

Inferring the demographic history of coppery titi monkeys (*Plecturocebus cupreus*) from high-quality, whole-genome, population-level data

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keywords: primate; haplorrhine; Pitheciidae; demographic inference; population history; population genetics

1 **Abstract**

2 Despite being an important biomedical model species for social behavior, the natural population
3 history of the coppery titi monkey (*Plecturocebus cupreus*) remains largely uncharacterized, in
4 part due to the scarcity of genomic resources available for the species. Apart from the inherent
5 interest in the demographic dynamics of this abundant platyrhine native to the Amazon forest
6 of Brazil and Peru, this quantification will also serve as a central component of future genotype-
7 to-phenotype studies, given the ability of historical population size change and structure to
8 generate genetic associations. In this study, we deep-sequenced the genomes of six unrelated
9 individuals and inferred a baseline demographic model based on observed levels and patterns of
10 variation in the non-coding regions of the genome. In characterizing these demographic
11 dynamics, we found that estimated population size changes correspond well to previously
12 described speciation times as well as to large-scale climatic changes relating to glaciation
13 patterns.

14 **Introduction**

15 The coppery titi monkey (*Plecturocebus cupreus*) is a relatively abundant and diminutive
16 platyrhine species primarily found in Western Brazil and Eastern Peru (Heymann et al. 2021).
17 Within this area, they are mainly restricted to habitats of lowland forests subject to periodic
18 seasonal flooding, their home ranges are generally non-overlapping, and offspring leave their
19 family units around 2 to 3 years of age (Mason 1966; Dolotovskaya et al. 2020; Conley et al. 2022).
20 With a lifespan of over 20 years (Zablocki-Thomas et al. 2023), *P. cupreus* is notable for being
21 characterized by a monogamous, pair-bonded mating system. Given that social monogamy is a
22 relatively rare social system in mammals, and pair-bonding is rarer still, this species has become
23 an important model to study the neurobiology of social behavior (e.g., Bales et al. 2007; Lau et
24 al. 2024; and see Bales et al. 2021). For example, in species characterized by this social system,
25 visually-associated brain regions have been found to contain a high density of receptors for the
26 social hormone oxytocin (Freeman et al. 2014), suggesting a key role of vision in governing this
27 behavior (Baldwin and Krubitzer 2018). This primate is thus also of great interest in a comparative
28 framework for the study of complex human social behavior and attachment, and considerable
29 work has focused on the systems of dopamine, oxytocin, and arginine vasopressin in the
30 hypothalamus, globus pallidum, and other limbic and cortical regions in this regard (Feldman
31 2017; Fischer et al. 2019).

32 *P. cupreus* is a member of the Western Amazon clade of the *moloch* group alongside *P.*
33 *moloch*, *P. brunneus*, *P. dubius*, and *P. caligatus*. The *moloch* group is believed to have diverged
34 around 3.78 million years ago (mya) during the drying of the Pebas system (a large lake and
35 floodplain covering much of what is now the Western Amazon) in the late Neogene period (Byrne

36 et al. 2018). Further changes to the landscape during the early Pleistocene are thought to have
37 led to the additional split in this group between Western and Eastern Amazonian clades around
38 1.95 to 3.44 mya. This was followed by multiple proposed speciation events including a split
39 between the clade containing *P. cupreus* and the clade containing *P. caligatus* around 1.44 to 1.95
40 mya, as well as subsequent subspecific divisions in *P. cupreus* (Byrne et al. 2016, 2018; Byrne
41 2017).

42 To complement these previous genus-level estimates, and given the biomedical
43 importance of *P. cupreus*, we here present a detailed demographic analysis of the species based
44 on novel, whole-genome, high-quality sequencing data from six unrelated individuals. In order to
45 perform this estimation, we implemented two of the most commonly used inference approaches
46 — $\delta a \delta i$ (Gutenkunst et al. 2009) and fastsimcoal2 (Excoffier et al. 2013) — both of which rely on
47 fitting models, and parameters underlying those models, to the empirically observed site
48 frequency spectrum (SFS). By utilizing patterns of genetic diversity at putatively neutral, intergenic
49 sites of the genome sufficiently distant from functional regions to avoid the confounding effects
50 of background selection (Soni and Jensen 2025; Soni, Versoza et al. 2025a; Terbot et al. 2025a,
51 Terbot et al. 2025b), the well-fitting demographic model described here provides new insights
52 into the population history of this species. Furthermore, this demographic inference will also
53 serve as a necessary neutral baseline model for future genomic scans of episodic positive or
54 balancing selection (Poh et al. 2014; Johri et al. 2022; Jensen 2023; Soni and Jensen 2024; Soni,
55 Terbot et al. 2025; Soni et al. 2025), related to, for example, the underlying genetic modifications
56 governing their social behavior, as well as to future association studies seeking to connect
57 genotypes to well-studied phenotypes. Our results suggest that the sample of this study was

58 derived from a single sub-population, and we found evidence of a size change history correlated
59 with past speciation events as well as glaciation / interglacial climatic patterns. As these climatic
60 shifts were associated with dryer and cooler weather, it is likely that these fluctuations were
61 related to the abundance of dry or temporarily flooded forest habitats of the sort preferred by
62 the species to this day.

63

64 **Materials and Methods**

65 *Ethics statement*

66 This study was performed in compliance with all regulations regarding the care and use of captive
67 primates, including the NIH Guidelines for the Care and Use of Animals and the American Society
68 of Primatologists' Guidelines for the Ethical Treatment of Nonhuman Primates. Procedures were
69 approved by the UC-Davis Institutional Animal Care and Use Committee (protocol 22523).

70

71 *Samples and sequencing*

72 We collected blood samples from six unrelated coppery titi monkeys housed at the California
73 National Primate Research Center (CNPRC) during routine veterinary care. DNA extracted from
74 each sample with the PAXgene Blood DNA System (Qiagen, Hilden, Germany) was used to prepare
75 individual libraries following a PCR-free protocol. Libraries were sequenced on an Illumina
76 NovaSeq 6000 (Illumina, San Diego, CA, USA) with a 2×150 bp sequencing configuration with a
77 target of $\sim 40\times$ coverage.

78

79 *Whole genome sequencing alignment and variant calling*

80 We removed adapters from the sequencing reads using TrimGalore v.0.6.10
81 (<https://github.com/FelixKrueger/TrimGalore>) with Cutadapt v.4.9 (Martin 2011) built-in and
82 subsequently mapped the reads to the reference genome sequence of the species, PleCup_hybrid
83 (NCBI GenBank ID: GCA_040437455.1; Pfeifer et al. 2024), using BWA-MEM v.0.7.17 (Li 2013).
84 Following best practices (Pfeifer 2017), we marked duplicate reads using the *MarkDuplicates*
85 function implemented in the Genome Analysis Toolkit (GATK) v.4.5.0.0 (van der Auwera and
86 O'Connor 2020) to remove technical duplicates from library preparation and sequencing.
87 Additionally, to avoid systematic biases in the base quality scores emitted by the sequencer, we
88 recalibrated base scores using GATK's *BaseRecalibrator* and *ApplyBQSR* functions together with
89 high-quality training data from pedigreed individuals of the species (Versoza et al. 2026a).
90 Afterward, we used GATK's *HaplotypeCaller* function to first call both variant and invariant sites
91 ('-ERC BP_RESOLUTION') from the high-quality recalibrated reads ('--minimum-mapping-quality
92 40') of each sample (with the PCR error correction disabled as a PCR-free library protocol was
93 followed during sequencing: '-pcr-indel-model NONE'), merged individual calls using GATK's
94 *CombineVCF* function, and then jointly genotyped all samples using GATK's *GenotypeGVCFs*
95 function with the '-all-sites' flag enabled. We limited the call set to autosomal, biallelic variant
96 ('--restrict-alleles-to BIALLELIC --select-type-to-include SNP') and monoallelic invariant ('--select-
97 type-to-include NO_VARIATION') sites genotyped in all individuals ('AN == 12') using the
98 *SelectVariants* function implemented in GATK v.4.2.6.1 (van der Auwera and O'Connor 2020) and
99 then filtered sites using the *VariantFiltration* function according to the recommendations of the

100 developers ('-filter QD<2.0 --filter-name QD2 -filter QUAL<30.0 --filter-name QUAL30 -filter
101 SOR>3.0 --filter-name SOR3 -filter FS>60.0 --filter-name FS60 -filter MQ<40.0 --filter-name MQ40
102 -filter MQRankSum<-12.5 --filter-name MQRankSum-12.5 -filter ReadPosRankSum<-8.0 --filter-
103 *name* ReadPosRankSum-8'). Additionally, we removed any sites overlapping repetitive / low-
104 complexity regions using the *intersect* function implemented in BEDTools v.2.30 (Quinlan and Hall
105 2010) based on the annotations of the coppery titi monkey reference genome (Pfeifer et al. 2024)
106 as well as those exhibiting extreme coverage (defined here as sites with less than 0.5, or more
107 than 2, times the mean sequencing depth of a sample) using the GATK *SelectVariants* function, as
108 such regions tend to be prone to mis-mapping, variant calling, and genotyping errors.

109

110 *Population genomic data for demographic inference*

111 As both direct and background selection can bias the inference of demographic history (Ewing
112 and Jensen 2014, 2016; Johri et al. 2020, 2021; Charlesworth and Jensen 2021, 2024), we
113 followed the recommendations of Johri et al. (2020, 2023) and restricted the high-quality call set
114 to putatively neutral genomic regions. To this end, we used BEDTools *intersect* v.2.30 (Quinlan
115 and Hall 2010) to exclude both sites overlapping with protein-coding sequence (Pfeifer et al.
116 2024) or non-coding regulatory sequence elements under selective constraint across primates
117 (Kuderna et al. 2024), thus controlling for the effects of purifying selection; we also excluded sites
118 located within 10 kb of exons, thus controlling for the effects of background selection. To improve
119 inference, these putatively neutral sites were phased using BEAGLE v.5.5 (Browning et al. 2021).

120

121 *Estimating population structure*

122 To determine the number of sub-populations present among the titi monkeys sequenced in this
123 study (six diploid individuals, or 12 haploids), we analyzed putatively neutral data from each
124 chromosome independently and for the entire genome combined using fastSTRUCTURE v.1.0 (Raj
125 et al. 2014) — a software that uses a variational Bayesian framework to implement the
126 optimization algorithms from the STRUCTURE program (Pritchard et al. 2000; Falush et al. 2003).
127 Specifically, we performed analyses for values of k (number of demes) from 1 to 5 and selected
128 the optimal number of demes based on the value of k that maximized the marginal likelihood.

129

130 *Inferring the population size-change history*

131 Our fastSTRUCTURE results strongly favored a single deme model. Thus, we analyzed single-
132 population demographic models with six different model structures (0 to 5 size change events)
133 using fastsimcoal2 v.2.8.0.0 (Excoffier et al. 2013, 2021; Marchi et al. 2024) — a software that
134 compares the composite likelihood scores of SFS simulated under various parameters to that of
135 the empirical SFS, and then selects the best-fitting parameters by maximizing this composite
136 likelihood while minimizing the difference between the simulated and empirical scores. For all
137 fastsimcoal2 models, we bounded population sizes between 1,000 and 10,000,000 haploid
138 genomes (i.e., 500 to 5,000,000 diploid individuals), and initially set the timing of events to
139 between 1 to 300,000 generations for the single-event model and to between 1 to 500,000
140 generations for all other models, though the upper limit for event timing was not bounded. For
141 each of the six model structures (0 to 5 size change events), we ran 500 replicates based on the

142 folded SFS, each with 150,000 rounds of simulation per parameter and 50 maximization cycles,
143 re-setting the parameter search after 10 consecutive failed cycles to improve the likelihood score
144 ('-n150000 -L 50 -y 10 -M -u -m'). We assumed a neutral mutation rate of 4.88e-9 /site/generation
145 and a recombination rate of 1e-8 events/site/generation. Notably, this mutation rate was based
146 on pedigree-based (i.e., direct) estimation (Versoza et al. 2026a). In order to examine the impact
147 of uncertainty in this underlying mutation rate, we also examined demographic model scaling at
148 a rate of 1.07e-8 /site/generation for comparison, as suggested by divergence-based (i.e.,
149 indirect) estimation using a six-year generation time and an estimated divergence time of 1.16
150 million years between the *cupreus* clade and the *caligatus* clade within the Western *moloch* group
151 (Soni, Versoza, et al. 2026). This range of rates is comparable to other estimates obtained from
152 non-human primates (see the reviews of Tran and Pfeifer 2018; Chintalapati and Moorjani 2020).
153 Similarly, the recombination rate was based on a recent estimate obtained from pedigree data in
154 the species (Versoza et al. 2026b), which too resembles rates observed in other non-human
155 primates (e.g., Versoza, Weiss et al. 2024; Soni, Versoza et al. 2025b; Versoza, Lloret-Villas et al.
156 2025).

157 Following the analyses using fastsimcoal2, we sought to confirm the estimated
158 demographic history using $\delta\alpha\delta\iota$ v.2.1.0 (Gutenkunst et al. 2009) — a demographic inference
159 software that optimizes parameters using a diffusion approximation approach and a continuous
160 approximation of the expected SFS under particular demographic models for comparison to the
161 observed SFS. We considered seven single-population models: the standard neutral model, as
162 well as 2-epoch (a single instantaneous population size change), 3-epoch (two instantaneous
163 population size changes), 4-epoch (three instantaneous population size changes), 5-epoch (four

164 instantaneous size changes), growth (exponential population size change), and bottlegrowth (an
165 instantaneous population size change followed by an exponential population size change)
166 models. For each model, we performed inference 100 times using the *dadi.Inference.optimize*
167 function, with a maximum of 300 iterations (*maxiter*) and [30, 50, 70] grid points (*pts*) (i.e., larger
168 than the haploid sample size of $n = 12$), together with the $\delta a\delta i$'s *perturb_params* function to
169 adjust the starting parameters two-fold up or down, within the parameter bounds defined in
170 Supplementary Table 1. As $\delta a\delta i$ infers the ancestral population size from θ , we calculated all other
171 parameters relative to this population size.

172

173 *Distinguishing between estimated demographic histories*

174 We determined the best-fitting fastsimcoal2 model by first comparing the composite likelihood
175 scores of the best parameterized version of each model and then assessing the number of
176 replicates for each model that represented improvements over the best-performing, next
177 simplest model. Additionally, we performed a final screening by quantifying the consistency of
178 the specific parameters estimated for each model's best performing replicates using z-scores,
179 calculated based on the mean and standard deviation of each parameter across those replicates.
180 For the $\delta a\delta i$ models, we selected the model with the highest log-likelihood score across all
181 replicates as the best-fitting model. To further define the best-fitting parameters for this model,
182 we ran another 100 inference replicates and determined the best-fit parameter combination
183 based on the highest log-likelihood score.

184 As the demographic histories inferred by fastsimcoal2 and $\delta\alpha\delta i$ were fairly distinct (see
185 Results below), we simulated data using fastsimcoal2 under the best-performing fastsimcoal2
186 models and the best-performing $\delta\alpha\delta i$ models to directly compare to the empirical data in order
187 to further study model fit, keeping all simulated polymorphic sites and producing a single
188 simulated SFS per replicate ('-n1 -m -s0 --jobs --header --noarloutput -u -k 6200000'). We
189 simulated 100 replicates of the entire set of putatively neutral sites across the chromosomes
190 (specifically, 22 autosomes were simulated with the same recombination and mutation rates used
191 during inference and chromosome sizes of 81,997,209; 57,596,708; 59,482,194; 51,452,482;
192 56,421,937; 37,428,171; 57,377,548; 42,072,168; 32,858,669; 16,254,630; 13,862,685;
193 78,475,508; 36,722,319; 41,001,960; 32,326,613; 37,251,058; 16,847,824; 37,884,098;
194 19,023,431; 37,470,834; 27,914,525; and 13,844,647 bps). We then averaged the SFS from each
195 replicate to produce the mean SFS for the best-performing fastsimcoal2 models and the best-
196 performing $\delta\alpha\delta i$ models and visually compared the mean SFS for each model to the empirical SFS.

197

198 **Results**

199 *Population genomic data for demographic inference*

200 To infer the demographic dynamics of the coppery titi monkey, we deep-sequenced the genomes
201 of six unrelated individuals housed at the CNPRC (Supplementary Table 2). After mapping the
202 sequencing reads to the species-specific reference genome (PleCup_hybrid; Pfeifer et al. 2024),
203 we called both biallelic variant and monoallelic invariant sites, limiting the dataset to putatively
204 neutral, autosomal regions to circumvent the biasing effects of purifying and background

205 selection on demographic inference (Ewing and Jensen 2014, 2016; Johri et al. 2020, 2021;
206 Charlesworth and Jensen 2021, 2024). In total, 6 million variants were discovered in the accessible
207 genome (Supplementary Table 3). Figure 1 provides a visual summary of this genome-wide,
208 neutral data, showing Watterson's θ and Tajima's D for each autosome.

209

210 *Estimating population structure*

211 The fastSTRUCTURE analyses strongly concluded that all samples were collected from a single
212 deme. The assignment of individuals to a specific deme was nearly complete with $Q > 0.99999$
213 ancestry components for all analyses. For both the full autosomal genome and individual
214 autosomes, a value of $k = 1$ provided the greatest marginal likelihood (for the full autosomal
215 genome, $L = -1.102912$ for $k = 1$; likelihood values for individual autosomes can be found in
216 Supplementary Table 4); moreover, the full autosomal genome as well as most autosomes
217 assigned all individuals to a single deme even for values of k greater than 1. Therefore, based on
218 these analyses, our sampled individuals are likely of a single deme origin.

219

220 *Inferring the population size-change history*

221 Based on this single deme result, we evaluated a variety of historical size change models (0 to 5
222 population size change events) using fastsimcoal2 (Excoffier et al. 2013), and the best
223 parameterization was chosen based on the maximum likelihood scores of each replicate. The best
224 performing models involved between 2 and 5 size change events (0-event: $L = -19,827,291.914$;

225 1-event: $L = -19,755,162.832$; 2-event: $L = -19,747,605.136$; 3-event: $L = -19,747,259.099$; 4-event:
226 $L = -19,747,248.682$; 5-event: $L = -19,747,239.622$). Diagrams of the best-performing parameters
227 for each of these models can be found in Figure 2 for the 3-event model, and in Supplementary
228 Figure 1 for all other models (numerical parameter values are provided in Supplementary Table
229 5). Considering an alternative mutational scaling for the best-fitting model (1.07e-8
230 /site/generation [supported by indirect estimation; Soni, Versoza, et al. 2026] instead of 4.88e-9
231 /site/generation as used above [supported by direct estimation; Versoza et al. 2026a]), we
232 observed a scaling down of estimated population sizes and more recent size change events
233 (Supplementary Figure 2). This result is to be expected, given that changing the neutral mutation
234 rate does not alter the SFS shape and thus does not alter the fit of the generalized model, but
235 rather serves to re-scale the underlying parameters (e.g., population sizes scale smaller to keep
236 the product of population size and mutation rate constant, and events scale more recently given
237 the population size-based generation time scaling). Thus, it is important to be mindful of the
238 impact of this underlying mutation rate uncertainty on the resulting demographic estimation;
239 nonetheless, as direct pedigree-based mutation rate estimation is considered to be the gold-
240 standard, it is fortunate to have such estimation available in this species.

241 For comparative purposes, we also performed demographic inference using $\delta a \delta i$
242 (Gutenkunst et al. 2009), an SFS-based neutral demographic estimator that infers population
243 history via diffusion approximation. We initially tested seven single-population demographic
244 models (see Material and Methods for more details), in order to identify the best-fitting model.
245 The 5-epoch model (in which four instantaneous size changes occur) had the highest log-
246 likelihood (-4,537.61), and the fewer parameters of the 3-epoch model (consisting of two

247 instantaneous size changes) also provided a strong fit despite a lower log-likelihood (-19,500.89;
248 and see Discussion below). Example diagrams of models are presented in Supplementary Figure
249 3 (specific numerical values scaled based on a mutation rate of 4.88e-9 /site/generation are
250 available in Supplementary Table 6).

251

252 *Distinguishing between estimated demographic histories*

253 As the composite likelihood scores emitted by fastsimcoal2 do not include any penalties for the
254 use of additional parameters (each additional size change event requires two additional
255 parameters), the relative improvement over simpler models, as well as the absolute difference
256 from the observed composite likelihood, are important considerations when selecting the
257 preferred model. The 3-event model is the simplest model within 50 units of the observed
258 composite likelihood, with the additions of the 4-event and 5-event models resulting in likelihood
259 scores with very minor improvements (Supplementary Table 7). Additionally, one would
260 anticipate better performing models to consistently produce replicates that represent
261 improvements over simpler models. The 1-event model produced 84.4% of replicates that
262 outperform the constant size model, the 2-event model produced 43.0% of replicates that
263 outperform the 1-event model, the 3-event model produced 5.8% of replicates that outperform
264 the 2-event model, the 4-event model produced 0.6% of replicates that outperform the 3-event
265 model, and the 5-event model produced 0.4% of replicates that outperform the 4-event model.
266 As such, the 3-event model is the most complex model still resulting in >5% performance
267 improvement amongst replicates. Finally, we compared the spread of the estimated parameters

268 for better performing replicates using z-scores for the 0-, 1-, 2-, and 3-event models
269 (Supplementary Figure 4). While the 0- and 1-event models are decidedly the most consistent in
270 the resulting estimated parameters, the parameter estimates of the 3-event model exhibit
271 comparatively less spread than the 2-event model. Taken together, these results thus suggest that
272 the 3-event history is the best-performing fastsimcoal2 model, though if additional parameters
273 are penalized more substantially, the 2-size change event model performs well with two fewer
274 parameters. Notably, the general history of the 3-event and 2-event models are highly similar,
275 suggesting strong growth over the past 1 million years followed by a very recent decline.

276 To compare the parameterized models of fastsimcoal2 and $\delta a \delta i$, we simulated SFS under
277 each of the estimated demographic models and visually compared the simulated SFS to the
278 empirically observed SFS. The mean simulated SFS of fastsimcoal2's best performing models (2-
279 event to 5-event models) all reasonably recapitulated the observed SFS; in contrast, the 3-epoch
280 and 4-epoch models from $\delta a \delta i$ resulted in SFS distinct from the observed SFS (Supplementary
281 Figure 5). Thus, the 3-event model of fastsimcoal2 continues to appear most consistent with the
282 observed data (Figure 3).

283

284 **Discussion**

285 Our results indicate that the sequenced individuals were sampled from a single population. While
286 previous results have suggested population structuring (Byrne et al. 2016), it is most likely that all
287 of our samples simply derived from a single deme and gene flow between / amongst demes is
288 restricted, at least in the genetic ancestry of this sample. Alternatively, if there is sufficient gene

289 flow amongst the demes, there may be no detectable genetic structuring. With regards to the
290 ancestral history of population size change, in order to distinguish between our best performing
291 models as derived from two commonly used inference approaches, we relied upon direct
292 comparisons between predicted and empirically observed SFS. Scaling the timings of events from
293 units of generations to years under these models (assuming a generation time of six years), a
294 number of notable observations arise. Firstly, the bottleneck estimated at 2.1 mya by fastsimcoal2
295 corresponds with the previously rapid speciation occurring in the *moloch* group about 1.44 mya
296 to 3.44 mya (Byrne et al. 2016, 2018; Byrne 2017). Moreover, the subsequent size changes
297 correspond to major climatic shifts during the Pleistocene (Figure 4). Notably, the timing of a large
298 population size expansion to nearly 2 million individuals is dated to about 786 kya, corresponding
299 to the end of the Mid-Pleistocene Transition in which the glaciation cycles shifted from a 41,000-
300 year periodicity to around a 100,000-year period; these longer cycles produced larger and more
301 stable glacial sheets which would have led to overall dryer and cooler conditions (Clapperton
302 1992; Cook and Vizy 2006). Finally, the most recent estimated size change event is a relatively
303 severe contraction dating to about 19 kya, which corresponds with the Pleistocene-Holocene
304 boundary and the end of the Last Glacial Maximum (Hughes et al. 2013; Palacios et al. 2020).

305 Thus, these inferred population size changes appear to fit with the general pattern in the
306 larger taxonomic group of range expansions and speciation following dryings of wetland
307 ecosystems such as the Pebas system (Byrne 2017; Byrne et al. 2018), as well as with the current
308 ecology of the coppery titi monkey relying on dry and/or seasonally wet terrestrial ecosystems.
309 As global climate change leads to warmer weather and changes in precipitation patterns including
310 increased river flooding (Almazroui et al. 2021; Alifu et al. 2022), this could lead to ecosystem

311 changes detrimental to the coppery titi monkey, a species otherwise thought to be under little
312 threat (Heymann et al. 2021). As such, an improved understanding of how past changes in climate
313 relate to the population sizes of species like the coppery titi monkey sheds light on how the
314 impacts of future climate change may be expected to affect species across the world, including
315 those not currently considered vulnerable. Finally, aside from gaining novel insights into the
316 population history of the species, this demographic null model will be useful for future genomic
317 studies which may seek to quantify selective dynamics (as discussed in Johri et al. 2022),
318 particularly given that this species is important as a model organism for the study of the
319 neurophysiology underlying social attachment and monogamous pair bonds.

320

321 **ACKNOWLEDGEMENTS**

322 DNA extraction, library preparation, and Illumina sequencing were conducted at the DNA
323 Technologies and Expression Analysis Core at the UC Davis Genome Center (supported by NIH
324 Shared Instrumentation Grant 1S10OD010786-01) and Novogene (Sacramento, CA, USA).
325 Computations were performed on the Sol supercomputer at Arizona State University (Jennewein
326 et al. 2023).

327

328 **FUNDING**

329 This work was supported by the National Institute of General Medical Sciences of the National
330 Institutes of Health under Award Number R35GM151008 to SPP and the California National
331 Primate Research Center Pilot Program (NIH P51OD011107). CJV was supported by the National
332 Science Foundation CAREER Award DEB-2045343 to SPP. KLB was supported by the Eunice
333 Kennedy Shriver National Institute of Child Health and Human Development and the National
334 Institute of Mental Health of the National Institutes of Health under Award Numbers
335 R01HD092055 and MH125411, and by the Good Nature Institute. JWT, VS, and JDJ were
336 supported by National Institutes of Health Award Number R35GM139383 to JDJ. The content is
337 solely the responsibility of the authors and does not necessarily represent the official views of
338 the funders.

339

340 **CONFLICT OF INTEREST**

341 None declared.

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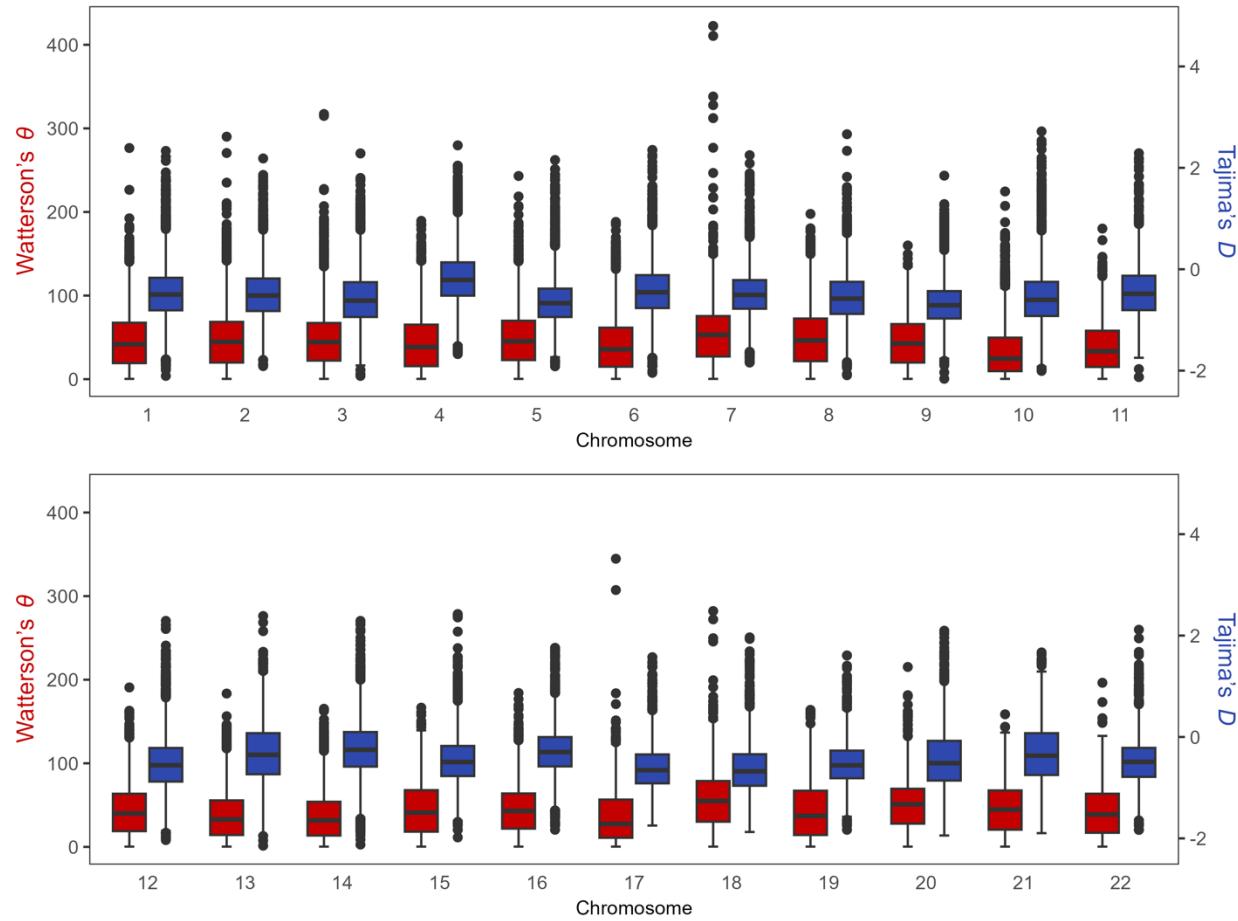


Figure 1: Summary of the genome-wide, neutral data being analyzed. The left axis provides the scaling for Watterson's θ (plotted in red), the right axis provides the scaling for Tajima's D (plotted in blue) – both based on 50 kb genomic windows – and the x-axis provides the chromosome being plotted.

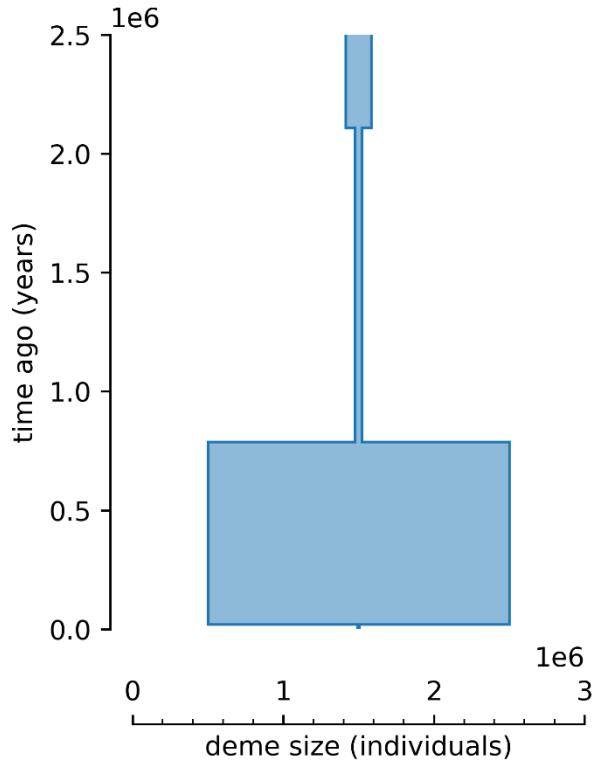


Figure 2: Diagram of best-performing fastsimcoal2 model, with 3 size-change events. The size of the population (in diploid individuals, scaled by 10^6) is represented by the width of the rectangles in the diagram, and the duration during which the population maintained that size (in years, scaled by 10^6) is indicated by the height of the rectangles in the diagram. Briefly, an ancestral population size of $\sim 170,000$ individuals contracted to $\sim 46,000$ individuals around 2.1 mya, grew to a population size of nearly 2,000,000 individuals within the past 1 mya, and contracted to $\sim 12,500$ individuals within the past 20,000 years.

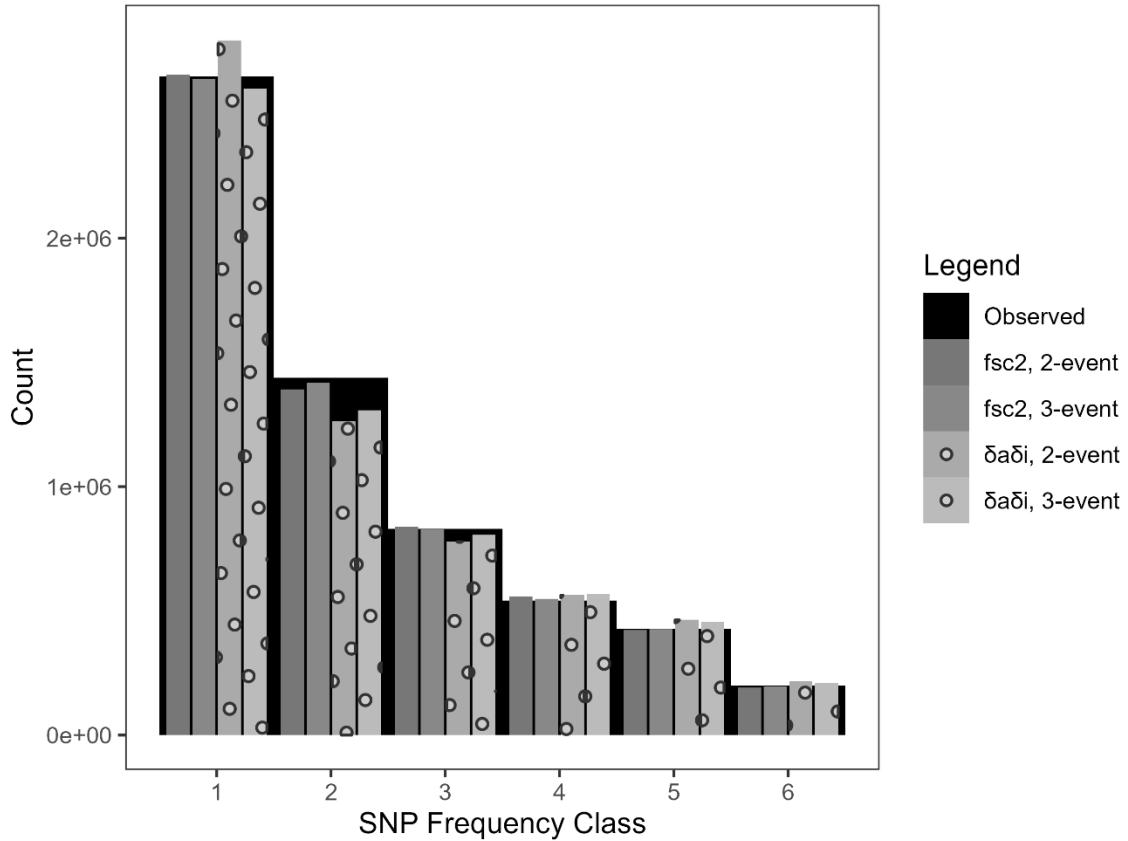


Figure 3: Mean simulated SFS for the two best fastsimcoal2 models (2-event and 3-event shown in solid gray bars, foreground) and two best $\delta\alpha\delta i$ models (shown in dotted gray bars, foreground) compared to the empirically observed SFS (black bar, background). SFS were simulated using fastsimcoal2 under the best parameters for each model. Diagrams of these models can be found in Figure 2 (fsc2, 3-event), Supplementary Figure 1 (fsc2, 2-event), and Supplementary Figure 3 ($\delta\alpha\delta i$, 2-event and $\delta\alpha\delta i$, 3-event). Mean simulated SFS for the 0-, 1-, and 4-event models parameterized by fastsimcoal2 can be found in Supplementary Figure 5.

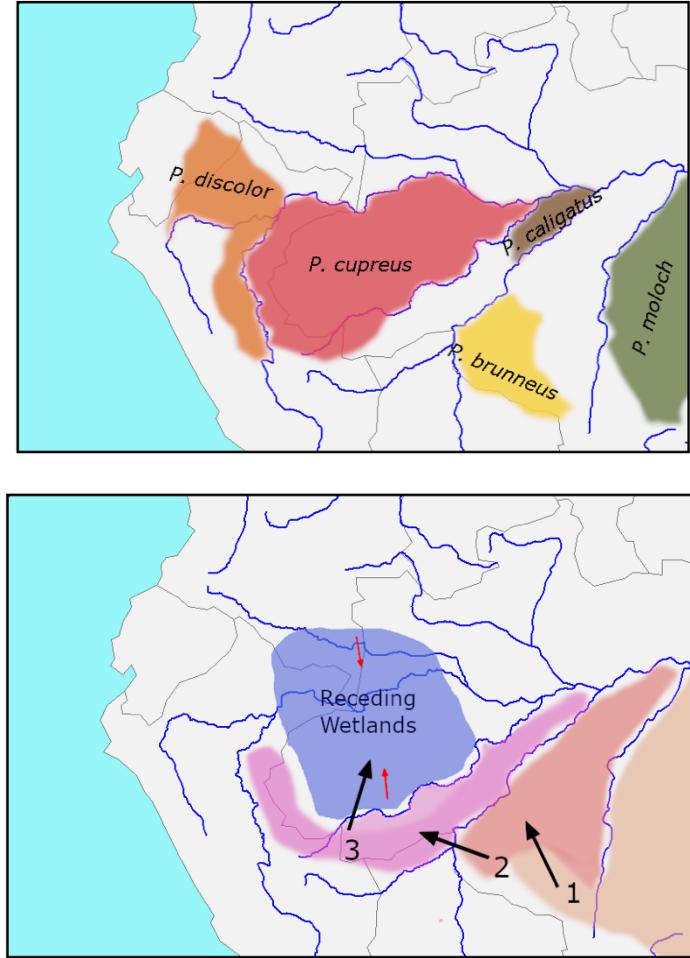


Figure 4: The biogeography underlying the modern and historical *P. cupreus* ranges. **Top panel:** Approximate current ranges of *P. moloch* and four species in the Western *moloch* group (*P. brunneus*, *P. caligatus*, *P. cupreus*, and *P. discolor*) based on data from the IUCN Red List (2025). Note that this is not an exhaustive depiction of all extant *Plecturocebus* species. **Bottom panel:** Diagram of the biogeographic model of speciation proposed by Byrne et al. (2018) for the Western *moloch* group. During the Pliocene, the final remnants of the mega-wetlands remaining from the Miocene Pebas and Acre systems (Hoorn et al. 2010) were receding and transitioning to *terra firme* rainforests (indicated in the diagram by the small red arrows in the "receding wetlands"), a process nearly finished by the early Pleistocene ~2.5 mya. Accompanying this was migration into the new rainforest ecosystems by the common ancestors of the *moloch* group, (1) first expanding North and West leading to the split in the clade containing *P. miltoni* and *P. hoffmanni* ~2.24 mya. Following this, further expansion (2) led to the divergence between the Eastern and Western *moloch* groups ~1.8-2.0 mya. Finally, as the ancestors of the Western *moloch* group reached the newest expansions of rainforest into the former mega-wetlands, (3) divergence between the members of the Western *moloch* group began ~1.8 mya. Note that the rivers depicted are their current locations and not necessarily related to the ancient waterways that were present throughout this timespan.