessible to hunters and are expected to have a lower adaptive capacity <i>Ordinal: 1 = ground-dwelling, highest accessibility to hunters; 2 = scansorial, intermediate high; 3 = arboreal, intermediate high; 4 = aerial, lowest accessibility.</i>			Accessibility (foraging stratum)
Nocturnal species may be pre-adapted to human hunting pressure , as hunting often causes shifts toward nocturnality . Therefore, species actively active at night are assumed to require fewer behavioral shifts and are considered more adaptive than diurnal species . <i>Binary: 0 = diurnal; 1 = nocturnal.</i>			Dispersal distance (hand wing index)
Species with r-strategies , characterized by fast life histories (e.g., early reproduction, high fecundity), are generally more resilient to anthropogenic pressures. Thus, species with fast life-history traits are assumed to have higher adaptive capacity than those with slower strategies (K) . <i>Values of the first principal component of a PCA computed based on generation length, age of first reproduction, litter size and litters per year. Higher values → r-strategies and lower → K-strategies.</i>			Life-history (clutch size)
Used as a proxy for global extinction risk , following IUCN Red List practices. Species with large ranges are considered less vulnerable to extinction , more genetically diverse , and more likely to be generalist , all contributing to greater adaptive capacity . <i>Global extent of occurrences of the species, continuous, in km².</i>			Geographical range size (extent of occurrences)
B. Adaptive capacity final score			
Adaptive capacity = ((min-max(accessibility) + 2×min-max(dispersal distance) + 3×min-max(life-history) + 4×min-max(geographical range size))/10			Formula
All traits' values are scale between 0 and 1 using min-max normalization function to conserve values distribution.			

3. References		
Data type	Source data	Supporting hypothesis
A. Probability of hunting		
Population density	Santini, L., Benítez-López, A., Dormann, C. F., & Huijbregts, M. A. (2022). Population density estimates for terrestrial mammal species. <i>Global Ecology and Biogeography</i> , 31(5), 978-994.	Bush, E. R., Baker, S. E., & Macdonald, D. W. (2014). Global trade in exotic pets 2005–2012. <i>Conservation Biology</i> , 29(5), 663-676.
Body mass	Soria, C. D., Pacifici, M., Di Marco, M., Stephen, S. M., & Rondinini, C. (2021). COMBINE: a coalesced mammal database of intrinsic and extrinsic traits.	Cash, L., Gumbs, R., & Devenish-Nelson, E. S. (2025). Assessing gecko susceptibility to international wildlife trade: A novel trait-based framework. <i>Biological Conservation</i> , 311, 111397.
Brain mass	Soria, C. D., Pacifici, M., Di Marco, M., Stephen, S. M., & Rondinini, C. (2021). COMBINE: a coalesced mammal database of intrinsic and extrinsic traits.	Hughes, L. J., Morton, O., Scheffers, B. R., & Edwards, D. P. (2023). The ecological drivers and consequences of wildlife trade. <i>Biological Reviews</i> , 98(3), 775-791.
Order & Family	IUCN Red List (2025). https://www.iucnredlist.org .	Hughes, L. J., Massam, M. R., Morton, O., Edwards, F. A., Scheffers, B. R., & Edwards, D. P. (2023). Global hotspots of traded phylogenetic and functional diversity. <i>Nature</i> , 620(7973), 351-357.
B. Trading information		
Trade scale	IUCN Red List (2025). https://www.iucnredlist.org .	Challender, D. W., Cremona, P. J., Malsch, K., Robinson, J. E., Pavitt, A. T., Scott, J., ... & Hoffmann, M. (2023). Identifying species likely threatened by international trade on the IUCN Red List can inform CITES trade measures. <i>Nature Ecology & Evolution</i> , 7(8), 1211-1220.
End uses	IUCN Red List (2025). https://www.iucnredlist.org .	Ingram, D. J., Coad, L., Milner-Gulland, E. J., Parry, L., Wilkie, D., Bakarr, M. I., ... & Abernethy, K. (2021). Wild meat is still on the menu: Progress in wild meat research, policy, and practice from 2002 to 2020. <i>Annual Review of Environment and Resources</i> , 46(1), 221-254.
C. Adaptive capacity		
Foraging stratum	Soria, C. D., Pacifici, M., Di Marco, M., Stephen, S. M., & Rondinini, C. (2021). COMBINE: a coalesced mammal database of intrinsic and extrinsic traits.	Butt, N., Halpern, B. S., O'Hara, C. C., Alcock, A. L., Poldoro, B., Sherman, S., ... & Klein, C. J. (2022). A trait-based framework for assessing the vulnerability of marine species to human impacts. <i>Ecosphere</i> , 13(2), e3919.
Nocturnality	Soria, C. D., Pacifici, M., Di Marco, M., Stephen, S. M., & Rondinini, C. (2021). COMBINE: a coalesced mammal database of intrinsic and extrinsic traits.	
Generation length, age of first reproduction, litter size, litters per year		
Extent of occurrences	IUCN Red List (2025). https://www.iucnredlist.org .	

Figure S1. Species-level Sensitivity and Adaptive capacity in mammals.

This figure provides a detailed description of the traits used to compute species-level Sensitivity and Adaptive capacity for mammals, including the rationale for trait selection and the associated references.

	1. Sensitivity		
	Subsistence	Product trade	Pet trade
	A. Probability of hunting (modelled likelihood)		
Status	1.1.1. IUCN General Use and Trade Classification Scheme (Version 1.0)		
Hunted	Code 1 ("Food – human") with scale marked as subsistence	Codes 1–12 and 14–17 (i.e., excluding pet trade).	Code 13 only
Trait	Human attractiveness		
Body mass	Larger and more abundant species are easier to find, capture, and yield higher nutritional or financial returns.		
Population density			
Color elaboration			
Beak length	Color elaboration, beak length, and tail length were included as proxies for species attractiveness, assuming that more distinctive morphological traits (e.g., vivid colors, long ornamentation) increase desirability for non-food uses such as handicrafts, jewelry, or display but also as pet and reflect culturally valued features.		
Tail length			
Order & Family	Because key traits are often unavailable across species, we used taxonomic order and family as proxies for unmeasured but phylogenetically conserved characteristics. This allowed us to partially capture lineage-specific factors likely influencing human preferences across hunting purposes, such as meat quality for subsistence, cultural or ornamental value for product trade, and attractiveness or tolerance to captivity for the pet trade. We also assumed that certain groups, like parrots or songbirds, may be preferentially targeted in ways not fully explained by available morphological traits.		
Info	Modelling		
Formula	Hunted ~ standardized(log(body mass)) + residuals(population density) + (1 order / family)	Hunted ~ standardized(log(body mass)) + residuals(population density) + elaboration + residuals(beak length) + residuals(tail length) + (1 order / family)	
Response	Binary variable: 1 if the species is hunted for the specific purpose, 0 if not.		
Fixed effects	Body mass: Log-transformed, then centered and scaled (mean = 0, SD = 1) to aid model convergence and interpretation.		
Random effects	Order and family: Hierarchical modelling were used to consider the phylogenetic relationships.		
Strategy	The model was trained on 70% of the dataset, with species evenly distributed across families to ensure taxonomic balance. The remaining 30% was used to predict the probability of a species being hunted based on the former model. This procedure was repeated 100 times so that each species was included in several test sets and received multiple predicted probabilities. The final probability per species was calculated as the mean across all these predictions.		
	B. IUCN trading information (composite score)		
Scores	Hypothesis		
Trade scale	This score reflects the geographic scale of trade based on IUCN data: local (1), national (2), and international (3). Scores are summed (range: 0–6), assuming broader trade increases pressure and species sensitivity.		
End uses	This score reflects the number of distinct use types per species (excluding pet trade, code 13) based on IUCN classifications. Species used for more purposes are assumed to face higher hunting pressure. Values range from 1 (single use) to 17 (multiple uses).		
Scores	Scoring		
Trade scale	Trade scale score = min-max(local + 2×national+ 3×international) If the species is known to be traded at a specific scale the value is 1 otherwise it is 0. Scores are scaled between 0 and 1 using a min-max normalization function to conserve the distribution of values.		
End uses	End uses score = min-max(∑ _{i=1} ¹⁷ code _i) If the species is known to be traded for a specific use the value is 1 otherwise it is 0.		
Final score	Trading information score = (Trade scale score + End use score)/2		Trading information score = Trade scale score
	C. Sensitivity final score		
Formula	Sensitivity = Probability of hunting for subsistence	Sensitivity = (Probability of hunting for product trade + Trading information score)/2	

	2. Adaptive capacity		
	Subsistence	Product trade	Pet trade
	A. Trait-based approach		
	Expected response		Trait
	Species less accessible to hunters, such as aerial species or that occupy higher forest strata, are considered to have higher adaptive capacity. In contrast, ground-dwelling species are more vulnerable and thus less adaptive. Ordinal: 1 = ground-dwelling, highest accessibility to hunters; 2 = insessorial, generalist or aquatic, intermediate; 3 = aerial, lowest accessibility.		Accessibility (Primary lifestyle)
	Species with longer dispersal distances are better able to escape hunting hotspots and recolonize areas when pressure decreases. As such, greater dispersal capacity is interpreted as higher adaptive capacity. We used the hand-wing index (HWI) a morphological proxy for dispersal ability, with higher values indicate better dispersion of species. Continuous, average number of eggs per breeding attempt		Nocturnality (diurnal or nocturnal)
	Species with r-strategies, characterized by fast life histories (e.g., early reproduction, high fecundity), are generally more resilient to anthropogenic pressures. Thus, species with fast life-history traits are assumed to have higher adaptive capacity than those with slower strategies (K). We used clutch size as a proxy for reproductive strategy, as it is the only widely available trait across species. Continuous, average number of eggs per breeding attempt		Life-history (generation length, age of first reproduction, litter size, litters per year)
	Used as a proxy for global extinction risk, following IUCN Red List practices. Species with large ranges are considered less vulnerable to extinction, more genetically diverse, and more likely to be generalist, all contributing to greater adaptive capacity. Global extent of occurrences of the species, continuous, in km².		Geographical range size (extent of occurrences)
	B. Adaptive capacity final score		
	Adaptive capacity = ((min-max(accessibility) + 2×min-max(nocturnality) + 3×min-max(life-history) + 4×min-max(geographical range size))/10)		
	All traits' values are scale between 0 and 1 using min-max normalization function to conserve values distribution.		
	3. References		
	Data type	Source data	Supporting hypothesis
	A. Probability of hunting		
Population density		Santini, L., Tobias, J. A., Callaghan, C., Gallego-Zamorano, J., & Benitez-López, A. (2023). Global patterns and predictors of avian population density. <i>Global Ecology and Biogeography</i> , 32(7), 1189-1204.	
Body mass			Bush, E. R., Baker, S. E., & Macdonald, D. W. (2014). Global trade in exotic pets 2006–2012. <i>Conservation Biology</i> , 28(3), 663-676.
Beak length		Tobias, J. A., Sheard, C., Pigot, A. L., Devenish, A. J., Yang, J., Sayol, F., ... & Schläuning, M. (2022). AVONET: morphological, ecological and geographical data for all birds. <i>Ecology letters</i> , 25(3), 581-597.	Cash, L., Gumbs, R., & Devenish-Nelson, E. S. (2025). Assessing gecko susceptibility to international wildlife trade: A novel trait-based framework. <i>Biological Conservation</i> , 311, 111397.
Tail length			Hughes, L. J., Morton, O., Scheffers, B. R., & Edwards, D. P. (2023). The ecological drivers and consequences of wildlife trade. <i>Biological Reviews</i> , 98(3), 775-791.
Elaboration		Santangeli, A., Haukka, A., Morris, W., Arkkila, S., Delhey, K., Kempenaers, B., ... & Mammola, S. (2023). What drives our aesthetic attraction to birds?. <i>npj Biodiversity</i> , 2(1), 20.	Hughes, L. J., Massam, M. R., Morton, O., Edwards, F. A., Scheffers, B. R., & Edwards, D. P. (2023). Global hotspots of traded phylogenetic and functional diversity. <i>Nature</i> , 620(7973), 351-357.
Order & Family		IUCN Red List (2025), https://www.iucnredlist.org .	Senior, R. A., Oliveira, B. F., Dale, J., & Scheffers, B. R. (2022). Wildlife trade targets colorful birds and threatens the aesthetic value of nature. <i>Current Biology</i> , 32(19), 4299-4305.
	B. Trading information		
Trade scale		IUCN Red List (2025), https://www.iucnredlist.org .	Challender, D. W., Cremona, P. J., Malsch, K., Robinson, J. E., Pavitt, A. T., Scott, J., ... & Hoffmann, M. (2023). Identifying species likely threatened by international trade on the IUCN Red List can inform CITES trade measures. <i>Nature Ecology & Evolution</i> , 7(8), 1211-1220.
End uses		General Use and Trade Classification Scheme (Version 1.0)	Ingram, D. J., Coad, L., Milner-Gulland, E. J., Parry, L., Wilkie, D., Bakarr, M. L., ... & Abernethy, K. (2021). Wild meat is still on the menu: Progress in wild meat research, policy, and practice from 2002 to 2020. <i>Annual Review of Environment and Resources</i> , 46(1), 221-254.
	C. Adaptive capacity		
Foraging stratum		Tobias, J. A., Sheard, C., Pigot, A. L., Devenish, A. J., Yang, J., Sayol, F., ... & Schläuning, M. (2022). AVONET: morphological, ecological and geographical data for all birds. <i>Ecology letters</i> , 25(3), 581-597.	
Dispersal distance			Butt, N., Halpern, B. S., O'Hara, C. C., Alcock, A. L., Polidoro, B., Sherman, S., ... & Klein, C. J. (2022). A trait-based framework for assessing the vulnerability of marine species to human impacts. <i>Ecosphere</i> , 13(2), e3919.
Clutch size		Marino, C., Leclerc, C., & Bellard, C. (2022). Profiling insular vertebrates prone to biological invasions: What makes them vulnerable?. <i>Global Change Biology</i> , 28(3), 1077-1090.	
Extent of occurrences		IUCN Red List (2025), https://www.iucnredlist.org	

Figure S2. Species-level Sensitivity and Adaptive capacity in birds.

This figure provides a detailed description of the traits used to compute species-level Sensitivity and Adaptive capacity for birds, including the rationale for trait selection and the associated references.

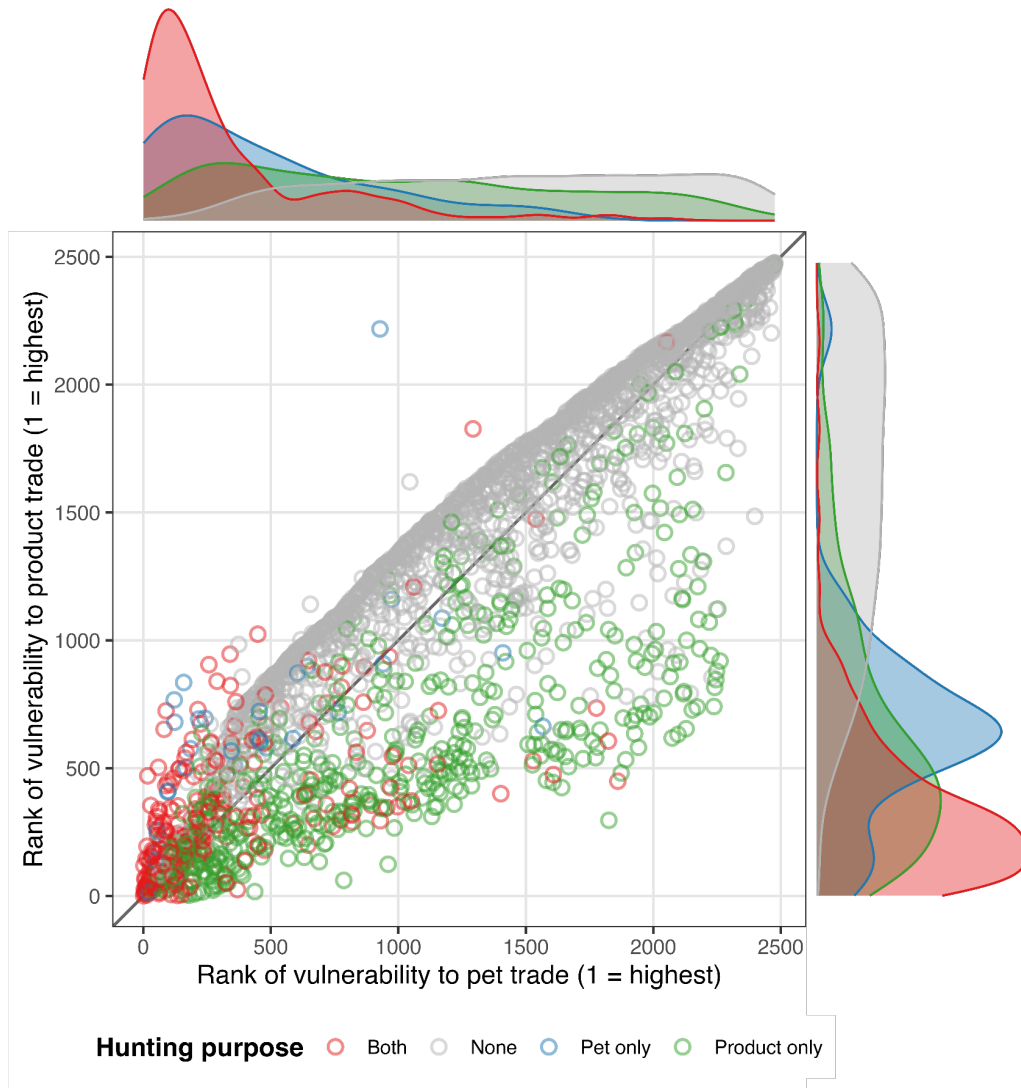


Figure S3. Distribution of vulnerability scores for tropical mammals hunted for pet and product trade, shown in relation to their hunting status.

Each point represents a species, positioned according to its rank in vulnerability for pet trade (x-axis) and product trade (y-axis), with lower values indicating higher vulnerability. Point colors reflect the hunting status of the species: whether it is hunted for pet trade, product trade, or both, or not hunted, based on our compiled database. The distributions along the x and y axes indicate the number of species per hunting category across vulnerability ranks.

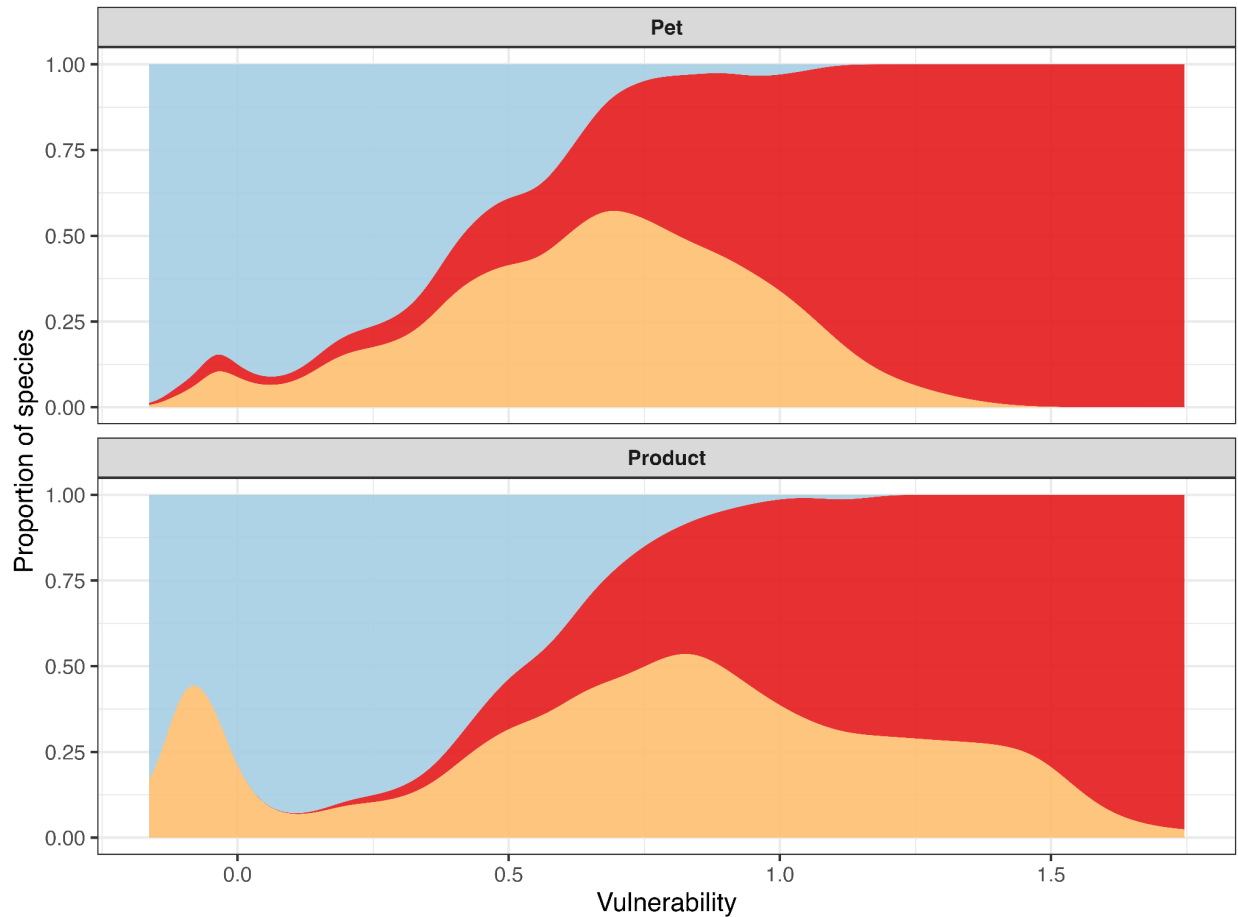


Figure S4. Proportion of IUCN hunting threat category according to species-level Vulnerability score for tropical mammals.

Each point represents a species, positioned according to its rank in vulnerability for pet trade (x-axis) and product trade (y-axis), with lower values indicating higher vulnerability. Point colors reflect the hunting status of the species: whether it is hunted for pet trade, product trade, or both, or not hunted, based on our compiled database. The distributions along the x and y axes indicate the number of species per hunting category across vulnerability ranks. Species assessed as threatened by hunting and threatened with extinction (i.e., listed as Vulnerable, Endangered, or Critically Endangered in the IUCN Red List) are shown in red. Species considered threatened by hunting but not classified as threatened with extinction (i.e., listed as Least Concern or Near Threatened) are shown in yellow. Species not assessed as threatened by hunting are shown in blue.

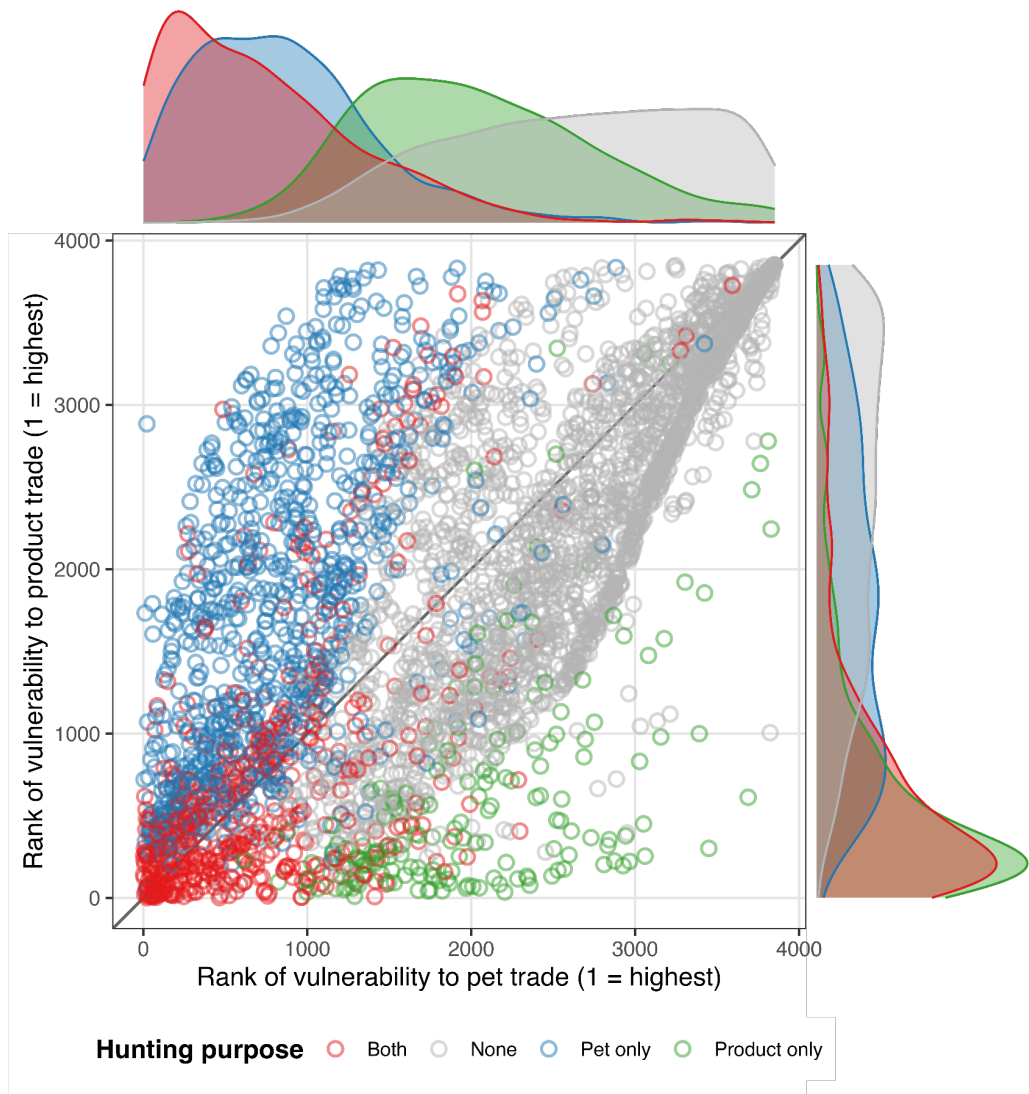


Figure S5. Distribution of vulnerability scores for tropical birds hunted for pet and product trade, shown in relation to their hunting status.

Each point represents a species, positioned according to its rank in vulnerability for pet trade (x-axis) and product trade (y-axis), with lower values indicating higher vulnerability. Point colors reflect the hunting status of the species: whether it is hunted for pet trade, product trade, or both, or not hunted, based on our compiled database. The distributions along the x and y axes indicate the number of species per hunting category across vulnerability ranks.

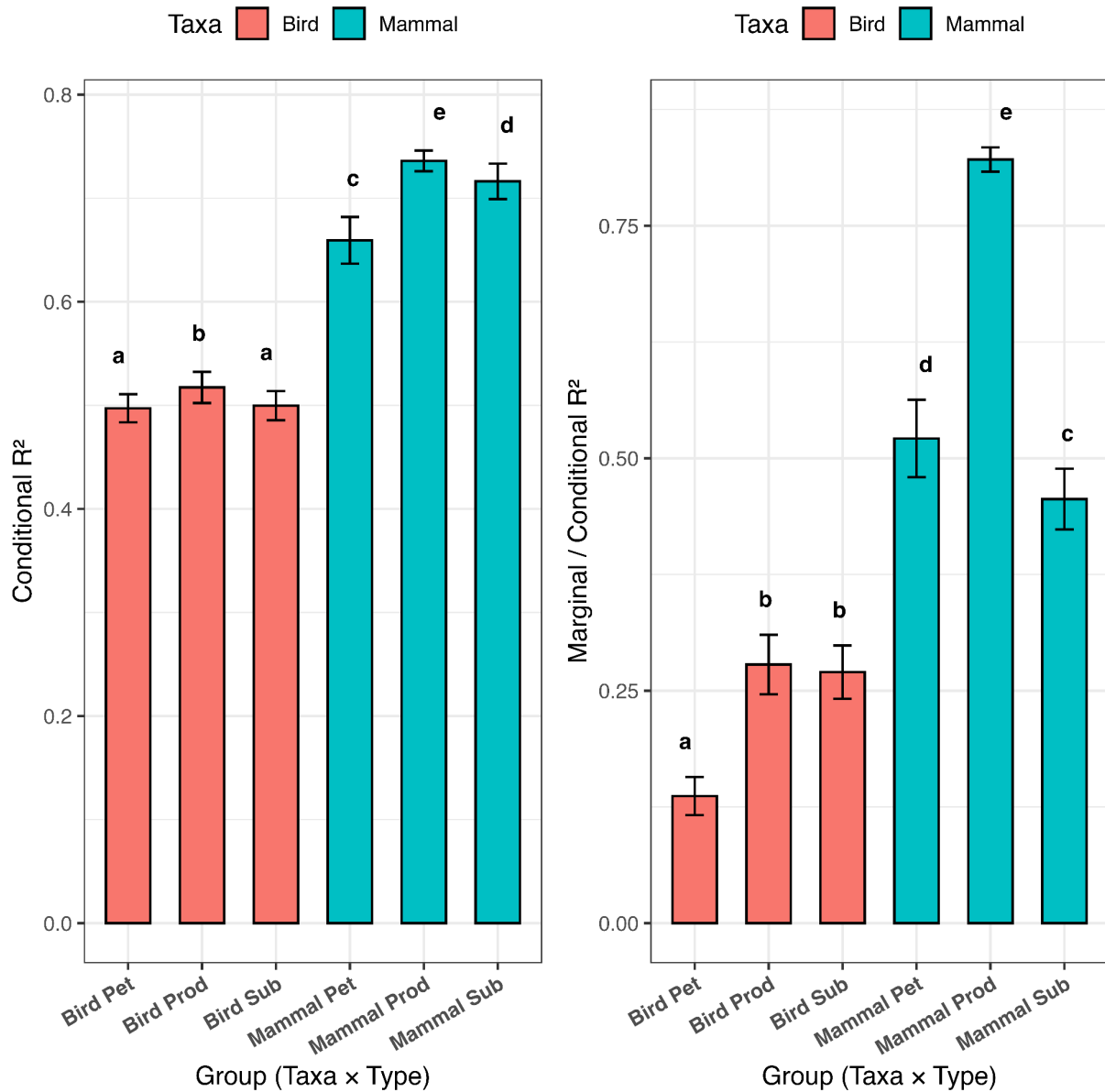


Figure S6. Goodness-of-fit of models predicting hunting likelihood from species traits and phylogeny.

The left panel displays the mean conditional R^2 of each binomial regression across 100 random subsets (each containing 70% of species), shown as bars, with error bars representing the associated standard deviations. The right panel shows the ratio of marginal to conditional R^2 , indicating the proportion of variance explained by phylogeny in each model. Each bar corresponds to a different hunting purpose (pet, product, subsistence), with birds shown in red and mammals in blue.

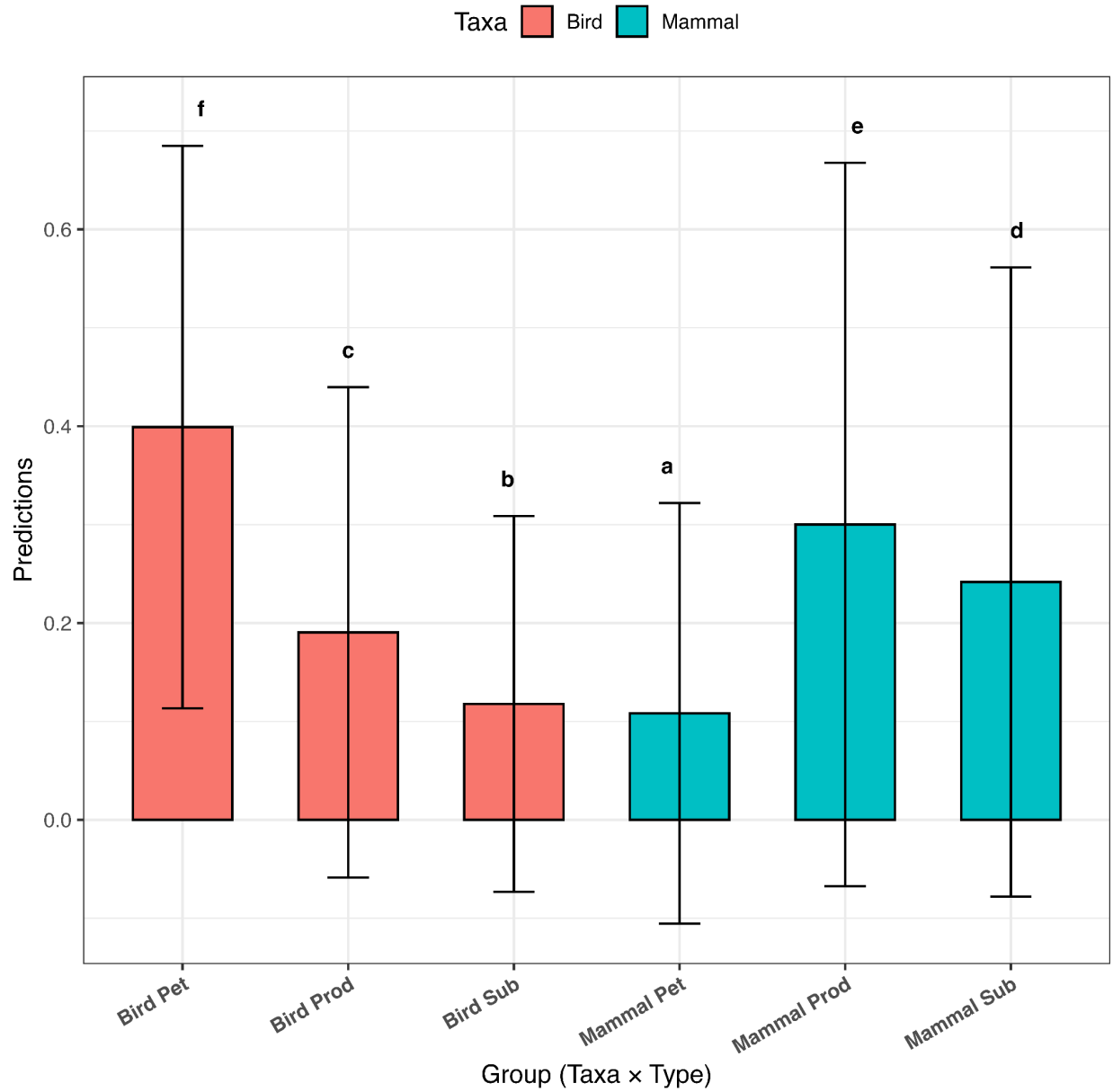


Figure S7. Predicted hunting likelihood of species based on traits and phylogeny.

Each bar shows the mean predicted probability of being hunted for a given purpose (pet, product, or subsistence), averaged across species. Birds are shown in red and mammals in blue. Error bars represent the standard deviation of predicted values across the species pool.

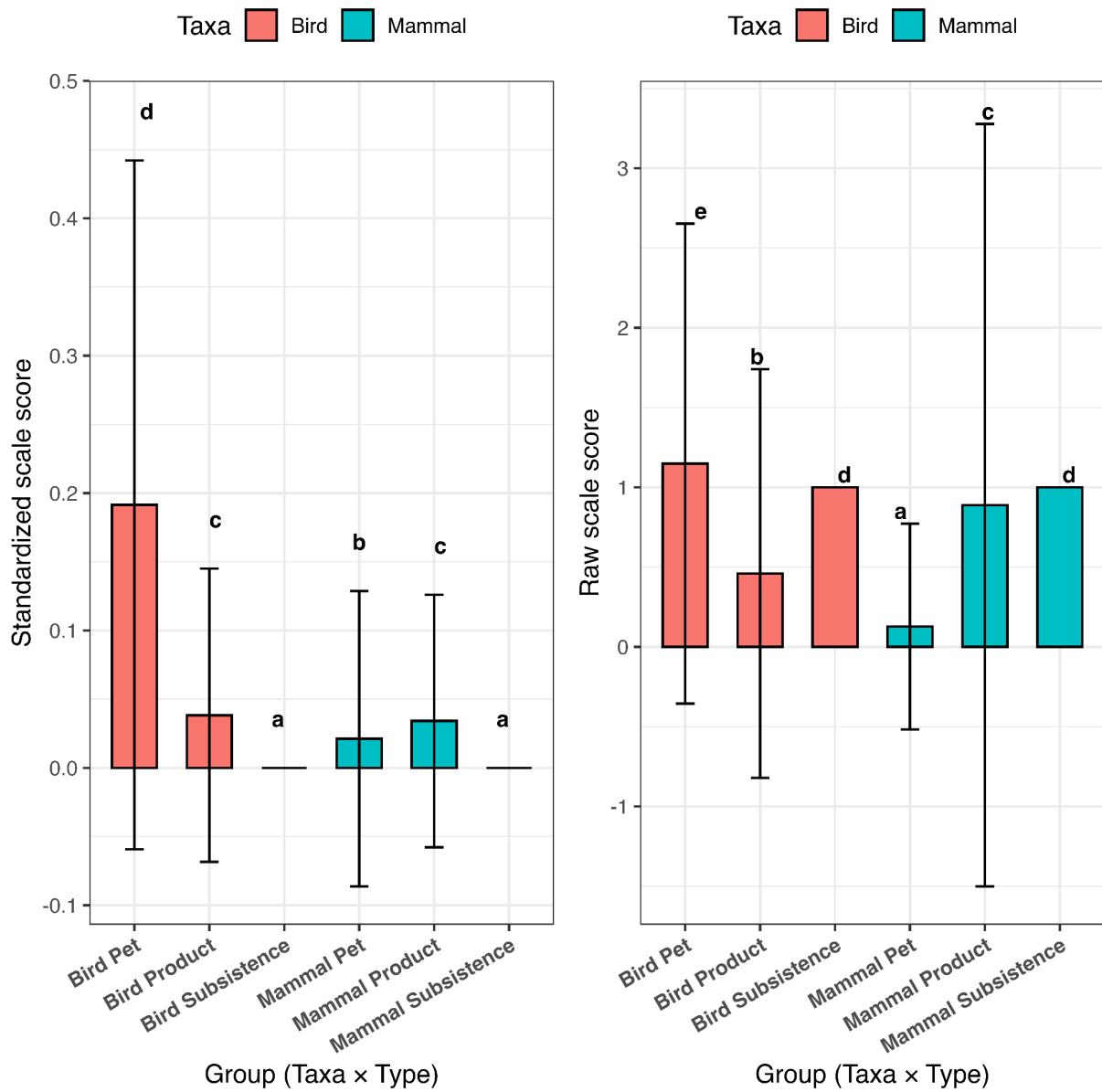


Figure S8. Distribution of trade scale scores across taxa and hunting purposes.

The left panel shows min–max scaled trade scores, with bars representing the mean and brackets indicating the standard deviation, across three hunting purposes: pet trade, product trade, and subsistence. Birds are shown in red and mammals in blue. The right panel displays the corresponding raw (unscaled) trade scores before standardization.

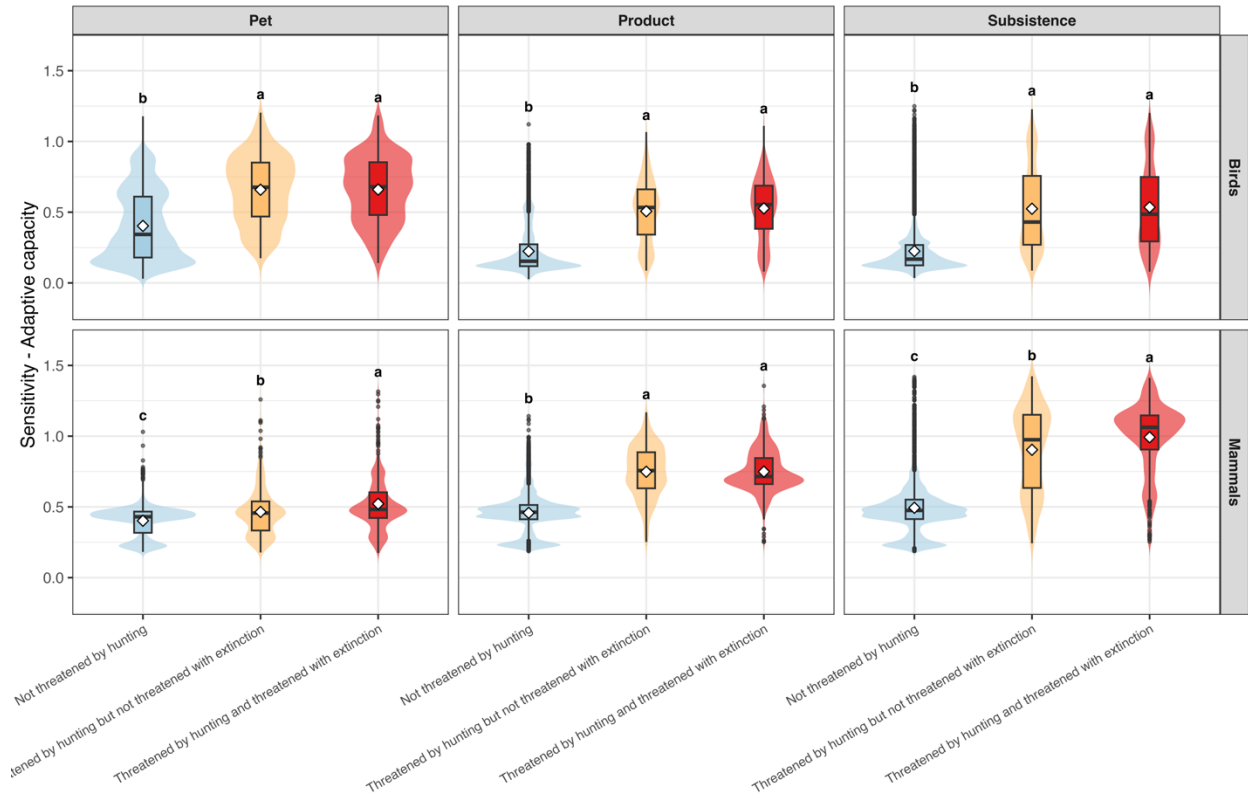


Figure S9. Summary of species-level Sensitivity - Adaptive capacity composite scores to hunting for tropical mammals and birds.

Violin plots show the distribution of scores across IUCN hunting threat categories, derived from the combination of IUCN threat status and hunting threat assessments. Species classified as threatened by hunting and at risk of extinction (i.e., listed as Vulnerable, Endangered, or Critically Endangered on the IUCN Red List) are shown in red. Species assessed as threatened by hunting but not considered globally threatened (i.e., listed as Least Concern or Near Threatened) are shown in yellow. Species not assessed as threatened by hunting are shown in blue. White diamonds represent the mean score for each category. Letters indicate significantly different groups based on post hoc pairwise comparisons of least-squares means with Šidák correction, where group “a” has the highest scores and group “c” the lowest. Post hoc tests were performed following the linear model: Sensitivity - Adaptive capacity ~ IUCN hunting threat category.

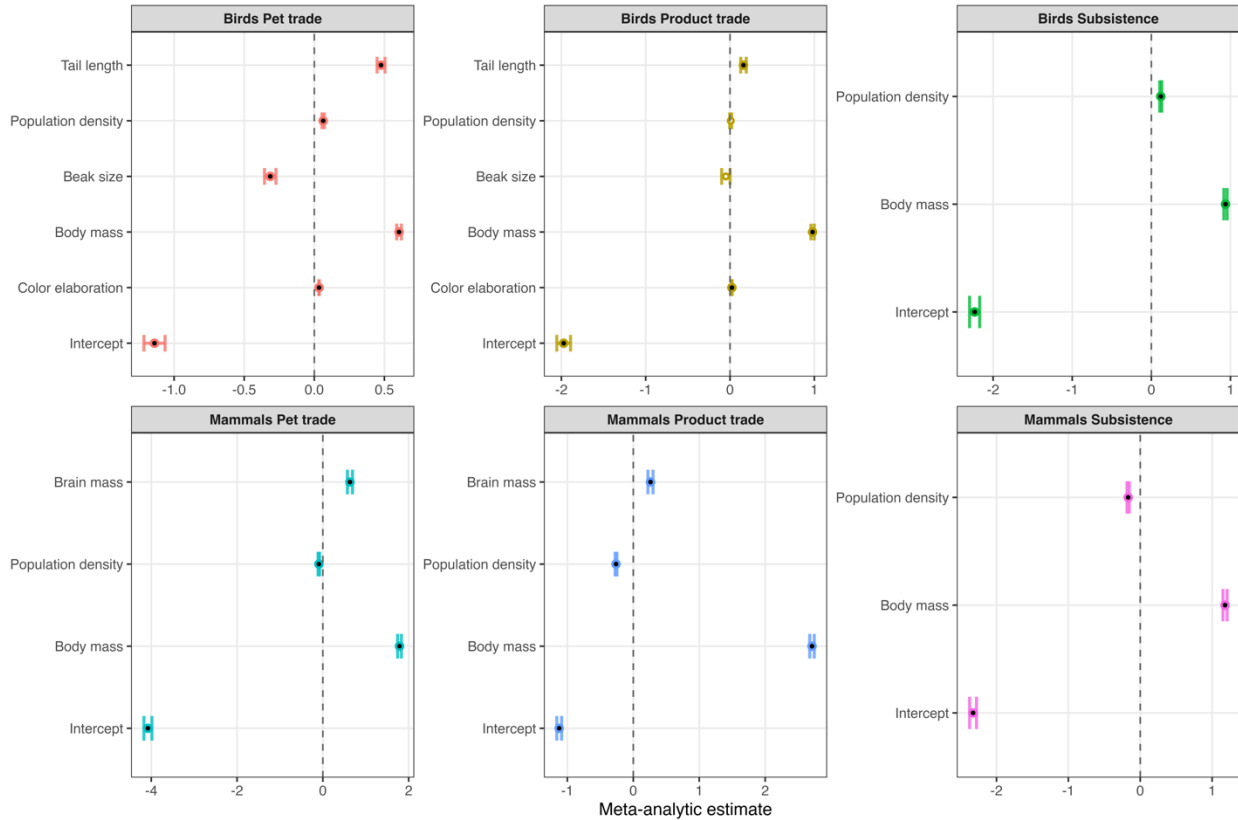


Figure S10. Trait importance in predicting species hunting status.

Importance of traits in predicting hunting status (1 = hunted, 0 = non-hunted) across 100 fitted generalized linear mixed-effects models. Tail length, population density, beak size and brain mass correspond to trait values controlled for body mass (i.e. residuals from body mass–trait regressions), and body mass was log-transformed and rescaled prior to analysis. Black dots indicate traits with effect sizes significantly different from zero across bootstrap iterations (95% confidence level), whereas white dots indicate non-significant effects.

Total family effects — Mammals Product trade

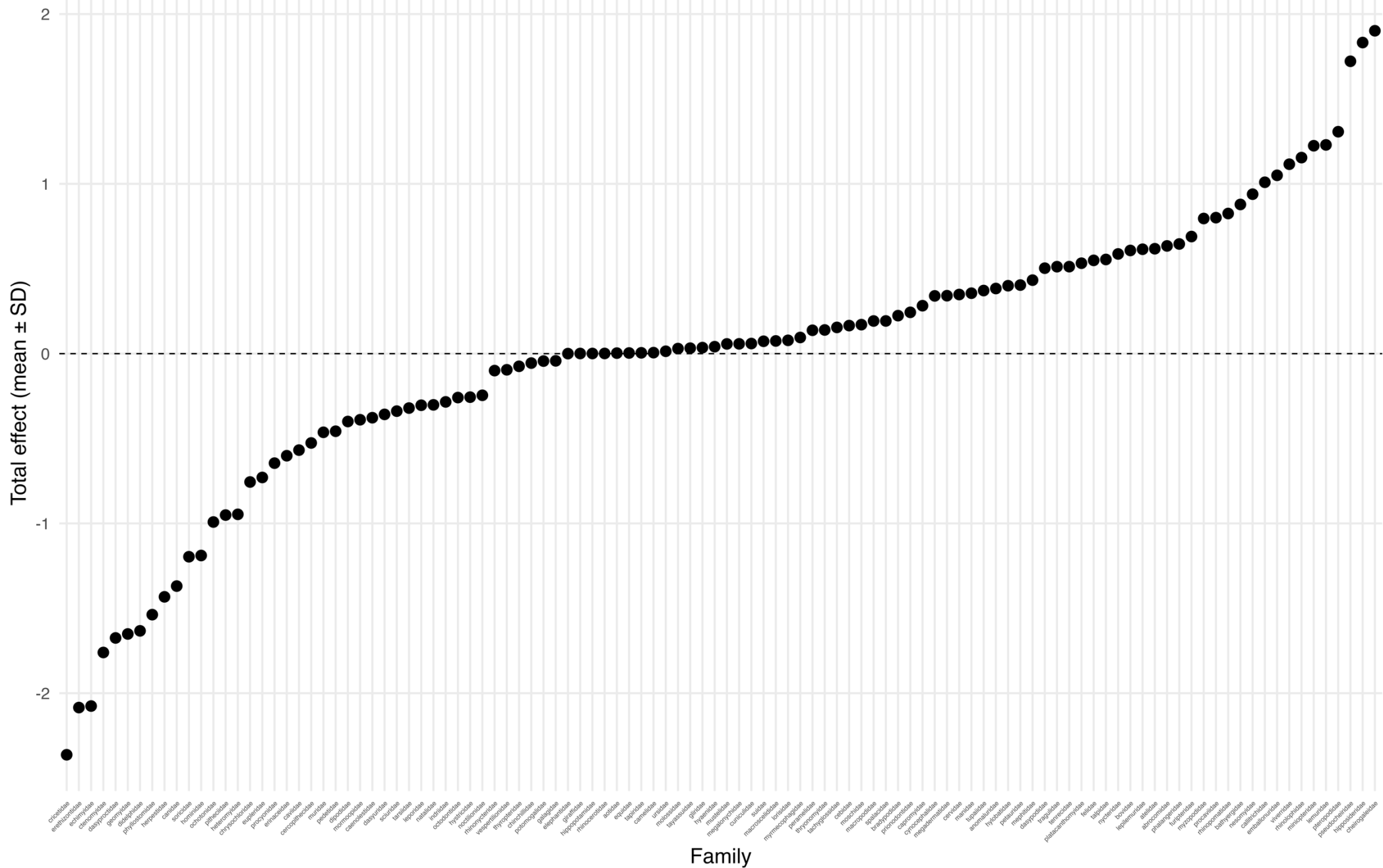


Figure S13. Family importance in predicting species hunting status for product trade of mammals.

Total family effects — Birds Subsistence

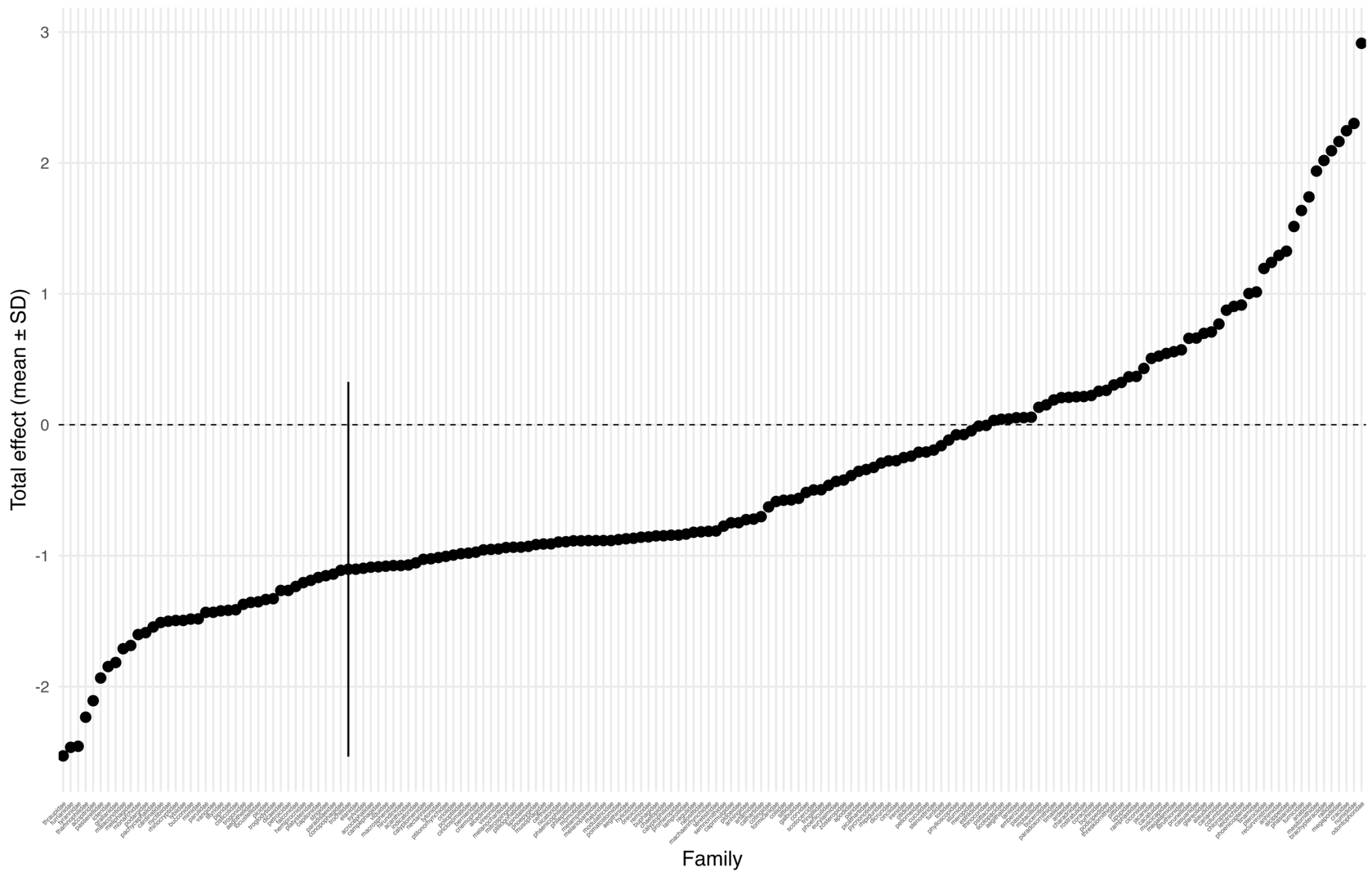


Figure S14. Family importance in predicting species hunting status for subsistence hunting of birds.

Total family effects — Birds Pet trade

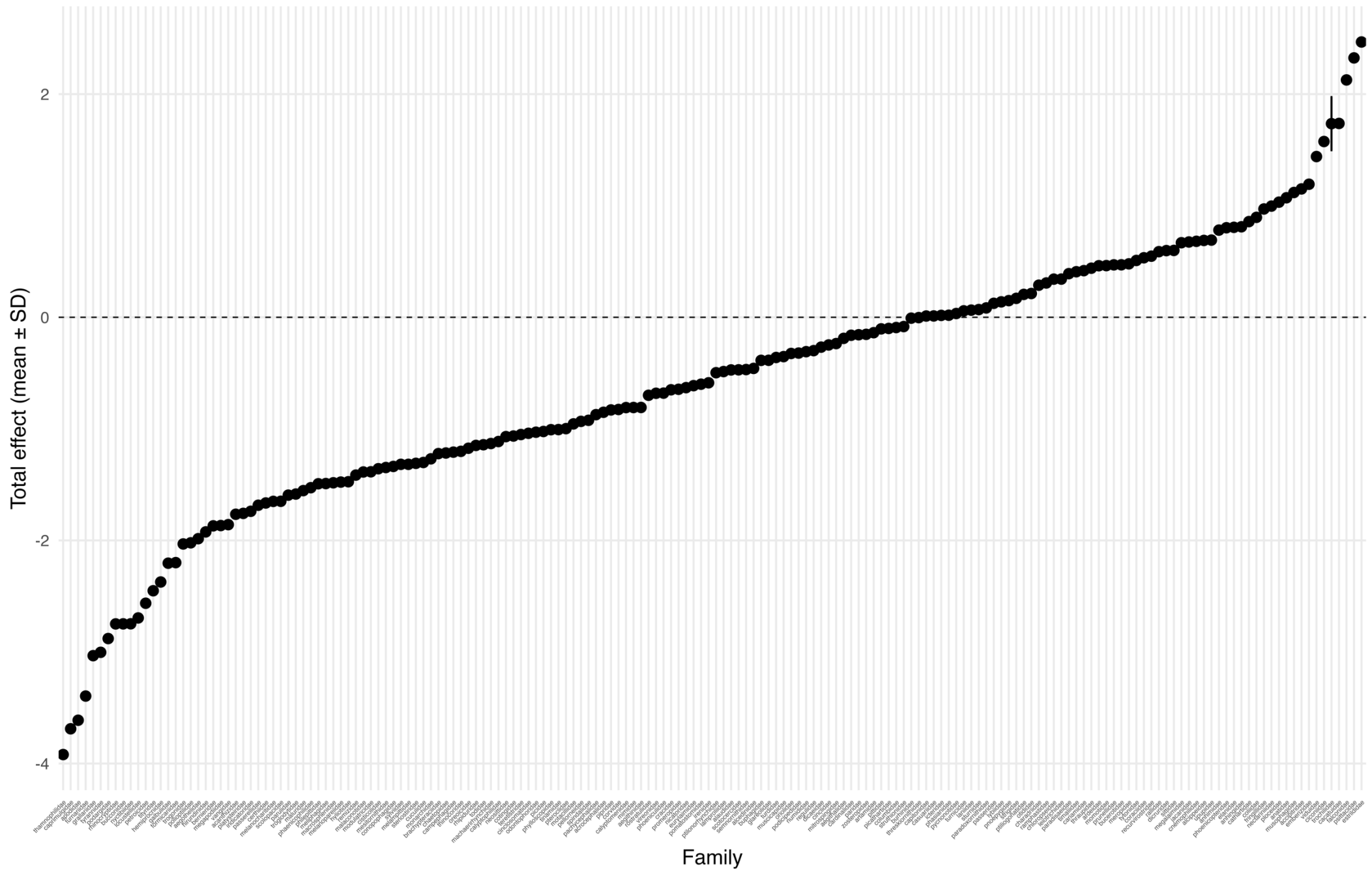


Figure S15. Family importance in predicting species hunting status for pet trade of birds.

Total family effects — Birds Product trade

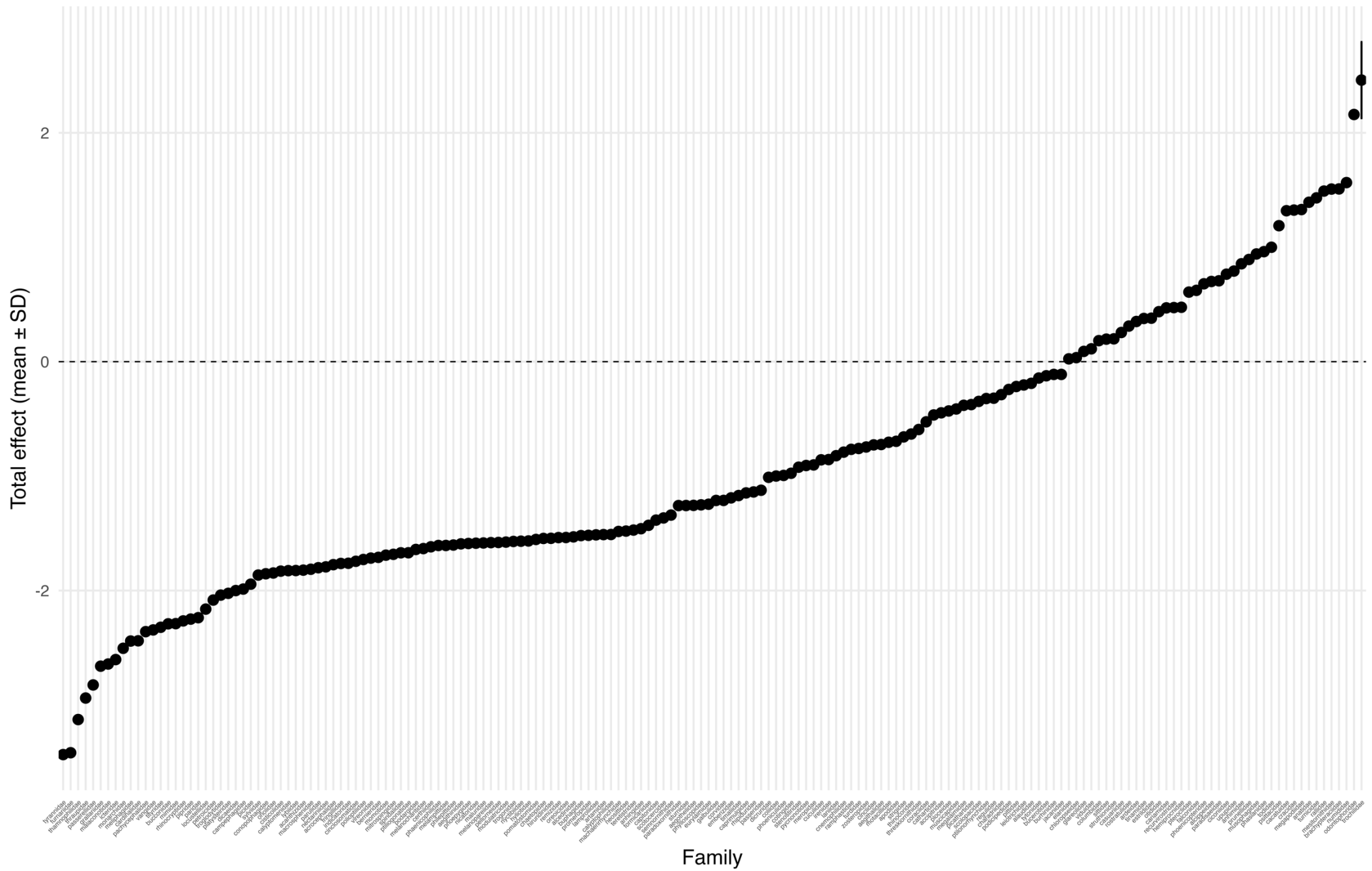


Figure S16. Family importance in predicting species hunting status for product trade of birds.

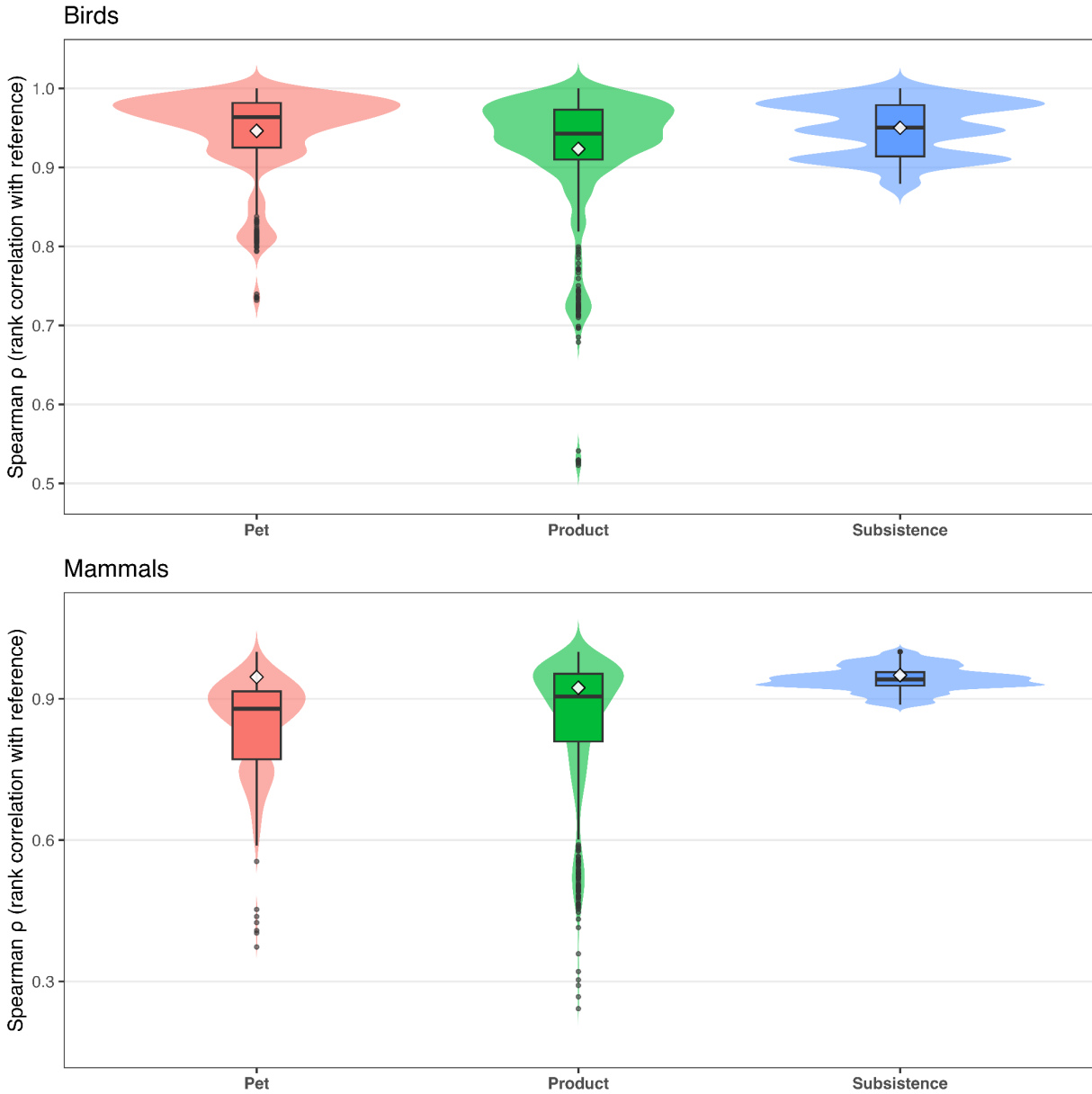
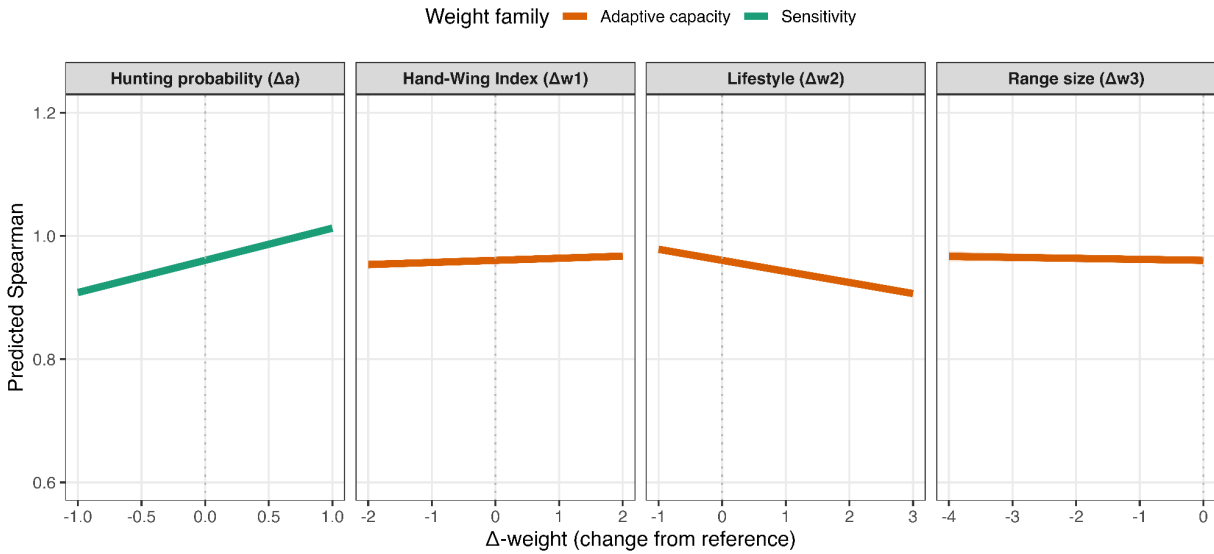


Figure S17. Effect of weighting scenarios on species' Sensitivity - Adaptive capacity scores.

Each point represents an alternative weighting scenario compared to the reference scenario used in the main analysis. The Spearman correlation coefficient indicates the rank correlation between species scores under the alternative and reference scenarios. Lower correlation values reflect greater sensitivity of species rankings to changes in weighting, highlighting the influence of score composition on vulnerability estimates. The top panel represent birds and bottom mammals.

Birds



Mammals

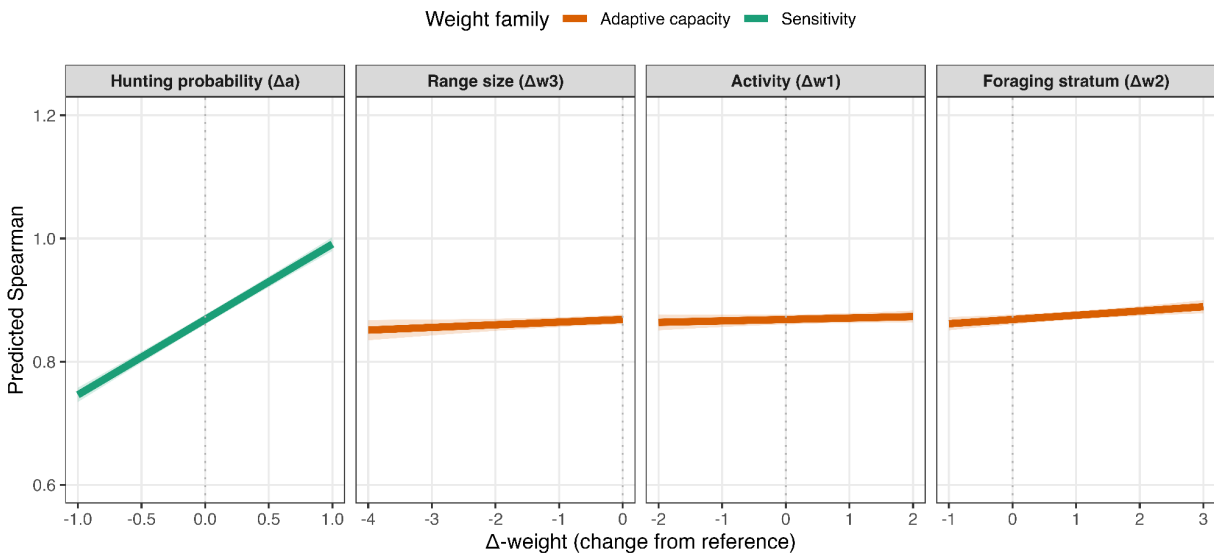


Figure S18. Influence of component weight changes on Sensitivity - Adaptive capacity score deviations.

Each line represents the marginal effect of changing the weight of a single component (trait) within the Sensitivity or Adaptive capacity score on the Spearman correlation between the alternative and reference scoring scenarios. Correlation reflects how much species-level rankings shift when the weight of a component is changed. Green lines correspond to components from the Sensitivity score; orange lines to those from Adaptive capacity. Because weights within each score family were constrained to sum to a

constant total, the influence of any one component is dependent on the weights of the others, thus one component per score family is omitted for interpretability.