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26							
27	ABSTRACT						
28	Aim Phenology, the temporal response of a population to its climate, is a crucial						
29	behavioral trait shared across life on earth. How species adapt their phenologies						
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to climate change is poorly understood but critical in understanding how species
will respond to future change. We use a group of flies (*Rhaphiomidas*) endemic
to the North American deserts to understand how species adapt to changing
climatic conditions. Here we explore a novel approach for taxa with constrained
phenologies aimed to accurately model their environmental niche and relate this

35 to phenological and morphological adaptations in a phylogenetic context.

- 36 **Taxon** Insecta, Diptera, Mydidae, *Rhaphiomidas*
- 37 **Location** North America, Mojave, Sonoran and Chihuahuan Deserts.

Methods We gathered geographical and phenological occurrence data for the 38 39 entire genus *Rhaphiomidas*, and, estimated a time calibrated phylogeny. We 40 compared Daymet derived temperature values for a species adult occurrence 41 period (phenology) with those derived from WorldClim data that is partitioned by 42 month or guarter to examine what effect using more precise data has on 43 capturing a species' environmental niche. We then examined to what extent 44 phylogenetic signal in phenological traits, climate tolerance and morphology can 45 inform us about how species adapt to different environmental regimes.

Results We found that the Bioclim temperature data, which are averages across monthly intervals, poorly represent the climate windows to which adult flies are actually adapted. Using temporally-relevant climate data, we show that many species use a combination of morphological and phenological changes to adapt to different climate regimes. There are also instances where species changed only phenology to track a climate type or only morphology to adapt to different environments.

Main Conclusions Without using a fine-scale phenological data approach, identifying environmental adaptations could be misleading because the data do not represent the conditions the animals are actually experiencing. We find that fine-scale phenological niche models are needed when assessing taxa that have a discrete phenological window that is key to their survival, accurately linking

- 58 environment to morphology and phenology. Using this approach, we show that
- 59 Rhaphiomidas use a combination of niche tracking and adaptation to persist in
- 60 new niches. Modeling the effect of phenology on such species' niches will be
- critical for better predictions of how these species might respond to future climatechange.
- 63 **KEYWORDS:** Environmental niche modeling, environmental adaptation,
- 64 phenology, Maxent, phyloclim, niche conservation, Daymet, niche partitioning
- 65

66 INTRODUCTION

67 Evaluating species response to climate change and predicting future 68 distributions is of concern to ecologists, evolutionary biologists and policy makers 69 interested in preserving biodiversity (Parmesan, 2006). In addition, identifying whether a particular species or population adapts to climate change by adjusting 70 71 its phenology or morphological/physiological traits, as opposed to changing its 72 range via dispersal, is key to predicting future distributions, extinctions (Holt, 73 1990) and community disassembly (Sheldon et al., 2011). Dispersal is often 74 assumed to be the primary response of populations and species to climate 75 change (Thomas et al., 2004); however, this might not be the case (Visser, 76 2008). Dispersal limitation and heterogeneous or fragmented landscapes could 77 preclude spatial tracking of climatic niches (Hof et al., 2011). In such cases, 78 populations must adapt their phenology and/or morphology in order to persist 79 (Hoffmann & Sgrò, 2011). Such adaptation, however, is often not accounted for 80 in models of species' responses to climate change (Bradshaw & Holzapfel 2008; 81 van Asch et al. 2007).

Phenology plays a critical role in the reproductive cycles and developmental processes of many organisms (Mitchell et al., 2008; Banta et al., 2012; Zohner & Renner, 2014; Gerst et al., 2017; Zhang & Hepner, 2017). The past century of climate change has already produced measurable changes in phenology, especially in plants (Ellwood et al., 2013; Everill et al., 2014; Zohner & Renner, 2014). Therefore, finding a better way to model critical environmental conditions linked to phenological cycles and examining how different species

adapt their phenologies is important for understanding species' ecologies and
their conservation. Phenological responses have been identified and tested
through long-term ecological studies (Miller-Rushing & Primack, 2008) but can
also be understood in a phylogenetic context along with morphological evolution.

Here, we use a group of flies (Diptera: Mydidae: *Rhaphiomidas* Osten Sacken, 1877; Fig. 1) endemic to the North American deserts to understand how species adapt to changing climatic conditions. Specifically, we are interested in whether the flies change their emergence time to track the same basic seasonal climate window, or whether the adult flies adapt physiologically/morphologically to changing climate during that window.

99 The genus *Rhaphiomidas* is distributed throughout the deserts of the 100 Southwestern United States and Northern Mexico (Cazier, 1985; Van Dam, 101 2010). Most species of Rhaphiomidas feed on floral nectar as adults and thus 102 phenological matching with their plant resources may be critical for both 103 mutualists. Species are either restricted to aeolian (wind-blown sediments) sand dunes (15/27 species) or loose alluvial sands (Van Dam, 2010), with many 104 105 species (9/27) endemic to a single dune system. *Rhaphiomidas* adults fly in the 106 spring and fall and are most active during spring and fall blooms. Some species 107 do not appear to feed as adults, making the synchronization of their activity all 108 the more important for reproductive success. Multiple studies have been 109 conducted on the behavior of adult flies, noting the temperatures requirements for adult flight activity (Toft & Kimsey 1982; Ballmer et al. 1994; Rogers & Mattoni 110 111 1993; Kingsley 1996). Larvae and pupae of *Rhaphiomidas* are entirely 112 subterranean at depths of up to 1.5 m (M.H.V.D pers. obs.) and thus only 113 experience the ambient climate for the short duration of their lives spent above 114 ground. This dramatically discrete phenology makes them ideal for studying 115 phenological response to climate.

Studies of climatic niches typically depend on species distribution models
to understand the correlation between a species' occurrences and underlying
climatic variables (Warren et al., 2018). Such studies rarely incorporate
phenology when reconstructing niche occupancy, often using only monthly

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averaged WorldClim data (Hijmans et al., 2005). Constraining climate data to
monthly averages may misrepresent the climate that species are actually
experiencing. Although the WorldClim variables are appropriate for capturing
realized niches based on abiotic environmental factors experienced year-round,
such as for perennial plants and some mammals, reliance on these variables
could lead to biased predictions for an entire suite of organisms that have
discrete phenologies.

127 To solve this problem, we used climate data that were averaged by day at a 1km square scale available from Daymet (Thornton et al. 2014). To measure 128 129 how species adapt to different climate conditions, the Daymet-based approach 130 was put in a phylogenetic framework to test whether phenological adaptation 131 (niche tracking) or physiological/morphological adaptation (niche adapting) has 132 occurred. A phylogenetic framework allows us to account for the role of shared 133 evolutionary history (Felsenstein 1985) in producing the observed correlations 134 between traits and niche preference. We can also infer the evolutionary history of adult niche preference and measure the rate at which changes have occurred. 135

136 Understanding how species adapt to climate change in different climate 137 regimes by adapting their morphology and physiology is also important for 138 mitigating extinction risk due to climate change (Visser, 2008). For many species 139 that rely on ambient temperature for thermoregulation, climate change is 140 predicted to have a negative effect on their survival (Quintero & Wiens, 2013). In 141 general, species or populations that are poikilotherms (commonly known as cold-142 blooded) have a darker coloration in colder environments (Shapiro, 1976; 143 Kingsolver & Wiernasz 1991). For example, reptiles become darker in colder 144 conditions to maintain activity (Bittner et al., 2002; Rosenblum, 2005). This 145 adaptation helps them achieve metabolic activity more quickly. We propose that 146 the dark coloration seen in some *Rhaphiomidas* species is an adaptation 147 facilitating absorption of more solar energy, thereby allowing increased activity in 148 cooler climates. Here we are not interested in prediction of niche equivalency, 149 per se, but are interested in linking the daytime temperatures the flies experience 150 with their phenology and body coloration. As *Rhaphiomidas* is found on habitat

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- 151 islands and cannot simply migrate to a new island range, we aim to infer how
- 152 these species adapt to different environmental conditions by using the
- 153 intersection of phenology, temperature and coloration.
- 154 155
- 156 METHODS
- 157 Analysis Pipeline

In order to test for phenological changes that track a niche and/or if
species adapt to environmental conditions, we analyzed a diverse set of data
(environmental and phylogenetic). The methods can be broken down into five
parts:

 We processed environmental variables and constructed niche models.
 We created predicted niche occupancy profiles (PNO, in particular thermal maximum) to relate the physical temperature corresponding to

- 165 probability densities of the niche model (Elith et al., 2011).
- 166 **3**) We constructed a time-calibrated phylogeny for *Rhaphiomidas*.
- 167
 4) Using the phylogeny, we tested whether species possessing dark
 168
 169
 adaptive response to colder temperatures and examined ancestral
- 170 state reconstruction using phylogenetic comparative methods to
 171 ensure this wasn't an artifact of inheritance.
- 172 5) We combined phylogenetic reconstructions of traits (morphology,
 - phenology and temperature) to see if sister species changed their
 - phenology relative to changes in temperature and morphology.
- 175

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176 DNA Data and Alignment

- 177 *Rhaphiomidas* sequences were taken from Van Dam & Matzke (2016).
- 178 Contigs were assembled and edited in Geneious Pro v. 4.6.4 (Biomatters Ltd.).
- 179 Sequences were aligned by ClustalW-2.0.10 (Larkin et al., 2007) with parameters
- 180 set to GAPOPEN=90.0, GAPEXT=10. Sequences were colored by amino acid in

181 Mesquite version 2.71 (Build 514) (Maddison & Maddison 2009) to check for stop182 codons.

183

184 *Phylogenetic Analyses*

185 We obtained data for 219 individuals, including 183 Rhaphiomidas 186 exemplars and 36 outgroup samples. These data comprised 2904 bp of mtDNA 187 (COI, COII, and 16S genes), and 3720 bp of nDNA (EF1alpha, PGD, snf, Wg, and CAD). The best partitioning scheme was determined in PartitionFinder 1.1.1 188 189 (Lanfear et al., 2012) using the 'greedy' algorithm. The partitioning scheme was 190 selected using the Akaike information criterion corrected for sample size (AICc). 191 Relationships among *Rhaphiomidas* species were reconstructed using Bayesian 192 Inference (BI) implemented in MrBayes 3.2 (Ronguist et al., 2012). Reversible-193 jump MCMC was used to explore the entire model space of the general time 194 reversible (GTR) substitution models for our different character sets 195 (Huelsenbeck et al., 2004). We ran two independent runs comprising eight total 196 Markov Chains for 70 million generations, sampling every 1000th generation. 197 Split-frequencies and log-likelihood curves were examined in Tracer 1.5.3 (Rambaut & Drummond 2018). 198

199 The first 35,000 of the 70,000 trees sampled were removed as burnin. 200 Standard deviation of split-frequencies < 0.05 between the two MrBayes runs 201 suggested reasonable convergence. A maximum clade credibility tree was 202 constructed with *DendroPy SumTrees* function (Sukumaran & Holder, 2010) 203 using median edge lengths. This tree was inspected for evidence of 204 mitochondrial introgression as in McGuire et al., (2007). The dataset was then 205 pruned to a single specimen per species, preferring specimens with the 206 most complete sequence that did not show signs of mitochondrial introgression. 207 This was done because Yule and Birth Death (BD) tree priors in BEAST treat 208 every tip as a species; a tree with multiple specimens for each species can result 209 in a biased date inference (Drummond & Bouckaert, 2015). The MrBayes tree 210 was pruned to the same specimens, and the pruned dataset was analyzed in 211 BEAST version 1.8.2 (Drummond et al., 2012) with the pruned MrBayes tree

212 serving as the starting topology for phylogenetic dating analyses. We used 213 stepping stone (SS) sampling (Drummond et al., 2016) to select the tree prior 214 (Birth-Death chosen over Yule) and clock model (a lognormal relaxed clock 215 chosen over strict clock). The MCMC process was run for 4x10⁷ generations 216 sampling every 1000 generations. Stationarity was assessed using Tracer 217 version 1.5.3. The effective sample size (ESS) for model parameters was also 218 examined to assess the adequacy of the post-burnin samples. The tree was 219 calibrated using a fossil calibration point for the origin of the Mydinae in the late 220 Cretaceous (Martill et al., 2007) using a normal distribution with a mean of 120 221 Ma and a standard deviation of ±10 Ma.

222

223 Data Acquisition/Niche Modeling

224 Specimen data for Rhaphiomidas were acquired from museum collections 225 (EMEC, CAS, UCR, LACM) and previously published literature (Cazier 1985; 226 Rogers and Mattoni 1993; Rogers and Van Dam 2007; Van Dam 2010), as well 227 as from the personal collection of M.H.V.D. Locations were georeferenced in 228 ArcGIS (ESRI 2011) and were recorded in both WGS 84 (degrees-minutes-229 seconds) and Lambert Conformal Conic projection required for Daymet 230 georeferencing (http://daymet.ornl.gov/datasupport). A total of 409 occurrence 231 points were included, with an average of 15 per species, median 13 and a range 232 of 10–40. Several species are endemic to a single dune system, so 10 points 233 were randomly scattered across the spatial extent of such dune fields. This 234 number was selected because it has been demonstrated to be a reasonable 235 minimum number of points needed for species distribution models using Maxent 236 (Hernandez et al., 2006; Evans et al., 2009, van Proosdij et al. 2016). To obtain 237 the most accurate possible temperature estimates when adult flies are active, we 238 extracted climate data from the Daymet climate data base (Thornton et al. 2014). 239 This allowed us to partition climate data by day and average over a species' 240 occurrence time (typically weeks) rather than using monthly averages. A list of 241 the Daymet tiles is provided in the Supporting Information. The 1 km by 1 km 242 resolution tiles were downloaded from years 1980–2011. A total of six variables

were used from the Daymet database (vapor pressure *vp*, day length *dayl*, precipitation *prcp*, solar radiation *srad*, temperature max *tmax* and temperature minimum *tmin*). The data totaled just over 2 terabytes of information. The first and last occurrence times were recorded from the specimen data (Fig. 1) and used to define the time slices to extract from the Daymet climate data.

248 Extracted environmental variables were averaged over the 30 years. 249 Precipitation data were summed by time slice and then averaged across years. 250 This procedure was performed in R statistical software with a custom script (see 251 Supporting Information). We utilized the R packages ncdf4, raster, maps and 252 dismo for this process (Hijmans & van Etten, 2012; Becker et al., 2017; Hijmans 253 et al., 2017; Pierce, 2017). Niche models were constructed in MaxEnt (Phillips et 254 al., 2006) using the R package *dismo*. We examined collinearity of predictors 255 using SDMTools (Warren et al., 2018; Warren et al., 2010).

To evaluate the extent to which Daymet and BioClim representations of the same geographic point diverge, we extracted temperature values from each respective raster layer for the same point. Because *Rhaphiomidas* are late spring and summer active species, we compared the values of the tmax (Daymet) data with Bioclim BIO5 (Max Temperature of Warmest Month) and BIO10 (Mean Temperature of Warmest Quarter).

262

263 Predicted Niche Occupancy

264 To identify how *Rhaphiomidas* lineages adapted to change in different 265 climate regimes, we constructed each species' predicted niche occupancy 266 (PNO) profile from the cumulative probability of occurrence against the 267 environmental data (Evans et al., 2009). We then used the PNO to calculate the 268 weighted mean for each species. PNO profiles were constructed in *phyloclim* 269 (Heibl & Calenge, 2013), and 100 random samples were drawn from the PNO 270 profile as in Evans et al. (2009) to calculate the weighted mean. Calculations for 271 PNOs from the Daymet data were derived using a slightly different method than 272 those for the Bioclim data. Because each one of our Daymet environmental 273 layers is unique to each taxon, some values were not found among layers. Thus, we first calculated the range across all individual taxa layers for a variable and
then merged the PNO files by taking the floor to the nearest °C. For instance,
32.5456845°C in species-A PNO and 32.59975962°C in species-B PNO were
changed to 32°C in the two PNOs, so they can then be used for calculating the
weighted means as above.

279

Evaluating the correlation between temperature and body color of Rhaphiomidas
We categorized fly coloration according to the following rules:1) if the first
3 abdominal tergites were almost entirely black, they were coded as dark, 2) if
the first 3 abdominal tergites were orange or silver they were coded as pale.
Because there were no intermediate states, we treated these as discrete.

285 To examine whether colder daytime temperatures are correlated with a 286 darker body color while accounting for shared evolutionary history, we used a 287 threshold model from quantitative genetics (Wright, 1934; Felsenstein, 2012), 288 using MCMC to sample the unknown liabilities in a postulated continuous trait 289 underlying a discrete character. We used the R package phytools 0.3-72 (Revell, 290 2012), which implements this model in the function *threshBayes*. To account for 291 differences in branch lengths and topologies from our posterior distribution of 292 trees, we sampled 10% of the posterior trees resulting in 3900 sampled trees. 293 We then measured the correlation between the two characters over this set of 294 trees. We ran the MCMC chain for $5x10^6$ generations sampling every 1,000 295 generations for each tree. After examining the trace plot of the posterior, we set a burn-in of 10%. 296

297

298 Identifying Coloration Shifts

To identify shifts in coloration, we reconstructed ancestral states for coloration on the phylogeny. First, we sorted the trees from the BEAST posterior (minus the burnin) according to their topologies (grouping identical topologies together). We used the *DendroPy SumTrees* function (Sukumaran & Holder, 2010), taking median edge lengths, to create a representative strict consensus tree for each set of unique topologies. We then used a Bayesian threshold model implemented in *phytools* with the function *ancThresh*, running 2.5x10⁵ MCMC
 generations sampling every 1,000 with a burnin of 50 over each unique topology.

308 Ancestral State Reconstructions and Evaluating Climate Disparity Through Time 309 To reconstruct ancestral states for the continuous traits of temperature 310 and occurrence time (phenology), we first determined the best evolutionary 311 model, Brownian Motion (BM) or Ornstein–Uhlenbeck (OU), given our tree and 312 data using the *fitContinuous* function in *geiger* (Harmon et al., 2008). In instances 313 where the OU model was selected, we used a modified version of the phytools 314 function contMap where the internal anc.ML function was set to the OU model. 315 Ancestral state estimates were used to measure the relative amount of 316 disparity between sister nodes using *geiger*'s disparity function to calculate the 317 average squared Euclidean distance in each clade. To visualize the amount of 318 change between nodes on the tree, we plotted a phenogram for both traits using 319 the *phenogram* function of *phytools*. We also calculated the difference between 320 parent and daughter node values (normalized temperature and phenology) from 321 our *contMap* reconstructions using a custom R script utilizing functions from 322 BioGeoBEARS (Matzke 2014). These values were used to color the branches

323 and help visualize the change in trait values along the tree.

324

325 **RESULTS**

7

326 Molecular Data and Phylogenetics

327 The BEAST analysis indicated that *Rhaphiomidas* is sister to the 328 remaining Mydidae, and these groups together are sister to the Apioceridae (see 329 Supporting Information). All model parameters had an ESS (effective sample 330 size) >200, suggesting sufficient sampling of the posterior distribution. The root 331 node of *Rhaphiomidas* is estimated to have diverged 70 ± 42Ma (node height 332 95% HPD), with most of the species diversifying in the last 18.5 ± 11 Ma. 333 Terminals showing evidence of introgression were removed, leaving a topology 334 that was also congruent with species concepts. From the Stepping Stone 335 sampling results, we rejected the strict clock prior and Yule tree prior in favor of

the relaxed lognormal clock prior and the Birth-Death tree model (SupportingInformation).

338

339 Niche Modeling Results

340 First, we compared the distributions of point values for temperature 341 extracted from raster layers between the Daymet tmax data and Bioclim BIO5 342 and BIO10. We found that the Bioclim data did not adequately reflect the 343 conditions that these species were experiencing as adults (Fig. 2). Many of the Bioclim values were outside of the species' temperature range and further did not 344 345 show differentiation between allochronic species, especially in the case of BIO5. 346 Because the measurements of these two data sets are otherwise congruent 347 (Hijmans et al. 2005), this difference is mostly due to the time periods binned in 348 making the rasters. As the maximum temperature is key to understanding further 349 hypotheses of morphological adaptations, we proceeded using the Daymet raster 350 layers because they are more representative of the environmental conditions that 351 these species experience.

352 The collinearity between the predictor variables varied between strongly 353 correlated (tmax and tmin) to highly uncorrelated (vapor pressure and solar 354 radiation) (see Supporting Information). Given the small number of predictors and 355 the biological importance of tmax and tmin we left both of these predictor 356 variables in further analyses of species' niches. The contribution of the six 357 bioclimatic variables varied considerably between species. Variables, such as 358 precipitation, consistently contributed to large percentages of the model 359 probability – 90% in the case of *R. undulatus*. Other variables such as DayLength 360 contributed modestly to the model predictions, ranging up to 30% for *R. xanthos*. 361 AUCs varied from 0.65 to 1 (see Supporting Information). The weighted mean for tmax ranged from 25.1 – 38.5° C across species. 362

363

364 Evaluating the Correlation between Temperature and Body Color

365 The mean correlation coefficient between color and temperature is -0.70 366 over all trees, indicating that as temperature decreases, there is a trait change from pale to dark (pale coded as 0 and dark coded as 1; Fig. 3). The 95% HPD
varied from -0.93 to -0.25, and none of the individual trees examined had a 95%
HPD that overlapped with zero (Supporting Information). Because this is a
Bayesian analysis, significance is assessed through the 95% credible interval
and its overlap with 0. Our 95% credible interval does not overlap with zero (Fig.
3).

373

374 Identifying Coloration Shifts

The common ancestor of *Rhaphiomidas pachyrhynchus* and *R. episcopus* was estimated to have dark coloration in all tree topologies. Only 2/48 topologies (representing only 3/3900 trees) had any other nodes reconstructed as dark in coloration. Thus, the ancestral states are likely pale for all but one node in the tree. The results of the maximum clade credibility tree are shown in Fig. 4.

Ancestral State Reconstructions and Evaluating Climate Disparity Through Time
 The OU model was an overwhelmingly better fit than BM for weighted
 mean tmax dAICc [OU:0, BM:32.6278], but BM was slightly preferred for

384 phenology dAICc [OU:0.441541, BM:0].

385 The results of the *contMap* reconstructions suggest most species of 386 Rhaphiomidas tend to occupy a relatively warm climate space, and most species 387 occur in late spring with only a few phenological shifts from spring to fall 388 (Fig. 5). We find relatively few nodes where there is more disparity in 389 temperature than in phenology (6 of 26), with 4 of 26 nodes showing 390 approximately equal disparity between temperature and phenology and 16 of 26 391 nodes showing more disparity in phenology than in temperature (Fig. 6). In 392 addition, the largest shifts in temperature occur at the terminal nodes in the tree, 393 whereas large shifts in phenology occur at both internal and terminal nodes (Fig. 394 7). 395

396 **DISCUSSION**

397 Our results indicate that extracting climate data to match species' 398 phenological activity better exemplifies environmental conditions than the 399 traditional Bioclim variables. Understanding the basic life history of an organism 400 can go a long way toward producing more realistic niche models. Many animals, 401 especially desert-adapted species, partition their life histories in response to local 402 conditions and so share similar phenologies. For example, desert tortoises, 403 Gopherus agassizii, spend the majority of their life underground in burrows, only active above ground for 153 hours per year (Nagy & Medica 1986). Modeling the 404 405 effects of phenology on such species' niches will be critical for better predictions 406 of how these species might respond to future climate change. Additionally, our 407 results show that *Rhaphiomidas* species adapt to different environments by 408 evolving darker coloration (in colder conditions) and shifting phenologies.

409

410 Using Accurate Temporal Data Improves Biological Insight

411 Our approach can be tailored to produce species specific environmental 412 layers to best capture conditions that species are actually experiencing. This can 413 be seen by examining the raw values obtained from the raster layers (Fig. 2). For 414 example, when we look at a set of species that are partially sympatric but are 415 separated temporally, the Bioclim data does not recover many differences 416 between the species. By contrast, the Daymet data shows temperature values as 417 completely separate or partially overlapping for both species. For example, 418 Rhaphiomidas sp. "arenagena" is active earlier in the year compared to R. sp. 419 "rex". Their Bioclim BIO5 profiles overlap in temperature, whereas they do not 420 overlap in the Daymet inference. This is seen with all the species that are 421 partially sympatric but separated in time, as well as for some of the allopatric 422 species that are also separated in time.

This result demonstrates a larger point that ecological inferences, such as testing for phylogenetic niche conservation of a trait related to temperature or another environmental variable, should not be made based on data that do not accurately link environmental data to the traits in question. By using environmental layers that are tailored to a species' phenology in space and time, 428 this will lessen misinterpretations of evolutionary trends, such as niche

- 429 conservatism, due to the autocorrelation between geography and environment
- 430 for species in allopatry (Warren et al. 2014). An abundance of data sources, such
- 431 as Daymet, NDVI, and other MODIS data that are binned in daily or bi-weekly
- 432 intervals, provide the much-needed data to make more accurate ecological and
- 433 evolutionary inferences.
- 434
- Niche Shifts Through Color Evolution and Niche Tracking Through Changes in 435 436 Phenology

437 *Rhaphiomidas* adapt to cooler conditions by evolving large areas of 438 maculation (i.e. becoming darker), allowing them to emerge at times when 439 conditions are less than optimal for them to fly efficiently or at all. Combining our 440 threshBayes and ancThresh analyses, and the evidence from behavioral 441 observations of activity (Cazier 1985; Kingsley 1996, 2002), we interpret the dark 442 coloration of the cooler temperature species as an adaptation to warm 443 themselves in order to take flight. This adaptation for dealing with cooler 444 temperatures has allowed *Rhaphiomidas* to deviate from their thermal mean (as 445 determined from ancestral state reconstructions) and allowed them to expand to 446 new habitats.

447 Results from *threshBayes* analyses recover a significant and relatively 448 strong correlation between temperature and coloration. This correlation is 449 expected as Rhaphiomidas adults are usually only active above 26.6 °C 450 (Kingsley, 1996, 2002). Efficient warming for adequate flight is likely especially 451 important for larger flies, such as Rhaphiomidas species, as their greater mass 452 would require more time and energy to heat up. This phenomenon of darker 453 coloration allowing ectotherms to warm themselves has been demonstrated in 454 many taxa (Clusella Trullas et al., 2007; Svensson & Waller, 2013).

455 Our *ancThresh* results consistently recovered one ancestral node as dark 456 in coloration – the *R. pachyrhynchus* and *R. episcopus* parent node. All other 457 transitions in the tree were from pale to dark coloration, occurring only along the 458 terminal branches, indicating that the observed dark coloration is not simply due

to inheritance but instead a response to cooler environments. However, there are
two dark *Rhaphiomidas* species that occur in relatively hot environments – *R. episcopus* and *R. trochilus*. In the case of *R. episcopus*, its dark coloration
appears to be because the transition to this coloration occurred in the ancestor
(Fig. 4). The reason the dark coloration is maintained in these species is not
entirely clear and requires further investigation.

465 The ancThresh reconstructions in concert with the results from contMap can facilitate the identification of environmental niche tracking and/or adaptation 466 to niches via phenology or coloration change. We found that all species were 467 468 most likely pale in coloration ancestrally, indicating that changes are likely 469 influenced by environment and not solely inheritance. We identified that some 470 species evolved phenologies that are divergent relative to their sister taxon 471 (Table 1). In addition, only one species experienced a shift in coloration solely as 472 a response to cooler temperatures – R. acton maculatus. The other dark species 473 changed both phenology and coloration, save R. pachyrhynchus and R. 474 episcopus, which share a dark coloration ancestor. All other dark species, except 475 *R. episcopus*, have denser setation (hairs), perhaps serving as insulation and 476 providing additional morphological evidence of adaptation to a cool environment. 477 Our findings demonstrate that most *Rhaphiomidas* species tend to change 478 their phenology as opposed to adapting their coloration to fit the climate, 479 suggesting that phenology is a more labile trait. For example, R. sp. "rex" 480 emerges about a month earlier than its sister taxon, R. acton. For both species, 481 their phenologies coincide with late spring blooms in their different ranges 482 (personal obs., M.H.V.D.). A phenology much later or earlier would render them 483 unable to take advantage of these nectar resources. Their phenology should be a 484 balance between resources availability and optimizing temperature. However, 485 some species do not feed as adults, such as *R. hirsuticaudus* (Cazier 1985, 486 personal obs. M.H.V.D.), so phenology should play an even more important role 487 for such species to synchronize their emergence for reproduction.

488

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679 SUPPORTING INFORMATION

- 680 Supporting Information link: <u>https://figshare.com/s/0db26157b3b8c4cb3804</u>,
- 681 https://figshare.com/s/a680df82acaa692ecd79
- 682

683 DATA ACCESSIBILITY

- 684 We have permanently uploaded all relevant data to figshare to make the
- 685 research fully reproducible: Supporting Information link:
- 686 https://figshare.com/s/0db26157b3b8c4cb3804
- 687 https://figshare.com/s/a680df82acaa692ecd79
- 688

689 AUTHOR CONTRIBUTIONS

690 M.H.V.D. performed sampling, sequencing, phylogenetic dating, and wrote the

691 first paper draft. A.J.R. wrote R scripts for Daymet data processing and PNO

692 calculations, and M.H.V.D. and M.S.B. contributed to additional R scripts and

- 693 informatics pipelines. All authors contributed to experimental design, analyses of
- 694 the data, and final paper draft.
- 695

696 **BIOSKETCHES**

697 **Matthew H. Van Dam** is interested in the interaction of geological processes and

natural history of organisms in shaping biogeographical patterns; he is also

699 interested in weevil systematics, including their evolution and improving

- 700 phylogenomic methods.
- 701 Andrew Rominger is interested in how and why evolutionary history drives
- contemporary ecological dynamics. He approaches this challenge both from a
- theoretical perspective, building and testing synthetic theories of biodiversity
- based on statistical mechanics, and from an empirical perspective, collecting and

analyzing new data about the evolution and ecology of arthropod diversity inisland-like systems.

Michael S. Brewer uses genomics tools, bioinformatics, and arthropods as
 model organisms to answer broad evolutionary questions, especially those
 concerning the mechanisms that create and maintain biodiversity. Specific
 interests include taxonomy, biogeography, phylogenetics, and the evolution of
 complex traits (e.g., venomics, color evolution, and complex trait evolution).

712



		Phenological	Temperature	
	Dark (D)	shift relative	shift relative	
	or Light	to sister	to sister	Relative combined change to
	(L)	taxon or	taxon or	environment relative to sister
Taxon	species	node	node	taxon or node
R. xanthos	L	none	slightly cooler	no adaptive response
			slightly	
R. painteri	L	none	warmer	no adaptive response
R. forficatus	L	earlier in year	warmer	adaptive niche tracking, phenology
				niche adapting, phenology and
R. socorroae	D	later in year	cooler	color
			slightly	
R. moapa	L	earlier in year	warmer	adaptive niche tracking, phenology
R. parkeri	L	earlier in year	none	adaptive niche tracking, phenology
R. tarsalis	L	later in year	warmer	adaptive niche tracking, phenology
R. hasbroucki	L	earlier in year	cooler	adaptive niche tracking, phenology
				niche adapting, phenology and
R. scopaflexus	D	earlier in year	cooler	color
R. "arenagena"	L	later in year	warmer	adaptive niche tracking, phenology
R. undulatus	L	later in year	none	adaptive niche tracking, phenology
R. auratus	L	earlier in year	none	adaptive niche tracking, phenology
				niche adapting, phenology and
R. acton maculatus	D	later in year	slightly cooler	color
			slightly	
R. "pseudonigricaudis"	L	earlier in year	warmer	adaptive niche tracking, phenology
R. "rex"	L	earlier in year	none	adaptive niche tracking, phenology

R. acton	L	later in year	none	adaptive niche tracking, phenology
			slightly	
R. trochilus	D	later in year	warmer	adaptive niche tracking, phenology
R. aitkeni	L	none	none	no adaptive response
R. nigricaudis	L	earlier in year	none	adaptive niche tracking, phenology
R. ballmeri	L	earlier in year	none	adaptive niche tracking, phenology
				niche adapting, phenology and
R. terminatus	D	earlier in year	cooler	color
R. terminatus				niche adapting, phenology and
abdominalis	L	later in year	warmer	color
R. episcopus	D	none	warmer	no adaptive response
R. pachyrhynchus	D	none	cooler	no adaptive response
				niche adapting, phenology and
R. hirsuticaudus	L	later in year	warmer	color
				niche adapting, phenology and
R. spinicaudus	D	earlier in year	cooler	color
R. brevirostris	L	earlier in year	warmer	adaptive niche tracking, phenology

715

716 **Table 1.** Summary of results identifying whether species adapt by tracking a

niche by changing their phenology (adaptive niche tracking) or by strictly

adapting to their niche through changing their coloration (niche adapting) or a

combination of both. The factor(s) that evolved is/are listed after the adaptive

response (niche tracking or niche adapting).

721

722

Figure 1. Upper left, *Rhaphiomidas pachyrhynchus* adult male, *R. sp. "pseudonigricaudis"* adult male. Central panel, Activity duration of *Rhaphiomidas*species. Upper right, daily values over a species' adult activity length. Lower
left, resulting raster layers for each environmental variable averaged or summed
in the case of precipitation over the activity length period of a species. Lower
right, resulting environmental niche model from custom raster layers for a
species.

731 **Figure 2.** Box plots of temperature values extracted from occurrence points:

732 Mean daily maximum temperature (tmax) from Daymet data (yellow), Bioclim

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- 733 Bio10 mean temperature warmest quarter (blue), Bioclim Bio5 maximum
- temperature warmest month (green). *R. "arenagena"* and *R. "rex"* are partially
- 735 sympatric but emerge at different times (allochronic). *R. hasbroucki* and *R.*
- 736 *parkeri* are also partially sympatric but are allochronic. *R. tarsalis* is the sister
- taxon to *R. hasbroucki*, they are allopatric and allochronic.
- 738

Figure 3. *threshBayes* posterior density distribution of the correlation between *Rhaphiomidas* body color (dark or light) and Daymet mean daily maximum temperature. The histogram shows the posterior distributions of 3900 trees (10% of the sampled trees), the solid red line indicates the grand mean, the dashed lines indicate the mean of the 95% confidence intervals. None of the individual 95% confidence intervals from the set of trees overlap with zero, indicating a significant correlation, robust to topology and branch lengths.

746

Figure 4. *Rhaphiomidas* maximum clade credibility tree, with ancestral state
reconstructions for body coloration. Ancestral light or dark coloration was
reconstructed via the *ancThresh* function in the *phytools* R package (Revell
2012). The analysis was run for 2.5x10⁶ MCMC generations, sampling every
1000, with a burnin of 50.

752

7

Figure 5. Results of the *contMap* ancestral state reconstructions. Left tree, ancestral state reconstructions for mean daily temperature maximum value, warmer colors along branches indicate warmer maximum temperatures. Right tree, ancestral state reconstructions for mid-occurrence times, warmer colors along branches indicate occurrence times later in the year. Orange rectangles indicate species with a light coloration, black boxes indicate species with a dark coloration.

760

Figure 6. Cladewise disparity in phenology and temperature. **Top**, *Rhaphiomidas*

chronogram with nodes colored by age, correlating to colors used in the panels

below. **Middle**, temperature and phenological cladewise disparity of each subtree

measured as average squared Euclidean distance. The Y-axis represents the
cladewise disparity, and the X-axis is measured in millions of years. Bottom,
temperature and phenological cladewise disparity of each subtree measured as
average squared Euclidean distance. The Y-axis represents the cladewise
disparity, and the X-axis is node chronological order, oldest to youngest. Arrows
indicate nodes that are followed by a transition from light to dark coloration along
one of their descendant branches.

771

772 Figure 7. Color phenogram for mean daily maximum temperature (right half) and 773 phenology (left half). Branch colors represent relative differences from parent to 774 daughter nodes, similar to differences in the placement of parent to daughter 775 nodes along the Y-axis as represented in the phenograms below, but phenogram 776 nodes represent values not relative differences. Left half colors represent shifts 777 to warmer or cooler temperatures between nodes (warmer colors = warmer shifts 778 in temp., cooler colors = colder shifts in temp. relative to parent node), right half 779 branch colors represent shifts in phenology (shifts later in year = warmer colors, 780 earlier in year = cooler colors) relative to parent node. Orange rectangles indicate 781 species with a light coloration, and black boxes indicate species with a dark 782 coloration.

783 784

Figure 10





Comparison of Temperature Data Sources between Allochronic Species



Posterior Rhaphiomidas color temperature correlation









jbi_13663_f2.pdf Comparison of Temperature Data Sources between Allochronic Species



Posterior Rhaphiomidas color temperature correlation



R-squared







Phenological and Temperature clade disparity

Phenological and Temperature clade disparity

node chronological order

