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12	ecological gradient
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34 Abstract

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Janzen's influential "mountain passes are higher in the tropics" hypothesis predicts restricted gene flow and genetic isolation among populations spanning elevational gradients in the tropics. Few studies have tested this prediction, and studies that focus on population genetic structure in Southeast Asia are particularly underrepresented in the literature. Here, we test the hypothesis that mountain treeshrews (Tupaia montana) exhibit limited dispersal across their broad elevational range which spans ca. 2300 meters on two peaks in Kinabalu National Park (KNP) in Borneo: Mt. Tambuyukon (MT) and Mt. Kinabalu (MK). We sampled 83 individuals across elevations on both peaks and performed population genomics analyses on mitogenomes and SNPs from 4,106 ultraconserved element loci. We detected weak genetic structure and infer gene flow both across elevations and between peaks. We found higher genetic differentiation on MT than MK despite its lower elevation and associated environmental variation. This implies that, contrary to our hypothesis, genetic structure in this system is not primarily shaped by elevation. We propose that this pattern may instead be the result of historical processes and limited upslope gene flow on MT. Importantly, our results serve as a foundational estimate of genetic diversity and population structure from which to track potential future effects of climate change on mountain treeshrews in KNP, an important conservation stronghold for the mountain treeshrew and other montane species.

Keywords: elevational range, mountain treeshrews, conservation genetics, population genomics,

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ultraconserved elements, mitogenomes

Introduction

Tropical ecosystems are global hotspots of biodiversity and endemism. To explain the higher diversity in lower latitude regions, Janzen (1967) proposed that the greater temporal thermal stability and spatial environmental heterogeneity on tropical mountains should select for narrow thermal tolerances which in turn reduce effective dispersal and increase population isolation across elevational gradients (Ghalambor, Huey, Martin, Tewksbury, & Wang, 2006; Gill et al., 2016). Numerous studies support the first prediction of the hypothesis that species in the tropics have narrower elevational ranges than those in the temperate zone (Ghalambor et al., 2006; McCain, 2009). Fewer studies have tested the second prediction that restricted gene flow among populations spanning elevational gradients results in genetic divergence (Ghalambor et al., 2006). Available data regarding this prediction are contradictory: some studies have found significant population genetic divergence across elevations, for example, in insects (Gueuning et al., 2017; Polato et al., 2018) and in endotherms including birds (Bertrand et al., 2014; DuBay & Witt, 2014; Gadek et al., 2018; Linck, Freeman, & Dumbacher, 2019) and mammals (Feijó et al., 2019). Others detected high rates of gene flow alongside adaptive phenotypic divergence (Branch, Jahner, Kozlovsky, Parchman, & Pravosudov, 2017; Cheviron & Brumfield, 2009).

Few studies have investigated the spatial population genetic structure of small mammals across elevational gradients in tropical montane ecosystems (Muenchow, Dieker, Kluge, Kessler, & von Wehrden, 2018). Thus, the influence of elevational gradients on gene flow in terrestrial endotherms at small spatial scales is not well understood. Studying spatial population genetic structure in the montane tropics is important not only because it allows for hypothesis testing regarding the effects of elevational gradients on genetic structure, but also because it enables researchers to identify distinct evolutionary units warranting protection and to establish benchmarks from which to monitor responses to changing global environmental conditions (Camacho-Sanchez et al. 2018; Castillo Vardaro, Epps, Frable, & Ray, 2018; Moritz, 1994). This is critical given the vulnerability of tropical montane ecosystems to the impacts of global climate

change (GCC) (Feeley, Stroud, & Perez, 2017; Lenoir & Svenning, 2015).

Here, we investigate the genetic structure of the mountain treeshrew, *Tupaia montana*, across its full elevational range on two mountains in Kinabalu National Park (KNP), Sabah, Borneo: Mt. Kinabalu (MK) and Mt. Tambuyukon (MT) (Figure 1). The mountain treeshrew provides an interesting system in which to study the effect of environmental gradients on population structure because it has a broad elevational distribution compared to other small mammals in KNP (Camacho-Sanchez, Hawkins, Tuh Yit Yu, Maldonado, & Leonard, 2019; Nor, 2001). On MK, the species occurs from ca. 900 meters above sea level (masl) to at least 3200 masl, encompassing four vegetation zones; on MT it ranges from ca. 900 meters to the summit at 2,579 masl, including three vegetation zones (Kitayama, 1992). Given the temperature lapse rate in KNP at -0.55°C per 100 meters of elevation gain (Kitayama, 1992), mountain treeshrews experience a 12.65°C average range in temperature on MK, which is higher than the thermal neutral zone for most small mammals (Khaliq, Hof, Prinzinger, Böhning-Gaese, & Pfenninger, 2014). On MT, mountain treeshrews experience an 8.8°C temperature range (Camacho-Sanchez et al., 2018).

Mountain treeshrews exhibit facultative mutualism with pitcher plants in the genus *Nepenthes* – treeshrews consume the plants' carbohydrate-rich secretions and defecate into the pitchers, providing the plants supplementary nitrogen and phosphorous (Chin, Moran, & Clarke, 2010; Clarke et al., 2009). Although mountain treeshrews provide critical nutrients to the plant, the importance of the plant to treeshrews is unknown. The range of mountain treeshrews exceeds that of the plants - none of the plants are distributed below 1200 masl or above 2650 masl. As such, treeshrews are not reliant on them for nutrients even in high elevations areas without fruiting trees.

We test the hypothesis that, consistent with Janzen's (1967) hypothesis, restricted gene flow across the steep ecological gradient that mountain treeshrews inhabit has resulted in significant genetic differentiation. Although the ecology of mountain treeshrews is poorly understood, our hypothesis is informed by observations of small home ranges (Emmons, 2000; Payne, Francis, & Phillipps, 2016) and phenotypic changes associated with elevational changes (Hinckley et al., in review). We predict that mountain treeshrews will exhibit significant differentiation in neutral genetic markers 1) between mountains, due to limited dispersal across

the lowland habitat that connects them, and 2) across elevations – with greater differentiation on MK due to its higher elevation and associated environmental variability.

To test our predictions, we analyze both mitochondrial genomes (mitogenomes) and nuclear ultraconserved element (UCE)-associated single nucleotide polymorphism (SNP) markers from mountain treeshrews collected across their full elevational range in KNP in a population genetics framework. Previous studies have shown that UCEs are sufficiently variable to resolve shallow phylogenies on a phylogeographic scale, (Faircloth et al., 2012; Harvey, Smith, Glenn, Faircloth, & Brumfield, 2016; Mason, Olvera-Vital, Lovette, & Navarro-Sigüenza, 2018; Smith, Harvey, Faircloth, Glenn, & Brumfield, 2014) including intraspecific phylogenies (Giarla et al., 2018), and to answer questions regarding recently diverged species (Oswald et al., 2016; Winker, Glenn, & Faircloth, 2018). However, ours is one of the first studies to describe the intraspecific variability of SNPs derived from UCE loci at a fine spatial scale.

Materials and methods

Sample collection

We trapped small mammals on both MK and MT within KNP (6°09′N 116°39′E) during two field seasons in 2012 and 2013. At 4,095 meters above sea level (masl), MK is the tallest mountain in the Sundaland biogeographic region. It is relatively young, having reached its present height ca. 1 million years ago (Mya) (Hall et al., 2009). Eighteen kilometers to the north of MK, the less-studied MT stands at 2,579 masl (Figure 1a). MT is older - its major uplift occurred as part of a different geological process, as part of the Crocker Range, 7–11 Mya (Hall et al., 2009).

Our trapping methodology and permitting information is described in Camacho-Sanchez et al. (2019). Briefly, we set traps from ca. 503 to 3,466 masl on MK and ca. 331 to 2,509 masl on MT and (Figure 1a). The mountain treeshrew was the most frequently caught species, representing 37.5% of all catches. For this study, we included 92 *Tupaia* individuals: 84 mountain treeshrews and eight outgroup individuals from three congeners, the pygmy treeshrew

147	(<i>T. minor</i> , $n = 2$), the large treeshrew (<i>T. tana</i> , $n = 5$), and the ruddy treeshrew (<i>T. splendidula</i> , $n = 1$)
148	= 1), the sister species of the mountain treeshrew (Roberts, Lanier, Sargis, & Olson, 2011; Table
149	S1).
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151	Laboratory methods
152	Laboratory work was performed at the Center for Conservation Genomics (CCG),
153	Smithsonian Conservation Biology Institute, Washington, DC. We extracted DNA from liver and
154	ear punch samples using a DNeasy Blood and Tissue Kit (Qiagen, Valencia CA) following the
155	manufacturer's protocol. We amplified whole mitogenomes in two fragments using long range
156	PCR, fragmented the PCR products to an average length of 500 base pairs (bps) using a Qsonica
157	Q800R sonicator (QSonica, Newtown, CT, USA), and prepared single-indexed DNA libraries
158	for sequencing using a Kapa LTP Library Preparation kit (Kapa Biosystems, Wilmington, MA)
159	following Hawkins et al. (2016). We pooled libraries equimolarly and sequenced on an Illumina
160	MiSeq with 2 × 100 base pair (bp) reads (Illumina, Inc., San Diego, CA).
161	We used in-solution DNA hybridization to enrich genomic DNA for UCEs following
162	Hawkins et al. (2016). We sheared DNA extracts and constructed indexed libraries as above. We
163	quantified libraries using a Qubit® fluorometer (Life Technologies) with a 1× dsDNA HS assay
164	kit and multiplexed 4-8 samples equimolarly prior to enrichment. We used a NimbleGen SeqCap
165	EZ® kit (Roche, Basel, Switzerland) containing 54,689 unique 60-bp DNA probes representing
166	5,561 vertebrate UCE loci with an average of 4× tiling per base per locus to enrich multiplexed
167	libraries following the manufacturer's protocol. Post-enrichment libraries were amplified with
168	12-14 cycles of PCR using Kapa HiFi HotStart DNA polymerase (Kapa Biosystems,
169	Wilmington, MA) following the manufacturer's protocol.
170	Following visualization on a Bioanalyzer 2100 (Agilent Technologies, Santa Clara, CA)
171	with High Sensitivity DNA kits, enriched libraries were quantified via qPCR using the Kapa
172	Biosystems Illumina Library Quantification Kit (Kapa Biosystems, Wilmington, MA). Samples
173	were pooled equimolarly and sequenced with 2×150 bp reads on Illumina HiSeq2000 (Semel
174	Institute of Neurosciences, UCLA, & University of Copenhagen, Denmark) and MiSeq® (CCG)
175	platforms.

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Mitogenome assembly and alignment

We analyzed mitogenomes to investigate the population structure and genetic diversity of mountain treeshrews. Because mitogenomes are inherited matrilineally and are not subject to recombination, they are frequently used to investigate population structure, colonization history, and species' demographic histories (Harrison, 1989).

Mitogenome amplicon reads were quality filtered with Trimmomatic v0.33 (Bolger, Lohse, & Usadel 2014) with parameters SLIDINGWINDOW: 4:15 and MINLEN: 36. Since the only publicly available mitogenome representing any *Tupaia* species (the northern treeshrew, *T.* belangeri NC 002521; Schmitz, Ohme, & Zischler, 2000) is highly divergent from our study species (Roberts et al., 2011), we first generated reference mitogenomes for the mountain treeshrew and 3 more closely related outgroup species: the pygmy treeshrew, large treeshrew, and ruddy treeshrew. For each species, we selected one individual with the highest number of sequencing reads (pygmy treeshrew, BOR 443; large treeeshrew, BOR 010, & ruddy treeshrew, UMMZ174429) and assembled sequences de novo with the MIRA v1.0.1 plugin in Geneious v9.1.2 (Biomatters Ltd.), using 'Quality Level Accurate' and default settings. Quality filtered sequence reads were mapped to the appropriate reference using BWA-MEM v0.7.10 (Li 2013) with default parameters. We also assembled mitogenomes from UCE-enriched library sequences (Supplemental Information). Consensus sequences were generated with Geneious (lowest coverage to call a base 5× and Highest Total Quality parameters) and aligned with the MAFFT v7.450 plugin (Katoh, Misawa, Kuma, & Miyata. 2002). We transferred annotations from the northern treeshrew reference to the consensus sequences. To rule out the presence of nuclear copies of mitochondrial genes (NUMTs), we translated all protein-coding genes to check for frame shifts or stop codons.

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Genetic diversity and population structure

Because the inclusion of close relatives can bias estimates of genetic diversity and structure (Goldberg & Waits, 2010), we removed first-order relatives identified by our SNP dataset and performed all subsequent mitogenome analyses with the reduced data (hereafter "unrelated dataset"). We defined haplotypes and calculated haplotype diversity (H_d), nucleotide

diversity (π), and Tajima's D using DNAsp v6.12.03 (Librado & Rozas 2009). We estimated the differentiation between MK and MT and between high and low elevations within each peak through analysis of molecular variance (AMOVA) in Arlequin v3.5 (Excoffier & Lischer, 2010) with a permutation test of 10,000 replicates to assess statistical significance. We visualized relationships among haplotypes by generating a median-joining network with PopART v1.7 (Leigh & Bryant, 2015).

Phylogenetic analysis and modeling demographic history

We performed phylogenetic analyses to place the mitochondrial lineages detected in our mountain treeshrew samples within an evolutionary framework with respect to other Bornean treeshrew species in the *Tupaia* clade (i.e. the large treeshrew, pygmy treeshrew, and ruddy treeshrew), and to confirm the monophyly of the mountain treeshrew within the group. We used PartitionFinder v2.0 (Lanfear, Calcott, Ho, & Guindon, 2012) to select partitions and substitution models and estimated a phylogeny using MrBayes v3.2.6 (Ronquist & Huelsenbeck, 2003). We then used BEAST v.1.8.4 (Drummond & Rambaut, 2007) to estimate the timing of divergence between the mountain treeshrew mitochondrial lineages we identified.

To infer demographic history, we performed a Bayesian coalescent skyline plot analysis using BEAST v2.0 (Bouckaert et al., 2014). We used a time to most recent common ancestor (TMRCA) prior of 450,000 years before present (lognormal distribution, $\mu = 0.45$, $\sigma = 0.2$), the estimated date of divergence between the two mitochondrial lineages as determined by the dating analysis performed in BEAST (Supplemental Information).

Genotyping UCE-associated SNPs

To generate the SNP dataset, we followed the PHYLUCE v.1.5.0 pipeline with default parameters (Faircloth, 2016) for sequence trimming, *de novo* assembly of contigs, identification of UCE loci, and sequence alignment. We generated a pseudo-genomic reference by aligning each locus with MAFFT v7.407 and trimming using Gblocks v0.91b with default parameters (Castresana, 2000). We then used Geneious to generate a consensus sequence for each locus, replacing ambiguity codes with an appropriate nucleotide at random. We used Picard v1.106 (http://broadinstitute.github.io/picard/), and SAMtools v1.9 (Li et al., 2009) to create sequence

237	automate alignment of trimmed reads from each sample to the reference with BWA-MEM
238	v0.7.17, and then called SNPs with the HaplotypeCaller tool of the Genome Analysis Toolkit
239	v3.7 (McKenna et al., 2010) following Giarla and Esselstyn (2015). Using VCFtools v0.1.16
240	(Danecek et al., 2011), we removed SNPs that failed to pass GATK quality filters (QD < 2.0 \parallel
241	$FS > 60.0 \parallel MQ \leq 40.0 \parallel HaplotypeScore > 13.0 \parallel MappingQualityRankSum \leq -12.5 \parallel MappingQuali$
242	ReadPosRankSum < -8.0), and selected SNPs with a minimum depth of coverage of 8 per
243	individual and a minor allele frequency \geq 5%. We used $HD_plot.py$ (McKinney, Waples, Seeb,
244	& Seeb, 2017) to filter SNPs resulting from putative paralogs or wrongly assembled contigs from
245	the dataset by removing SNPs with heterozygosity > 0.75 and a read-ratio deviation score D > 10 .
246	The D statistic is a measure of deviation from the expected allelic read ratio of 1:1 when reads
247	are summed over all heterozygous individuals. This method more accurately identifies true SNP
248	loci than methods relying on read depth or heterozygote excess alone (McKinney et al., 2017).
249	After filtering with HD_plot.py, we further filtered SNPs that that were out of Hardy-Weinberg
250	Equilibrium (HWE) after Bonferroni correction for multiple comparisons ($p < 10^{-5}$) using
251	VCFtools v0.1.16 because strong deviations from HWE are usually indicative of genotyping
252	error (Chen, Cole, & Grong-Ginsbach, 2017). To generate a set of unlinked SNPs, we selected
253	one SNP per UCE using VCFtools v0.1.16 '-thin 2000'. We used the unlinked SNP dataset with
254	10% missing data for all SNP-based analyses except calculation of genetic diversity and
255	effective population size, Principal Components Analysis (PCA), Discriminant Analysis of
256	Principal Components (DAPC) and Bayesian cluster analysis with STRUCTURE v2.3.4
257	(Pritchard, Stephens, & Donnelly, 2000), for which we used a dataset with no missing data.
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259	Generating phased pseudo-haplotype sequences
260	In order to include multiple SNPs per UCE locus as well as invariant sites for the
261	MIGRATE-N analysis, we generated multiple sequence alignments of pseudo-haplotypes. We
262	did this by using the EMIT_ALL_SITES output mode of the GATK HaplotypeCaller tool. We
263	filtered the resulting VCF file to include only UCE loci with at least one SNP with no more than
264	10% missing data. We then generated alignments from the VCF file with a custom Ruby script,
265	vcf2aln v0.4.2 (https://github.com/campanam/vcf2aln, Supplemental Information). This script

dictionaries and reference indices from the reference. We used the PHYLUCE script snps.py to

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utilizes phasing information where present and randomly selects an allele where phase is unresolved.

We trimmed the phased UCE sequence alignments with Gblocks v.0.91b (Castresana, 2000) using default parameters and quantified informative sites with the phyluce align get informative sites.py PHYLUCE script. For the final dataset used in the MIGRATE-N analysis, we retained only loci with at least one and fewer than 10 parsimony informative sites (PIS) in order to increase the signal-to-noise ratio of our dataset. MIGRATE-N calculates model and parameter likelihoods for each locus independently and averages results across loci taking into account the posterior distributions of each (Beerli & Palczewski, 2010). Uninformative loci with flat posterior distributions contribute less to the final average; therefore, removing invariant loci should not bias our results, while including them increases computation time. We removed loci with more than 10 PIS, i.e. more than ca. two standard deviations above the mean (x = 3.6, SD = 4) because their diversity is likely artificially high due to errors introduced during de novo assembly or sequence alignment (Gilbert, Wu, Simon, Sinsheimer, & Alfaro, 2018). Gilbert et al. (2018) showed that filtering sites on the basis of signal-to-noise in a concatenated UCE alignment improved the resolution of hard-to-resolve nodes in the Neoaves phylogeny, and that after filtration, the topology converged on that derived from a much larger dataset.

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Genetic diversity and effective population size

We removed individuals that were identified as first-degree relatives (parent-offspring or full siblings) according to the KING v2.1.4 software (Manichaikul et al., 2010), i.e. those with kinship coefficients ≥ 0.18 . Using the unlinked SNPs with 10% missing data, we first calculated pairwise kinship values and identified putative family groups with the KING software and then ran a PC-AiR analysis with GENESIS v2.2.2 (Conomos, Reiner, Weir & Thornton, 2016) in R v3.6.3 (R Core Team 2019, applies to all subsequent use of R) to identify an "unrelated" subset of individuals. We used GenAlEx v6.503 to estimate the statistical power of the SNP dataset to differentiate individuals by calculating P_{IDsib} , the probability of two individuals having identical genotypes assuming siblings are present in the data (Waits, Luikart, & Taberlet, 2001).

We calculated average expected and observed heterozygosity (H_e and H_o) and the

inbreeding coefficient (F_{IS}) with VCFtools v0.1.16 using our SNPs with no missing data. We also concatenated FASTA alignments of UCE sequence pseudo-haplotypes for all individuals in the unrelated dataset and used the maximum composite likelihood method to calculate nucleotide diversity (π) in MEGA v7.0.26 (Kumar, Stecher, & Tamura, 2016).

We estimated effective population sizes (N_e) using the linkage disequilibrium model with random mating (Waples & Do, 2008) implemented in NeEstimator v2.1 (Do et al., 2014). We report estimated N_e values using 'Lowest Allele Frequency Used' 5% and 95% confidence intervals generated by the 'Parametric method' for unrelated individuals for each population cluster identified by STRUCTURE separately.

Population structure

We characterized population genetic structure using the SNP dataset with no missing data. We performed PCA and DAPC with the Adegenet v2.1.1 package (Jombart, 2008) in R. For the DAPC analysis, we first conducted *K*-means clustering and selected the number of clusters based on the lowest Bayesian Information Criterion (BIC) value. We performed cross-validation to determine the number of PCs to retain by calculating the lowest root mean squared error. We then ran DAPC, retaining 20 PCs and 2 discriminant functions.

We used STRUCTURE v2.3.4 to infer the number of population clusters (K) and the proportion of individual membership assigned to each cluster (q_k). We used a burn-in of 500,000 steps followed by 1,000,000 recorded steps, tracking the probability of the data given K (LnP(D)) to ensure that we ran the program long enough for the values to stabilize. We used the admixture model, no location priors, and assumed correlated allele frequencies (Falush, Stephens, & Pritchard, 2003). We performed a simulation with K from 1 to 7 with 10 replicates each and identified meaningful K values using the ΔK method (Evanno, Regnaut, & Goutdet, 2005) implemented in STRUCTURE HARVESTER v0.6.94 (Earl & vonHoldt, 2012). We combined replicate runs using CLUMPP v1.1.2 (Jakobsson & Rosenberg, 2007).

To quantify the levels of differentiation between population clusters identified by STRUCTURE, we performed an AMOVA and calculated pairwise $F_{\rm ST}$ values using the SNP dataset with 10% missing data in GenAlEx v6.5 (Peakall & Smouse, 2012), with 10,000 permutations to generate the null distribution. To investigate local spatial genetic structure, we

performed a Mantel test using ade4 v1.7 (Dray & Dufour, 2007) in R on both the full and unrelated dataset. We tested for a correlation between pairwise genotypic distance and Euclidean geographic distance with 9,999 permutations to generate the null distribution. We also generated a Mantel correlogram to test for spatial autocorrelation between pairs of treeshrews at different distance classes using GenAlEx. We first calculated pairwise linear geographic and genotypic distances, and then used the 'Spatial' option with 9,999 permutations. We defined 7 distance classes (0.2, 1.0, 2.0, 5.0, 10.0, 15.0, and 18.0 km) based on Sturges's Rule (Sturges, 1926), chosen to ensure sufficient comparisons within each class. Finally, we calculated the average, median, and maximum geographic distances between pairs of individuals in each kinship class corresponding to first, second, third-order, and distant relatives (Table 1) as an additional way to quantify the decay of genetic relatedness with distance. To test for significant differences between the means in each kinship class, we performed a one-way ANOVA in R with a Tukey Honest Significant Differences test and a Bonferroni correction for multiple comparisons (Combs, Puckett, Richardson, Mims, & Munshi-South, 2018).

Migration and population models

We used the program MIGRATE-N v3.6 with its Bayesian implementation (Beerli, 2005) to compare support for six different models of population structure and migration (diagrams of hypotheses in Figure 2). We used the phased pseudo-haplotype sequence dataset for this analysis to take advantage of the higher information content in DNA sequences relative to SNPs. Although our workflow may generate chimeric sequences in instances where phase is unresolved, we do not expect that this would affect model selection (Andermann et al., 2018; P. Beerli *pers. comm.*). However, to ensure that phase did not affect model inference, we ran the MIGRATE-N analysis twice with different configurations of variants within haplotypes while maintaining all other settings.

We compared models to test our *a priori* hypotheses of significant genetic structure and limited gene flow between MK and MT and between high and low elevations. We also included models of population structure based on the STRUCTURE results in order to compare migration rates and directionality between population clusters. The models included the following: 1) panmixia, 2) four populations (high elevation MK, low elevation MK, low elevation MT and

high elevation MT) with bidirectional migration between adjacent pairs, 3) three populations (high elevation MT, low elevation MT and all of MK) with bidirectional migration between adjacent pairs, 4) three populations with migration between all pairs, 5) two populations (high elevation MT separate from all others) with bidirectional migration, and 6) two populations with unidirectional migration from high elevation MT (Figure 2).

For model 2, we assigned individuals to populations based on their sampling location: low elevation individuals < 2000 masl, and high elevation \geq 2000 masl. For models 3, 4, 5, and 6, we assigned individuals based on STRUCTURE output for K=3 and K=2, respectively. We randomly selected five individuals from each population cluster (n=10 haplotypes). We did not include all individuals because for coalescent processes, increasing the sample size above this does not necessarily improve accuracy, but substantially increases computation time (Felsenstein, 2005). For each model, we ran two long chains of 20,000,000 steps, sampled every 100 steps with 50,000 steps per chain discarded as burn-in, and with four heated chains. To ensure comparability across models, we ran the most complex model first and used the same prior distributions and run parameters for all subsequent models. We assessed chain mixing through acceptance ratios and ESS of parameters and genealogies (ESS \geq 40 million). We calculated log Bayes factors (LBF) and model probability using the Bezier approximation of the marginal model likelihood and the formula described in (Beerli & Palczewski, 2010).

Results

DNA Sequencing

We obtained mitochondrial genome sequences from 83 mountain treeshrew individuals (MT423905–MT423940) and 8 sequences from three congeners (MT442045–MT442052): the large treeshrew (n = 5), the small treeshrew (n = 2), and the ruddy treeshrew (n = 1).

Mitogenomes were sequenced to an average depth of $50\times$.

We sequenced UCEs from 80 mountain treeshrews (SRA accession PRJNA629376).

Each UCE-enriched library was sequenced with a mean of 2.3 million reads (914,104–

383 7,011,836), yielding a mean of 3,344 UCE loci (2,137–3,489) per sample. The total number of

UCE alignments that we used to generate the pseudo-reference was 4,106, and the mean length

was 495 bps (149-2167 bps). After aligning reads to the pseudo-reference and quality filtering,

there were 7,861 SNPs including multiple SNPs per locus. After removing loci with more than 10% missing data across individuals, 3,168 SNPs remained. The unlinked SNP dataset included 1,794 independent SNPs. Removing loci with missing data left 684 unlinked loci. In the phased pseudo-haplotype sequence alignment dataset used for the MIGRATE-N analysis, 1,664 UCE alignments remained after removing loci with less than one (114 loci) and more than 10 PIS (16 loci) (Figure S1).

Mitogenomes: genetic diversity, population structure, and demographic inference

There were 36 unique mitochondrial haplotypes in the dataset that included close relatives (n = 83), and 34 among the 58 unrelated individuals. All subsequent analyses were performed with the unrelated dataset. H_d was high, at 0.977 (SD 0.008), and π was 0.00583 (SD 0.0006). Phylogenetic analyses show that mountain treeshrews are a monophyletic group with two deeply divergent lineages, each present on both mountains (Figure S2, partitions and substitution models in Table S2). Outgroup relationships were consistent with the phylogenetic hypothesis presented in Roberts et al. (2011). The average number of nucleotide substitutions per site between the two lineages is 0.013. The BEAST dating analysis suggests that the two mitochondrial lineages diverged ca. 450,000 ybp (95% Highest Posterior Density, HPD, 346,000–631,900 ybp, Figure S3).

The median joining haplotype network (Figure 3) shows that the two mountain treeshrew haplogroups are present on both MT and MK. Three haplotypes are found on both mountains (Table S3). Including related individuals, haplogroups 1 and 2 are found in near equal proportion on MK and MT (16 and 14 individuals, respectively), while haplogroup 1 is more frequent on MT (46 out of 53 individuals) (Figure 4). The AMOVA on the unrelated dataset showed significant differentiation between the two mountains ($F_{\rm ST}=0.133$, p=0.00812), with 13.3% of variance accounted for by differences between mountains and 86.7% within mountains. To test our prediction of significant differentiation across elevations, we then divided the population into high (≥ 2000 masl) and low (< 2000 masl) elevation groups on each peak. The results showed that 90.42% of the total variance is accounted for by within-group variation, and 9.58% among ($F_{\rm ST}=0.096$, p=0.027). Pairwise comparisons showed significant differences between high elevation MK and low elevation MT ($F_{\rm ST}=0.15$, p=0.023) and high elevation MK and high

416 elevation MT ($F_{ST} = 0.18$, p = 0.013); all other comparisons were not significant. 417 We performed Tajima's D test on an alignment including all unrelated individuals (n =418 57) and separately on alignments with individuals from each haplogroup (haplogroup 1, n = 43; haplogroup 2, n = 14) and each mountain (MK, n = 25; MT, n = 32) because unaccounted for 419 420 population structure can bias results even with high rates of migration among locations (Städler, 421 Haubold, Merino, Stephan, & Pfaffehuber, 2009). In all cases the test was not significant, 422 indicating a lack of evidence for recent population contraction, expansion, or selection. 423 Similarly, in the Bayesian skyline plot analysis, 95% HPD of the population change parameter 424 included zero; therefore, we cannot reject the hypothesis of zero demographic changes in the last 60,000 years. 425 426 427 *UCE loci:* genetic diversity 428 Pairwise kinship calculations revealed several groups of putatively related individuals. 429 After removing first-order relatives (n = 22 with kinship ≥ 0.18) from the dataset, 58 individuals 430 remained, including 33 from MT and 25 from MK. The nucleotide diversity of the filtered UCE 431 pseudo-haplotype alignment used in the MIGRATE-N analysis (1,664 concatenated UCE 432 alignments) for all 58 unrelated mountain treeshrews was 0.0017 (SE 0.000022). The nucleotide 433 diversity of the unfiltered alignment, including invariant loci and those with > 10 PIS (3,935) 434 UCE alignments) was 0.0015 (SE 0.000016). Using the SNP dataset with no missing data, 435 average individual heterozygosity for all 80 individuals was 0.23 (SD 0.027), and the average 436 inbreeding coefficient ($F_{\rm IS}$) was 0.012 (SD 0.12). For the 58 unrelated individuals, average 437 heterozygosity was 0.23 (SD 0.027), and F_{IS} was 0.019 (SD 0.12). Bartlett's test revealed that 438 the variances in observed and expected heterozygosity were not significantly different ($K^2 =$ 439 1.68, p = 0.2). Average $F_{\rm IS}$ was higher on MK than MT, but the difference was not significant 440 (0.04 and 0.01 respectively, Welch two-sample t-test p = 0.2). Using the dataset with 10% 441 missing data, the probability of two individuals having identical genotypes assuming siblings are present (P_{IDsib}) was 1.54×10^{-199} . 442 443 444 Population Structure 445 Both DAPC and STRUCTURE indicated that the most likely number of population

clusters was two and the second most likely was three, as determined by BIC and the ΔK method, respectively. The ΔK method is biased toward K = 2 (Janes et al., 2017; Campana, Hunt, Jones, & White, 2011) and simulation studies have shown that the mean probability (MeanLnP(K)) output from STRUCTURE performs better in scenarios with high gene flow and low F_{ST} (Latch, Dharmarajan, Glaubitz, & Rhodes, 2006). Because K = 3 produced the highest MeanLnP(K) in STRUCTURE (Table S4a), we consider this a relevant model and show the proportion of individual membership in each cluster as defined by each of the two analyses for both K = 2 and K = 3 (Figure 5). Results with higher K values are shown in Figure S4. We also ran STRUCTURE separately for individuals caught on MK and MT, with settings described above except we ran simulations for K = 1-5. We found no evidence of structure among MK individuals; MT individuals were divided into two clusters - one with individuals ≥ 2000 masl and one with individuals < 2000 masl, with individuals of mixed ancestry at 2000 masl (Tables S4b & S4c).

Cluster membership is mostly concordant between DAPC and STRUCTURE, except STRUCTURE assigned mixed ancestry to many individuals while DAPC did not. This is not unexpected as previous studies have shown that DAPC may underestimate admixture (Frosch et al., 2014) while STRUCTURE is more accurate at assigning mixed ancestry (Bohling, Adams & Waits, 2012). When K = 2, individuals at 2000 and 2400 masl on MT form a separate cluster from low elevation MT + MK (Figures 4 & 5), with mixed ancestry individuals at 2000 masl MT. This shows that the most prominent population subdivision does not separate the two mountains or high and low elevations on MK as we predicted; rather, high elevation MT is distinct. For K = 3, the divisions are between high elevation MT, low elevation MT, and MK, with individuals at Poring Hot Spring on the eastern slope of MK (900 masl) and 2000 masl MT assigned mixed ancestry (Figure 5). This suggests that no significant substructure exists among MK individuals despite the greater elevational range on this mountain, and that gene flow occurs between MK and MT.

The PCA shows a similar pattern. PC1 (7% variation explained) separates the two mountains, with overlap among individuals at 900 masl. PC2 (4% variation explained) partially separates individuals by elevation, with lower elevation individuals at the midline and right of center, and high elevation individuals on the left (Figure 6). The "horseshoe" shape of the plot is

typical in isolation-by-distance (IBD) scenarios where genetic similarity decays with geographical distance (Novembre & Stephens, 2008). Because of the spatial pattern evident in our PCA, we ran a spatial PCA analysis (sPCA, Jombart, 2008), which explicitly incorporates spatial autocorrelation between samples and allows for the visualization of genetic structure in space. The results showed the greatest differentiation between high elevation MT and MK, with weaker, intermediate differentiation separating individuals at low elevation MT and Poring Hot Springs (Figure S5).

With K=2, after removing individuals that could not be assigned to a STRUCTURE cluster (cutoff q_k value < 0.6), $F_{\rm ST}$ is 0.05 (p=0.0001). The AMOVA showed that most variation (95%) is partitioned within clusters and only 5% between them. With K=3, removing individuals with q_k values < 0.6, $F_{\rm ST}$ between MK and low elevation MT was 0.035 (p=0.001), between MK and high elevation MT 0.092 (p=0.0001), and between low elevation MT and high elevation MT $F_{\rm ST}=0.065$ (p=0.0005) (Tables 2a & 2b). The AMOVA showed that 94% of variation is distributed within clusters, and 6% among them.

Including data for all 80 individuals, the Mantel test revealed a significant, positive correlation between genotypic distance and geographic distance (r=0.287, p=0.0001). Including only the 58 unrelated individuals, the correlation was weaker but statistically significant (r=0.05, p<0.0001). The correlogram showed significant positive autocorrelation between individuals at distances of 200 m and less $(r=0.091, p\ r\text{-rand} \ge p\ r\text{-data} = 0.0001)$ and between 200 m and 1 km $(r=0.036, p\ r\text{-rand} \ge p\ r\text{-data} = 0.0001)$; autocorrelation was no longer significant at 2 km $(r=-0.001, p\ r\text{-rand} \ge p\ r\text{-data} = 0.598)$. At subsequent distance classes (5, 10, 15, and 18 km), individuals have greater genetic distance than expected at random $(p\ r\text{-rand} \le r\text{-data} = 0.009, 0.0001, 0.0001, 0.0001, respectively)$ (Figure S6). The average geographic distance between pairs of first-order relatives (e.g. parent-offspring or sibling pairs) was 162.5 m, second order (e.g. half siblings or grandparents-grand-offspring pairs) was 1.2 km, third order was 4.8 km, and between distant or 'unrelated' individuals was 12 km (Table 1); this suggests that in a single generation, individuals on average are unlikely to disperse beyond 162.5 m. Differences between first and third, first and distant, second and distant, and third and distant relatives were significant (p < 0.05).

Population and migration models

Model 4 (Figure 2) was the best fit model as determined by Bayes Factors in the MIGRATE-N analysis, followed by Model 5 (Table S5); this was consistent across both runs of the program with alternative phasing. Model 4 divided the population into three groups: high elevation MT, low elevation MT, and MK, with high rates of bidirectional migration between all pairs (Table S6). Model 5 divides the population into high elevation MT and low elevation MT + MK with bidirectional migration (Figure 2). Across models, the mean migration rate from high elevation MT to MK was greater than from MK to MT (1.3–19×, Table S6).

The results from NeEstimator suggest a larger effective population size on MT (< 2000 masl + ≥ 2000 masl) than MK despite less available habitat on MT (250 vs. 125 breeding founders, respectively; Table 2 and Supplemental Information).

Discussion

Levels of gene flow across elevations

Our results are not consistent with Janzen's hypothesis (Janzen, 1967), which predicts narrow elevational distribution and restricted gene flow across elevational gradients in tropical montane species (Ghalambor et al., 2006). We report evidence of high gene flow between MK and MT as well as between low and high elevations on both peaks, indicating that neither the lowland habitat connecting the two peaks, nor the steep elevational gradient across which mountain treeshrews occur on each peak, has significantly limited effective dispersal.

The KNP mountain treeshrew population is best described as comprising two or three clusters, but the primary subdivision does not correspond to the two peaks or separate high and low elevation MK as predicted. Rather, the summit region of MT was consistently recovered as distinct in both STRUCTURE and DAPC (Figure 5a). When dividing the population into three clusters, low elevation individuals at Poring Hot Springs on the eastern slope of MK show mixed ancestry with low elevation MT (Figure 5b). Additionally, the MIGRATE-N analysis supports the division of individuals into three population clusters (high elevation MT, low elevation MT, and MK), with high migration rates between all pairs (Figure 2, Table S6). If gene flow were restricted due to limited elevational dispersal or selection against cross-elevation migrants, we

would expect to find greater genetic differentiation on MK because of the broader elevational range and associated diversity of environmental factors on this slope compared to MT. However, the summit of MT was consistently recovered as the most distinct population cluster while individuals caught along the entire elevational gradient on MK form a single cluster (Figures 4 & 5). This suggests that elevation and covarying environmental conditions are not the primary variables influencing mountain treeshrew genetic structure in KNP.

The first prediction of Janzen's (1967) hypothesis, that topical montane species tend to have narrower elevational ranges than those in the temperate zone, has been shown to apply across taxonomic groups including endotherms like birds (Ghalambor et al., 2006) and bats (McCain, 2009). However, McCain (2009) found that in rodents there was either no relationship between elevational range and latitude or range size increased with decreasing latitude. This finding could be explained by the presence of cryptic species pairs or genetic differentiation separating low and high elevation populations. Supporting this hypothesis, some studies of small mammals in Southeast Asia have found strong, cryptic genetic differentiation across elevations, for example, in squirrels (den Tex, Thorington, Maldonado, & Leonard, 2010; Hinckley, Hawkins, Achmadi, Maldonado, & Leonard, 2020), shrews (Eldridge, Achmadi, Giarla, Rowe, & Esselstyn, 2018), and mice (Heaney et al., 2011; Justiniano et al., 2015). However, McCain (2009) hypothesized that rodents may cope with the lower temperatures associated with increasing altitude through behavioral adaptations. Our finding of high gene flow across a broad elevational extent in mountain treeshrews is not inconsistent with McCain's hypothesis. In addition, Hinckley et al. (in review) found that mountain treeshrews exhibit ecophenotypic changes associated with elevation, including significantly smaller ears and tails and denser hair at higher elevations; these patterns were consistent on both MT and MK. Hinckley et al. suggest that these phenotypic changes, in combination with behaviors including diurnal activity patterns and nesting, may allow the species to persist across broad environmental conditions which is rare among small mammals in this landscape (Camacho-Sanchez et al., 2019; Hinckley et al., in review; Nor, 2001). Further research is necessary to determine whether the phenotypic changes observed in mountain treeshrews in KNP are due to phenotypic plasticity, adaptive differentiation despite gene flow, or a combination of these factors.

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Population genetic structure shaped by IBD and historical dynamics

The population genetic pattern observed is partly consistent with IBD, as evidenced by 1) the small, but significant, positive correlation between pairwise geographic distance and genetic distance, 2) spatial autocorrelation between samples drops off at a distance of 2 km (Figure S6), and 3) pairwise $F_{\rm ST}$ between the non-adjacent MT summit and MK clusters is greater than the value between neighboring clusters (Table 2a). High gene flow rates between adjacent demes across the landscape, with relatively short dispersal distances as suggested by the correlogram (Figure S6) and ANOVA (Table 1), could have generated the clinal pattern we observe (Figure 5); however, this does not explain the distinctiveness of the summit MT cluster. The Euclidean distance between the lowest and highest sampled points on MK (ca. 13.5 km) is greater than the distance between the lowest and highest sampling points on MT (ca. 4.5 km), yet there is more population genetic differentiation on MT. This indicates that the structure we observe is not due to isolation-by-distance or isolation-by-elevation alone, and that genetic similarity decays with geographic distance at unequal rates in this landscape (Figure S7a).

Historical population dynamics likely contributed to the observed population genetic structure. Without data from other Bornean localities, it is difficult to determine what process(es) generated the pattern. However, we suggest a plausible scenario given known information about the relative ages of MT and MK and the degree of divergence between the mountain treeshrew and its sister species. MT reached its current elevation earlier (ca. 11–7 Mya) than MK (ca. 1 Mya) (Collenette, 1964; Hall, 1998; Liew, Schilthuizen, & bin Lakim, 2010). This suggests that MT was available for colonization prior to the split of mountain treeshrews from ruddy treeshrews ca. 4 Mya (Roberts et al., 2011). If mountain treeshrews were resident on MT prior to a second colonization event, this could explain the signature of two population clusters. We find higher-than-average genetic diversity among individuals at high elevation MT despite its smaller habitat area (Figures 1a & S7b), which is consistent with our hypothesis that this region maintained a relatively stable, or recently reduced, effective population size over time relative to MK. The lower rate of gene flow upslope to high elevation MT relative to gene flow towards MK that we observed in the MIGRATE-N analysis (Table S6) may have preserved the signature of this cluster. It is not clear what factors may be limiting upslope gene flow, but one hypothesis is that it is related to a significant shift in the plant community that occurs between 1450 masl

and the summit (van der Ent, Cardace, Tibbett, & Echevarria, 2018). Supporting this hypothesis, trapping success of mountain treeshrews and other small mammals is low from 1500 to 1800 masl, and increases above 2000 masl (Camacho-Sanchez et al., 2019). In addition, Hinckley et al. (in review) show differences in musculature related to mastication across elevations, and suggest that these differences may be due to changes in the plant community, i.e., there are fewer fruiting trees at high elevations and a larger portion of invertebrates like beetles in the mountain treeshrew diet.

By contrast, the lack of differentiation across MK could have been influenced by an upslope shift at the mountain treeshrew's upper elevational limit enabled by climate warming and upslope shifts in montane forest since the Last Glacial Maximum (LGM) (Cannon, Morley, & Bush, 2009; Hall et al., 2009). Upslope shifts in montane forest during this period of warming could have enabled range expansion at high elevations, in addition to range contraction at low elevations. Mountain treeshrews on MT likely did not experience a concurrent upslope range shift since MT has a much lower summit which, unlike the summit of MK, was never covered in ice (Hall et al., 2009). The lack of a population expansion signature in the mountain treeshrew mitogenome data could be explained by unrestricted gene flow between adjacent areas during expansion (Pierce, Gutierrez, Rice, & Pfennig, 2017). As predicted for a recent expansion, we find lower-than-average genetic diversity among high elevation MK individuals (≥1600 masl) in our SNP data using estimated effective migration surface modeling (Petkova, Novembre, & Stephens, 2016) to visualize genetic diversity on the landscape (Figure S7b).

Mito-nuclear discordance

The population genetic pattern inferred from our mitogenome data is discordant with the nuclear SNP dataset, although it is not inconsistent with a scenario of two colonization events to KNP. Phylogenetic analyses revealed two divergent mitochondrial lineages within mountain treeshrews; both lineages are found on both mountains, but haplogroups 1 and 2 are equally represented on MK while haplogroup 1 is more frequent on MT (Figures 3 & 4). As mentioned above, MT provided montane habitat earlier than MK. If KNP were colonized a second time by mountain treeshrews from the Crocker Range, this would explain the presence of two sympatric, divergent lineages within Kinabalu Park. The greater frequency of haplogroup 2 on MK could be

explained by the closer geographic proximity of MK to the Crocker Range (Figure S8), combined with male-biased dispersal limiting the movement of haplogroup 2 from MK to MT. There is no information on dispersal differences between sexes in mountain treeshrews. Male-biased dispersal is common among mammals (Greenwood, 1980), but female-biased dispersal has been documented in the large treeshrew (Munshi-South, 2008). Lack of recombination in the mitochondrial genome would have retained the signature of divergence between the two haplogroups whereas recombination in nuclear SNPs would result in genetic admixture between the two groups.

This pattern could also be the result of a single colonization event of two sympatric lineages that diverged elsewhere in Borneo, for example, due to isolation in interglacial refugia and mixing during glacial maxima when montane forest was at its maximum extent (Cannon et al., 2009; den Tex et al, 2010). However, this scenario implies that the colonization of KNP by mountain treeshrews would have occurred after the divergence between the two lineages ca. 450,000 ybp, which is relatively recent compared to the age of MT (at least 7 million years) and the age of the species (ca. 4 million years). Additionally, multiple colonization events to MK have been inferred in other taxa, including plants in the genus *Rhododendron* (Merckx et al., 2015).

Gawin et al. (2014) documented a similar pattern in mountain blackeyes (*Chlorocharis emiliae*) in Borneo; they found two divergent mitochondrial haplogroups on MK, with one lineage sister to a lineage found on Mt. Trus Madi, a mountain south of MK within the Crocker Range (Figure S8). The pattern inferred from SNP data in a subsequent study was not concordant, with a single lineage found on MK (Manthey et al., 2017). This similar pattern may indicate a common colonization history between mountain blackeyes and mountain treeshrews. Future studies should include broader geographic sampling of mountain treeshrews, including individuals from across the Crocker Range, to test the hypothesis of multiple colonization events and to determine the phylogeographic history of this species in Borneo.

UCEs for fine-scale population genomics

Here, we show that sequence capture of ca. 5,000 UCEs yielded two highly informative datasets (i.e. SNPs and phased pseudo-haplotype sequences) suitable for population genomics on

a fine spatial scale. These datasets resolved patterns of fine-scale, weak population structure in mountain treeshrews within KNP, an area of approximately 754 km². The SNP dataset provided sufficient statistical power to identify individuals with high probability ($P_{IDsib} = 1.54 \times 10^{-199}$), to identify putative family groups using pairwise kinship estimates, and to reveal patterns of population structure with low levels of differentiation (Figures 5a & 5b, Tables 2a & 2b).

Although our results suggest that UCE loci may be sufficiently variable for population genomic studies, more research is necessary to determine the substitution rate of these markers and its effect on demographic parameters derived from the site-frequency spectrum (Winker et al, 2018). Previous studies have suggested that the highly conserved cores of UCE loci are subject to strong purifying selection. While the strength of selection decreases and the substitution rate increases with distance from the core (Katzman et al. 2007), UCE-flanking regions may have lower diversity than other genomic markers, leading to an excess of rare alleles (Cvijović, Good, & Desai, 2018).

UCEs are valuable for studying species like the mountain treeshrew for which few genomic resources are available. RAD-seq methods also do not require reference genomes and can generate an order of magnitude more loci than UCE-based methods; this dense genomic sampling enables investigation of both neutral and adaptive differentiation (Hohenlohe et al., 2010), which is particularly important for defining conservation units (Funk, McKay, Hohenlohe, & Allendorf, 2012). However, for inferences regarding population structure and gene flow, it has been shown that fewer than 100 informative SNP loci are sufficient (von Thaden et al., 2020) and here we analyzed 1,794 independent SNPs. Additionally, the average heterozygosity of our UCE-derived SNPs is 0.23, similar to that reported in RAD-seq studies of other small mammal populations, including mice of the genera *Apodemus* (0.28, Cerezo, Kucka, Zub, Chan, & Bryk, 2020) and *Peromyscus* (0.148-0.239, Garcia-Elfring, Barrett, & Millien, 2019).

In summary, although more research is needed into the substitution rate of UCE loci and its effect on demographic inferences, our results show that UCE capture methods can be used for fine-scale population genomics, providing an additional tool for studying non-genome enabled species. UCE capture produces data with similar information content and has several benefits over RAD-seq, including 1) enabling the direct comparison of inferences drawn from the same

set of loci across species, allowing conclusions to be drawn about the effects of historical processes on diverse taxa (Lim et al., 2020), 2) offering repeatability such that studies can compare inferences for the same species across time and geographic regions (Harvey et al., 2016), and 3) enabling the use of low-quality DNA, including DNA derived from historical museum specimens (Hawkins et al., 2016; Lim et al., 2020; Lim & Braun, 2016, Tsai et al., 2019).

Conservation Implications

As a tropical montane species, the mountain treeshrew may be impacted by global climate change, which is predicted to shift montane communities in KNP upslope ca. 490 m by 2100 CE (Camacho-Sanchez et al., 2018; Still, 1999) assuming mild Intergovernmental Panel on Climate Change scenarios (IPCC 2013, www.ipcc.ch/report/ar5/wg1/). Although the factors that limit the mountain treeshrew at its lower elevational boundary are unknown, assuming that the species tracks the predicted 490 m upslope shift - whether because of climatic limitations or ecological interactions with lowland species expanding upslope - we predict that it will experience range contraction. The species already occupies the upper elevational limits within KNP, so an upslope shift in the lower bound of its distribution could not be countered with expansion at its upper limit. The lack of strong population structure across elevations means that upslope dispersal of lower elevation mountain treeshrews on MK will likely not increase extinction risk by introducing maladaptive genetic diversity (Weiss-Lehman & Shaw, 2019). However, reduction in available habitat could make the species vulnerable.

We also predict that in this scenario of upslope habitat shifts, mountain treeshrews would maintain connectivity between MK and MT. However, the Crocker Range has few peaks above 1400 masl, and connectivity between KNP and the rest of the Crocker Range could be severed (Figure S8). This highlights the importance of KNP as a future refugium for montane species, as it contains the highest peak in the region and the greatest high-elevation forested area. Conservation efforts should focus on protecting forest habitat at 900 masl outside the park to facilitate gene flow and preserve genetic diversity.

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742	
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1121	
1122	Table 1. Geographical distances between pairs of individuals with different levels of estimated
1123	relatedness based on analysis with the KING software. ANOVA and Tukey Honest Significant
1124	Differences test showed significant differences in distances between all pairs except first and
1125	second-order relatives and second and third-order relatives ($p < 0.05$).
1126	

			Average	Median	Max
			distance	distance	distance
Kinship	Relatedness	n	(m)	(m)	(m)
-	First order (Parent-				
> 0.18	offspring, siblings)	42	162.5	100.8	570.1
	Second order (e.g. half-				
0.177 - 0.0884	siblings)	56	1247	322.8	25850
0.0883 - 0.0442	Third order (e.g. cousins)	112	4819	793.0	26490
< 0.044	Distant or unrelated	2932	12310	15960	29430

Table 2. Effective population sizes and pairwise F_{ST} of population clusters with **a**) K = 3 and **b**)

K = 2. MK, Mount Kinabalu; MT, Mount Tambuyukon. N_e estimates are on the diagonal with

95% CI in parenthesis; F_{ST} estimates are below the diagonal, with associated p-values above the

1132 diagonal.

a)

K = 3	MK	MT < 2000mas1	MT > 2000mas1
MK (n=22)	125 (105–152)	0.00120	0.00010
MT < 2000 masl (n=19)	0.035	202 (157–282)	0.00050
MT > 2000 masl (n=11)	0.092	0.065	48 (40–59)

b)

K = 2	MK + MT < 2000mas1	MT > 2000masl
MK + MT < 2000 masl (n=36)	180 (160–205)	0.0001
MT > 2000 masl (n=18)	0.050	57 (52–63)

1140 Figure text.

1141	
1142	Figure 1a. Map of mountain treeshrew distribution (inset modified from IUCN 2019, with a
1143	white star indicating the location of Kinabalu National Park, KNP), and a map of sampling
1144	locations within KNP, Sabah, Borneo. Park boundaries are demarcated by dashed lines, transects
1145	by black lines, and sampling locations by white circles, with elevations at each site labeled.
1146	Shading indicates the lower and upper portions of mountain treeshrew habitat, with 900–2000
1147	masl shown in medium gray and >2000 masl in dark grey. The total number of mountain
1148	treeshrews collected and the number of unrelated individuals included in our analyses at each
1149	trapping site are as follows (unrelated/total): MK 900, 6/6; 1600 5/6; 2200 5/5; 2700 4/4; 3200
1150	5/5; MT 900 4/4; 1300 4/6; 1600 4/4; 2000 14/22; 2400 7/14.
1151	Figure 1b. Image of a mountain treeshrew and a pitcher plant (Nepenthes lowii), KNP (Photo
1152	credit: Chien C. Lee). The two species exhibit a mutualistic relationship in which mountain
1153	treeshrews feed on the sugary secretions provided by the plant and in turn provide the plant
1154	phosphorous and nitrogen through feces (Chin, Moran, & Clarke, 2010).
1155	
1156	
1157	
1158	
1159	Figure 2. Population structure and migration models evaluated using MIGRATE-N, with model
1160	rank shown below each numbered model. The best model according to Bayes factors is model 4,
1161	followed by model 5. Log marginal likelihood values are listed in Table S5. MT, Mt.
1162	Tambuyukon; MK, Mt. Kinabalu; High ≥ 2000 masl; Low ≤ 2000 masl.
1163	
1164	
1165	
1166	Figure 3. Median joining network of 34 mitogenome sequences in the 'unrelated' dataset.
1167	Haplotypes are numbered H1-H36; H4 and H16 are not included because they were removed
1168	when close relatives were trimmed from the dataset. Dashed lines represent the number of base
1169	pair differences between haplotypes except in cases where the number of differences exceeds 40.
1170	Colors correspond to the two mountains (MT, orange; MK, blue). The two haplogroups are not

shown to scale and are separated by 186 bp substitutions. Circle area is proportional to the number of individuals with each haplotype; the legend shows the size for 1 and 10 samples, respectively.

Figure 4. Elevations sampled on Mt. Kinabalu (900, 1600, 2200, 2700, and 3200 masl) and Mt. Tambuyukon (900, 1300, 1600, 2000, and 2400 masl) with the distribution of mitochondrial haplogroups per elevation shown below each transect line and SNP clusters above. Colors of

Tambuyukon (900, 1300, 1600, 2000, and 2400 masl) with the distribution of mitochondrial haplogroups per elevation shown below each transect line and SNP clusters above. Colors of each transect line correspond to localities on inset map (dark blue, MK; light blue, Poring Hot Spring MK; orange, MT). Mitogenome pie charts indicate, for each elevation, the number of treeshrews sampled with a haplotype from mitochondrial haplogroup 1 (light grey) and 2 (dark grey). SNP pie charts indicate for each elevation the proportion of ancestry assigned to cluster 1 (light grey) and cluster 2 (dark grey) by STRUCTURE with K = 2, which was determined by the Evanno method to be the most likely number of clusters. The area of each circle is proportional the number of individuals sampled at each elevation.

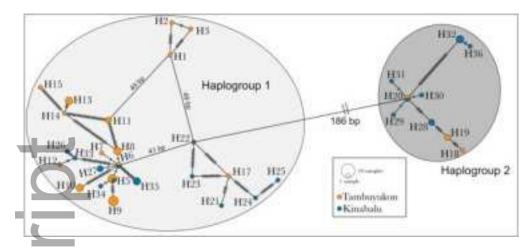
Figure 5. Cluster membership according to DAPC and STRUCTURE for **a**) K = 2 and **b**) K = 3. For each analysis, K = 2 was the best-fitting number of clusters, followed by K = 3. Each horizontal line represents a single individual with shading showing how much of each's ancestry can be attributed to each cluster. Individuals are arranged from high elevation Mt. Tambuyukon to low elevation Mt. Tambuyukon followed by low elevation Mt. Kinabalu to high elevation Mt. Kinabalu. Elevations and mountains are labeled on the Y-axis.

Figure 6. PCA plot with individuals caught on Mt. Kinabalu shown in blue circles and Mt. Tambuyukon in orange triangles. Individuals sampled at lower elevations are shaded with light colors and high elevation with dark, and each point is labeled with the sampling location elevation. PC1 explains 7% of variance and PC2 explains 4%.





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