

1

2 **TITLE:** How the Past Impacts the Future: Modelling the Performance of Evolutionarily Distinct
3 Mammals through Time.

4 **KEYWORDS:** living fossil; evolutionary distinctness; evolutionary potential; Mammalia; fossil
5 record; phylogeny

6 **AUTHORS:** D.J. Bennett^{1,2}, M.D. Sutton³ and S.T. Turvey⁴

7 **AFFILIATIONS:**

8 1. Gothenburg Global Biodiversity Centre, Box 461, SE-405 30 Gothenburg, Sweden

9 2. Department of Biological and Environmental Sciences, University of Gothenburg, Box 461,
10 SE-405 30 Gothenburg, Sweden

11 3. Department of Earth Sciences and Engineering, Imperial College London, London, SW7 2BP,
12 UK.

13 4. Institute of Zoology, Zoological Society of London, London NW1 4RY, UK.

14

15 **EMAILS:**

16 dominic.john.bennett@gmail.com, m.sutton@imperial.ac.uk and samuel.turvey@ioz.ac.uk

17

ABSTRACT

How does past evolutionary performance impact future evolutionary performance? This is an important question not just for macroevolutionary biologists who wish to chart the phenomena that describe deep-time changes in biodiversity but also for conservation biologists, as evolutionarily distinct species – which may be deemed “low-performing” in our current era – are increasingly the focus of conservation efforts. Contrasting hypotheses exist to account for the history and future of evolutionarily distinct species: on the one hand they may be relicts of large radiations, potentially “doomed” to extinction; or they may be slow-evolving, “living fossils”, likely neither to speciate nor go extinct; or they may be seeds of future radiations. Here we attempt to test these hypotheses in Mammalia by combining a molecular phylogenetic supertree with fossil record occurrences and measuring change in evolutionary distinctness (ED) at different time slices. With these time slices, we modelled future ED as a function of past ED. We find that past evolutionary performance does indeed have an impact on future evolutionary performance: the most evolutionarily isolated clades tend to become more evolutionarily distinct with time, indicating that low-performing clades tend to remain low-performing throughout their evolutionary history.

200 words max

INTRODUCTION

36
37

38 Evolutionary distinctness (ED; [1]) is a measure of the isolation of a species in a phylogenetic tree,
39 expressed in millions of years. Many conservation biologists are interested in the conservation of
40 species that are highly evolutionarily distinct as these species represent a disproportionately large
41 amount of evolutionary history [1, 2]; they may be likened to “living fossils” [3]. Furthermore, ED has
42 often been correlated (albeit contentiously; [4]) with trait distinctiveness. Consequently, it is often
43 argued (and disputed [5]) that by targeting many evolutionarily distinct species, we would likely be
44 capturing greater trait diversity, and would then be preserving ecosystem functions and services [6].
45 However, interpretation of the “conservation value” of distinct species is not straightforward, and
46 targeting them for conservation attention may be legitimately questioned if they are deemed more
47 likely to become extinct regardless of human activity [4, 7]. Being members of species-poor lineages,
48 we might consider the evolutionarily distinct as potentially “doomed” to extinction if they are simply
49 the tail-ends of once-diverse clades [8, 9], and/or evolutionary “dead-ends” [10]. Alternatively, the
50 distinctness of such species may garner them with unique adaptations that would allow them to respond
51 differently to future environmental or ecological change [1, 11, 12], allowing them novel opportunities
52 to radiate into recently vacated ecological space [13]. In this scenario, evolutionary distinctness may be
53 related to G.G. Simpson’s “phylogenetic fuse”: the idea that lineages may persist for long periods of
54 time “tinkering” at low species number before exploding in diversity at a later time point [14]. Yet
55 another interpretation is that evolutionarily distinct species may be members of long-lasting lineages
56 that neither go extinct nor diversify in great numbers (“panchronic” *sensu* [15]). Finally, a neutral
57 model could be proposed in which the origin and future potential of evolutionarily distinct species is
58 not influenced by *any* overarching processes or phenomena.

59 Little is known about the future evolutionary potential of evolutionarily distinct lineages.

60 Multiple studies have found that lineage age does not correlate with extinction risk [16-18].

61 Additionally, we know that extinction risk today is non-randomly distributed across the tree of life [19-
62 22], although this does not appear to translate into higher extinction risks for evolutionarily distinct
63 species [23-26]. However, these latter studies are mainly based on recent rates and patterns of
64 extinction vulnerability and resilience, and species and clades at risk of extinction can radically vary
65 over longer periods of geological time, such as during mass extinctions [27]. In particular, although the
66 fossil record represents a uniquely important long-term archive that can be used to trace patterns of
67 lineage diversity and diversification through time, few studies have hitherto explicitly attempted to test
68 how past evolutionary performance has impacted future evolutionary performance using the fossil
69 record, particularly from a conservation perspective (see [28] for one such recent example).

70 ED is most often calculated at the species-level [1], but we can also define a clade's ED as the
71 average ED of all descendant species. It is therefore possible to assess the relationship between the ED
72 of a clade at a given time point (ED_{t_0}) and its subsequent ED at a later time point (ED_{t_1}). We might
73 expect a linear relationship between the ED values of the two time points if ED does not influence
74 diversification (dotted line, figure 1). Such a model, however, does not take into account differences in
75 the ages of trees between different time points and the number of species in a tree. A better null model
76 is able to take into account these differences and may not be linear. In figure 1, we outline a series of
77 possible scenarios for the relationship between past and future ED based on simulated birth-death tree
78 models. The null model is generated from simulations where evolutionary distinctness has no impact
79 on future speciation or extinction rates ("Null", figure 1). If future evolutionary potential of species is
80 influenced by how evolutionarily isolated a clade is, the relationship should diverge from this line. For
81 example, under a strict "panchronic" scenario, clades with low ED are more likely to contain species
82 that will go on to speciate more in the future, so should have lower mean ED at the next time point as
83 they will then share a similar proportion of the tree among more species, whereas clades with high ED
84 are less likely to speciate and should hence show an increase in their mean ED over time ("Pan.", figure
85 1). Alternatively, under a strict "evolutionary relict" scenario, species with mid-ranging ED become

86 increasingly more evolutionarily distinct up to the point of extinction and therefore show ED that is
87 increasingly higher than expected in successive time points, while high ED should tend towards
88 expectation as the whole clade goes extinct (“Rel.”, figure 1). Finally, we might consider the less
89 discussed idea that highly evolutionarily distinct clades are more likely to diversify due to their
90 differences from other taxa, “phylogenetic fuse” [14] (“P.F.”, figure 1).

91
92 [INSERT FIGURE 1 HERE]

93 FIGURE 1. Polynomial, linear modelling of possible general relationships between ED at time points in the past (t_0 , x-axis) and in the
94 future (t_1 , y-axis) as determined from simulated birth-death trees under different scenarios. ED is natural logged to create a normal
95 distribution. Trees were rescaled to make their branch lengths comparable to the Mammalian tree of life. Dark-grey indicates 95%
96 confidence interval. Dotted lines indicate past ED matching future ED and are added for reference. “Null” indicates the model where
97 speciation and extinction rates are independent from evolutionary distinctness. This model is repeated in subsequent panels as the solid,
98 black line. Tendencies above this line indicate higher than expected evolutionary distinctness at the next time step, and below the line,
99 lower than expected evolutionary distinctness at the next time step. In the panchronic scenario (Pan.), mid to high values lead to higher
100 values. In the evolutionary relict scenario (Rel.), mid to high ED leads to increasing ED up to a maximum value at which point the whole
101 clade becomes extinct. In the phylogenetic fuse scenario (P.F.), low to mid ED leads to higher values, and high values lead to low values.
102 These curves were generated from birth-death tree-growth simulations where biases can be introduced based on tip evolutionary
103 distinctness. Scenarios are based on those described in [3]. For more details on how these simulations were created see electronic
104 supplementary material, methods and results.

105
106 Here, we compare ED between mammalian clades at different time points to investigate how
107 evolutionary distinctness changes at the clade level through time. We use mammals due to their well-
108 established phylogenetic tree [29] and the availability of relatively well-sampled fossil data [30]. We
109 generate large molecular-fossil phylogenetic trees by taking a large mammalian supertree and adding
110 fossil tips using a taxonomically constrained stochastic process. We then use these large trees to take
111 time slices at comparable time points, and track the evolutionary distinctnesses of identifiable clades
112 and species across these time points to generate an ED_{t_0} and ED_{t_1} dataset. With this dataset we then test
113 whether the $ED_{t_1} \sim ED_{t_0}$ relationship is non-linear and whether it corresponds to any previously

114 identified scenarios of evolutionary diversification in relation to ED as outlined above. Our results
115 establish a robust new baseline for understanding the likely potential of evolutionarily distinct species
116 today in terms of their future contribution to global biodiversity and its implications on their
117 conservation.

METHODS AND MATERIALS

118

119 All of our analyses were performed in the R environment (v3.5) and the scripts for reproducing these
120 results can be found on the primary author's GitHub page ([https://github.com/DomBennett/Project-](https://github.com/DomBennett/Project-karenina)
121 [karenina](https://github.com/DomBennett/Project-karenina)).

122 Mammalian fossil data were downloaded from the Paleobiological Database (PBDB) [31] using
123 the R package paleobioDB [32] on 25/09/2018. All records were constrained to 'Mammalia'. In total
124 109,536 fossil occurrence records were downloaded. These records were converted to species temporal
125 records by merging records with shared species names and identifying minimum and maximum species
126 ages. Taxonomic named ranks were determined for every species record, and records lacking
127 taxonomic information below the family level were removed (438 records). Records with temporal
128 ranges extending beyond the age of the mammalian supertree (166.2 MY) were also excluded (121
129 records). In total 19,028 species records remained, representing 128 families and 6,659 genera. The
130 temporal distribution was skewed towards the recent; most observations occurred in the first 18 MY
131 (0.0059 MY – 0%, 7.0 MY – 25%, 17.7 MY – 50%, 39.7 MY – 75%, 164.8 MY – 100%).

132

133 *Phylogenetic Placement of Fossils*

134 Fossil species were added to a time-calibrated, molecular-based phylogenetic supertree of 4,510 extant
135 mammal species [29]. Taxonomic information was added to the tree by identifying the most likely
136 taxonomic group for every node, by matching descendants to named entries in the NCBI taxonomic
137 database [33] via the Global Names Resolver [34]. For every node, the lowest shared taxonomic group
138 was selected from all taxonomic named ranks of matching named entries. In the NCBI taxonomy under
139 mammals there is up to 12 taxonomic ranks (from superorder to subgenus) for each species. Taxonomic
140 groups were identified for 6,603 of the 6,618 nodes in the tree (>99%).

141 Tips representing fossil species were added to the supertree using the `pinTips()` function in the
142 R package `treeman` [35]. The position for each fossil species was constrained to edges directly parent to
143 or descending from the node(s) with the lowest-ranked matching taxonomic label (with any edge or
144 part of an edge younger than the minimum age of the fossil species excluded). Where these constraints
145 left multiple possible attachment points, one was chosen at random. For example, if a fossil is matched
146 to a given genus name, then the fossil tip could be added to the edge leading to this genus or to any of
147 the edges that make up the genus. The time of extinction for fossil species was determined as a random
148 point between its split from the tree and its youngest possible age (electronic supplementary material,
149 figures S1-S2). Fossil species added to the tree thus all became extinct within their estimated age range,
150 and their origination occurred before or during their estimated age range.

151 The stochastic fossil-adding process was iterated to generate a distribution of possible
152 molecular-fossil trees; 100 iterations were deemed sufficient as initial analyses demonstrated that trees
153 generated through this process had similar distributions of ED values. In total a mean $18,964 \pm 16$
154 fossil tips were added to the original 4,510 tipped mammalian supertree for each iteration. To assess
155 whether the stochastic fossil-adding process was biasing results, the process was repeated with fossil
156 lineages and age ranges randomly assorted, so that fossil placement was not constrained by their actual
157 ages or taxonomy. Before analysing changes in ED between time points, we first tested whether the
158 random set of trees differed significantly from the non-random set (electronic supplementary material,
159 methods and results). If the random set were to not differ, then this would indicate that the fossil-record
160 informed pinning is no different from random placement.

161

162 *Determining Change in ED*

163 For each tree generated through fossil-addition, a ‘time slice’ was taken to generate an ultrametric tree
164 representing a phylogeny up to a given time point (electronic supplementary material, figure S2). For

165 each of these slices, EDs were calculated for all tips using the method of [1], with ED of internal nodes
166 calculated as the mean ED of all descendants of that node. In order to generate ultrametric trees that
167 were as equally sampled as possible, time slices were taken at the midpoints of each epoch (Upper
168 Jurassic to Recent; electronic supplementary material, table S1). ED_{t_0} and ED_{t_1} datasets were generated
169 from the two distributions by matching ED values from one epoch to the next for all species/clades that
170 spanned two or more epochs. Mean ED values were calculated for species/clades that occurred more
171 than once across the tree distributions (later termed *shared nodes*). All values were converted to their
172 natural logarithm before analysis, to convert the skewed distribution of ED to a normal distribution.
173 Our datasets of species/clades were supplemented with taxonomic information (genus and order), the
174 number of species present in the tree at t_0 , and the time (in MY) between t_0 and t_1 .

175

176 *Modelling*

177 **Mixed-Effects Models**

178 ED values of epoch-to-epoch transitions are not straightforward to compare: the ED values in one
179 epoch will not be independent of those from another because many of the taxa are the same; transitions
180 differ in tree age and starting number of tips at t_0 ; the number of fossil records differ between each
181 epoch (older have fewer than recent); and transition time-steps are not the same (electronic
182 supplementary, table S1). To account for these factors and control for differences between epochs, we
183 used linear mixed-effects models (LMEMs) [36, 37]. We modelled future ED as a function of past ED
184 ($ED_{t_1} \sim ED_{t_0}$) with the option of including a random-effects structure that was able to incorporate both
185 epoch and taxonomic information. We used an iterative model approach, starting with a basic LMEM
186 model and adding additional terms to the random effect structures until there was no longer any
187 significant or notable gain in explained variance. We compared models using ANOVA and the Akaike

188 Information Criterion (AIC) [38]. For more details on LMEMs and our approach see electronic
189 supplementary information, methods and results.

190

191

192

193 **The Three Models**

194 Using the LMEM framework, we generated two models to investigate how past ED affects future ED:
195 a linear observed model (*obs1*), a non-linear observed model (*obs2*), and an expected model (*exp*). We
196 generated *obs1* using the modelling framework as described above to generate the best-fitting linear
197 model of $ED_{t1} \sim ED_{t0}$ given different random effects structures. We then took the same random effect
198 structure to generate *obs2* by adding increasing numbers of orthogonal polynomial degrees to explore
199 increasingly complex non-linear relationships, until there was no longer any increase in explained
200 variance.

201 An expected model, akin to the “Null” birth-death model in figure 1., was built for comparison,
202 to represent $ED_{t1} \sim ED_{t0}$ in a ‘neutral’ scenario where past average ED for a clade has no impact on
203 future ED other than simply determining the starting points from which future ED can diverge. This
204 model was a function of ED_{t1} and the factors that influence ED between epochs: the number of tips in
205 the tree at $t0$ (n), the time difference between epochs (tm), and an ED_{t0} dummy variable (*dummy*). The
206 dummy variable was a coarsened representation of ED_{t0} calculated by rounding ED_{t0} to the nearest
207 integer and dividing the values by the maximum to generate values between 0 and 1. The variable
208 provided limited categorical information on ED_{t0} to the model (e.g. high ED, mid ED and low ED) and
209 acted as a basis from which ED_{t1} can then be estimated in conjunction with the other factors.

210 With these models we first tested whether $ED_{t1} \sim ED_{t0}$ is non-linear by comparing the goodness
211 of fit to the data of *obs1* and *obs2*, and then tested which of the simulated scenarios (figure 1) best
212 describe $ED_{t1} \sim ED_{t0}$ by visually comparing the best observed (*obs1* or *obs2*) to *exp*.

RESULTS

213

214 *Estimating the Linear Model*

215 The generated dataset consisted of 115,810 species/clade ED values, recorded across the nine epoch-to-
216 epoch transitions. The distribution of shared nodes across the iterated trees was bimodal, with the
217 majority of species/clades occurring 12 or fewer times (1 - 0%, 3 - 25%, 12 - 50%, 39 - 75%, 100 -
218 100%). There was a positive non-linear relationship between ED_{t0} and ED_{t1} and differences between
219 the epoch-to-epoch transitions were substantial, particularly at low ED values. Two epoch-to-epoch
220 transitions (Jurassic Upper to Cretaceous Lower [JU-CL], Cretaceous Lower to Cretaceous Upper [CL-
221 CU]) showed a different relationship from the others (electronic supplementary material, figure S3),
222 probably due to limited availability of data points for these epochs (6,321 and 2,288 for CL-CU and
223 JU-CL, respectively, versus a mean of 15,314 for all other epoch transitions) and the much longer time
224 separating them (39.5 MY and 31.5 MY for CL-CU and JU-CL, respectively, versus a mean of 11.9
225 MY for all other transitions). We consequently removed JU-CL and CL-CU transitions from all
226 subsequent analyses.

227 We determined the best linear model of $ED_{t1} \sim ED_{t0}$ to be *m2i* (table 1). This model incorporated
228 a random effects structure that consisted of independent slopes for both epochs and a hierarchical
229 taxonomic random effect (order/genus). However, we did not consider model choice to be crucial in
230 interpretation of results, as estimated slopes were similar across all models (0.63-0.73).

231

232 TABLE 1. Increasingly complex models for estimating the best observed linear model, *obsI*. Formulae (*f*) [37], intercepts (Int), slopes
 233 (Slp), degrees of freedom (DF), Akaike Information Criterion (AIC), and significance (P) are indicated. Significance is indicated by
 234 comparing the current row's model to the last significant model (*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$). The selected linear model (*m2i*)
 235 is highlighted in bold.

Id.	<i>f</i>	Int	Slp	DF	AIC	P
m0	$ED_{t1} \sim ED_{t0}$	1.1068	0.7342	1	49,418	
m1a	$ED_{t1} \sim ED_{t0} + (1 epoch)$	1.2101	0.7148	4	21,337	
m1b	$ED_{t1} \sim ED_{t0} + (ED_{t0} epoch)$	1.2274	0.7061	6	17492	***
m2a	$ED_{t1} \sim ED_{t0} + (ED_{t0} epoch) + (1 order)$	1.2219	0.7100	7	16568	***
m2b	$ED_{t1} \sim ED_{t0} + (ED_{t0} epoch) + (1 genus)$	1.3483	0.6642	7	10,459	***
m2c	$ED_{t1} \sim ED_{t0} + (ED_{t0} epoch) + (1 order/genus)$	1.3562	0.6638	8	10,296	***
m2d	$ED_{t1} \sim ED_{t0} + (ED_{t0} epoch) + (1 id)$	1.2646	0.6920	7	16,372	
m2e	$ED_{t1} \sim ED_{t0} + (ED_{t0} epoch) + (1 order/id)$	1.2626	0.6951	8	15,557	
m2f	$ED_{t1} \sim ED_{t0} + (ED_{t0} epoch) + (ED_{t0} order)$	1.2111	0.7144	9	16,378	
m2g	$ED_{t1} \sim ED_{t0} + (ED_{t0} epoch) + (ED_{t0} genus)$	1.4242	0.6274	9	7,255	***
m2h	$ED_{t1} \sim ED_{t0} + (ED_{t0} epoch) + (ED_{t0} id)$	1.2726	0.6882	9	16,379	
m2i	$ED_{t1} \sim ED_{t0} + (ED_{t0} epoch) + (ED_{t0} order/genus)$	1.4010	0.6405	12	7,106	***

236

237

238 *Estimating the Non-Linear Model*

239 We compared the best linear model (*m2i*) with a range of non-linear models, using the same random
240 effects structure, based on orthogonal polynomials generated from ED_{t0} for different exponents. Using
241 ANOVA and AIC values, as expected, we found all the polynomial models to have significantly better
242 fits than the linear model, indicating that evolutionarily distinct clades do have differences in
243 diversification potential (table 2). Of the non-linear models, we determined *m3b*, the 3rd order
244 polynomial model, to be the best; this model had one of the lowest AICs and a low χ^2 P-value
245 indicating goodness-of-fit. While there were significant improvements in AIC in higher orders of
246 polynomial model, the drops in AIC were small (< 1%), and were not considered sufficient to warrant
247 the greater model complexity. Additionally, we repeated the final plotting analysis (figure 2) and found
248 similar trends for all higher-order polynomial (> 3) models, indicating that any conclusions are not
249 affected by our choice of the lower order polynomial model.

250

251

252 TABLE 2. Increasingly complex models for estimating the best observed non-linear model, *obs2*. Order of polynomial (Poly), degrees of
253 freedom (DF), Akaike Information Criterion (AIC), and significance (P) are indicated. All models share the same model formula as *m2i*.
254 Significance is indicated by comparing the current row's model to the last significant model (***) $p < 0.001$, ** $p < 0.01$, * $p < 0.05$). The
255 selected non-linear model (*m3b*) is highlighted in bold.

Id.	Poly	DF	AIC	P
m2i	1	12	7,106	
m3a	2	13	4,727	***
m3b	3	14	4,513	***
m3c	4	15	4,501	***
m3d	5	16	4,493	**
m3e	6	17	4,473	***
m3f	7	15	4,674	

256

257

258 *Estimating the Expected Model*

259 We found the best-expected model to be $n2b$, which incorporates the ED_{t0} dummy variable (*dummy*)
260 with three orders of polynomial, difference in time between epochs (tm) and the starting number of
261 species in a Mammalian tree at the beginning of an epoch (n), as well as a genus random effects
262 structure of random slopes for *dummy* (table 3). Although it is likely that a model with random slopes
263 for all three fixed effects would have produced a better fit, this model and models with multiple random
264 effects did not converge indicating model over-fitting. Again, we found only marginal improvement
265 with the use of a hierarchical taxonomic random effects structure (order/genus). Consequently, we
266 limited our random-effects structure to one non-hierarchal factor.

267

268 TABLE 3. Expected models, *exp*, of ED_{t1} against difference of time between epochs (*tm*), number of species in the tree at *t0* (*n*), and an
 269 ED_{t0} dummy variable generated from the rounded figures of ED_{t0}. Formulae (*f*) [37], degrees of freedom (DF), Akaike Information
 270 Criterion (AIC), and significance (P) are indicated. Significance is indicated by comparing the current row's model to the last significant
 271 model (***p* < 0.001, ***p* < 0.01, **p* < 0.05). The '-' indicates the separation of linear models and linear mixed-effects models. The
 272 selected expected model (*n2b*) is highlighted in bold.

Id.	<i>f</i>	DF	AIC	P
n0a	ED _{t1} ~tm	3	118,248	
n0b	ED _{t1} ~n	3	114,116	
n0c	ED _{t1} ~tm+n	4	113,934	***
n0d	ED _{t1} ~dummy	3	71,796	
n0e	ED _{t1} ~dummy+tm+n	5	49,229	***
n1a	ED _{t1} ~dummy+tm+n+(1 order)	6	48,182	-
n1b	ED _{t1} ~dummy+tm+n+(1 genus)	6	35,783	***
n1c	ED _{t1} ~dummy+tm+n+(1 id)	6	47,644	
n1d	ED _{t1} ~dummy+tm+n+(dummy genus)	8	31,649	***
n1e	ED _{t1} ~dummy+tm+n+(tm genus)	8	32,141	
n1f	ED _{t1} ~dummy+tm+n+(n genus)	8	31,262	
n2a	ED _{t1} ~poly(dummy, 2)+tm+n+(dummy genus)	9	30,721	***
n2b	ED_{t1}~poly(dummy, 3)+tm+n+(dummy genus)	10	30,496	***
n2c	ED _{t1} ~poly(dummy, 4)+tm+n+(dummy genus)	11	30,472	***

273

274

275

276 *Comparing the Expected and the Observed*

277 We compared the expected model (*exp*, *n2b*) with the best observed polynomial model (*obs2*, *m3b*) by
278 plotting the parameterised lines to create figures analogous to figure 1. Because these models generate
279 tens of thousands of individual lines (one line per genus per epoch transition), plotting all outputs
280 directly would make visual interpretation of trends difficult, so we constructed a representative dataset
281 consisting of 100 equally spaced ED_{t0} values spanning from the observed minimum to observed
282 maximum for 100 random selections of all genera across all epochs. This representative dataset
283 consisted of 70,000 rows. We used the dataset to predict ED_{t1} for *obs2* and plotted the predicted values
284 by calculating the median and 95% CIs across genera and epochs (figure 2).

285 For both the best non-linear model when compared to the expected model, we found that, on
286 average, high averaged clade ED_{t0} values (above $\sim e^{2.5}$ or ~ 12 MY) tended to lead to higher than
287 expected ED_{t1} values, a pattern that was most consistent with the “panchronic” scenario; showing
288 increasing divergence from the expected model at higher ED_{t0} values. For low values of averaged clade
289 ED_{t0} (below $\sim e^{1.5}$ or ~ 5 MY) we found that ED_{t1} was lower than expected, indicating clades with low
290 ED tended to speciate more than clades with high ED. These patterns were consistent across the
291 different epochs (electronic supplementary material, figure S6). Additionally, upon repeating the above
292 analyses for non-taxonomically informed stochastic fossil placement in the molecular-fossil trees, we
293 were able to rule out that our results were the product of random fossil placement (electronic
294 supplementary material, methods and results).

295

296 [INSERT FIGURE 2 HERE]

297 FIGURE 2. Predicted $\log(ED_{t1})$ values generated from the best-observed linear (*obs1*, solid red line) and expected model (i.e. “dummy
298 variable”, *n2b*, solid black line) for a representative dataset of a range of $\log(ED_{t0})$ values, a random subset of one hundred genera, and all
299 epoch-to-epoch transitions. When compared to figure 1, the observed relationship most closely resembles the “panchronic” scenario.
300 Dotted line indicates $\log(ED_{t0}) = \log(ED_{t1})$. Estimates across the different genera and epoch-to-epoch transitions are median averaged and
301 95% CIs were calculated, with values representing natural logged millions of years (1 = 2.7, 2 = 7.4, 3 = 20.1, 4 = 54.6, 5 = 148.4).

302

DISCUSSION

303
304
305
306
307
308
309
310
311
312
313
314
315
316
317
318
319
320

In order to determine the future evolutionary potential of clades composed of evolutionarily distinct species, we modelled future evolutionary distinctness as a function of past evolutionary distinctness using data generated from the mammalian fossil record. We find that taxa that are or have been evolutionarily distinct are more likely to become more evolutionarily distinct in the future. These findings fit closest to a “panchronic” scenario for the evolution of the evolutionarily distinct; evolutionarily distinct taxa in this scenario are disproportionately composed of “living fossils” that experience both reduced rates of extinction and speciation [15]. Observed results differ from what would be expected from an “evolutionarily relict” (“dead-end”) scenario, in which species most commonly become evolutionarily distinct by being the sole survivors of a once-large clade (figures 1-2). The observed model shows a slow gain in ED for clades that are *already* very evolutionarily distinct; however, in an “evolutionarily relict” scenario, clades with mid to low ED – below e^2 or 7 MY – at t_0 should tend to reach high-ED at t_1 . Instead, these clades have lower ED at t_1 . Equally, our results are not compatible with a “phylogenetic fuse” scenario in which evolutionarily distinct clades tend to be the seeds of future diversity, because taxa with high ED were not observed to lead to taxa with low ED over time.

321 **Potential Biases**

322 Our results indicate that the randomness of the fossil-adding process is likely to have *reduced* (not
323 generated) the non-linearity of the observed results. Firstly, upon comparing the models fitted to the
324 taxonomically informed versus randomly added distribution of molecular-fossil trees, we showed that
325 the pattern for high ED values in t_0 leading to even higher ED values in t_1 was stronger in the
326 taxonomically informed distribution. Secondly, the observed non-linearity was greatest for the data
327 points in which we have the greatest confidence, as high ED values in t_0 led to even higher ED values

328 in *tI* for the species/clades that were shared more than fifty times across tree iterations (electronic
329 supplementary material, “Comparing Model Outcomes between the Real and Random”).

330 The level of detail of the fossil taxonomy limits the placement of fossils (electronic
331 supplementary material, figure S1). This issue is more likely to affect the ED estimates of lower-level
332 clades (e.g. at the genus or subfamily level) than higher-level clades, because although fossil species
333 may be added to the wrong subfamily due to lack of taxonomic resolution, they are very unlikely to be
334 added to the wrong family. Nonetheless, the taxonomic misplacement of fossil species will impact
335 estimates of ED. Another source of error in the placement of fossil species is their age of speciation and
336 extinction. Ages of appearance are likely to be underestimated due to the Signor-Lipps effect [39].
337 Although this effect is not directly accounted for using any statistical or mechanistic models, the
338 effect’s impact should be mitigated by our fossil-adding process, in which origination of fossil lineages
339 was set to occur before or during the estimated age ranges. Both of these sources of error could
340 theoretically introduce bias that might account for some or all of the non-linearity observed in our
341 model outputs, but it is difficult to conceive of a mechanism by which taxonomic or dating errors could
342 produce the strong observed patterns. Additionally, we note that phylogenetic trees that are not wholly
343 accurate can still produce metrics more similar to true values than would be expected [40].

344 Taphonomic (preservational) inconsistencies in the fossil record are potentially another source
345 of bias [41]. To produce the observed non-linearity in our model outputs, a bias where species with
346 high ED were sampled less frequently than species with low ED would be required. One mechanism
347 that could achieve a fossil bias of this kind might be differential sampling of evolutionarily distinct
348 species if they have smaller body sizes and/or population sizes [42]. However, no studies have found
349 significant correlations between evolutionary distinctness and population size, and many studies
350 suggest that evolutionarily distinct species tend to have *greater* body mass for a range of taxonomic
351 groups [43-46], which may be associated with increased likelihood of representation in the fossil
352 record, e.g. [47]. In mammals body mass is only weakly or not at all correlated with ED [12].

353 Additionally, taphonomic biases are likely to be strongly taxonomically controlled, for example
354 because related species are likely to occupy similar habitats [48]. However, the non-linear relationship
355 in our model outputs is detected even when using a random effects structure that controls for inter-
356 relatedness. We therefore consider it very unlikely that this potential scenario for bias is responsible for
357 generating the patterns that we observe.

358

359 **Implications for Conservation Biology**

360 Palaeontology and macroevolution have an important potential role to play in informing conservation,
361 and our study demonstrates how fossil data can be used to provide unique insights for conservation
362 prioritisation and decision-making. Funds are limited and not all species can be saved; prioritisation is
363 therefore key to conservation strategy [49, 1, 12]. To date, most species-level conservation
364 prioritisation has been focused on well-known charismatic taxa such as tigers, rhinos and polar bears
365 [50, 51], as well as on highly threatened species in urgent need of conservation [52]. One approach to
366 move away from this bias has been to place greater conservation effort on evolutionarily distinct
367 species (e.g. [53-55]), based in part upon the supposition that such taxa might contribute to future
368 evolutionary potential; that is, they represent “cradles” of future diversity, as opposed to “museums” of
369 past diversity [56]. One such widely publicised effort has been to rank species for conservation
370 prioritisation based on their “EDGE” (Evolutionarily Distinct and Globally Endangered) score [1, 12].
371 However, arguments arise over the usefulness of investing efforts into species that may already be
372 evolutionarily “doomed” [7, 4]. Indeed a recent study found that conservation strategies that prioritise
373 the preservation of evolutionarily distinct species led to a reduction in the number of future lineages
374 [28].

375 The findings of our investigation of large-scale fossil data provide an important new perspective
376 on this conservation question. It is clear that, at a broad global scale and based on data for mammals,
377 focusing conservation attention on evolutionarily distinct species will not safeguard the overall future

378 “evolvability” of life on Earth, as implied by a “phylogenetic fuse” scenario [14]. However, our results
379 are equally not indicative of an evolutionary “dead-end” scenario for the origin and future of
380 evolutionarily distinct species over geological time [8, 9]. These taxa are neither doomed nor the likely
381 seeds of future radiations; our findings demonstrate that they are likely to remain evolutionarily
382 distinct, and appear to be merely the slow evolving ends of the tree of life. Although the exact
383 mechanism for what may cause the increasing distinctness of the distinct is not tested here, the results
384 corroborate with studies demonstrating the widespread phenomenon of age-dependant speciation [57-
385 59].

386 Our findings may appear to argue against special prioritisation of evolutionarily distinct species,
387 contrary to the philosophy of the “EDGE” approach. However, we definitely do not advocate
388 withdrawing conservation attention from these species. While our study provides a new overview of
389 the likely persistence and future diversification of evolutionarily distinct species and clades, thus
390 challenging one of the general justifications that has been proposed for conserving such species, these
391 findings provide a broad pattern across the Mammalia as a whole; we are unable to predict whether any
392 specific species or clade within this major animal group may indeed diversify in the future, to what
393 extent, or at what time, in response to any number of possible future ecological scenarios. Indeed, we
394 note that whereas our analyses are based upon data for speciation and extinction events across deep
395 time caused by non-anthropogenic processes, current-day global biodiversity loss is driven by
396 anthropogenic processes and is likely to be associated with different patterns of species vulnerability or
397 resilience [60, 61], including the generation of “artificially evolutionarily distinct” or “neo-relict”
398 clades which were species-rich before the Late Quaternary but have experienced disproportionate
399 levels of human-caused extinction (e.g., proboscideans, sloths) [22].

400 Furthermore, future potential is only one criterion for targeting conservation effort, both
401 quantifiable and intangible factors should also be considered. Conserving evolutionary history and the
402 breadth of mammalian biodiversity is an important goal in and of itself, for a variety of biological

403 reasons (e.g. trait diversity and its relationship with ecosystem function and complexity; [46]) and other
404 reasons (e.g. ethical, financial, cultural), irrespective of the possible future evolutionary trajectory of a
405 given species or clade. Evolutionarily distinct lineages have just as much of a right to survive the
406 Anthropocene as do any others, and their unique representation of more independent evolutionary
407 history than ‘normal’ lineages may still be considered worthy of particular attention.

408

409

410

ACKNOWLEDGEMENTS

411 The authors wish to thank P. Wagner and G. Gorman for initial reviews and feedback, as well as, the
412 contributors to the Paleobiology Database who made this study possible. The authors would also like to
413 thank Arne Ø. Mooers and two anonymous reviewers whose comments and suggestions greatly
414 improved the paper.

415

FUNDING

416 This project was funded by a Natural and Environmental Research Council (NERC, UK) PhD. grant.

417

419

420

421

422

423

424

425

426

427

428

429

430

431

432

433

434

435

436

437

438

439

440

441

442

443

444

445

1. Isaac, N. J. B., Turvey, S.T., Collen, B., Waterman, C. and Baillie, J.E.M. 2007. Mammals on the EDGE: conservation priorities based on threat and phylogeny. *PloS One*, 2(3):e296.
2. Rosauer, D.F. and Mooers, A.Ø. 2013. Nurturing the use of evolutionary diversity in nature conservation. *Trends in Ecology and Evolution*, 28(6):322–3.
3. Bennett, D.J., Sutton, M.D., and Turvey, S.T. 2018. Quantifying the living fossil concept. *Palaeontologia Electronica*, 21.1.14A:25
4. Winter, M., Devictor, V. and Schweiger, O. 2013. Phylogenetic diversity and nature conservation: where are we? *Trends in Ecology and Evolution*, 28(4):199–204
5. Mazel, F., Pennell, M.W., Cadotte, M.W., Diaz, S., Dalla Riva, G.V., Grenyer, R., Leprieur, F., Mooers, A.Ø., Mouillot, D., Tucker, C.M. and Pearse, W.D. 2018. Prioritizing phylogenetic diversity captures functional diversity unreliably. *Nature Communications*, 9, 2888
6. Millennium Ecosystem Assessment. 2005. *Ecosystems and Human Well-being: Biodiversity Synthesis*.
7. Krajewski, C. 1991. Phylogeny and diversity. *Science*, 254(5034):918–919.
8. Nagalingum, N. S., Marshall, C.R., Qental, T.B., Rai, H.S., Little, D.P. and Mathews, S. 2011. Recent synchronous radiation of a living fossil. *Science*, 334:796–799.
9. Mouquet, N. Devictor, V., Meynard, C.N., Munoz, F., Bersier, L-F. and Chave, J. 2012. Ecophylogenetics: advances and perspectives. *Biological reviews of the Cambridge Philosophical Society*, 87(4):769–85.
10. Parsons, P. 1994. Habitats, stress, and evolutionary rates. *Journal of Evolutionary Biology*, 397:387–397.
11. Redding, D. W., DeWolff, C. V. and Mooers, A. Ø. 2010 ^{[[1]]}_{SEP}Evolutionary distinctiveness, threat status and ecological oddity in primates. *Conserv. Biol.* 24, 1052–1058.
12. Collen, B., Turvey, S.T., Waterman, C., Meredith, H.M.R., Kuhn, T.S., Baillie, J.E.M. and Isaac, N.J.B. 2011. Investing in evolutionary history: implementing a phylogenetic approach for mammal conservation. *Proceedings of the Royal Society of London B - Biological Sciences*, 366(1578):2611–22.
13. Schluter, D. 2000. *The Ecology of Adaptive Radiation*. Oxford University Press, Oxford.
14. Cooper, A. and Fortey, R. 1998. Evolutionary explosions and the phylogenetic fuse. *Trends in Ecology and Evolution*, 13(4):151–156.

- 446 15. Bennett, D.J., Sutton, M.D. and Turvey, S.T. 2017. Evolutionarily distinct “living fossils” require both lower
447 speciation and lower extinction rates. *Paleobiology*, 43(1):34–48.
- 448 16. Van Valen, L. 1973. A new evolutionary law. *Evolutionary Theory*, 1:1–30.
- 449 17. Alroy, J. 1996. Constant extinction, constrained diversification, and uncoordinated stasis in North American
450 mammals. *Palaeogeography, Palaeoclimatology and Palaeoecology*, 127:285– 311.
- 451 18. Ezard, T.H.G., Aze, T., Pearson, P.N., and Purvis, A. 2011. Interplay between changing climate and species’
452 ecology drives macroevolutionary dynamics. *Science* 332:349–51
- 453 19. Nee, S. and May, R. 1997. Extinction and the Loss of Evolutionary History. *Science*, 278(5338):692–694.
- 454 20. von Euler, F. 2001. Selective extinction and rapid loss of evolutionary history in the bird fauna. *Proceedings of the*
455 *Royal Society of London B - Biological Sciences*, 268(1463):127–130.
- 456 21. Purvis, A. Agapow, P-M. Gittlemann, J.L. and Mace, G.M. 2000. Nonrandom Extinction and the Loss of
457 Evolutionary History. *Science*, 288(5464):328–330.
- 458 22. Mooers AØ, Goring SJ, Turvey ST, Kuhn TS. 2009. Holocene extinctions and the loss of feature diversity. In
459 Turvey ST (Ed.) *Holocene Extinctions: 263-277*. Oxford University Press, Oxford.
- 460 23. Verde Arregoitia, L.D., Blomberg, S.P. and Fisher, D.O. 2013. Phylogenetic correlates of extinction risk in
461 mammals: species in older lineages are not at greater risk. *Proceedings of the Royal Society of London B -*
462 *Biological Sciences*, 280(1765):20131092.
- 463 24. Jetz, W., Thomas, G.H., Joy, J.B., Redding, D.W., Hartmann, K. and Mooers, A.Ø. 2014. Global Distribution and
464 Conservation of Evolutionary Distinctness in Birds. *Current Biology*, 24(9):919-930.
- 465 25. Tonini, J.F.R., Beard, K.H., Ferreira, R.B., Jetz, W. and Pyron, R.A. 2016. Fully-sampled phylogenies of
466 squamates reveal evolutionary patterns in threat status. *Biological Conservation*, 204(A):23-31.
- 467 26. Stein, R.W., Mull, C.G., Kuhn, T.S., Aschliman, N.C., Davidson, L.N.K., Joy, J.B., Smith, G.J., Dulvy, N.K. and
468 Mooers, A.Ø. 2018. Global priorities for conserving the evolutionary history of sharks, rays and chimaeras. *Nature*
469 *Ecology & Evolution*, 2:288-298.
- 470 27. Jablonski, D. 1995. Extinctions in the fossil record. In *Extinction Rates*. 25–44.
- 471 28. Cantalapiedra, J.L., Aze T., Cadotte M.W., Dalla Riva G.V., Huang D., Mazel F., Pennell M.W., Ríos M. and
472 Mooers A.Ø. 2019. Conserving evolutionary history does not result in greater diversity over geological time scales.
473 *Proc. R. Soc. B*, 286(1904).
- 474 29. Bininda-Emonds, O. R. P., Cardillo, M., Jones, K. E., MacPhee, R. D. E., Beck, R. M. D., Grenyer, R., ... Purvis,
475 A. 2007. The delayed rise of present-day mammals. *Nature*, 446(7135), 507-12.

- 476 30. Liow, L.H. Fortelius, M., Bingham, E., Lintulaakso, K., Mannila, H., Flynn, L. and Stenseth, N.C. 2008. Higher
477 origination and extinction rates in larger mammals. *Proceedings of the National Academy of Sciences of the*
478 *United States of America*, 105(16):6097–6102.
- 479 31. The Paleobiology Database 2018. The Paleobiology Database. [<https://paleobiodb.org>] (25/09/2018)
- 480 32. Varela, S., González-Hernández, J., Sgarbi, L.F., Marshall, C., Uhen, M.D., Peters, S. and McClennen, M. 2015.
481 paleobioDB: An R package for downloading, visualizing and processing data from the Paleobiology Database.
482 *Ecography*, 38(4):419–425.
- 483 33. Federhen, S. 2012. The NCBI taxonomy database. *Nucleic Acids Research*, 40(Database issue), D136–43.
- 484 34. Global Names Architecture 2018. Global Names Resolver. [<https://resolver.globalnames.org/>] (25/09/2018).
- 485 35. Bennett, D.J., Sutton, M.D. and Turvey, S.T. 2017. treeman: an R package for efficient and intuitive manipulation
486 of phylogenetic trees. *BMC Research Notes*, 10(1):30.
- 487 36. Fisher, R.A. 1919. XV. The Correlation between relatives on the supposition of Mendelian inheritance.
488 *Transactions of the Royal Society of Edinburgh*, 52(2):399–433.
- 489 37. Bates, D. Mächler, M., Bolker, B., and Walker, S. 2015. Fitting Linear Mixed-Effects Models Using lme4. *Journal*
490 *of Statistical Software*, 67(1):48.
- 491 38. Akaike, H. 1974. A new look at the statistical model identification. *IEEE Transactions on Automatic Control*,
492 19(6), 716–723.
- 493 39. Signor III, P. W. and Lipps, J. H. (1982) "Sampling bias, gradual extinction patterns, and catastrophes in the fossil
494 record", in *Geological implications of impacts of large asteroids and comets on the Earth* (ed. L. T. Silver and P. H.
495 Schultz), *Geological Society of America Special Publication*, vol. 190, pp. 291–296.
- 496 40. Rodrigues, A.S.L., Grenyer, R., Baillie, J.E.M., Bininda-Emonds, O.R.P., Gittlemann, J.L., Hoffmann, M., Safi,
497 K., Schipper, J., Stuart, S.N. and Brooks, T. 2011. Complete, accurate, mammalian phylogenies aid conservation
498 planning, but not much. *Proceedings of the Royal Society of London B - Biological Sciences*, 366(1578):2652–60.
- 499 41. Shipman, P. 1981 *Life History of a Fossil: An Introduction to Taphonomy and Paleoecology*, Harvard University
500 Press, Cambridge, Massachusetts.
- 501 42. Cooper, R.A. Maxwell, P.A., Crampton, J.S., Beu, A.G., Jones, C.M. and Marshall, B.A. 2006. Completeness of
502 the fossil record: Estimating losses due to small body size. *Geology*, 34(4):241–244.
- 503 43. Ricklefs, R.E. 2005. Small clades at the periphery of passerine morphological space. *The American Naturalist*,
504 165(6):651–9.

- 505 44. Latiolais, J.M., Taylor, M.S., Roy, K. and Hellberg, M.E. 2006. A molecular phylogenetic analysis of strombid
506 gastropod morphological diversity. *Molecular Phylogenetics and Evolution*, 41(2):436–444.
- 507 45. Magnuson-Ford, K., Ingram, T., Redding, D.W. and Mooers, A.Ø. 2009. Rockfish (*Sebastes*) that are
508 evolutionarily isolated are also large, morphologically distinctive and vulnerable to overfishing. *Biological
509 Conservation*, 142(8):1787–1796.
- 510 46. Redding, D.W., DeWolff C.V. and Mooers, A.Ø. 2010. Evolutionary distinctiveness, threat status, and ecological
511 oddity in Primates. *Conservation Biology*, 24(4):1052–1058.
- 512 47. Turvey ST, Blackburn TM. 2011. Determinants of species abundance in the Quaternary vertebrate fossil record.
513 *Paleobiology* 37: 537-546.
- 514 48. Foote, M. and Raup, D.M. 1996. Fossil preservation and the stratigraphic ranges of taxa. *Paleobiology*, 22(2):121–
515 140.
- 516 49. Vane-Wright, R. I., Humphries, C. J. and Williams, P. H. 1991 What to protect—systematics and the agony of
517 choice. *Biol. Conserv.* 55, 235–254.
- 518 50. Mace, G., and Collar, N. 2002. Priority-setting in species conservation. In K. Norris and D. Pain (Eds.),
519 *Conserving Bird Biodiversity: General Principles and their Application* (*Conservation Biology*, pp. 61-73).
520 Cambridge: Cambridge University Press.
- 521 51. Entwistle, A. and Dunstone, N. 2000. *Priorities for the Conservation of Mammalian Diversity: Has the Panda had
522 its Day?* Cambridge: Cambridge University Press.
- 523 52. Brooks, T. 2010. Conservation planning and priorities . In N.S. Sodhi and P.R. Ehrlich (Eds.), *Conservation
524 Biology for All*. Oxford Scholarship Online.
- 525 53. Celis-Diez, J.L., Hetz, J., Marín-Vial, P.A., Fuster, G., Necochea, P., Vásquez, R.A. Jaksic, F.M., Armesto, J.J.
526 2012. Population abundance, natural history, and habitat use by the arboreal marsupial *Dromiciops gliroides* in
527 rural Chiloé Island, Chile. *Journal of Mammalogy*, 93(1):134–148.
- 528 54. Biton, R. Geffen, E., Vences, M., Cohen, O., Bailon, S., Rabinovich, R., Malka, Y., Oron, T., Boistel, R. Brumfeld,
529 V. and Gafny S. 2013. The rediscovered Hula painted frog is a living fossil. *Nature Communications*, 4:1959.
- 530 55. Li, Y-Y., Tsang, E.P.K., Cui, M-Y. and Chen, X-Y. 2012. Too early to call it success: An evaluation of the natural
531 regeneration of the endangered *Metasequoia glyptostroboides*. *Biological Conservation*, 150(1):1–4.
- 532 56. Mace, G.M., Gittleman, J.J. and Purvis, A. 2003 Preserving the Tree of Life. *Science*, 300, 1707–1709.

- 533 57. Purvis, A., Fritz, S.A, Rodríguez, J., Harvey, P.H. and Grenyer, R. 2011. The shape of mammalian phylogeny:
534 patterns, processes and scales. *Proceedings of the Royal Society of London B - Biological Sciences*,
535 366(1577):2462–77.
- 536 58. Hagen, O., Hartmann, K., Steel, M. and Stadler, T. 2015. Age-dependent speciation can explain the shape of
537 empirical phylogenies. *Systematic Biology*, 64(3):432–440.
- 538 59. Rabosky, D.L. and Goldberg, E.E. 2015. Model inadequacy and mistaken inferences of trait- dependent speciation.
539 *Systematic Biology*, 64(2):340–355.
- 540 60. Cardillo, M., Mace, G.M., Jones, K.E., Bielby, J., Bininda-Emonds , O.R.P., Sechrest, W., Orme, C.D.L., Purvis,
541 A. 2005 Multiples causes of high extinction risk in large mammal species. *Science*, 30912391241
- 542 61. Turvey ST, Crees JJ, Li Z, Bielby J, Yuan J. 2017. Long-term archives reveal shifting extinction selectivity in
543 China’s postglacial mammal fauna. *Proceedings of the Royal Society B* 284: 20171979.
- 544